THE ETHICS ENGINE: OPERATIONALIZING REFLECTIVE PRACTICE IN INTERDISCIPLINARY AI IN EDUCATION TEAMS

by
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Abstract

Incorporating AI into educational technology products requires interdisciplinary collaboration and moral resilience to meet the needs of educators and students. Teams of ed tech professionals, including data scientists, AI engineers, learning scientists, user researchers, and instructional designers, must navigate challenges such as interdisciplinary communication, negotiating decision-making power balances, and navigating their understanding of one another's roles. These challenges impact their ability to integrate perspectives and maintain moral resilience. Inadequate integration of interdisciplinary perspectives across the team during design and development reduces the ability to address fairness, accountability, transparency, and ethics in AI-integrated product. Complex Adaptive Systems Theory analyzes how upstream team dynamics influence moral resilience and decision-making, leading to unintended consequences. An explanatory sequential study explores product team members' experiences, collecting quantitative data on disciplinary perspectives, attitudes toward AI, shared mental models, moral resilience, sociotechnical imaginaries, agile methodologies, and reflective design practice. This study suggests future support areas. Additionally, design thinking and reflective practices stand to benefit interdisciplinary ed tech teams, improving decision-making and overall design quality. A conversation-based assessment minimum viable product combining these approaches supports ongoing engagement in reflective practice and design thinking in the creation of learner- and educator-centered ed tech.

Keywords: Artificial intelligence in education, interdisciplinary team collaboration, Complex Adaptive Systems Theory, design thinking, reflective design practice.

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Dedication

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To my grandfather, Paul, who passed more than twenty years ago – you taught me to tinker, to create, to figure things out on my own. I'd like to think you'd appreciate the ways I've been cobbling together different generative AI approaches, even if AI wasn't something you ever worked with yourself.

I also think of my Irish ancestors, whose stories I continue to uncover. From my great-great-grandfather, a farmer who, according to family lore, would listen in on lectures at Trinity College Dublin, to the forebear who turned down a scholarship to MIT to keep a family business afloat, their pursuit of knowledge and dedication to family have shaped the values I hold dear.

And to my great-grandmother, whose name I share – I know you viewed higher education as frivolous, but I feel a kinship with you, nonetheless. For the first time this year, I saw an image of the town where you grew up, perched high on a green hill overlooking a blue bay. Though we never met, I think I understand you a little better now and admire your fortitude in crossing an entire ocean by yourself as a teenager just over 100 years ago.

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This work pays tribute to the love, sacrifice, and steadfast support of my family, two-legged and four-legged members alike.

Preface

As I finish writing this dissertation, we find ourselves in the middle of the fourth year of what many refer to as the modern era of artificial intelligence (AI). This is a time of rapid evolution, where the world is still grappling with the implications of AI's growing presence in nearly every aspect of life. Once confined to research labs and theoretical discussions, AI has become pervasive, touching industries, education, healthcare, and personal lives in ways we are only beginning to comprehend. Both its strengths *and* its weaknesses, as we know them today, represent just the surface of what might emerge in the coming years.

Reflecting on the work presented here, I am reminded of the dynamic nature of this field. Unlike those formally trained in AI, my own journey began on the job, learning through hands-on experience. This unconventional path has shaped my perspective, blending curiosity with a sense of urgency to understand not only how AI works but also its broader implications. It has taught me that AI is not just a technical tool but a societal force, requiring careful consideration of ethical divides, human-centered design, and unintended consequences.

This dissertation represents not just an academic undertaking but also a personal exploration of AI's role in education and collaboration. It is as much about the questions raised as the solutions proposed, reflecting a world still sorting out what it means to coexist with this potentially transformative technology. With this work, I insert my voice into a larger scholarly conversation guided by evidence and experience, offering insights into how we might navigate the opportunities and challenges ahead.

This preface is both a disclaimer and an editorial reflection. Consider it a snapshot of a moment in time, a testament to the evolution of ideas, and a reminder that we are all, in some way, learning as we go.

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Glossary

This glossary defines key terms used throughout this dissertation.

Term	Definition
Agile	A formal project management and software development framework emphasizing iterative development, cross-functional teams, and frequent feedback loops.
Artificial intelligence (AI)	Computer systems capable of performing tasks that typically require human intelligence, such as learning, reasoning, and problem-solving.
Artificial intelligence in education (AIEd)	The use of AI technologies in educational settings, including tutoring systems, learning analytics, and administrative chatbots.
Assessment design	The process of creating tools, tasks, and criteria to measure learners' knowledge, skills, or attitudes.
Complex adaptive systems (CAS)	Systems made up of many interacting agents whose collective behavior produces new, unpredictable outcomes through feedback, adaptation, and self-organization.
Conversation-based assessment (CBA)	An interactive method for evaluating learners' reasoning or understanding via structured dialogue (for example, with chatbots or live facilitators).
Data science	An interdisciplinary field focused on deriving insights from data through statistical analysis, computation, and visualization.
Evidence-centered design (ECD)	An approach to assessment that starts with defining knowledge or skills to measure and works backward to design tasks for evidence collection.
Group support systems (GSS)	Technology platforms that support group interaction, decision-making, and collaborative work (such as shared whiteboards or voting tools).
Instructional design	The systematic crafting of instructional materials and activities based on learning theory and empirical evidence to improve educational outcomes.
Learning science	A research-based field that examines how people learn for supporting the design of effective educational environments.
Minimum viable product (MVP)	The simplest version of a product that delivers core functionality to users and provides critical feedback for future development.
Moral resilience	The ability of an individual to maintain ethical integrity and respond constructively when facing moral adversity or complex ethical dilemmas.
Reflective practice	The active process of examining one's own assumptions and decisions before, during, and after professional actions.
Sociotechnical imaginaries	Shared visions about how technology and society should coexist, shaping design intentions and expectations.
Upstream vs. downstream	"Upstream" refers to design and decision-making phases; "downstream" refers to user impact and real-world consequences.
Value sensitive design (VSD)	A design approach that integrates human values (such as privacy, fairness, and autonomy) into all stages of technological development.

Executive Summary

Integrating artificial intelligence (AI) into educational technology (ed tech) products requires interdisciplinary collaboration and moral resilience to address the needs of educators and students. Teams of ed tech professionals including data scientists, AI engineers, learning scientists, user researchers, and instructional designers encounter challenges during product development such as interdisciplinary communication, power balance in decision-making, and role understanding. These challenges affect their ability to integrate diverse perspectives and maintain moral resilience. Inadequate interdisciplinary integration during the design and development phases reduces the ability to address fairness, accountability, transparency, and ethics in AI-integrated products.

Applying Complex Adaptive Systems Theory as a grounding theoretical lens to this problem of practice, I conducted a literature review to analyze how upstream team dynamics influence moral resilience and decision-making, emergent team member behaviors that can result in product design elements yielding unintended consequences during downstream classroom implementation (Waldrop, 1992). An explanatory sequential study informed by this literature review explores product team members' experiences, collecting quantitative data on disciplinary perspectives, attitudes toward AI, shared mental models, moral resilience, sociotechnical imaginaries, agile methodologies, and reflective design practice, complemented by qualitative data from interviews and surveys.

Key study findings include the importance of interdisciplinary integration in addressing fairness, accountability, transparency, and ethics in AI-integrated educational products (Khosravi et al., 2022). The study emphasizes the need for maintaining moral resilience among team members to navigate ethical challenges and prioritize the needs of learners and educators

(Rushton, 2017). It also highlights the role of design thinking and reflective practices in improving decision-making and design quality within interdisciplinary teams in accord with the findings of other researchers (Luckin & Cukurova, 2019).

The final chapter of this dissertation concerns the development of MeldED, a minimum viable product (MVP) combining design thinking and reflective practices, representing a confluence of all learnings from this applied dissertation undertaking. The MVP supports ongoing engagement in creating learner- and educator-centered educational technology. MeldED is available at catflynn.net and aims to facilitate continuous improvement and adaptation in AI-integrated product development.

By addressing communication challenges, power dynamics, and role understanding, interdisciplinary teams can create ethical and effective educational technology products. MeldED offers a practical solution to incorporating design thinking and reflective practices, ensuring that AI-integrated products are continuously refined and improved.

Chapter 1

Artificial Intelligence (AI) is rapidly evolving. In less than a century, AI has leapt off the pages of science fiction novels and landed right at our fingertips. With Open AI's implementation of the Generative Pre-trained Transformer 3 (GPT-3) language model into the ChatGPT interface, individuals can type nearly any request for AI to execute in a matter of seconds, be it a carefully worded client email (Harwell et al., 2022) or a term paper that meets all the professor's requirements (Woodcock, 2022). Roschelle (2022) identified two major challenges AI innovations pose for the field of education: (a) ensuring that the ability to research AI's use in education keeps pace with the rate of the technology's evolution and (b) sharing power in the creation of educational AI tools across disciplines to benefit from the wisdom of the collective.

These two challenges are interconnected and intertwined. As Dieterle and colleagues (2022) explain, the creation and implementation of AI educational technology (ed tech) perpetuate cyclical divides that produce both upstream and downstream effects. The three upstream effects consist of divides related to technological access, representativeness of data, and the diversity (or lack thereof) of teams developing and validating algorithms. The two downstream effects related to the classroom implementation of AI ed tech (AIEd) are how AI outputs are interpreted by educators and learners as well as how these outputs might further serve to perpetuate structural biases.

Helping ed tech teams anticipate AI's innovation curve amidst the hustle and bustle of the product development process requires actionable strategies to guide in-the-moment decision-making. These strategies must foster shared values aiding interdisciplinary collaborators during their interactions with one another to drive learner and educator success.

This chapter provides context on this sort of "in-the-moment" decision-making within interdisciplinary teams and explores the factors influencing emergent team member behaviors. The literature review presented in this chapter outlines how interdisciplinary product design and development teams in ed tech navigate multiple, sometimes competing, sources of feedback from inside their team and outside in the larger environment as they integrate AI into the design of learning tools. Applying Complex Adaptive Systems Theory (Waldrop, 1992) as an investigatory lens, this chapter will further articulate this problem, review relevant literature, and establish a conceptual framework to guide future empirical exploration.

Problem of Practice

This research is situated within ed tech organizations incorporating AI within new products. Ed tech companies implement product management as a working paradigm to distinguish their offerings in an increasingly competitive market by responding to shifting technologies and other external forces (Alphonso, 2023). AI, in particular, as a technology can deliver differentiating value to an ed tech product but requires multiple types of disciplinary expertise to implement successfully.

Interdisciplinary collaboration goes hand in hand with making new learning tools that appropriately use new technology's affordances, allowing the perspectives of data science, education, and user experience to inform the final product (Alam & Mohanty, 2022). Still, challenges arise when bringing together colleagues from varied domains. For AIEd product development teams as a collective, this may entail experiencing an imbalance of disciplinary perspectives during project work (Zawacki-Richter et al., 2019), role confusion obfuscating team members' areas of expertise and responsibility (Hwang et al., 2020), and general communication challenges typical of technically complex projects (Piorkowski et al., 2021). At the same time, individual team members confront complications at a personal level. These may include navigating their own different beliefs about AI (Rughiniș & Obreja, 2023) as they integrate their specific interdisciplinary knowledge (Hmelo-Silver & Jeong, 2021; Xu et al., 2023) to make ethical team decisions (Holmes et al., 2021) with their colleagues that anticipate and mitigate undesirable downstream effects of AI (Dieterle et al., 2022). Building evidence-based solutions to mitigate this problem of practice requires further study of factors that cultivate conditions conducive of team dynamics. As AIEd team members design learning tools that anticipate the realities of classroom implementation, balance is key. Possible solutions must integrate evidence and theory to promote ethical team decision-making in this professional context.

Theoretical Framework

Above all else, a team is a dynamic, interconnected system of people and ideas whose collaboration results in new behaviors shaped by context. Building on Ludwig von Bertalanffy's General Systems Theory (1968), the concept of Complex Adaptive Systems (CAS) extends these ideas into environments marked by uncertainty, emergence, and adaptation. Walter F. Buckley (1968) first coined the term "complex adaptive system" to describe social structures capable of reorganizing themselves through interactions among agents, rather than maintaining a static equilibrium. In the early 1990s, John H. Holland and colleagues at the Santa Fe Institute formalized these theories through computational models of emergence and adaptation. Mitchell Waldrop's influential book, *Complexity* (1992), then brought these ideas into public discourse, positioning CAS as the study of systems "on the edge of chaos," particularly in interdisciplinary innovation. Kevin Dooley's organizational CAS model (1997) subsequently translated these theoretical insights into practical analysis of how semi-autonomous agents within businesses interact to produce emergent organizational structures and behaviors.

Framing AIEd product teams as CAS highlights their character as evolving systems influenced by feedback loops, disciplinary perspectives, power relations, and environmental pressures. Within this framework, Xu and Ouyang's (2022) CAS model consisting of subject, information, technology, and environment offers a practical lens for analyzing how AI functions within and across these dynamic systems. This literature review will focus on those four components, setting aside "medium" for future exploration as downstream, classroom-level impacts become clearer.

Environment

AIEd team's environments set the stage for interdisciplinary collaboration and the challenges contained therein. AIEd product teams function as a CAS, responding to feedback from their environment. Environment refers to the underlying context in which subjects in a CAS engage (Waldrop, 1992). One study exploring CAS in a professional context analogous to AIEd, K-12 school systems, establishes CAS as open and social environments in which agents interact with external stakeholders along with other environments (Fidan & Balcı, 2017). Nothing happens in insolation, with each team member their own self-contained universe of feedback inputs. For example, feedback loops about past product or technology performance may inform the team's decision-making about next steps (Holland, 2006), so a team member with a recent lesson learned may be more sensitive to that matter than other colleagues.

The integration of these individual environmental inputs into the collective team's product design can impact learners and educators downstream in the longer term. How teams respond to their environments may be just as if not more important than team members' domain-specific expertise. Exploring emerging technology's impact on AI software development practices, Chang (2023) surveyed 128 software developers to prioritize factors influencing internal decision-making. Chang found that while employees' technical skills merited high consideration, considerations of employees' overall stress-resistance, team communication and sharing, and team collaboration capabilities took precedence. These individual and team capabilities point to a need to withstand environmental stressors such as competing sources of feedback and project constraints and deliberately exchange information through team interactions.

Domain-specific expertise paired with interdisciplinary team collaboration skills form a foundation for successful incorporation of AI in ed tech products. This environment's inherent complexity warrants special attention be paid to amplifying each team member's perspective and synthesizing them within the context of the larger team collective, holding support for diverging ideas while paving a path toward eventual consensus. The interdisciplinary composition of AIEd product teams at the Educational Testing Service (ETS) enables product development intentionally embedding AI capabilities in application design to personalize user experiences aligned with their desired educational goals (Herrick et al., 2022). Such teams are intended to integrate technical and pedagogical perspectives to inform AIEd product and design development, mapping currently available AI capabilities to defined user needs (Luckin & Cukurova, 2019). AIEd's broader context acts as the environment for this problem of practice, including the product teams upstream who create learning tools with AI and the educational settings where AIEd products are implemented downstream. This environment shapes the challenges as well as the opportunities that AIEd product development teams encounter in their work.

Subject

Subject refers to the people interacting within a CAS, a dynamic network populated with different agents (Waldrop, 1992). In the case of AIEd product teams, the agents are the individual team members who each contribute their own unique ways of knowing, including their disciplinary expertise as well as life and professional experiences. Individual factors can affect overall team performance. In another complex collaboration setting, healthcare, a quantitative study of 31 hospital units demonstrated evidence that high complexity healthcare teams allowing low individual autonomy and promoting high individual performance orientation create conditions for higher innovation performance (Glover et al., 2020). This points to a need for subjects to have guidance on roles, responsibilities, and expectations as they navigate complexity in their regular interactions with peers.

Applying this healthcare example to the context of an AIEd team building a complex AI application reinforces this need. In AIEd teams, a learning scientist works with a research scientist to articulate learning outcomes for a potential product because they need to articulate a theory of change that will (a) drive the product's learning design strategy and (b) lay a groundwork for future efficacy research throughout the product life cycle (Coggeshall, 2023). As the two subjects interact, they exchange information with one another and adapt their behaviors accordingly (Waldrop, 1992), iterating upon their individual and shared understanding as they collaborate. The resulting interplay between individual subjects in a CAS as they communicate on complex subject matter like technical project specifics brings to bear the importance of information processing and how it influences interdisciplinary collaboration.

Information

Within a CAS, information refers to the distribution and creation of knowledge, which can occur both individually and collectively (Waldrop, 1992). The non-linear dynamics within team-based CAS drive emergent practices as collaborators integrate internally- and externally-sourced information and feedback (Lindberg & Schneider, 2013). In other words, each CAS adapts as it processes information in such a way that cannot be completely explained by its individual agents alone. This leads to new properties, patterns or behaviors resulting from these unique blends of team interactions (Fidan & Balcı, 2017). This characteristic of CAS is known as emergence and is a vital factor for innovation (Turner & Baker, 2020). In team settings requiring substantial technical and domain-specific expertise, emergence plays a major role in how individual team members converge their unique perspectives toward a shared understanding.

Software development team case studies conducted by Werder and Maedche (2018) found that team agility is a key emergent state driving team members' ability to respond to changes in their environment. Agility impacts how teammates make sense of new information together as they iterate upon their already established goals. In an AIEd context, teams often concurrently intake new feedback from organizational and product leadership. Agile teams can nimbly adapt to new demands, but less agile teams could struggle to keep pace, suggesting another source for downstream implementation effects forged during upstream team decision-making. Two different AIEd product teams working at the same time could build completely different learning tools because of variation in their emergent states due to their agility in processing stakeholder feedback. Interactions between team members in a more agile team could yield variable product feature ideas or novel approaches to problem solving, whereas interactions in a less agile team could prove less inspired and indeed, overlook vital ethical considerations.

Technology

Technology facilitates AI's integration in educational media as defined In Xu and Ouyang's (2022) CAS framework. In the context of this literature review, technology refers to the platforms used to connect teams in developing and integrating AI capabilities into product design as well as the AI capabilities themselves. Incorporating AI within ed tech products is a byproduct of emergence. This happens when a complex system changes its behavior abruptly because of dynamics between subjects reacting to their environment (Srinivasan & Mukherjee, 2018). By mediating interactions between subjects within a CAS, technology has the power to positively affect emergent states including team cognition, trust, cohesion, and conflict as shown in a metanalysis of group support systems (GSS) used by virtual teams (Curşeu, 2006). The researchers found that GSS types varied in their affordances for impacting team collaboration outcomes, each posing its own benefits for achieving the principal task at hand. Process-structuring GSS facilitate team cognition along with greater trust and a sense of cohesion. Communication-supporting GSS aid teams in resolving their conflicts and facilitating idea exchanges. Information-processing GSS assist team cognition in service of shared goals.

AIEd teams may benefit from different GSS technologies to optimize their emergent behaviors driving product design, depending on their established team dynamics and professional environment. As such, any attempts to create such tools for AIEd team settings must deliberately build upon existing evidence-bases to establish a robust foundation as well as conduct primary research to understand team members' experiences to appropriately determine their needs.

Chapter 1 Overview

Reviewing relevant literature through the lens of Complex Adaptive Systems (CAS), this chapter synthesizes factors influencing AIEd product team members' emergent behaviors impacting product development. The literature review begins by analyzing AIEd as the larger environment in which subjects (interdisciplinary AIEd product team members) operate with a team based-CAS. Next, it describes how subjects' beliefs about AI influence their approaches to AIEd as well as how their interdisciplinary collaboration with teammates simultaneously may present challenges to goal attainment but also enrich the development process. Further unpacking the vital role of ethical decision-making in AIEd teams, the literature review explores moral resilience's role in navigating complex ethical decisions, drawing a parallel to the healthcare field. Finally, the literature review ends with a discussion of team integrative capacity (Salazar et al., 2012) as a potential area of investigation for supporting AIEd teams. The chapter concludes by recommending a conceptual framework weaving together these separate threads and suggesting a focus for an empirical study discussed in Chapter 2 to generate requirements for creating an applied dissertation project tailored to the established problem of practice.

Literature Review

This section surveys theoretical and empirical literature to delineate factors influencing upstream team collaboration factors in AIEd product design and development that impact the downstream experiences of learners and educators. Applying a CAS lens to this review frames this problem in terms of understanding (a) AIEd as the overarching environment in which interdisciplinary team member subjects engage, (b) how subjects' beliefs about AI influence how they process information exchanged in communications with colleagues about the products they are creating, (c) the challenges subjects encounter in their dynamic interdisciplinary team interactions, c) how individual mental models converge into a shared mental model to make ethical decisions, and d) how team integrative capacity affects moral resilience, which influences ethical decision-making during design and development through team interactions.

Bear in mind none of these factors act in isolation within a team-based CAS. Rather, these factors interact dynamically with one another. Each factor influences the other, evolving alongside the AIEd team and the product they are making. A deeper look at these interactions and their impacts on individual team members, their collective interactions, and resulting product impact suggests best practices for cultivating AIEd teams that can weather a complex professional context to make the best decisions for product users in their educational journeys.

AI in Education

AI and education represent a broad convergence of people and ideas. For decades, AI applications have been proposed or implemented to benefit learners and educators at all ages and stages. Specific AI capabilities have been engineered with a pedagogical focus. In one such case, Question Answering (QA) automates the generation of questions to assess young children's narrative comprehension, such as in the example of the FairytaleQA dataset (Xu et al., 2022). A poem generator tool piloted in a Finnish classroom facilitated human-machine co-creation with middle school-age writers and generative AI (Kangasharju et al., 2022). The tool suggested a draft poem for students to revise and encouraged experimentation with creative word choices and new poetic features, expanding young poets' artistic wheelhouses. Looking ahead to higher education and workforce development, quantitative models employ AI to aggregate and analyze large labor market data sets can be configured to predict near-future surges in specific skill sets, as shown in one study regarding the Information and Communication Technologies sector in Singapore, offering an early warning to faculty and professional staff that university curriculum updates may be warranted (Yazdanian et al., 2022). These examples illustrate the wide-ranging nature of the field and serve as an example of the bifurcated nature in which technical AI capabilities are generally connected with educational goals.

More specifically within the larger category of AI and education, AIEd is an interdisciplinary field that studies the application of AI technologies in educational settings to facilitate instructional design, learning, and assessment. AIEd engenders a dynamic and complex environment for the subjects interacting within interdisciplinary ed tech product development teams. Despite the richness of this environment as a professional context, AIEd is not without its challenges for team members developing innovative learning tools that incorporate AI.

Focus and Challenges

Since the early days of AI in the mid-twentieth century, pioneering educators and computer scientists have been investigating meaningful ways to apply the technology to both further understanding of student learning *and* improve machine cognition, according to a history of the field (Holstein & Doroudi, 2021). Indeed, as Yazdani and Lawler (1986), two of the field's founders, explain, researchers originated the field of AIEd in the late 1980s on the notion of focusing on the symbiotic overlap between AI and education. Members of the nascent AIEd community aimed to direct research efforts in support of shared areas of interest in teaching and learning processes.

Still, as the twenty-first century progresses, AIEd practitioners and researchers continue to encounter challenges in integrating technology into learning design or creating AI capabilities conducive to learning design integration. This is due to the technology-dependent and interdisciplinary nature of the field as Hwang and colleagues (2020) recount in the inaugural issue of the *Computers and Education: Artificial Intelligence* journal, calling upon interdisciplinary scholars to bridge their divides to pursue shared research goals. Challenges like those discussed by Hwang et al. result in computer scientists designing AI applications for education with little pedagogical strategy, echoing similar descriptions documented elsewhere by other researchers (Zawacki-Richter et al., 2019; Bartolomé et al., 2018). These common challenges suggest a larger pattern of disciplinary perspectives imbalance in upstream AIEd team interactions that could augment team decision-making.

Closer inspection of these findings prompt reflection on which disciplinary perspectives – technical or pedagogical – are privileged in the team decision-making process and how this could shape team dynamics and emergent behaviors. The systematic review of scholarly AIEd literature published since 2007 completed by Zawacki and Richter and team (2019) showed over 62 percent of articles originating from computer science and STEM departments and focused on AI's applications (profiling and prediction, intelligent tutoring systems, assessment and evaluation, and adaptive systems and personalization) rather than theoretical foundations of how to design learning experiences with the technology. Traveling farther back in time to 1960, Bartolomé and colleagues replicate similar findings in their own systematic review. Whereas all the 17 studies they sampled in their review mentioned tailoring learning experiences to individual learner needs, seven of the studies did not expand upon their operationalization of what constitutes personalized or adaptive learning. AIEd scholarship's tendency to research learning without grounding it explicitly in theoretical foundations informed by the learning sciences may be amplified in AIEd product development team dynamics to the detriment of product users.

The concrete ways these detriments appear in a classroom may be challenging to directly connect to more abstract team dynamics. Upstream team dynamics compromised by privileging one disciplinary perspective over another may impact educators and learners during implementation through reduced product quality. This could take the form of AIEd products that employ oversimplified learning strategies jeopardizing goal attainment, neglect to help learners generalize new knowledge and skills into different contexts, or even over-automate design features at the expense of teacher autonomy via flexible classroom implementation (Bhimdiwala, et al., 2022). In response to these types of tensions, AIEd practitioners have proposed guiding frameworks like fairness, accountability, transparency, and ethics (FATE) in AIEd to provide interdisciplinary collaborators with a shared frame of reference for ethical decision-making.

To proactively recognize and resolve challenges during product design, special focus must be given to FATE (Khosravi et al., 2022). Fairness ensures AIEd products do not amplify existing inequalities. Accountability means that product teams assume responsibility for any intended *and* unintended consequences they may have. Transparency involves AIEd teams ensuring that algorithms are explained to learners, teachers, and other stakeholders in an accessible way. Ethics encompasses designing, developing, and deploying AIEd in a moral way, respecting users as human beings. These multifaceted principles interrelate with one another, a CAS on their own, and can guide socially responsible innovation in AIEd. Ideally, FATE is embedded in interactions between product team members to ensure ethical decision making minimizing negative downstream effects.

Interdisciplinary Product Development

Interdisciplinary collaboration between AI developers, researchers, and educators is crucial for creating ed tech that can meet learners' needs (Luckin & Cukurova, 2019) and a cornerstone of the product approach undertaken in many ed tech organizations to drive market differentiation (Alphonso, 2023). Three empirical case studies presented by Luckin and Cukurova (2019) explain the importance of triangulating these perspectives and strengthening partnerships between disciplines, highlighting how these perspectives complement one another in (a) collecting and analyzing large educational datasets and (b) using the learning sciences to develop educational AI. Similar to the interdisciplinary composition of the teams studied by Luckin and Cukurova (2019), ETS AI Labs product teams are composed of experts representing at least three broad disciplinary areas (Herrick et al., 2022):

- **Learning Sciences and Instructional Design (LS&D)**: Learning science contributes theoretical framework and instructional design principles. Assessment contributes evaluation items and scoring recommendations.
- **User Centered Design (UCD)**: User experience researchers and impact research scientists conduct human-centered design research and testing of learning solutions, including interviews, design thinking sessions, surveys, and more, to rapidly incorporate user perspectives into the design process.
- **AI**: AI research and engineering research and create machine learning models. Data science contributes a plan for operationalizing the models into a scoring plan to operationalize assessments.

In these interdisciplinary AI teams, each team member offers a unique perspective rooted in their disciplinary expertise to inform the product vision and roadmap. Practitioners may vary in their goals. Take for instance, diverging perspectives on explainable AI, a type of AI that explains why it produced the output it produced (XAI). In a survey of multidisciplinary XAI goals, Mohseni and colleagues (2021) found team members who are less experienced with AI usually have design goals of reducing bias, data expert colleagues are more interested in using XAI to finetune the model's performance, and the AI experts on the team look to XAI to help guide the interpretation of the model's output. In the case of ETS AI Labs, the research foundations learning scientists offer to the team shape the pedagogical strategy driving the product's design and lay the groundwork for understanding the product's eventual success so that the impact researchers will develop a research plan for measuring at various points throughout the product's lifecycle (Herrick et al., 2022). Integrating these varied disciplinary perspectives in teammate interactions is key to helping CAS subjects process product knowledge within their complex professional contexts.

Attitudes Toward Agile Methodologies

Many ed tech organizations operate within a product management paradigm facilitated by agile methodologies (Alphonso, 2023) to maintain team alignment with strategic objectives and respond rapidly to any changes in course from inside or outside of the business. Product management in ed tech typically includes a designated team leader, often known as either a product manager or product owner, guiding a product through progressive iterations from concept to prototype to launch to continuous improvement (Salza et al., 2019). They are at point for gathering requirements for the product's design that ensure its features will meet customers' needs and achieve business goals. Product management creates conditions for teams to shape product visions that align with organizational business strategy as well as respond to (or even anticipate) market demands.

Product teams commonly employ agile methodologies to design and deliver new products. Originating in software development, agile methodologies allow organizations to quickly incorporate user and stakeholder feedback in product design (Begel & Nagappan, 2007). Agile methodologies include scrum in which pre-determined amounts of work are completed within a designated time, known as a sprint (Salza et al., 2019). Another agile methodology is known as lean design in which teams seek to reduce the amount of wasted work to operate as efficiently as possible (Leite et al., 2016). These methods encompass a system for strategically managing team members' time and talents while working on a product.

Agile teams are often interdisciplinary and consist of 5-10 people (Strode et al., 2022). These team members are dedicated to a product throughout all stages of its lifecycle (Strode et al., 2022). Agile methodologies are intended to increase collaboration to maximize the benefits of interdisciplinary collaboration as team members break down complex problems into smaller pieces, driving toward solutions (Moloto et al., 2020). By combining interdisciplinary perspectives, the team benefits from a more holistic understanding of users and what their needs are, setting the stage for enhanced decision-making throughout the design process (Specht & Crowston, 2022). With its emphasis on maximizing collaboration and productivity, agile appears to be a powerful tool for interdisciplinary teams.

Despite these aims, agile methodologies are not always positively perceived in an interdisciplinary setting, which may impede their successful implementation. One survey of interdisciplinary software development team members at Microsoft showed that methodologies are not consistently applied across teams, leading to confusion as different team members collaborate with one another and complexity as teams grow in size (Begel & Nagappan, 2007). A grounded theory study at Robert Bosch GmbH focused on changing leadership roles within agile teams, suggesting that gaps in leadership and role conflicts can cause team members to take on elements of the product manager or product owner roles, negatively impacting perceptions of agile methodologies and impacting team performance (Spiegler et al., 2021). A comparative case study of two development teams at IT security firm F-Secure determined that while agile methodologies can promote communication, they can also overwhelm team members with too much information and create communication gaps, resulting in negative perceptions of agile (Pikkarainen et al., 2008). Together, these empirical studies suggest that agile methodologies may complicate interdisciplinary team collaboration in AIEd, particularly team members' ability to anticipate downstream consequences of product implementation during their decision making.

Downstream Effects

Failure to integrate disciplinary perspectives in AIEd product teams may perpetuate a vicious cycle of upstream and downstream divides that could result in suboptimal decisions negatively impacting end users (Dieterle et al., 2022). Beyond the previously discussed examples of disciplinary imbalance impacting learning strategy implementation in *Focus and Challenges*, AI capabilities pose ethical implications that may pass through product development unnoted without the right team dynamics. For example, AI-generated text plagiarism detectors tend to misclassify non-native English writing samples as AI-generated (Liang et al., 2023), negatively impacting learners' self-concept. In another case, repairing automatically generated text when co-authoring with an AI-writing tool may require learners to contribute substantial affective label when generated output contradicts their identities (Perrotta et al., 2022). Models may pretrain on data including hate speech and misinformation (Feng et al., 2023), perpetuating systemic biases that incur disproportionate harm to marginalized learners in the form of derogatory terms embedded in generated input they could engage with in the classroom. Adopting a longer term view, the tendency of people to speak more transactionally to AI agents in oral communication tasks than they would a human (Timpe-Laughlin et al. 2023), may cause younger generations to take a more detached tact with interpersonal communication and lead to exacerbated societal fractures. Observable outcomes of such downstream effects could include unfairly reduced grades for students who are English language learners, increasing cognitive load demands in the form of added emotional labor, exposing students to hate speech, or making it even harder for humans to connect person-to-person. Each of these research findings related to AI's downstream effects is worrisome enough alone, but together they suggest the possibility to amplify into larger-scale concerns.

In spite of their good intentions demonstrated by working in an education-adjacent sector, AIEd product team members may not realize the full downstream implications of their design decisions (Holmes et al., 2021). Without educator peers to consult, computer scientists may design AI applications with no grounding in pedagogical strategy (Zawacki-Richter et al., 2019; Bartolomé et al., 2018), and educators may not understand the full functionality and implications of implementing an AI capability in a learning experience when they cannot ask more technical peers questions (Hwang et al., 2020). Because they eventually travel back upstream, these downstream effects have the potential to exponentially replicate. As an AIEd product is released into the classroom, how teachers and learners experience its implementation will become another point of feedback for the team-based CAS from the external environment. Effective AIEd product teams will anticipate the possibility of negative implementation experiences during product user testing prior to release. It is incumbent upon teams to be as adaptive as possible, responding to user feedback signals proactively during the design process.

Beliefs About AI

AI and its implications for education are just beginning to be understood. In the summer of 2022, a Google software engineer named Blake Lemoine claimed an AI chatbot created by the company had achieved a sentient state, so struck was he by the authenticity of his interactions with the technology (Rughiniș & Obreja, 2023). A later internal review by Google disproved Lemoine's claims, but social media discourse debated what the incident portended for the future of AI and how people think about it and treat it as a fellow agent within a CAS such as education. Regina Rini, a philosopher at York University, tweeted, "I don't expect to ever meet a sentient AI. But I think my students' students' students might, and I want them to do so with an open mind and a willingness to share this earth with persons unlike ourselves. That only happens if we make such a future believable" (2022). As technology evolves, so do the ways human beings think about AI and its role in education. Investigating people's perceptions of the Lemoine case on social media with a qualitative content analysis, researchers found evidence of four types of anticipatory ethics related to emerging technologies like AI, ranging from optimism to pessimism (Rughiniș & Obreja, 2023). These sets of beliefs about AI include sociotechnical imaginaries and attitudes toward AI. They offer a glimpse into the different ways AIEd product team members might perceive AI at present and anticipate future downstream consequences.

Sociotechnical Imaginaries

Projects involving complex and specialized technical and scientific domains like AIEd encode a collectively held ideal vision of society known as a sociotechnical imaginary (Jasanoff & Kim, 2009). Sociotechnical imaginaries both reinforce technological systems' design and reflect their designers' specific ways of knowing the world including social values and vision for society. Common jargon used in AIEd hint at prominent sociotechnical imaginaries within the field. Ed tech stakeholders commonly use the term "learning solution" to describe AIEd products. This terminology problematizes education (and also frames AIEd as its natural solution) and offers a mental model for teams to use as a shared point of reference (Rahm & Rahm-Skågeby, 2023). Sociotechnical imaginaries shape how AIEd teams interact and process information during product development, influencing their emergent behaviors during decision-making.

Terminology like "learning solutions" are reflective of a common sociotechnical imaginary in AIEd known as "technological solutionism," that often appears in ed tech companies' product marketing language (Davies et al., 2020). "Technological solutionism" is an enduring trend in which educational institutions aim to personalize learning with AI as a means of fixing large-scale systemic issues. In a Delphi panel study, Davies and colleagues (2020) interviewed twenty experts from Europe and the United States leading at the intersection of ed tech and AI. The researchers used interview transcripts to construct a knowledge graph charting actors, connections, concepts, and institutions intersecting with ed tech and AI. Ultimately, the authors found for-profit ed tech companies tended to use language promoting personalized learning and learning science. Davies et al. speculated ambiguous terminology prevalent in AIEd is at the root of this phenomenon, which is arguably further exacerbated by role confusion and general communication challenges discussed in a later section.

Sociotechnical imaginaries complicate upstream product team decision-making and perpetuate systemic inequities downstream during classroom implementation. The "technological solutionism" sociotechnical imaginary suggests AIEd team members lack a common baseline of what learning science is and how it can offer an empirical foundation for product development strategy. Recall Luckin and Cukurova's observation from their qualitative AIEd product development team case studies that most commercial AI developers know little about learning sciences research (2019). Additional studies focused on deconstructing dominant narratives of AI by ed tech companies (Blikstein et al., 2022; Renz & Hilbig, 2020) echo sociotechnical imaginaries of solutioning education by delivering personalized learning experiences and learning analytics afforded by AI technology. "Technological solutionism" as a sociotechnical imaginary also reflects deeply ingrained systemic biases. Quantitative discourse analyses of qualitative data focused on understanding broader conceptions of AI internationally suggested a bias toward Western notions of success in learning and operationalization of standards through rubrics (Nemorin et al., 2022; Dixon-Roman et al., 2020). More globally held narratives like "technological solutionism" impact product development at a local level through emergent team collaboration behaviors.

Other sociotechnical imaginaries beyond "technological solutionism" are shaping the field of AIEd. Another example of an AIEd sociotechnical imaginary, "algorithmic idealism" (Davis et al., 2021), uncovers faulty premises at the foundation of AIEd. This notion assumes a just society under which AI will surely replicate equitable conditions, but this is not the case as evinced by Dieterle and colleagues' framework of cyclical ethical effects in AIEd. Virtual technologies can introduce very real consequences into the real world. In one example of "algorithmic idealism" gone awry, Riberi and colleagues' 2021 ethnographic study showed how an AI-powered vulnerability algorithm designed to equitably allocate school funding to public schools in Chile may indeed perpetuate systemic biases by influencing how students, parents, and staff construct definitions of who and what factors constitute economic vulnerability.

Sociotechnical imaginaries provide a means to reframe current reality and forge a better future. "Algorithmic reparation," described by Davis and Williams (2021), offers an alternative sociotechnical imaginary with applications for AIEd teams. The researchers reviewed secondary literature to connect machine learning to intersectionality, explain why machine learning reproduces societal inequalities, and determine shortcomings in current fair machine learning practices. By identifying these deficiencies, they rationalized why a reparative approach that actively combats algorithmic inequality is preferable. Like Roschelle (2022), Davis and Williams (2021) also advocate for distributed power in AI creation. Because distributed power approaches are novel within the larger field of AI, future studies must investigate their effectiveness in mitigating negative downstream effects for product users in classroom settings. As the interplay between factors cultivating interdisciplinary collaboration in AIEd becomes better studied, teams must remember they have the agency (and the duty!) to reject sociotechnical imaginaries that do not fully serve their users and replace them with new ones that do.

Attitudes Toward AI

Emerging technologies like AI pose an additional layer of complexity to interdisciplinary team collaboration in AIEd product design. As AI evolves, people process in real time how the technology and its shifting affordances will affect day-to-day matters of living and learning. A 2022 survey conducted on behalf of the World Economic Forum revealed that 60 percent of adults worldwide anticipate AI will change their everyday life within the current decade (Boyon). In the United States alone, 45 percent of adults report feeling equal parts excited and concerned about the technology, citing employment displacement due to automation and privacy violation as top worries (Rainie et al., 2022). These findings represent snapshots of isolated moments within AI's more recent evolution, subject to ebb and flow with the times and technologies. Still, they point to an urgent need to continually monitor team member perceptions of AI as a factor for influencing AIEd product development.

Beyond varying levels of expertise in AI that the upcoming section on disciplinary collaboration will address, people tend to think about AI in different ways and vary in their general attitudes toward the new technology (Sindermann et al., 2022). Surveying participants from China, Germany, and England, Sindermann and colleagues learned that across the world, some people adopt a positive attitude toward AI whereas others possess a more negative outlook with determining factors including gender and personality (2022). Cultural values may also play a role in attitudes toward AI. A study of 3,000 American adults who were also technology workers studying in a graduate computer science program demonstrated individualism, egalitarianism, risk aversion, and techno-skepticism inform people's attitudes toward AI (O'Shaughnessy et al., 2023). Generally, the researchers found that experts are more likely to be enthusiastic about AI but able to hold more nuanced views than laypeople. People may also adopt different attitudes toward AI due to how their stakeholder role influences their perception of the technology's perceived benefits. In the example of clinical healthcare, a metanalysis of 27 research studies found that people possessed generally positive attitudes toward AI healthcare applications though there was variation among stakeholder roles (Scott et al., 2021). For example, those with prior AI experience had a higher positive outlook, clinicians worried about personal liability due to AI-related error, and consumers feared about a reduced level of clinician oversight and participation in decision-making.

Together, sociotechnical imaginaries collectively conceptualizing AI and individual attitudes toward AI can influence how AIEd team members develop products together. Individual team members approach AIEd product design with their own attitude regarding AI that will inform their mental model regarding the product's purpose that will be integrated within the team mental model, a process that will be discussed in a later section of this chapter. At the same time, team mental model integration is augmented by the team's sociotechnical imaginary of AI. If all team members have positive attitudes toward AI and hold a shared "technological solutionism" sociotechnical imaginary, enthusiasm may stifle skepticism during the design process. An overly rosy view of the technology can hamper the team's ability to recognize and remediate downstream effects for teachers and learners in the classroom.

Interdisciplinary Collaboration Challenges

Interdisciplinary team configurations offer an avenue for differentiating value for ed tech product development (Alphonso, 2023). While interdisciplinary team collaboration has been less extensively studied in ed tech, additional fields like healthcare and the social sciences provide a wealth of research elucidating common interdisciplinary collaboration challenges. In these fields, interdisciplinary collaboration brings many benefits, positively impacting patient care quality and outcomes in healthcare (Fewster-Thuente & Velsor-Friedrich, 2008), producing solutions to public policy puzzles (Edelenbos et al., 2017), along with centering students and educators in educational technology design (Hmelo-Silver & Jeong, 2021; Xu et al., 2023). Yet, the approach is not without its difficulties.

Across settings, three main challenges face interdisciplinary teams: communicating effectively across disciplines, understanding one another's roles and responsibilities, and perpetuating power imbalances (Choi & Pak, 2007). Beyond creating a less-than-ideal work environment for the interdisciplinary team members, these challenges can negatively impact the lives of the people their collaboration is intended to benefit. Lapses in communication and collaboration between interdisciplinary healthcare workers can harm patient health outcomes (Fewster-Thuente & Velsor-Friedrich, 2008). A 2018 case study conducted by Hanson surfaced confusion over roles and responsibilities hampers interdisciplinary software development teams consisting of engineers, data scientists, and social science researchers, causing application release delays for users when one teammate does not understand the value that their colleague from a different discipline can add and neglects to solicit their input. These types of challenges can impact interdisciplinary AIEd teams' ability to integrate their individual mental models, disciplinary perspectives, and beliefs about AI to help them make ethical decisions that support educators and learners downstream.

Disciplinary Knowledge Integration

Interdisciplinary team collaboration brings together professionals with varying areas of expertise to pursue a shared goal and integrate their knowledge (Moirano et al., 2020). Several professional contexts rely upon interdisciplinary collaboration for essential work functions, including healthcare, policy, and education (Choi & Pak, 2006). In healthcare, interest in convening interdisciplinary professionals including doctors, nurses, and unlicensed assistive personnel as a united team materialized in the early 1970s (Blue et al., 2010). In this interdisciplinary patient-centered care model, each care team member acts in a specific role and coordinates with colleagues to help the patient or client achieve their goals and positively impact the quality of care (Fewster-Thuente & Velsor-Friedrich, 2008). A mixed methods study of interdisciplinary healthcare staff at a metropolitan hospital found that conducting patient rounds as an interdisciplinary team unit increased team communication, positively impacting patient care quality and staff job satisfaction (Gausvik et al., 2015). Similar human-centered efforts by interdisciplinary teams also appear in the public policy sphere as shown by a case study commissioned by the European Union that found when policy makers monitor government sponsored research projects for elements specific to interdisciplinary collaboration, they can facilitate successful outcomes (Edelenbos et al., 2017). In another public policy example, people's frustration with slow and impersonal bureaucratic systems motivated higher education academics, North Carolina mental health and child and family officials, and local community service providers to collaborate outside disciplinary boundaries and create a family-centered practice model (Powell et al., 1999). While interdisciplinary collaboration is a tried-and-true tradition in academia commonly found at universities that emphasize interdisciplinary teaching and research (Harris, 2010), a deliberately human-centered approach is a newer innovation. In ed tech, interdisciplinary collaboration often takes the form of Human-Computer Interaction, bringing together computer scientists, cognitive scientists, psychologists, and educational researchers and promoting a human-centered approach to the design of learning experiences (Hmelo-Silver & Jeong, 2021; Xu et al., 2023). These fields' interdisciplinary collaboration challenges closely mirror those in AIEd, although AIEd's are compounded by invisible factors like beliefs about AI that can shape the team mental model and impact decision-making as later sections of this chapter will discuss.

Role Confusion

Digital product design and development requires team members to discern where one colleague's expertise ends, and another's begins. Because these teams contain several unique roles, this can sometimes be easier said than done (Hanson, 2018). Some roles are more highly technical and emphasize engineering and programming skills whereas others are more human-centered and emphasize specific research skills. Reflecting on the software development team case study, Hanson (2018) highlights a need for teams to self-organize disciplinary perspectives integration and identify boundary objects, or artifacts easily understandable to all, which can be a tall order on top of regular design and development duties. Working within a technology-dependent and cross-disciplinary field, AIEd product team members must understand their colleagues' points of view to ask the right questions about pedagogical strategies related to AI along with specific functionalities of AI technologies (Hwang et al., 2020).

Software developers working on AI applications sometimes describe optimizing machine learning models as both "an ongoing science and an art" and themselves as "mere mortals" (p. 168), often relying on more expert colleagues to help them troubleshoot when they receive unexpected results (Hill et al., 2016). This stratification in disciplinary expertise between technical teammates – software developers applying AI technology and their AI engineer counterparts who built the capabilities – is widened with less technical peers specializing in human factors domains such as learning science, user experience, and assessment. In the absence of detailed documentation or guidance about the technology they are seeking to incorporate, team members may not know whom or even *what* to ask when they are considering how an AI capability might be implemented in an educational product to best support a learning goal.

Power Imbalances

Power imbalances in interdisciplinary team decision-making result in real-world consequences. Qualitative interviews of social workers in interdisciplinary care teams with medical staff may feel marginalized because their colleagues devalue their recommendations as less scientifically grounded, causing their perspective – containing key insights about the patient's personal context – to be discounted in team decisions (Murphy & McDonald, 2004). Power dynamics play a role in how comfortable team members feel in raising possible concerns about how AI is implemented in a solution. An empirical investigation of AI fairness checklists with 48 practitioners surfaced concerns that acting as an individual AI ethics advocate could negatively impact career advancement or produce other adverse social effects (Madaio et al., 2020). Although some of this study's participants viewed fairness checklists as a launchpad to rich team discussions about AI's possible downstream effects, others worried they might prove counterproductively reductive, condensing ethical and technical complexity into a black-and-white matter of compliance. A survey of product practitioners showed that 30 percent of team members working on digital products felt like not everyone had an equal say in team decisions (Torres, 2023). When prompted to share the reasons for this, respondents indicated issues around learning how to collaborate in their different roles by leveraging and sharing their domain-specific knowledge and expertise along with confusion around processes and decision-making.

In their systematic review of AIEd research, Zawacki-Richter and colleagues (2019) noted that computer science and STEM researchers authored most of the research articles in the field and that there was a dearth of scholarly discussion examining pedagogical theories and ethical implications. This is troubling because it suggests an imbalance of disciplinary perspectives and a lack of critical reflection to guide research focus in a fledgling field. In a separate review of AIEd research, Chen and colleagues (2020) observed a similar pattern and found that when scholars (rarely) write about learning theories, they almost always gravitate toward constructivism. This finding suggests researchers and, by extension, AIEd product designers and developers, neglect to explore the possibilities presented by alternative pedagogies and could benefit from engaging additional perspectives. Rather than check "yes" or "no" on a checklist or complete separate tasks in their own functional areas, interdisciplinary designers and developers of ed tech using AI must come together to consider how their choices can have the potential to exemplify existing inequities or create new ones, making it imperative to integrate pedagogical and technical perspectives (Holstein & Doroudi, 2021). Otherwise, such disciplinary hierarchies within teams reduce complex team interactions such as rich discussions regarding a design decision's ethical implications to an aside in the meeting chat or something to address in a later version of the finished product.

Knowledge Communication

Communication is known to be a top barrier impeding interdisciplinary team collaboration (Rawlinson et al., 2021). Modeling and representing knowledge across disciplines during product design has posed two specific challenges for interdisciplinary communication (Chandrasegaran, et al., 2013). First, inherent institutional knowledge management challenges obscure a project's design decision history and locating relevant procedural information such as internal checkpoints or key decision-makers. Second, multiple levels of knowledge transmission further hamper communication: such levels could be between two colleagues, two teams, or even two organizations. Product team members navigate several communication streams across their organization at different levels to access and share vital information for their day-to-day work, which can be complicated by increasing team sizes and organizational pressures to move up product launches (Curtis et al., 1988). These general communication challenges pose many hurdles for any team, interdisciplinary or not.

The inherently complex and specialized nature of AI exacerbates typical team communication hurdles encountered in most projects. Studying interdisciplinary AI developers at IBM with varying levels of technical expertise, Piorkowski and colleagues (2021) cataloged a variety of communication gap issues arising between colleagues. These issues included rectifying mismatched expertise by helping less technical colleagues better understand models' inner workings, building teammates' trust in others' fields or disciplines, and managing realistic expectations (both within the team and with external stakeholders) about AI's capabilities and limitations. Underlying the primary goal of creating an AIEd product are secondary goals of ensuring all team members can influence the product's design, understanding the different lines of expertise available on the team, and establishing productive communication patterns as a foundation for interdisciplinary team collaboration.

Ethical Team Decision-Making

AIEd product design entails m/itigating "known unknowns" (and "unknown unknowns" that may or may not reveal themselves during the design process). Recognizing and mitigating these downstream AI implications of AI related to fairness, accountability, transparency, and ethics (Khosravi et al., 2022), requires an understanding of individual and team factors influencing ethical decision-making beyond individual beliefs about AI. How AIEd colleagues conceptualize ethical behavior in their field is a useful place to start this discussion. Members of the AIEd community recognize the importance of acting ethically, but good intentions on their own are no defense against unintended consequences (Holmes et al., 2021). Indeed, in a survey of 60 AIEd researchers, a portion of them indicated the belief that working within the field of education is unto itself “doing ethics” (Holmes et al., 2021, p. 518). Within ethical decision-making in AIEd, there is a difference “between doing ethical things and doing things ethically, to understand and make pedagogical choices that are ethical, and to account for the ever-present possibility of unintended consequences” (Holmes et al., 2021, p. 505). Currently, there is no established common ethical framework for AIEd as the Holmes (2021) study explains. In the absence of an agreed upon ethical decision-making model, Interdisciplinary AIEd teams must optimize the processes they use to integrate their various perspectives and individual beliefs about AI and make ethical decisions supporting product design as a group.

As AIEd product teams interact and make design decisions with downstream implications, it is important for team members to recognize that ethics goes beyond stopping unethical actions. Rather, ethics also entails considering when inaction is unethical (Holmes et al., 2021). Bisconti and colleagues (2023) suggest an iterative design methodology that incorporates a narrative approach, specifically for interdisciplinary groups working with AI that systematically facilitates the integration of interdisciplinary perspectives when anticipating possible downstream effects. To help AIEd product teams adopt such practices, it is vital to understand the roles played by individual and team mental models and moral resilience in influencing ethical decision-making..

Mental Models

A mental model characterizes an individual's personal conceptual framework of how and why a system currently operates and how it might operate in the future (Rouse & Morris, 1986). It is their unique representation of the environment, its agents, social interactions, and the person's own beliefs about their decisions and their consequences. In a team-based CAS, people revise their mental models as they adapt their behaviors based on feedback from inside the team and from the external environment. As established, individual collaborators vary in their unique concepts and priorities for the ed tech product their teams are creating and may adapt their mental models as they encounter new perspectives. On an AIEd team, one person might have mental models of their professional role, the team's structure and function, and the product they are working on, be it a computerized assessment, an interactive digital textbook, or an online course.

Hughes and Hay (2001) provide an example of varying team member mental models in action and explore implications for ed tech products. Hughes and Hay's (2001) study investigates optimal design processes for incorporating diverse stakeholder mental models. The researchers requested team members create individual concept maps portraying their perceptions of key project ideas and priorities, which the project manager aggregated into a centralized project map. The researchers concluded that team members held contrasting conceptualizations of what mattered the most in the project and why. Promoting ethical team member behaviors in AIEd requires operationalizing a design approach to knit together separate perspectives and drive a shared vision forward. Converging individual mental models into a shared team vision is known known creating a team mental model (Klimoski & Mohammed, 1994). As shown by the example of Hughes and Hay's eLearning team, creating a team mental model entails conscious investment of time and effort but yields dividends in terms of ethical decision-mkaing.

Researchers have investigated how team mental models are created. Investigating innovation in interdisciplinary teams, Ness and Søreide (2014) analyzed creative knowledge processes among collaborators in the oil industry and in research by conducting an ethnographic field study. After interviewing and observing participants in their contexts, the researchers identified six phases that explains how teams integrate their individual perspectives into innovative ideas. It is the middle of this process, deemed the “Room of Opportunity” that proves most vital, in which teams begin to process their shared disciplinary knowledge, imagine new ideas with their shared knowledge, and refine those concepts. In a critical analysis of their interdisciplinary research partnership, Timmis and Williams (2017) recommend interdisciplinary teams treat interdisciplinarity itself as a boundary object within the collaboration process. Like the “Room of Opportunity” described by Ness and Søreide, actively grappling with interdisciplinarity creates a sort of “in-between” space in which teammates can benefit from one another’s point of view.

Strong leaders of interdisciplinary teams recognize their colleagues’ expertise and skill sets and intentionally create conditions for knowledge sharing and idea generation. They facilitate interactions that reduce the separation between teammates and promote convergence of their mental models enriched by their collective diversity of disciplinary knowledge (Moirano et al., 2020). When this does not happen, the consequences have the potential for disaster later. For example, AI engineers sometimes focus on the technical elements of model development, which could lead to not considering the full social realities of implementation in the classroom and overlooking important ethical implications as concluded in an ethnographical study of AI engineers in Canada (Govia, 2020). Summarizing case studies depicting interdisciplinary collaboration in AIEd driven by a learning sciences lens, Luckin and Cukurova (2019) describe the benefits of having researchers teach their developer colleagues about the pedagogical evidence foundation for their product, making a case for bringing interdisciplinary teammates into regular contact with one another. Far from a straightforward process, mental model integration on interdisciplinary AIEd teams is complex, involving dynamic interactions over as they share knowledge and formulate new ideas.

Ways of Knowing

Human development lends useful insights for optimizing shared mental model creation on teams. Comprised of adults with diverse levels of professional experience and expertise, interdisciplinary AIEd teams approach shared mental model building from different developmental contexts. Adult constructive-developmental theory (Kegan, 1980) explains that cognitive development extends into adulthood with it being possible for individuals to achieve more complex ways of knowing as they develop and learn from new experiences. The foundational developmental stage for adults, instrumental, is characterized by a binary mindset that is rules oriented. The most complex developmental stage, self-transforming, is more flexible and self-reflective. Each developmental stage equates to a way of knowing. These ways of knowing have been interpreted for the context of adult education and leadership as a tool to support leaders in tailoring their feedback and coaching to developmentally diverse teams (Drago-Severson & Blum-DeStefano, 2017; Drago-Severson & Blum-DeStefano, 2018). Facilitating shared reflection with one or more peers to stretch the limits of one's current understanding of a complex matter, collegial inquiry is one approach that can support connections between developmentally diverse teammates (Drago-Severson, 2009; Drago-Severson & Blum-DeStefano, 2017). Team convenings are one way to foster collegial inquiry. In this model, individuals synthesize a complex issue that they have faced and present it to their peers for questions and feedback, reducing assumptions and increasing reflectiveness (Drago-Severson et al., 2013). In a different study, Drago-Severson and team (2011), implemented this model with graduate students and found they reported a deeper understanding of course subject matter and a heightened consciousness of adult development and its implications for peer collaboration. Considering applications for adult development approaches to educational leadership for higher education faculty and administrations, Stewart and Wolodko (2016) emphasized that it is essential for people who are responsible for designing learning experiences to understand the conditions under which learners increase the complexity of their own thinking, even if their area of expertise is more technical than educational. Variation between teammates in their ways of knowing can impact the conversations they have. In interactions between AIEd product team members, consisting of educationally and technically oriented colleagues, developmental diversity can make the difference in whether ethical implications are a nuanced conversation people are open to investing time to engage in or better added to the project backlog as a future action item.

Moral Resilience

Individuals must remain vigilant in the face of morally complex, confusing, or distressing situations to consistently make ethical choices (Rushton, 2017). Should team members fail in this endeavor, they may experience ethical dissolution, a gradual erosion of moral integrity (Jackson et al., 2013). A variety of elements such as time pressures, normative expectations, and ambiguous policies, may produce gradual shifts in emergent team behaviors. Originating conceptualized within the context of nursing, moral resilience is a person's ability to hold true to their values when they feel constrained by a challenging situation (Rushton, 2017), providing a protective buffer against ethical dissolution. While moral resilience originated within healthcare, its relevance extends to other professions, including education, in which dynamic, interdisciplinary team-based systems shape daily choices (Young & Rushton, 2017; DeMarco, 2023).

Despite the construct's wide applicability, moral resilience is under taught and studied as a concept, according to Bauer and Hermann (2022). They argue that "technomoral resilience," the ability to navigate shifting moral norms and values alongside technological change, may be an important form of moral resilience to teach nurses who must make choices about how to integrate technology in their day-to-day duties. In one of the examples the authors share, nurses working in elderly care must grapple with the notion of care robots that can assist with lifting patients into their beds or provide social companionship and could benefit from additional support to make choices about incorporating such tools into their work. Of these two capabilities, Bauer and Hermann (2022) report, the latter is more socially accepted.

Seeking to validate the conceptual scholarship on moral resilience, one study of professionals working on interdisciplinary healthcare teams including physicians, social workers, and chaplains confirmed that moral resilience plays a role in disciplines beyond nursing (Holtz et al., 2018). Holtz and colleagues (2018) requested 184 interprofessional clinicians and 23 nonhealthcare providers they collaborate with provide descriptive definitions of moral resilience to understand how stakeholders understand the concept. Three primary themes (personal and relational integrity and buoyancy) and three subthemes (self-regulation, self-stewardship, and moral efficacy) aligned with skills and qualities that help people achieve moral resilience emerge from the qualitative data. To build collective moral resilience in a team context, Delgado and colleagues (2021) propose communities of practice as a tool for practitioners to discuss ethical challenges and build up these skills identified by Holtz et al. (2018). They advocate for this approach because it can help team members reframe their relationship with challenges and adopt a more distanced, reflective stance and channel their energy toward inquiry rather than frustration. Baratz (2015), aiming to socialize the concept of moral resilience within the education community, surveyed 123 teacher trainees about their perceptions of the concept. Baratz learned that future teachers perceived moral resilience both in terms of the organization in which they teach as well as the mental mechanisms that contribute to resilience and support interactions between subjects within a CAS.

Within the CAS of AIEd, product development teams can apply moral resilience to adapt and continue to develop their interdisciplinary collaboration as they respond to moral challenges or dilemmas. Moral resilience emerges as AIEd product teams learn from the questions they pose to one another and grapple with the ethical considerations sparked by design decisions. Product team members learn to rely on one another as resources in their own fields and leverage desk and/or user researchers to self-organize and investigate possible downstream effects to resolve them prior to release with learners or educators.

Reflective Design Practice

Reflective design practice can support interdisciplinary AIEd product team collaboration, creating a space for team members to make new meaning. Critical reflection of one's assumptions offers a lens into how as people mature into adulthood, they accumulate new ways of making meaning from the world around them and changing their worldviews. Mezirow's transformative learning theory (1997, 1998) characterizes this phenomenon as a person shifting their current frame of reference, consisting of structures of their core assumptions, to a new one. Critically reflecting on their assumptions helps adults think for themselves rather than frames of references presented to them by others.

When it comes to the context of interdisciplinary professional collaboration in AIEd product development, replacing a team member's existing assumptions with new ones can be difficult to achieve. Grounded in concepts of adults' cognitive development, the Immunity to Change framework emphasizes the value of focusing professional development programs around helping people deconstruct whatever underlying assumptions may be hindering their progress. In other words, mapping people's immunities to change creates opportunities for people to reflect upon their existing assumptions in support of acquiring new frames of reference presents a twofold benefit (Helsing et al., 2009). Not only do people continue their continued cognitive development into adulthood but also they improve their professional practice.

The literature offers examples of such benefits of reflective design practice. In a retrospective case study of interdisciplinary professionals collaborating on teacher training curricula (Bopardikar, et al., 2021), the researchers found that intermeshing of ideas from each disciplinary perspective resulted from the availability of shared design artifacts, also known as boundary objects, which were co-created and offered a shared point of reference for shared reflection. This externalization of concepts into prototypes facilitated productive reflection throughout the design process. Scanlon and colleagues (2019), employing a qualitative design-based research methodology to investigate their experiences designing technology-enhanced learning, identified reflective approaches as a coping strategy for the challenges of interdisciplinary working. Their interviews revealed holding space to bridge gaps in understanding about each discipline's role early in development sustained progress throughout the project. Evaluating the impact of a team development intervention for interdisciplinary scientific teams, a quantitative study surveyed program participants, found that the workshop model improved team members' buy-in of interdisciplinary collaboration, demonstrating gains in readiness to collaborate and team trust (Morgan et al., 2021). The researchers in this study did not observe any gains in other areas like goal clarity, process clarity, and role ambiguity, underscoring the importance of ongoing team interactions in improving these outcomes. This finding suggests the importance of intentional reflective design practice that allows team members to build a shared understanding of project goals, team roles, and overall process. Reflective design practice can enhance ways of working in interdisciplinary product teams, particularly in the field of AIEd. Reflective design practice fosters deeper understanding and metacognitive awareness among teammates, resulting not only in the continued professional growth of each team member but also in optimizing the design of ed tech products.

Team Integrative Capacity

As the previous sections of this chapter recounting the overarching system of AIEd and dynamic interactions between interdisciplinary stakeholders to process and adapt to information about AI within and outside their environment demonstrate, morally resilient knowledge integration to make ethical product design decisions is far from a straightforward process. To understand the nonlinear nature of AIEd product team collaboration requires exploration of team integrative capacity as an emergent state from this complex and adaptive system. Integrative capacity involves cognitive and social processes along with related emergent states that influence the ability of a team to merge diverse knowledge (Salazar et al., 2012). Integrative capacity refers to the collective potential a team possesses to contend with different barriers they may encounter, like role confusion, power imbalances, and knowledge communication challenges described in a previous section, as they seek to integrate knowledge and innovate new solutions. Integrative capacity facilitates team processes central to building a shared understanding of tasks and goals, integrating diverse disciplinary perspectives, and encouraging more sophisticated and reflective ways of knowing regarding downstream effects of AIEd product implementation (Tebes & Thai, 2018). Integrative capacity facilitates what would be called a holding environment in the adult constructive-developmental parlance (Drago-Severson & Blum-DeStefano, 2018). When individual team members interacting within an AIEd product team optimize their integrative capacity to integrate the best of their disciplinary expertise with the best of their reflective thinking, they can challenge and support one another in proactively responding to downstream effects.

Design methodologies offer ways to support morally resilient AIEd product teams while building their integrative capacity. Bisconti and colleagues' iterative design methodology framework (2023) suggests strategies for fostering dynamic interdisciplinary interactions between AI research collaborators that could prove beneficial for AIEd product teams. Their methodology consists of four phases, reminiscent of Ness and Søreide's "Room of Opportunity" in which facilitated knowledge integration sparks idea generation and innovative idea refinement: (a) defining the hypothesis space, (b) constructing a common lexicon, (c) building scenarios to explore future possibilities, and (d) interdisciplinary self-assessment. These concepts guide AIEd product teams in proactively adapting to environmental feedback as they strategically anticipate possible ethical challenges posed by innovative teaching and learning tools built with AI before they can affect people who are using them in a classroom setting.

Conclusion

"Vanderbilt has decided to disable Turnitin's AI detection tool for the foreseeable future. […] We do not believe that AI detection software is an effective tool that should be used," announced Michael Coley on behalf of Vanderbilt University in August 2023. The announcement came just four months after Turnitin, a leading academic integrity tool integrated into many online learning platforms, suddenly released an AI-powered plagiarism checker with little advance notice to customers at universities. Citing an unacceptable false positive rate of four percent (Coley, 2023) and the tendency for such detectors to exhibit bias against non-native English speakers (Liang et al., 2023), Vanderbilt University opted to inactivate the tool in favor of teaching faculty how to establish clear expectations with students about how to use AI in their writing process. This AIEd product example shows a breakdown of team interactions in which, somewhere along the line, knowledge failed to integrate, for reasons unknown. Knowledge integration fueled by team dynamics and moral resilience can promote ethical decision-making and reduce such downstream occurrences like the case of Turnitin at Vanderbilt. By facilitating scalable ethical decision-making and collaborative practices, ed tech companies can create environments for interdisciplinary teams to produce innovative AI-powered learning tools that prioritize ethical considerations and responsible use.

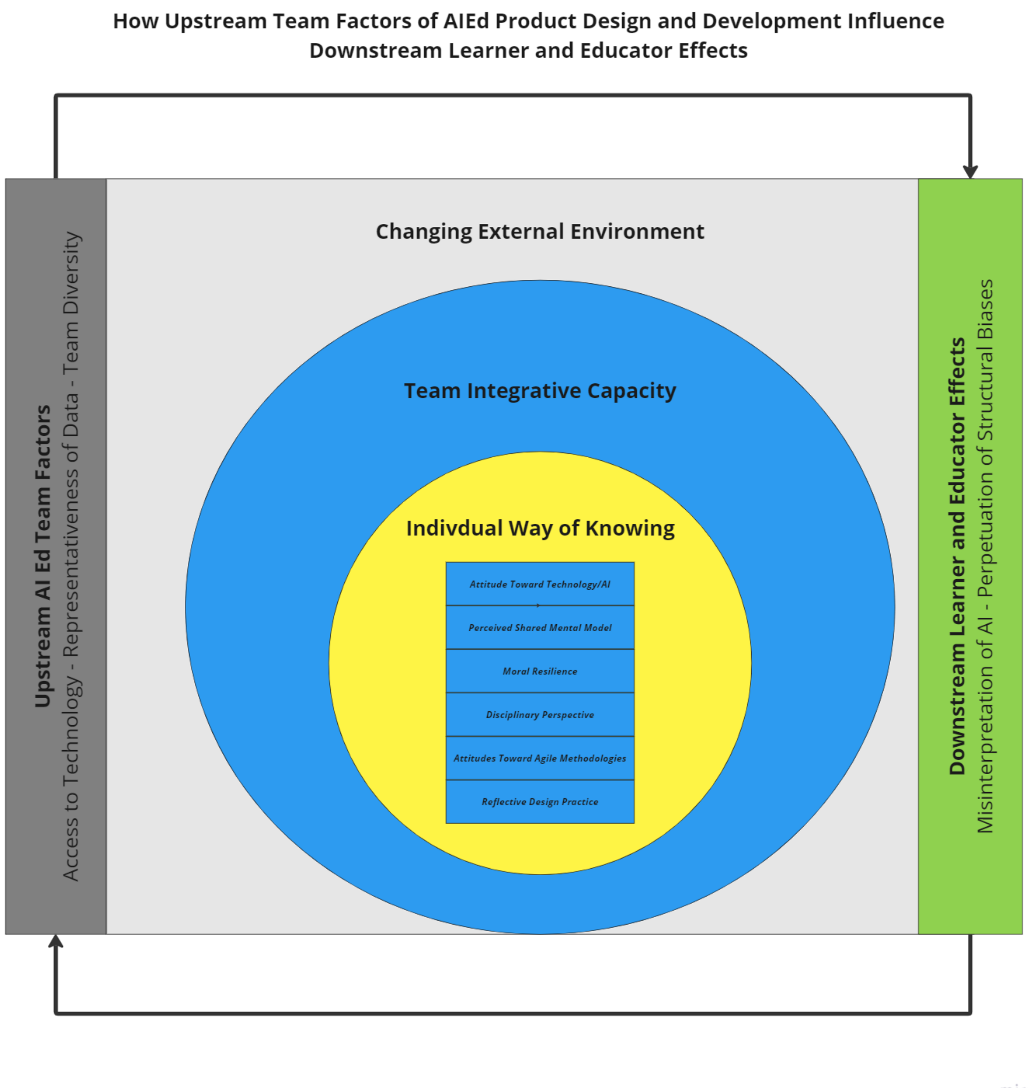
Complex Adaptive Systems Theory guided an exploration of literature in this chapter to establish the field of AIEd as a CAS, focusing on interdisciplinary product development team members and their dynamic interactions. Beyond their discrete disciplinary expertise, people's individual attitudes toward AI and teams' collectively held sociotechnical imaginaries of the technology's purpose in education inform their individual mental models. Team members' individual ways of knowing and mental resilience inform how team members navigate cognitively complex conversations related to ethical decision-making. Underlying all of this is a team's integrative capacity to bring together information internal and external to team interaction, facilitating the teams' ability to create AIEd products that deliver a best-in-class experience for learners and educators. Weaving together these dynamic, and oftentimes, nonlinear factors, a conceptual framework articulated in the next section presents a path forward for further elucidating this problem of practice in service of generating possible solutions.

Conceptual Framework

Chapter 1 established a series of upstream factors influencing the behaviors of interdisciplinary product teams acting within the larger environment of AIEd as they create learning tools integrating AI and must make design decisions, often weighing uncertainties of how emerging technology will impact classroom implementation. Figure 1 proposes a conceptual framework hypothesizing relationships between factors of interest in further empirical investigation of how upstream AIEd team factors influence downstream effects on learners and educators. The conceptual framework represents the dynamic interactions between interdisciplinary product development teams as they design learning tools incorporating AI within the larger environment and CAS of AIEd. Individual team members, represented in yellow, function as subjects within the system, each processing new information from the external environment through various lenses, including their own attitudes toward technologies such as AI, their moral resilience, and their own disciplinary perspective. The team, represented in blue, integrates these pieces of information to a degree, depending on the extent to which team knowledge has been successfully established. Because each individual team member contributes their own unique perspective, these individual factors are represented in the blue team color to emphasize these recur for each person. Amidst a rapidly changing external environment, team members must continuously revise their individual and shared mental models, anticipating and responding to downstream effects of AIEd implementation on learners and educators. Such downstream effects could include how AI models might be misinterpreted in an educational setting and how AI perpetuates systemic biases. These downstream effects also may feed back into upstream factors influencing AIEd product development teams' processing of information in their external environment.

Figure 1

Conceptual Framework



Chapter 2

Interdisciplinary educational technology (ed tech) product teams integrating artificial intelligence (AI) within learning tools and experiences must negotiate a host of individual and collective factors during upstream product design decision making as outlined in Chapter 1. Together, these teams form complex adaptive systems that dynamically interact with one another as well as subjects outside their environment. Upstream factors include team members' individual mental models comprised of making meaning of AI in education (AIEd) from their unique disciplinary standpoint, their attitudes toward AI, and how they approach complex decision making to ensure they uphold their own values and ways of knowing in the design process. On a team level, upstream factors entail the extent to which teams integrate members' individual mental models of AI's possibilities for education and disciplinary knowledge into a shared vision that anticipates downstream consequences. In a world in which AI is quickly evolving, and society is only beginning to understand its downstream effects in classroom and workplace implementation, it behooves AIEd teams to actively engage in these considerations throughout the design process. Chapter 2 describes a needs assessment study I conducted to further investigate the factors from Chapter 1's Conceptual Framework within my professional context and progress toward an applied project responding to this problem of practice.

Context of Study

Interdisciplinary collaboration has increased to optimize processes and products in settings as diverse as public policy, healthcare, and education (Choi & Pak, 2006). Ed tech companies bring together interdisciplinary professionals to design human-centered products incorporating technologies like AI to help teachers and learners achieve their goals (Alphonso, 2023). Combining multiple perspectives including instructional design, learning science, data science, user experience, assessment development, and AI engineering, the experts on these teams can create educational products forged on a solid evidence-based foundation melding together the best of all worlds (Herrick et al., 2022). Ed tech settings using such staffing models relevant to this study include assessment development organizations, academic publishers, universities, and corporations with training departments. Still, complications inherent to interdisciplinary product innovation teams persist, including interdisciplinary collaboration between colleagues (Moirano et al., 2020), varying individual conceptualizations of key concepts and priorities (Hughes & Hay, 2001), and convergence of a shared mental model (Cannon-Bowers et al., 1993). These complications may produce negative downstream effects on product users' experiences in their learning context (Dieterle et al., 2022). Shedding light on the dynamic and adaptive interactions of ed tech product teams may yield insights regarding the design of learning experiences integrating emerging technology.

While some areas of the ed tech sector have slowed in the years following the height of the COVID-19 pandemic, ed tech companies focused on creating products incorporating AI continue to attract interest from investors (Glasner, 2023). As new AI capabilities attract popularity such as in the case of generative AI in the wake of ChatGPT's November 2022 release, ed tech companies such as Quizlet, Khan Academy, Duolingo, Coursera, and Higgz develop tools integrating them (Kshetri, 2023). Alongside them, legacy companies like the Educational Testing Service (ETS), established in 1947, are also reimagining their portfolios with AI (Williams, 2023). Efforts emerging across these different organizations to build new AIEd products yield a rich landscape of educational innovation.

Innovating in ed tech comes with its challenges, particularly when AI is an organizational priority. 86 percent of ed tech executives surveyed reported cross-departmental silos present an obstacle to their staff's success (Ed-tech Leadership Collective, 2023). A qualitative content analysis of 18 ed tech companies combined with interviews of ed tech leaders revealed a lack of systematic processes is impeding AI's incorporation into ed tech offerings (Alam & Mohanty, 2022). Other qualitative studies, such as Kousa and Niemi's (2022) focused investigation of challenges facing ed tech companies as it pertains to AI, compound this Alam and Mohanty's (2022) finding. Kousa and Niemi (2022) found, through their interviews with ed tech subject matter experts, that product team members lack an ability to anticipate and assess AI's consequences in society. Other researchers have described how ed tech confronts data management challenges, stemming from a dearth of partnerships between those focused on teaching and learning and those focused on data and technology (Khosravi et al., 2023) along with knowledge sharing challenges incurred by commercial AI developers not seeking out the pedagogical expertise of their learning science colleagues (Luckin & Cukurova, 2023). As AI continues to evolve, this moment presents an unparalleled opportunity to probe the different experiences and practices of AIEd product team members working at various ed tech companies on different learning tools.

To that end, I conducted this study through my professional networks, both internal (ETS) and external (LinkedIn), with the goal of reaching individuals at organizations like Duolingo, Khan Academy, and Southern New Hampshire University who work on interdisciplinary teams creating AI-enabled learning products. Given that the ed tech sector employs over 100,000 people (Barnett & Li, 2023), even layoffs of 8,000 employees (Tower, 2023) represent a sizable impact. To ensure demographic relevance, I analyzed EEOC data on Educational Services professionals, which included ed tech companies. I found approximately 70 percent identify as White, 11 percent Black or African American, 9 percent Hispanic, and 7 percent Asian, with women representing about 64 percent of this workforce (EEOC, 2021). These demographics aligned with those I expected in my study population. By gathering insights from professionals across different companies, I aimed to capture a more nuanced understanding of AIEd product development.

Statement of Purpose

This study aims to illustrate how individuals on interdisciplinary teams in the emerging field of AIEd collaborate. The individual team member serves as the unit of analysis to support a needs assessment for developing resources that enhance interdisciplinary collaboration skills. While organizations like ETS invest in AI engineering, others like my former employer, Southern New Hampshire University, partner with experts such as Google to advance AI efforts (Butschi, 2021). Given the ongoing learning curve surrounding AI, I adopt a broad scope to explore interdisciplinary collaboration across a variety of AI-related ed tech projects.

Research Questions

This study is guided by the premise that AI reflects and amplifies societal values. AI models embody the biases of their creators. Accordingly, I pose the following three research questions to guide the needs assessment:

1. How do individual ed tech product team members conceptualize AI's role in education?
2. How well do ed tech product teams integrate their disciplinary knowledge and beliefs about AI into a shared mental model?
3. How morally resilient are ed tech product team members in complex design decision making regarding AI's possible downstream effects during implementation?

Factors

This study consisted of two phases: an anonymous online survey and follow-up interviews with a random sample of participants who opted in. The participants worked on interdisciplinary ed tech product teams designing tools that incorporate AI. I investigated seven key factors: attitudes toward AI, perceived shared mental model, sociotechnical imaginaries, moral resilience, reflective design practice, attitudes toward agile methodologies, and disciplinary perspectives. Table 1 summarizes each factor's definition and relevance. To better understand the interplay among these factors, I used a mixed methods design, integrating both quantitative and qualitative data to explore participants' beliefs, experiences, and practices.

Table 1

Factors for Empirical Study

Factor	Definition
Moral Resilience	An individual's ability to hold true to one's values when they feel constrained by a challenging situation (Rushton, 2017)
Attitude Toward AI	An individual's positive and negative attitudes toward AI (Schepman & Rodway, 2020)
Sociotechnical Imaginaries	An individual's emotional response to and perceived likelihood of various possible futures related to AI (Sartori and Bocca, 2023)
Perceived Shared Mental Model	Extent to which an individual perceives a collective understanding of main project tasks and ways of working with their teammates (Van Rensburg et al., 2022)
Disciplinary Perspective	An individual's area of professional training and expertise (Hanson, 2018)
Reflective Design Practice	Extent to which an individual engages in reflection during the design process (Tracey et al., 2021)
Attitudes Toward Agile Methodologies	Individual team member attitudes and morale concerning agile software development (Begel & Nagappan, 2007).

Attitudes Toward AI

Individual team members' conceptualizations of how AI was being used in the product they are working together to create is operationalized in this study as individual team members' attitudes toward AI. People's attitudes toward AI diverge from their general attitudes toward technology (Schepman & Rodway, 2020). Attitudes toward AI include people's general comfort level with and perceived capability of (in comparison to human performance) AI applications. The collective team's vision for a product absorbs these individual notions of AI.

Perceived Shared Mental Model

The perceived shared mental model refers to the extent to which team members share a collective understanding of the task, the team, and how they work together (van Rensburg et al., 2022). Instead of observing multiple, remotely distributed interdisciplinary product teams, I measured the convergence of shared mental models by asking participants about their perceived shared mental models with respect to their work. The extent to which individuals perceive they share a mental model with teammates may have influenced their comfort with making designs during the design process that anticipate downstream implementation challenges.

Sociotechnical Imaginaries

Designing AIEd products could be bounded by an assumed sociotechnical imaginary that AI is an "educational solution" that can "fix" education's problems (Rahm & Rahm-Skågeby, 2023, p. 2). Sociotechnical imaginaries are a shared understanding of how society should ideally be. They both reflect and reinforce how people working with technology conceptualize them (Jasanoff & Kim, 2009). Through analyzing people's specific reactions to possible futures for AI, interdisciplinary AIEd product teams could unpack commonly held sociotechnical imaginaries in AIEd product development and start to identify possible challenges in interdisciplinary team collaboration.

Moral Resilience

With its origins in the nursing and healthcare field, moral resilience is a person's ability to hold fast to their individual ethical values in the face of adversity (Rushton, 2017). Because it is pertinent to a professional setting encompassing complex problem-solving and interdisciplinary collaboration, the concept of moral resilience applies to nonhealthcare professions as well (Young & Rushton, 2017). Moral resilience can offer a lens into individual capacity to weather challenging conversations about downstream effects of AI during the decision-making process.

Disciplinary Perspectives

Teams creating learning tools and experiences that integrate AI in some capacity could include a wide range of job titles, some of which may mean something different from institution to institution. The survey followed the model established by Herrick and colleagues (2022) in which team members were grouped into three functional categories – user-centered design (focusing on user experience design and research and product efficacy research); learning science (focusing on learning science theory and research, assessment design, and instructional design); and AI (focusing on AI engineering, data science, and software development).

Team Attitudes and Morale Concerning Agile Methodologies

Software development teams commonly use agile software development (ASD) methodologies (Srinivasan & Mukherjee, 2018). Combining consistent team ceremonies and helping team members amass momentum through streamlining processes, ASD can help teams succeed in their goals. A survey of multidisciplinary software developers at Microsoft found that most viewed the approach favorably with benefits to morale and productivity (Begel &

Nagappan, 2007). How teammates perceived ASD methodologies may support their perception of a shared mental model.

Reflective Design Practice

Reflecting during the design process is a necessary step to optimize decision-making (Tracey et al., 2022). Researchers have described the negative impacts of a failure to engage in reflective design practice, particularly concerning AI (Govia et al., 2020; Macgilchrist, 2019). Thinking through the implications of technology design decisions such as the training of a machine learning algorithm or considerations for implementations can mitigate inequitable downstream effects (Dieterle et al., 2020). Understanding the extent to which product team members actively engaged in reflective thinking while designing lends context to their perceptions of a shared mental model, moral resilience, sociotechnical imaginaries, and attitudes towards AI.

Method

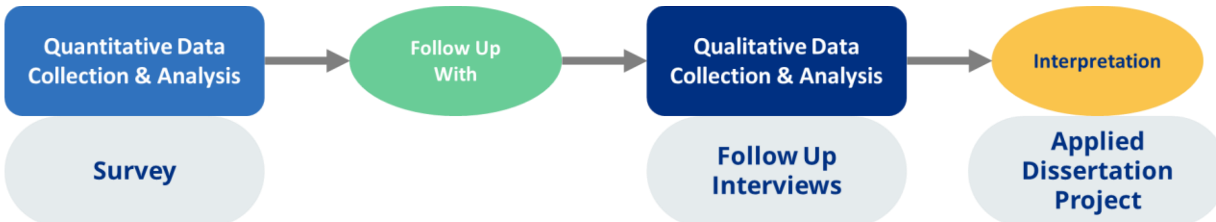
In this study, I used a mixed methods design to investigate factors associated with interdisciplinary collaboration in ed tech product teams. My participants included individuals currently or recently working in the educational technology space in interdisciplinary roles. The Participants section defines these roles in greater detail. I obtained approval for this research protocol from the Johns Hopkins Institutional Review Board (IRB).

Research Design

I followed an explanatory sequential mixed methods design, as shown in Figure 2, which I adapted from Ivankova and colleagues (2006). I began with a survey to gather insights about interdisciplinary product team members working in AIEd. After conducting a preliminary analysis of the survey's quantitative results, I used those findings to inform the focus of follow-up qualitative interviews with a small group of participants who opted in. I then interpreted the combined qualitative and quantitative data to support a needs assessment for my proposed application dissertation project.

Figure 2

Explanatory Sequential Research Design



Participants

My survey participants included professionals who were currently working or had recently worked on interdisciplinary product teams in the educational technology sector. These professionals held a wide range of job titles, including but not limited to learning scientist, instructional designer, learning experience designer, learning engineer, assessment developer, assessment specialist, curriculum designer, user experience designer, user experience researcher, impact scientist, research scientist, data scientist, AI engineer, machine learning scientist, product manager, and product owner. Before launching the study, I estimated I could reach about 100 people who met these criteria within my immediate professional network. My recruitment materials ultimately received over 2,500 unique views on LinkedIn.

Participant Recruitment

I recruited participants through professional networks and learning communities, including LinkedIn. I posted an invitation that introduced the research topic, encouraged interested individuals to participate, and welcomed them to share the post with others (see Appendix A). I also received permission from my employer to post the survey in internal communication channels (see Appendix B). At the end of the survey, I included a link to a separate form for participants to indicate their interest in a follow-up interview.

Quantitative Sampling

A total of 17 individuals began the quantitative survey, and 8 participants completed it in full. Table 2 presents descriptive statistics about the study population. Just over half of respondents identified as female. Most participants (n = 9) were between the ages of 35 and 44. Of the respondents, 29.4% identified as Asian, 5.9% as Black or African American, 47.1% as White or Caucasian, and the remainder declined to respond.

The sample also reflected interdisciplinary diversity. About 23.5% of participants worked in technical roles, such as AI engineering, data science, or software development. Another 11.8% aligned with user-centered research roles like UX design, UX research, or product efficacy research. Approximately 16.8% represented learning-focused roles, such as learning science, assessment design, or instructional design. One participant self-identified their role as "Other."

Table 2

Demographic Characteristics of Participants

Participant characteristic	**Full sample**	
	N	%
Gender		
Female	9	52.9
Male	5	29.4
Non-binary or third gender	1	5.9
Cases Missing	2	11.8
Age		
18-24 years old	1	6.7
25-34 years old	2	13.3
35-44 years old	9	52.9
45-54 years old	1	5.9
55-64 years old	1	5.9
65+ years old	1	5.9
Cases Missing	2	11.8

Race		
Asian	5	29.4
Black or African American	1	5.9
Prefer not to say	1	5.9
White or Caucasian	8	47.1
Cases Missing	2	11.8
Ethnicity		
Hispanic or Latino	1	5.9
Non-Hispanic or Latino	14	82.4
Cases Missing	2	11.8
Employment Status		
Working full-time	10	58.8
Working part-time	1	5.9
Student	1	5.9
Other	2	11.8
Retired	1	5.9
Cases Missing	2	11.8
Years in Role		
Less than a year	1	5.9
1-3 years	1	5.9
4-5 years	3	17.6
6-10 years	3	17.6
10-15 years	1	5.9
15-20 years	1	5.9
Cases Missing	7	41.2
Functional Area		
Learning and assessment	3	16.8
Research	2	11.8
Technology	4	23.5
Other	1	6.7
Cases Missing	7	41.2

Qualitative Sampling

For the qualitative stage of my study, I interviewed three participants who had completed the initial study survey and expressed interest in a follow-up interview. Two of the participants identified as female, and one identified as male. Their roles spanned across different functional areas: one participant worked in technology, another in research, and the third in learning and assessment. This diversity provided insight into interdisciplinary perspectives within AIEd product development teams.

Positionality

Awareness of my own researcher positionality was a critical input for formulating the methodology for this mixed methods study. Positionality refers to the researcher's unique worldview and their stance toward a research project as it pertains to social and political context (Holmes, 2020). In short, a researcher's positionality consists of their assumptions about what they know of the world around them. As Milner (2007) points out, there may be aspects of how I as a researcher perceive the world based on my own cultural and racial experiences that I may not be fully aware of. This positionality statement represented the commencement of a continued undertaking throughout this study as I unpack my identity, biases, and relationship to participants along with the professional context and infer implications for my research.

I identify as a cisgender heterosexual White female. English is my first language, and I am an American. I grew up in the Northeastern United States where I now make my home. I am 33 years old and have ADHD. I grew up with my sister, Erin, who lived with a severe developmental disability. She passed away almost ten years ago, and my parents are the primary family I have left. Although I grew up working class, I am now solidly middle class. I own my home.

Throughout my educational history, teachers regarded me as a high-achieving student. I enrolled in honors and AP coursework in high school. I then pursued undergraduate and graduate degrees at Harvard University prior to enrolling in this doctoral program at Johns Hopkins. My educational background, appropriately themed to the focus of this investigation, is in the history of science and mind, brain, and education. I have long been fascinated by how interdisciplinary collaborators can work together to advance scientific and technological innovation.

I have over ten years of experience in innovative online learning and assessment. I worked in online instructional design and innovation at one of the largest universities in the United States before transitioning to a learning scientist role at one of the nation's oldest educational testing companies, supporting the development of new forms of testless assessment that surface key insights for learners and decision makers. I regularly collaborate across disciplinary lines, often seeking support and advice from technical and design colleagues throughout my day-to-day work.

A desire to improve my practice has motivated my pursuit of this research. I want to be the best learning scientist I can be and promote a culture of excellence on my team. I strive to produce quality ed tech products that purposefully integrate AI to meet learner and educator needs.

Because of my racial and educational background, I recognize the privilege I hold in society. I have carried that awareness with me while interpreting both the quantitative and qualitative findings of this study. I also understand that different ed tech companies may prioritize different goals than those held by my organization or myself. As such, I have factored those perspectives into my analysis to maintain a broader, more inclusive view.

Throughout this study, I committed to minimizing bias by consulting diverse data sources and practicing ongoing reflexivity. As recommended by Guba (1981), I maintained a study journal to reflect on my evolving positionality and critically examine how my perspectives influenced my interpretations over the course of this research.

Measures and Instrumentation

The survey I administered for the study included items requesting demographic background information as well as select items adapted from previously validated measures described in the following section (see Appendix C). I asked participants to share details about their age, gender identity, race, ethnicity, employment status, highest level of education, professional training, current team role, professional context, the type of technology they work with, and whether they collaborate internally, externally, or both. To encourage participation and completion, I designed the survey to take no more than fifteen minutes to finish. At the end of the survey, I included a link to a separate follow-up recruitment survey (see Appendix D), where participants can provide their contact information if they are interested in participating in a brief interview.

I collected quantitative data by administering this survey electronically, embedding it in recruitment materials using an anonymous hyperlink. For qualitative data, I used a semi-structured interview protocol to explore participants' experiences working on interdisciplinary product teams more deeply. When participants completed the survey, I assigned each respondent an anonymous identification number. If they opted into an interview, I used the separate follow-up survey to gather their contact information, keeping their original survey responses anonymous. During the follow-up interviews, participants elaborated on their experiences and expanded on themes that emerged in the initial survey analysis.

General Attitudes Towards Artificial Intelligence Scale

The General Attitudes Towards Artificial Intelligence Scale (GAAIS) uses a five-point Likert scale to measure attitudes toward AI (Schepman & Rodway, 2020). The scale consists of 32 items that evaluate positive attitudes toward AI and negative attitudes towards AI. Although it is a newer scale, the GAAIS has demonstrated evidence of both convergent and discriminant validity (Schepman & Rodway, 2022). This study used both subscales in full (see Appendix C). Sample scale items included "For routine transactions, I would rather interact with an artificially intelligent system than with a human" (Schepman & Rodway, 2022, p. 2279), "Artificial Intelligence can have positive impacts on people's wellbeing" (Schepman & Rodway, 2022, p. 2279), and "I shiver with discomfort when I think about future uses of Artificial Intelligence" (Schepman & Rodway, 2022, p. 2279). Participant responses to these items offer a sense of prevailing attitudes toward AI I further analyzed by disciplinary perspective.

Five-Factor Perceived Shared Mental Model Scale

The Five-Factor Perceived Shared Mental Model Scale is a 20-item scale that measures the degree of shared understanding among team members (van Rensburg et al., 2022). It uses a five-point Likert scale to assess the content and accuracy of the shared mental model. The Five-Factor Perceived Shared Mental Model Scale has demonstrated good reliability, internal consistency, convergent validity, and divergent validity. Van Rensburg and colleagues (2022) designed the scale to work in different settings, so it is appropriate for the variety of contexts encompassed in my sample. My survey used the full 20-item version of the scale (see Appendix C). Finishing the stem "Team members have a similar understanding about…" (van Rensburg et al., 2022, p. 10) sample scale items included "each other's skills for doing various team tasks" (van Rensburg et al., 2022, p. 10) , "specific strategies for completing various tasks" (van Rensburg et al., 2022, p. 10), and "coordinating the timing of our work" (van Rensburg et al., 2022, p. 10). Participants' overall impressions of their team mental model provided insights into their overall attitudes toward AI.

AI Scenarios Questions

The study measures participants' sociotechnical imaginaries by adapting a protocol used by Sartori and Bocca (2023) in which they presented eight different future narratives of AI for participants to both react emotionally to and indicate their perception of the likelihood of this narrative coming true (see Appendix C). Sample scenarios included "AI could make our daily life easier, free from the routine chores that computers can do for us" (Sartori & Bocca, 2023, p. 448), "AI could replace the need for real humans in work, relationships and social activities" (Sartori & Bocca, 2023, p. 448), and "AI could become our friend, to listen to us when we need it and to fulfill our desires" (Sartori & Bocca, 2023, p. 448). Participants' reactions to these possible futures of AI complemented my analysis of their perceptions of their team's shared mental model and their individual attitudes toward AI.

Moral Resilience Scale

The Rushton Moral Resilience Scale measures participants' moral resilience (Rushton, 2017; Heinze et al., 2021). Based on results of researchers' successful validation of this instrument with non-nursing staff, the Responses to Moral Adversity and Moral Efficacy sub-scales supported investigation of moral resilience in this study (see Appendix C). Sample scale items included "After facing a challenging ethical situation, lingering distress weighs me down" (Rushton et al., 2024), "When I am confronted with an ethical challenge, I am able to articulate the ethical conflict" (Rushton et al., 2024), and "I can think clearly when confronting an ethical challenge, even when I feel pressured" (Rushton et al., 2024). Moral resilience data from study participants provided me with additional context for understanding individual team members' perceptions of their team's shared mental model.

Disciplinary Perspectives Questions

The study survey collected information about participants' disciplinary perspectives along with nonidentifying demographic information about their age band, professional training, team role, and project work (see Appendix C). Due to job title differences across institutions, I organized disciplinary perspectives into three functional categories to support analysis: user-centered design, learning science, and AI. Pre-established criteria informed these groupings. Sample questions I developed include "What is your current job title," "How many years have you been working in this role," and "What is your area of professional training?" Together, these questions lent vital context for my analysis of participant responses.

Usage and Perceptions of Agile Software Development Survey Questions

A survey created by Begel and Nagappan (2007) measuring software development team members' perceptions of agile methodologies implemented in industry served as a model for this study's investigation of interdisciplinary AIEd product team members' perceptions of agile methodologies. I excerpted select items from the original survey, containing questions both about teams' usage of specific agile methodologies and individuals' perceptions of their utility and impact on team morale, for this study's instrumentation (see Appendix C). Sample scale items included "Adopting Agile methods positively impacts my team's morale" (Begel & Nagappan, 2007, p. 259), "My team collaborates more effectively with Agile than without" (Begel & Nagappan, 2007, p. 259), and "Agile is working well for me" (Begel & Nagappan, 2007, p. 259). Understanding participants' attitudes toward agile methodologies helped me explore how their perceptions of this way of working could influence their perception of their team's shared mental model.

Reflective Practice Questionnaire

The Reflective Practice Questionnaire (RPQ) consists of a series of four item subscales designed for respondents to self-rate statements regarding their reflective practice on a three-point scale ranging from never to sometimes to always (Priddis & Rogers, 2018). Sample subscales used in the study survey (see Appendix C) included uncertainty, confidence in communication, and desire for improvement. Items included statements like "When reflecting with others about my work I become aware of things I had not previously considered" (Priddis & Rogers, 2018, pp. 94-95), "Sometimes I am unsure if my planning for users is the best possible way to proceed" (Priddis & Rogers, 2018, pp. 94-95), and "Sometimes I am unsure that I properly understand the needs of users" (Priddis & Rogers, 2018, pp. 94-95). The scale is validated for individuals working across service industries including education, nursing, and psychology, making it an attractive instrument for this investigation of interdisciplinary collaboration. During their initial validation of the RPQ, Priddis and Rogers (2018) uncovered evidence suggesting that reflective practice supports confidence and drives individuals' desire for self-improvement. Participants' RPQ response data augmented my understanding of how reflective practice could shape team members' perceptions of a shared mental model.

Follow Up Interviews

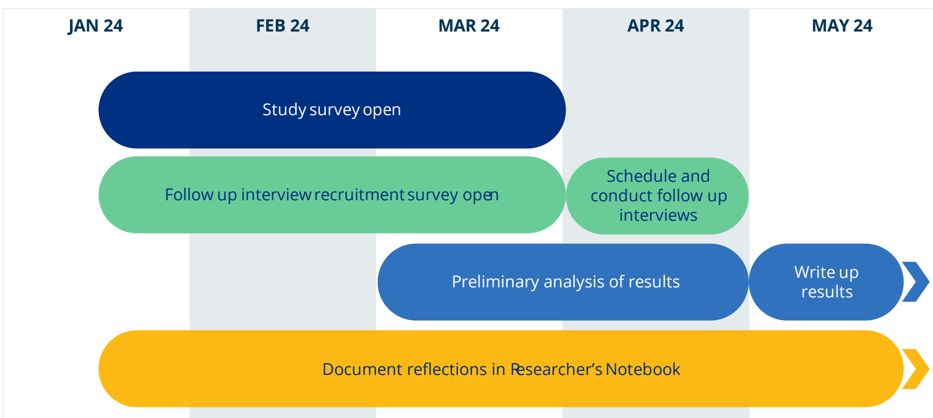
Individual qualitative interviews took place with a small group of respondents who consented to a brief follow-up conversation with the researcher. Preliminary analysis of study data informed prioritization of questions put forth to participants from the follow-up interview protocol (see Appendix E). I scheduled interviews to last no longer than 30 minutes. These interviews allowed me to follow up on emerging themes gleaned from preliminary data analysis and to paint a more detailed portrait of the realities of interdisciplinary collaborations across different ed tech organizations.

Procedure

Following approval from the Johns Hopkins University Homewood IRB, data collection for the study transpired between January and April 2024. Figure 3 depicts the study timeline in further detail. Participants could access the survey from January to March, and follow-up interviews happened in late March and early April. Analyzing and synthesizing results occurred during the remainder of spring 2024.

Figure 3

Study Timeline



Alongside data collection, analysis, and synthesis, I regularly recorded my reflections in a private research journal.

Data Collection Methods

I collected quantitative data using an online Qualtrics survey. The end of the quantitative survey directed participants to a second survey where they could express interest in participating in optional follow-up interviews with me to contribute qualitative data. I aimed to conduct a maximum of five half-hour follow-up interviews with survey respondents who indicated interest in discussing their experiences one-on-one to expand upon themes detected after a preliminary analysis of quantitative survey data.

Data Analysis

The study's data analysis consisted of three phases: quantitative analysis, qualitative analysis, and mixed methods analysis. The quantitative analysis comprised the preliminary analysis of quantitative survey data. Next, the qualitative analysis phase focused on the qualitative coding of follow-up interview transcripts, informed by initial quantitative findings. Finally, the mixed methods analysis integrated the first prior analysis phases.

Hypotheses

Three hypotheses informed quantitative analysis. H_1, the first null hypothesis, stated that there is no difference in how individual ed tech product team members conceptualize AI's role in education. The corresponding alternative hypothesis was that there is a difference between how individual ed tech product team members conceptualize AI's role in education. H_2, the second null hypothesis, was that there is no relationship between team members' integration of knowledge and beliefs about AI and their perception of a shared team mental model. The corresponding alternative hypothesis was that there is a relationship between team members' integration of knowledge and beliefs and their perception of a shared team mental model. The third null hypothesis was that there is no relationship between team members' functional areas of expertise and their moral resilience. The corresponding alternative hypothesis was that there is a relationship between team members' functional areas of expertise and their moral resilience.

Quantitative Analysis

The preliminary analysis phase commenced upon completing initial quantitative data collection with the survey. This phase centered on exporting the survey results from Qualtrics and importing them into SPSS. To clean the data, I created new variable columns in SPSS and referenced the scoring instructions for each scale to calculate composite scores for each respondent. I monitored high-level results as they came in. Observing balanced representation in the three major functional areas (learning and assessment, research, and technology) during this stage of research validated my decision to prioritize questions about individual conceptions of AI and ways of working on an interdisciplinary team during the follow-up interviews.

Concurrent to conducting the follow-up interviews, I computed descriptive statistics for the study sample to determine any high-level patterns meriting further exploration. I used a cross-tabulation of key variables organized by participants' functional areas to further investigate.

Qualitative Analysis

During the qualitative analysis phase, I qualitatively coded transcripts (Saldaña, 2021), following a grounded theory approach (Charmaz, 2006). After conducting each interview, I logged a new entry in their reflective practice journal to unpack my own positionality. At the same time, I also drafted a brief memo highlighting my initial impressions on key themes, following the recommendation of Charmaz (2006). This process helped me track my thought processes throughout the data collection and analysis phases of research and acted as a stopgap measure against the introduction of bias.

Qualitative analysis efforts entailed coding three transcripts of follow-up interviews with AIEd product team members. I took an inductive approach to coding, reflecting my intention to center participants' experiences and voices (Braun & Clarke, 2006). An in vivo coding method grounded my interpretation in the framing words used by participants (Saldaña, 2009). Systematically, I completed a standard set of steps to code each interview transcript following the steps defined by Creswell (2009). First, I reviewed each interview transcript in its entirety to help familiarize myself with key topics and resolve any transcription errors. Next, I developed an initial set of codes for each of the transcripts, based on this first round of review. Third, I completed a second round of coding, seeking to expand upon preliminary codes and beginning to draw thematic connections between transcripts. Finally, I concluded qualitative coding by synthesizing identified themes in relation to the three overarching research questions framing this study.

Mixed Methods Analysis

Following the quantitative and qualitative research phases, I applied mixed methods analysis to draw connections between datasets. Comparing emergent qualitative themes with quantitatively established patterns and relationships supports a more robust synthesis of. Given the applied ed tech product development setting of this research, mixed methods can combine qualitative and quantitative research to "produce more complete knowledge necessary to inform theory and practice" (Johnson & Onwuegbuzie, 2004, p. 21). Mixed methods research also bolstered the potential generalizability of this study, which was useful in light of the smaller sample size for the first two research phases (n=15 for the quantitative survey and n=3 for the follow-up interviews).

The Pillar Integration Process (Johnson et al., 2019) offered a foundation for mixed methods exploration of all three research questions: AI conceptualization, knowledge integration, and moral resilience. Johnson and colleagues' (2019) four-stage technique facilitates the integration of qualitative and quantitative findings in a transparent and rigorous way. After listing quantitative data points and qualitative codes on the outermost columns of the table, I used the innermost columns to match the two where appropriate. Quality checks occurred after initial matches to ensure alignment. I constructed pillar themes informed by matched data and codes.

Methodological Integrity

To bolster the study's credibility and trustworthiness, I maintained a reflective journal as recommended by Guba (1981). I started the journal upon beginning study recruitment and maintained it throughout data collection and analysis. Using an electronic task app, I set weekly reminders to enter new entries as I progressed. I recognized the potential for my positionality as a member of an AIEd product team to influence my meaning-making while making choices about statistical procedures during the quantitative analysis phase and determining codes and themes during the qualitative analysis phase. I committed to recording my reflections regularly to practice reflexivity and mitigate bias (Nadin & Cassell, 2006). Proactively tending to sources of possible bias allowed me to take steps to strengthen my study's trustworthiness and credibility (Finlay, 2002).

Findings and Discussion

Findings

This section summarizes key findings from each stage of the study. It reviews quantitative, qualitative, and mixed methods results and suggests future directions to address this problem of practice.

Quantitative Findings

Conceptualization of AI's Role in Education. The mean score for positive attitudes toward artificial intelligence (M = 3.3977) among team members was higher than the mean score for negative attitudes (M = 2.8611). This finding suggests that respondents generally exhibited a more optimistic disposition rather than a skeptical one concerning artificial intelligence.

Additionally, the standard deviation for positive attitudes toward AI was 0.36017, indicating relatively low variability among respondents in their optimism, whereas the standard deviation for negative attitudes was 0.54676, reflecting greater dispersion in responses.

Respondents worried the most about two possible future visions of AI in particular from the scenarios defined by Sartori and Bocca (2023). The most feared narrative of AI's future was obsolescence, that AI would supplant people in work, relationships, and social activities. The second-most-feared narrative was alienation that AI’s success at meeting people’s needs would drive humans apart from one another. Respondents gravitated most favorably toward a possible future vision of AI in which the technology gives people more freedom to spend less time on tedious, easily automated tasks.

Integration of Knowledge and Beliefs. A majority of respondents (n=6) reported their teams followed Agile methodologies in their daily team practices. The same number of respondents indicated their teams navigated remote work in some aspect. One half of this group (n=3) stated some teammates work in a physical office, whereas the others worked remotely and the other half statde all team members worked remotely (n=3). On average, respondents tended to rate their perception of their team’s shared mental model positively (3.7313) and their perception of agile practices less favorably (2.7667). Adoption of reflective practice in daily work was high on average (3.8125), but showed a high standard deviation of 1.39852, suggesting some variation among respondents.

Moral Resilience. Respondents’ moral resilience scores tended to be high on average (3.2266). In line with previous research of moral resilience with non-nursing professionals (Heinze et al., 2021), I also calculated subscores for the Responses to Moral Adversity and Moral

Efficacy subscales. These subscores were noticeably lower than the global moral resilience scores on average: 1.8438 for moral efficacy and 2.6250 for moral adversity.

Qualitative Findings

Qualitative analysis relating to the study's three research questions resulted in 55 unique codes and 13 unique themes. The Codebook presented in Appendix F lists all codes and themes derived from the coding process along with the source quotes by participants.

Conceptualization of AI's Role in Education. Three themes emerged from the data for the first research question regarding how people conceptualize AI's role in education.

The first theme, **Time Saver**, originated from the following emergent codes: *save time*, *support human or reduce their effort, efficiency*, *time saving*, and *give teachers more room to do things they want to do/take things they do not want to do off their plate*. This theme reflected interviewees' tendency to frame AI as a means to freeing up teacher and student schedules by building efficiencies where it makes sense to do so. Participant 2 explained of AI's purpose in education, "[Y]ou want to take stuff off [the teacher's] plate that they don't want to do while still giving them more room to do things that are interesting to them." This statement was echoed by Participant 1, who "see[s] AI as a tool for efficiency."

The second theme, **Thinking Intentionally**, derived from the following emergent codes: *tool*, *reproducing human decision making*, and *match educator questions*. This theme described how interviewees take a deliberate approach to incorporating AI in educational technology product design. Participant 1 characterized AI as a "tool to be leveraged." Participant 2 thought of AI as a way of "reproducing human decision making," and framed their thoughts around "what's the most useful goal of [an] AI system in that regard." Participant 3 centered user needs in their conception of AI in their work with automated insights, explaining they want to help educators "find the report that best matches their question."

The third theme, **Retaining Human Autonomy**, stemmed from the following emergent codes: *support tasks they want to have control over instead over complete automation*, *give teachers more room to do things they want to do/take things they do not want to do off their plat*e, and *do not replace the effort students need to put in to learn*. This theme referred to interviewees' awareness of and desire to strike a balance between incorporating AI in product design to make users' lives easier but still ensuring they retain control where appropriate. Participant 2 drew this distinction, emphasizing they strive to design tools that "support the grading rather than completely replace it with an automated system." Participant 2 expanded on this point, highlighting the need to avoid "replacing the work on the student side" to ensure students are still putting in the effort they need to learn.

Integration of Knowledge and Beliefs. Six themes emerged from the data for the second research question regarding how product team members merge their individual perspectives into a shared mental model.

The first theme, **Knowledge Imbalance**, derived from the following emergent codes: *a lot of people are looking for AI to do something they do not know how to do*, *disagreement about what AI should and should not be used for*, *knowing what AI is good at and what it is not*, *people not knowing what they mean by AI*, and *knowledge is power/trepidation can silo people*. Ths theme represented differences in what team members know about AI as well as how they think about its applications. Due to their technical expertise, multiple interviewees possessed more knowledge about AI than their peers. Participant 3 likened some internal stakeholders' perceptions of AI to "magic pixie dust" that the product team can "sprinkle on top of the product." Participant 2 called out a trend of colleagues "looking for AI to do something that they don't know how to do," seemingly echoing this sentiment. Participant 1 noted that such imbalances in knowledge alter power dynamics, creating "siloes" and "trepidation" within the team.

The second theme, **Viewing Through Multiple Lenses**, derived from the following emergent codes: *branch out and reach out, bridges education and technology*, *identifies as more technical and responsible for explaining advantages and disadvantages*, *follows people and organizations outside of discipline*, *multidisciplinary*, *team members have learned outside of their expertise*, and *pulling from many sources (lenses) when sharing with team*. This theme illustrated the tendency of interviewees and/or their teammates to embrace multiple disciplinary lenses in their product team collaboration. Participants 1 and 3 mentioned how they intentionally rely upon different types of professional training in their day-to-day work. Participant 1 incorporated sources from different disciplines when sharing information with teammates. Trained in both education and technology, Participant 3 envisioned themself as an intermediary between both groups, taking the lead on exploring technology and explaining "advantages and limitations of the technology to other members of the product team who may not have a strong educational background." Both these participants observed the benefits of multidisciplinary collaboration, noting that team members have started to increase their knowledge base outside of their field or discipline (Participant 3) and that this process can result in creative solutioning (Participant 1).

The third theme, **Drawing Boundaries**, derived from the following emergent codes: *defining desired results*, *goals and boundaries matter*, *knowing what AI is good at and what it is not*, and *mixed feelings*. This theme conveyed the importance of product team members creating a shared understanding of product inputs such as goals, strategy, and ethical values. Participant 2 recommended starting with the end goal in mind, being able to articulate what success looks like for an AIEd product as well as a lack of success. Participant 1 also suggested building an awareness of team members' "mixed feelings" on AI to strengthen product team collaboration.

The fourth theme, **Tailoring Communications**, derived from the following emergent codes: *communication matters*, *frame in terms of outcomes and goals*, not *being colocated might help team collaboration*, and *work with someone to understand their wants*. This theme characterized the need for product team members to adapt their communication approaches to meet the varied viewpoints of their colleagues. Participant 2 underscored the importance of understanding team collaboration as a "negotiation of responsibility, of expertise, [and] of boundaries," explaining "all these things [must be] articulated and understood by the group." Participant 3 wondered if a lack of colocation might increase the importance of communication, requiring product teams to communicate more clearly. They elaborated, "I think it might actually be helping us, that we're not collocated. But the fact we are remote from one another means we have to write things down. And we have to be clear about communication – and that could have gone either way."

The fifth theme, **Learning Together**, derived from the following emergent codes: *demonstrations help people understand limitations*, *discovery learning*, *educate people about the right tool for the right job*, *do education in both directions*, *get great insight*, *trying the technology and debriefing*, and *resolving a fear or trepidation around a topic or its use case*. This theme accounted for interviewees' descriptions of learning during product design work. Participant 3 detailed the need to "educate people about the right tool for the right job," using the limitations of language models as an example. This interviewee found hands-on demonstrations can help team members better understand what AI can and cannot do. This observation was echoed by Participant 2, who found value in prototyping examples with stakeholders (such as letting teachers experiment with an AI grading procedure) and then debriefing on lessons learned iteratively. Participant 1 highlighted the "discovery" nature of product work that team members must be "open" to, citing the "empowering" nature of knowledge to "resolve fear or trepidation around a topic or use case."

The sixth theme, **Considering Business Strategy**, derived from the following emergent codes: *focus development resources on the most helpful features*, *keep costs down*, and *managing scope is biggest challenge*. This theme corresponded to how product team members may factor in business needs within team decision making. Participant 3 explained that software development resources must be strategically allocated and that "we need to focus them on features that will actually help." Participant 2 raised the matter of cost effectiveness, citing the expense of collecting data and being strategic about sourcing basic data to inform model development.

Moral Resilience. Four themes emerged from the data for the third research question.

The first theme, **Policy Guardrails**, derived from the following emergent codes: *GDPR*, *ensuring compliance*, and *using policy as a guide*. This theme reflected how interviewees use relevant external policies like GDPR and elements of legal compliance like terms and conditions as a shared ethical benchmark. Participant 3 highlighted a general understanding of AI and data law as beneficial, using them to "frame a question to the legal expert when I need it" and if "this is what we want to design, what do we need to put in place to make sure we're compliant." Participant 2 referred to GDPR as guidance for their user data control advocacy during the design process, helping them to push back to ensure the product implements certain user controls.

The second theme, **Anticipating User Needs and Behaviors**, derived from the following emergent codes: *danger of false positives/negatives*, *speculative design*, *controlling for random events*, *nonidentifying information can still impact privacy*, and *understanding user receptiveness*. This theme represented interviewees' activities around predicting the downstream effects of design decisions related to AI. Working in automated reporting for educational institutions, Participant 3 stated they would never use generative AI for academic reporting because large language models are known to hallucinate and present inaccurate information as accurate. They explained, "False positives and false negatives are both really bad, so that's what we've had to explain the requirements about accuracy and the requirements about how we do calculations." Participant 1 engages with methodologies that help them imagine the unknown, sharing they have "played lots in the speculative design space and future and foresight strategy." Participant 2 also considered hypothetical scenarios like students unexpectedly incorporating sensitive information in essays, emphasizing the need to be ready for different eventualities.

The third theme, **Team Decision Making**, derived from the following emergent codes: *anticipating paths for team based on project decisions*, *establishing ethical lines for project*, *discovering possibilities for technology*, and *embracing complexity*. This theme encompassed how interviewees meld their individual perspectives with their teammates' to make ethical design decisions about ed tech products. Participant 1 pointed to a need for teams to "embrace the complexity and different people we might be able to serve," suggesting they view the work as "discovery" and "explorative." Participant 2 mentioned the need to fully weigh consequences at each decision point, viewing them as "two paths forward."

The fourth theme, **Communication**, derived from the following emergent codes: *communicating about the downstream explicitly*, *having a conversation with the user*, and *involving AI folks in design to manage expectations*. This theme described how interviewees regarded communication's role in ensuring product design reflects anticipated downstream implications. They discussed how interactions happen at different levels in ed tech product work. Exchanges between team members should be intentional and straightforward, according to Participant 2. They advocated for more technical team members participating in the design process to facilitate the "back and forth before you so say no, this is what the product needs to be." There were also conversations product teams should have with their user, specifically around data privacy and known risks of data collection as Participant 2 also explained.

Mixed Methods Findings

After using the Pillar Integration Process (Johnson et al., 2019) to synthesize quantitative data and qualitative codes from the first two research phases, I produced the joint display of mixed methods findings shown in Figure 4.

Figure 4

Mixed Methods Findings Joint Display

<table>
<tr><td colspan="5">How do ed tech product team members' qualitative descriptions of team collaboration in AIEd reflect their quantitative attitudes and perceptions?</td></tr>
<tr><td>QUANT data</td><td>QUANT categories</td><td>Pillar building themes</td><td>QUAL categories</td><td>QUAL codes</td></tr>
<tr><td>Team members' mean positive attitude toward AI (3.3977) was higher than their mean negative attitude toward AI (2.8611), suggesting respondents tended to be more optimistic than skeptical when it comes to their thoughts about AI.</td><td>Product team member tendency toward AI optimism</td><td>Conceptualizing AI as a tool that can help educators and learners</td><td>Thinking Intentionally (tool, reproducing human decision making, and match educator questions)</td><td>"[AI]'s a tool to be leveraged." – Participant 1.

"What's the most useful goal of [an] AI system in that regard." – Participant 2</td></tr>
</table>

Respondents gravitated most favorably toward a possible future vision of AI in which it gives people more freedom to spend less time on tedious, easily automated tasks.	Preferred product team sociotechnical imaginary	Imagining a future of AIEd that helps educators and learners spend more time on what matters most to them	Time Saver (*save time*, *support human or reduce their effort, efficiency*, *time saving*, and *give teachers more room to do things they want to do/take things they do not want to do off their plate*)	"[Y]ou want to take stuff off [the teacher's] plate that they do not want to do while still giving them more room to do things that are interesting to them." – Participant 2
The most feared narrative of AI's future was obsolescence, that AI would supplant people in work, relationships, and social activities.	Least preferred product team sociotechnical imaginary	Avoiding a future in which AI compromises human autonomy	Retaining Human Autonomy (*support tasks they want to have control over instead over complete automation*, *give teachers more room to do things they want to do/take things they do not want to do off their plat*e, and *do not replace the effort students need to put in to learn*)	"[S]upport the grading rather than completely replace it with an automated system." – Participant 2
A majority of respondents (n=6) indicated their teams navigate remote work in some aspect. One half (n=3) report some teammates work in a physical office, and the other half report all team members work remotely (n=3).	Product team tendency toward remote work with minimal colocation	Recognizing the importance of clear communication in the context of remote and interdisciplinary work	Tailoring Communications (*communication matters*, *frame in terms of outcomes and goals*, not *being colocated might help team collaboration*, and *work with someone to understand their wants*)	"I think it might actually be helping us, that we're not collocated. But the fact we are remote from one another means we have to write things down. And we have to be clear about communication – and that could have gone either way." – Participant 3
On average, respondents tended to rate their perception of their team's shared mental model positively (3.7313)	Product team member tendency toward a positive perception of shared team mental model	Taking initiative to explore new disciplinary perspectives and build shared understanding	Viewing Through Multiple Lenses (*branch out and reach out*, *bridges education and technology*, *identifies as more technical and responsible for explaining advantages and disadvantages*, *follows people and organizations outside of discipline*, *multidisciplinary*, *team members have learned outside of their expertise*, and *pulling from many sources (lenses) when sharing with team*)	"[I] explain advantages and limitations of the technology to other members of the product team who may not have a strong educational background." – Participant 3
Adoption of reflective practice in daily work was high on average (3.8125).	Product team member tendency toward reflective practice	Learning and reflecting throughout the design process	Learning Together (*demonstrations help people understand limitations*, *discovery learning*, *educate people about the right tool for the right job*, *do education in both directions*, *get great insight*, *trying the technology and debriefing*, and *resolving a fear or trepidation around a topic or its use case*)	"I think knowledge is in an incredible tool of not only empowering, but also like you know, resolving maybe a fear or a trepidation around a topic or its use case." – Participant 1
Respondents' moral resilience scores tended to be high on average	Product team member tendency toward overall	Competing priorities impact decision-making	Considering Business Strategy (*focus development resources on the most helpful features*, *keep*	"We need to focus [software development resources] on features that

(3.2266). Responses to Moral Adversity and Moral Efficacy average subscores were noticeably lower than the global moral resilience scores: 1.8438 for moral efficacy and 2.6250 for moral adversity.	high moral resilience but some what lower action and self-belief		*costs down*, and *managing scope is biggest challenge*)	will actually help [product strategy].” – Participant 3

Discussion

Together, the researcher’s quantitative, qualitative, and mixed methods analyses explain how interdisciplinary AIEd product team members conceptualize what AI should be in an educational setting, construct a shared team mental model of a product vision, and navigate the design process. The six pillars documented in Figure 4 determined from the Pillar Integration Process (Johnson et al., 2019) reflect this synthesis.

Conceptualization of AI’s Role in Education

This study’s findings suggest that AIEd product team members proceed in their work intentionally, taking the lead from needs articulated by educators and learners to guide their work. This is evident in how frequently participants described AI as a tool. Participants gravitated toward future scenarios in which AI gives people more time to spend on what matters the most to them. Accordingly, they expressed the most concern about future scenarios in which AI tries to replace humans, making what makes people unique obsolete.

Integration of Knowledge and Beliefs

Notably, this study surfaces the potential impact of colocation and how it might impact AIEd product team collaboration as team members integrate their knowledge and beliefs. As one participant observed, remote work drives a greater need for more intentional communication. AIEd product team members recognized the importance of clear communication, especially in the context of remote and interdisciplinary work. This finding also connects to participants’ reports of team members taking the initiative to embrace new disciplinary perspectives as they build shared understanding, stepping outside their original area of expertise to learn more and better appreciate their teammates' perspectives.

Moral Resilience

When it comes to moral resilience, this study's findings indicate the importance of team learning and reflection. Participants reported frequently engaging in reflective practice throughout the design process. In interviews, participants pointed towards shared learning experiences among teammates as being particularly valuable. At the same time, AIEd team members acknowledge they navigated competing priorities during decision-making. Business strategy impacted how product team members thought about how to structure projects strategically to optimize resources.

Limitations and Conclusions

This study's generalizability to populations outside of the researcher's professional context and proximate professional network is limited. Because I used a convenience sampling method, it is possible the population immediately accessible to me may not fully represent the AIEd product community, posing a threat to external validity (Gliner et al., 2009). Following the lead of Rudolph and colleagues (2019), I have reported study population characteristics and discussed representativeness concerns in an effort to be transparent.

The seven themes yielded by the mixed methods analysis point to a need for communication tools and practices that help interdisciplinary AIEd product team members build upon shared values regarding AI and education, reflect on downstream implications of team decision-making during the design process, and balance competing priorities impacting decision-making. Conducting a reflective case study of interdisciplinary collaboration, Bossio and colleagues (2014) point to the need for strategic and holistic approaches to interdisciplinarity during team collaboration, allowing team members shared space to navigate individual disciplinary priorities and shared team goals. In the healthcare (Nancarrow et al., 2014) and construction (O'Brien et al., 2003) fields, interdisciplinary teams have benefitted from structured reflective practice tools. Design thinking has emerged in the education field as one such way of helping teams of education professionals practice reflexivity (McDonald et al., 2018), supporting newly formed interdisciplinary teams in concept generation and solutioning (Seidel & Fixon, 2013). The next chapter explores a possible intervention informed by this study, combining design thinking and reflective practice methods to support the interdisciplinary collaboration of AIEd product teams.

Chapter 3

Interdisciplinary artificial intelligence in education (AIEd) product teams operating in educational technology (ed tech) organizations bring together diverse perspectives to design learning solutions incorporating AI. Interdisciplinary team settings allow professionals to pursue a shared goal while integrating their varied areas of expertise (Moirano et al., 2020). In the case of AIEd product teams, these areas of expertise include user-centered design, learning science and instructional design, and enabling AI technology (Herrick et al., 2022). Complex Adaptive Systems Theory (Waldrop, 1992) frames these teams as complex adaptive systems (CAS) that use feedback from the surrounding environment to inform their behaviors both at an individual and collective level. In CAS, individual and collective meaning-making influences AIEd product team members as they anticipate downstream implications of decisions made during the design process.

Many ed tech teams employ agile methodologies to efficiently facilitate product development (Alphonso, 2023; Salza et al., 2019). Agile is a product design approach that facilitates the completion of previously scoped quantities of work within a specified time frame known as a sprint (Salza et al., 2019). This structuring of work allows teams to more nimbly respond to user and stakeholder feedback during the product design process (Begel & Nagappan, 2007. Despite this aim, team members sometimes perceive agile methodologies as a source of communication gaps (Pikkarainen et al., 2008) and role confusion (Spiegler et al., 2021). These structures frame how team members converge their individual perspectives into a shared vision.

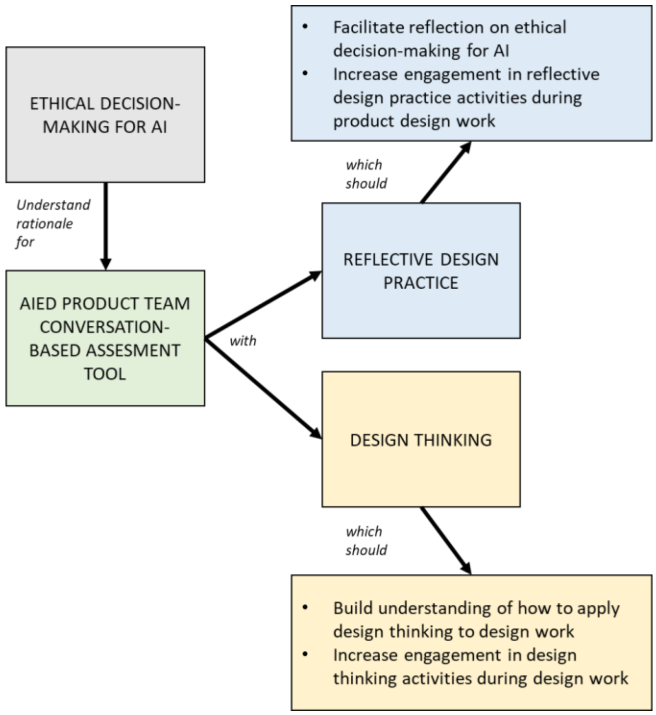
The literature review showed how AIEd introduces unique considerations for interdisciplinary teams (Holstein & Doroudi, 2021). For example, computer science research outnumbers education research in AIEd publications, suggesting an imbalance in disciplinary perspectives (Zawacki-Richter et al., 2019). Researchers (Luckin & Cukurova, 2019) have found team members of different disciplinary perspectives vary in terms of how they think about AI and consider project priorities (Mohseni et al., 2021). Technological solutionism (Rahm & Rahm-Skågeby, 2023) is a commonly held vision of AI in ed tech that impacts how team members anticipate downstream implications. Other interdisciplinary collaboration challenges include role confusion (Hanson, 2018), power imbalances (Murphy & McDonald, 2004), and knowledge communication (Rawlinson et al., 2021).

Interdisciplinary teams must converge individual beliefs into shared mental models (Klimoski & Mohammed, 1994). To have the fortitude to navigate complex ethical decision-making involving unknown downstream implications of new technology, team members must be morally resilient (Rushton, 2017). An important cornerstone of cultivating moral resilience are reflective practice and empathy (Rushton et al., 2023). Reflective design practice (Bopardikar et al., 2021) is an approach that can facilitate teaching reflection throughout the design process.

The Theory of Change, *Facilitating Shared Meaning-Making for Interdisciplinary AIEd Product Teams*, (Figure 5) encompasses the literature reviewed in Chapter 1 and the results of its synthesis along with findings from an explanatory sequential study I conducted, which is described in Chapter 2. This study surfaced a set of themes aligned with the literature that suggested a need for additional team collaboration support. To ensure AIEd product team members produce products that anticipate downstream consequences, ed tech organizations must equip them with communication tools and practices that support their convergence of shared AI and education priorities, reflective design practice, and balancing of business and product priorities. The model depicted in Figure 5 outlines relationships between research and best practices on combining design thinking and reflective practice methods to support interdisciplinary collaboration of AIEd product teams in service of ethical decision making for AIEd products.

Figure 5

Theory of Change



Ed Tech Product Team Functional Areas

This intervention's primary audience is interdisciplinary product teams working in the ed tech sector. These teams adhere to the model previously outlined by Herrick and colleagues (2022) and discussed in Chapter 1. Interdisciplinary ed tech teams generally represent three functional areas: a) user-centered design supported by research and theory of intuitive web interfaces and interactions that support intuitive navigation; b) learning science and instructional design supported by the research and theory of how people learn; and c) enabling AI technology supported by engineering, data science, and software development. This section explores each functional group of stakeholders, highlighting their key priorities and tensions related to their work creating ed tech products.

User experience (UX) design principles promote a seamless learner journey in ed tech product development (Minichiello et al., 2018). In keeping with its naming, UX centers the needs of users throughout the product development process. UX brings user voices' to the product team through collecting their insights on product prototypes early and often throughout the product design process (Herrick et al., 2022). UX design approaches and tools include rapid prototyping and user research, grounded in design thinking research (Quintana et al., 2020). Ed tech team members point to the value of UX-informed practices, such as user testing, and design thinking to ensure that learning tools anticipate classroom needs and are ready for the realities of implementation (Young, 2024). This perspective offers a foundation for considering downstream ethical implications of AI implementation in the classroom.

Research from the cognitive and psychological sciences, also known as learning sciences, establishes a theoretical and empirical foundation for ed tech product design (Herrick et al., 2022). Instructional design refers to the application of learning science research and theory to the creation of educational experiences. In the case of ed tech, this sometimes involves formulating learning strategy to make the most of emerging technologies (Seels, 1989). In the case of AI, there is still much for learning designers to learn about the realities of implementation (Feldstein, 2023). Given their eye toward detail evident in their work contributing a robust learning strategy to product design, this perspective gravitates toward critical reflection, questioning underlying assumptions made by themselves and other team members.

Additional roles on ed tech product teams provide a more technical perspective. Such roles include AI engineering, data science, and software development. Integrating AI in education continues to increase, requiring additional technological resources to facilitate implementation (Luan et al., 2020; Walter, 2024). At the same time, big data generated by learning analytics continue to guide education research and policymaking (Crompton & Burke, 2023). This functional area can advise on what is currently feasible with AI capabilities and other technologies. They may shed light upon possible implementation challenges as long as colleagues in the other functional areas ask the right questions at the right time.

Design Thinking

Design thinking is a human-centered, iterative problem-solving process implemented in various fields, including ed tech product development. It involves understanding user needs, challenging assumptions, ideating innovative solutions, creating prototypes, and testing these solutions (Seidel & Fixon, 2013). This approach encourages multidisciplinary collaboration, making it particularly effective in ed tech product development where the integration of diverse expertise is crucial.

Seidel & Fixson (2013) highlight the application of design thinking in novice multidisciplinary teams, emphasizing the benefits and limits of design methods and reflexive practices. In the context of ed tech product development, this suggests the importance of fostering a culture of reflection and iterative improvement among team members. Morgan et al. (2021) further discuss the role of design thinking in innovation, underscoring the need for a user-focused framework and a non-linear, continuous approach. This resonates with the work of Kaygan (2023), who discusses design thinking's strength in fostering interdisciplinary collaboration in a team setting.

Ge & Wang (2021) and Kelton & Saraniero (2018) provide insights into the application of design thinking in STEM education. These works highlight the potential of design thinking in fostering creativity and innovation in educational settings. Mayowski and colleagues (2019) discuss the role of design thinking in various sectors of life, including education. This reinforces the idea that design thinking, with its emphasis on user needs and iterative problem-solving, is a valuable tool in the development of ed tech products. By integrating these insights, ed tech professionals can leverage design thinking to create innovative, user-centered products that effectively address the needs of learners and educators.

Shared Interdisciplinary Facilitation

Science, Technology, Engineering, Art, and Mathematics (STEAM) museum education offers an example of how design thinking practices support interdisciplinary collaboration. Kelton and Saraniero (2018) describe how an unlikely partnership between a science center, art museum, and university mathematics faculty produced new professional development offerings as they established the STEAM Professional Learning Laboratory. Incorporating a rotating shared-facilitation model, the researchers found this approach effectively mitigated tensions resulting from an imbalance of disciplinary voice in the program design. Such tensions included which perspective carried the most weight in decision-making and exploring the edges of each discipline (i.e., the creative side of math and the quantitative side of art). Although at times uncomfortable, explicitly engaging in conversations about these tensions between disciplinary areas proved generative in revealing new possibilities for collaboration. Creating collages about each subject area helped the interdisciplinary collaborators unpack their perceptions as they navigated these conversations. Ultimately, the STEAM Professional Learning Laboratory transformed many participants' perceptions of the other subject areas. For example, art and science museum colleagues gained a newfound appreciation for math, finding their previous anxiety toward math reduced and their own curiosity piqued. The experience also sparked an ongoing resource-sharing culture between colleagues. This approach seeks to bring together interdisciplinary professionals across different institutions, so future research may further elucidate whether this approach works as effectively for interdisciplinary collaborators working within the same organization.

Reflective Design Practice

Regular reflective practice in healthcare is a key habit to building moral resilience (Rushton et al., 2023). Reflective design practice may be a transformative approach in product design, enabling professionals to critically analyze and refine their work. Weixelbaum et al. (2013) suggest that such practice involves a series of tools that foster metacognitive awareness among designers, allowing them to evaluate and enhance their creative processes. This reflective cycle not only aids in personal growth but also contributes to the collective knowledge within a product development team, leading to more innovative outcomes.

Researchers (Higgins & Smith, 2022; Smith, 2015) highlight the role of reflection in fostering a culture of continuous improvement and learning within various professional settings. By engaging in reflective design practice, professionals can break down complex problems into more manageable pieces, consider the implications of alternative solutions, and arrive at informed team decisions supporting user needs and aligning with ethical standards. This practice is essential for maintaining a competitive edge in the fast-paced world of product innovation.

Incorporating insights from Bopardikar et al. (2021), Nancarrow et al. (2015), and O'Brien et al. (2003), it is clear that reflective design practice is not just a tool for individual growth but a strategic asset for interdisciplinary teams and organizations. Reflective design practice encourages a holistic view of the design process and facilitates the convergence of different disciplinary perspectives. This ensures that products not only meet functional requirements but also anticipate future needs and possible downstream challenges, ultimately leading to more meaningful and successful products.

Interprofessional Reflective Practice

An example of the value reflective practice brings to an educational setting comes from mid-2010s Ontario, Canada (Smith, 2015). During this time, the province updated its kindergarten instructional model. Replacing the previous half-day program taught by a single certified kindergarten teacher, Ontario's Ministry of Education implemented a new program consisting of a full-day experience taught by a teaching team of a certified kindergarten teacher and a registered early childhood educator. To prepare for this change, the leading teaching and early childhood education centers in the province created a series of professional learning offerings. Smith (2015) recounts these efforts as a shared inquiry project for emancipatory professional learning, guided by a three-pronged conceptual framework. The three framework components – an interprofessional summer institute, external advisory team, and provincial inquiry-based practices – each play a role in supporting interprofessional collaboration and ethical practice. Narrative-based inquiry processes embedded in the offerings facilitated participants' joint critical reflection and analysis. Outcome measures included program outputs like a participant-led interprofessional collaboration framework for the province and participant feedback forms on the program experience. Program organizers concluded the experience by modeling emancipatory professional learning processes successfully, with key feedback themes including a commitment to individual action, a desire to share their learnings with their school community, and a transformed way of knowing their own practice.

Conversation-Based Assessment

Chapter 2's data analysis revealed a need for communication tools and practices that support teams in achieving three objectives: a) building upon shared values regarding AI in education; b) engaging in reflective design practice; and c) balancing competing priorities impacting decision-making. In other fields, reflective practice (Nancarrow et al., 2014; O'Brien et al., 2003) and design thinking (Seidel & Fixon, 2013) have supported improved team collaboration. Table 3 contains additional examples of how these approaches have supported interdisciplinary teams.

This chapter proposes a minimum viable product (MVP) of a conversation-based assessment (CBA), to support individual development on core interdisciplinary skills including reflective practice and design thinking. An MVP is the most basic version of a product that is possible to build for testing hypotheses regarding a product's potential to impact users (Moogk, 2012). A CBA is a measurement instrument that gathers data about what a learner knows and can do, leveraging conversational agents and/or dialogue systems to facilitate exchanges that allow for people to demonstrate their decision-making processes and elaborate upon their responses (Zapata-Rivera et al., 2023; Zapata-Rivera et al., 2024).

The CBA MVP supports team members in attaining the long-term outcomes of increasing capacity for anticipatory ethical design decision-making that mitigates negative implications of AI during classroom implementation and meeting or exceeding established benchmarks for product efficacy and performance post-launch. For the decision-making outcome, team members will engage in individual training about anticipatory decision making, which can help team members anticipate the downstream effects of AI during implementation in a classroom setting (Dieterle et al., 2022). This will contribute toward balancing team members' attitudes toward AI in the short-term, which is important due to the tendency of AI experts to hold more positive views of AI than non-experts who tend to be more pessimistic (O'Shaughnessy et al., 2023). Consequently, this will help align team vision in the medium-term as team members merge their individual mental models into a shared representation (Klimoski & Mohammed, 1994, Hughes & Hay, 2001). For the long-term outcome of product efficacy and performance, teams will build their capacity for reflective practice and design thinking at an individual and group level (Bopardikar, et al., 2021, Scanlon et al., 2019). In the short-term, the CBA MVP will help individuals adopt these practices in their day-to-day work. In the medium-term, the CBA MVP will help team members integrate their perspectives to work together more effectively, improving both team and product performance in the long-term.

Table 3

Overview of On-The-Job Interdisciplinary Team Development Efforts

Study	Context	Approach Employed	Intervention	Outcomes
Morgan et al., 2021	Clinical and translational science	Design thinking	A team development workshop consisting of 8 sessions across 2 half-days, employing multiple methods including lectures, modules, and role plays	Attendees positively received the workshop, especially the session focused on psychological safety. Readiness to collaborate and behavioral trust increased.
Higgins & Smith, 2022	Animal disease prevention	Reflective practice	A developmental evaluation led by an external evaluator embedded on the project team mapped emergent collaboration patterns between interdisciplinary members of a distributed team working on a multiyear grant project.	The developmental evaluation approach provided the facilitator and program director with real-time guidance on optimizing collaboration and offered a time-saving approach to team reflection.
Kaygan, 2023	Food engineering and industrial design	Design thinking	An interdisciplinary studio design course supported students' transition through the four stages of becoming a performing interdisciplinary team.	Four suggestions include emphasizing the importance of new ways of thinking, encouraging positive social relations, revealing disciplinary differences, and adequately representing each discipline.
Ge & Wang, 2021	Learning space design	Design thinking	Teams of interior design, architecture, and instructional design students collaborated in a	Domain differences impacted team communication and

			challenge to design an active learning space for K12 schools.	design thinking processes. Technology helped teams produce visual representations of ideas and bridge understanding.
Smith, 2015	Kindergarten and early childhood education (ECE)	Reflective practice	A 2-day summer institute used narrative inquiry to facilitate joint critical reflection and analysis to develop an interprofessional collaboration framework for teaching teams of kindergarten teachers and ECE educators	Participant feedback themes included a commitment to acting at an individual level, sharing learnings with their school community, and transforming their own practice.
Kelton & Saraniero, 2018	Museum education	Design thinking	Interdisciplinary museum exhibit design teams employed a rotating shared-facilitation model and created collages about each subject area	Transformed participants' understanding of other subject areas increased and invited resource-sharing between colleagues.
Mayowski et al., 2019	Biomedical research	Design thinking	A 2-day workshop delivered to early career investigators consisting of four hands-on sessions to teach team science skills including team forming, meetings, teamwork, and feedback	Researchers observed a statistically significant improvement in team science skills and confidence.

Functional Area Engagement

Reflective practice and design thinking are key approaches to engaging interdisciplinary ed tech product teams, fostering continuous improvement and innovation across user-centered design, learning science and instructional design, and technology functional areas. Table 4 outlines how the design toolkit will engage specific functional areas.

For user-centered design professionals including UX researchers and UX designers, reflective practice fosters empathy and understanding of user needs. By consistently reflecting on user feedback and behaviors, designers can identify pain points and areas for improvement, leading to more intuitive and engaging web interfaces that anticipate (and maybe even delightfully surpass) user needs (Norman, 2013; Cross, 2011). Design thinking complements reflective practice by promoting rapid prototyping and user testing, ensuring that designs incorporate feedback from implementation in the real world (Brown, 2008) as well as benefit from new insights generated from reflection.

For the learning science and instructional design functional area, reflective practice deepens understanding of how people learn and allows for the refinement of pedagogical strategies guiding product design. By regularly evaluating learning outcomes and theories of change, educators and designers can gain valuable insights into effective teaching methods, enhancing learning experiences for students (Bransford et al., 2000; Merrill, 2002). Design thinking builds upon reflective practice by fostering collaborative ideation and iterative feedback loops, enabling the development of innovative instructional strategies that cater to diverse learner needs (Sawyer, 2014). This approach ensures that learning solutions are not only evidence-based but also adaptable and responsive to learner needs.

For the technological capabilities functional area, which includes AI engineers, data scientists, and software developers, reflective practice enhances problem-solving skills and ensures high standards of quality and innovation. Regular reflection on technical challenges and solutions promotes a culture of continuous improvement and innovation, crucial for maintaining the integrity and performance of educational technologies (Liedtka, 2015; Brown & Katz, 2019). Design thinking supports this by encouraging cross-disciplinary collaboration and rapid prototyping, allowing technical teams to develop and test functional prototypes quickly and efficiently (Beckman & Barry, 2007; Martin, 2009). This collaborative and iterative approach ensures that technological solutions are both cutting-edge and pedagogically sound.

Table 4

Engagement of Three Functional Areas

Functional Area	Reflective Practice Benefits	Design Thinking Benefits	Citations
User-Centered Design	Reflecting on user feedback and behaviors helps designers better understand user needs and pain points, fostering empathy	Encourages rapid prototyping and testing with users, ensuring designs are user-friendly and intuitive	Brown (2008); Kolko (2015)
Learning Science and Instructional Design	Reflecting on instructional strategies and outcomes leads to better insights into effective teaching methods	Facilitates brainstorming sessions with diverse stakeholders to generate innovative instructional strategies that cater to diverse learning needs	Sawyer (2014); Bransford et al. (2000)
Technology Capabilities	Reflecting on technical challenges and solutions helps engineers and data scientists develop more effective problem-solving strategies	Promotes teamwork between engineers, designers, and educators to develop tech solutions that are both innovative and pedagogically sound	Liedtka (2015); Brown & Katz (2019)

Conversation-Based Assessment

Conversation-based assessment (CBA) holds promise as a on-the-job learning solution, particularly for employees who have limited time for professional development.. The CBA MVP will collect data about not only what written or spoken products learners generate while completing the experience but also the process they take to arrive at their answers, using an approach called evidence-centered design (ECD) (Mislevy et al., 2012). ECD is particularly effective for measuring people's collaboration skills in real time, enabling a measurement framework conducive to exploring the impact of conversation dynamics on team outcomes (Polyak et al., 2017). The assessment design of the CBA MVP will facilitate further needs assessment of product team members' reflective practice and design thinking skills across functional areas, informing future expansion of skills measured by the assessment, such as facilitating design thinking in a team setting.

CBAs have demonstrated promise in influencing learning outcomes across contexts. In a classroom setting, CBAs designed to use structured questioning akin to the Socratic method improved learners' critical thinking and argumentation skills in addition to content knowledge (Paul & Elder, 2007). A CBA known as AutoTutor employed natural dialogue to coach students in specific subject matter, ultimately increasing problem-solving ability and content comprehension (Graeser et al., 2004). Affective Tutoring System, another CBA, included conversational agents configured to adjust their responses based on their perceptions of students' perceived emotional states, which increased their motivation and learning while minimizing negative emotions like frustration (D'Mello et al., 2007). In a medical training setting, CBAs enable role play with patients to improve professional reasoning and communication skills (Stevens et al., 2006). Simulating real-life conversations for ethical decision-making (Ahn et al., 2013), CBAs have also been used to support ethical reasoning and perspective-taking.

The CBA MVP's design builds upon Chapter 2's data analysis. CBA design and development is a five-step process, beginning with the identification of which cognitive processes, skills, or strategies will be measured (Zapata-Rivera et al., 2023). The themes summarized in the joint display table provide a starting point for the CBA MVP's focal constructs. These skills include reflective practice and design thinking, which Table 5 breaks down in greater detail. Aligned target constructs originate from the World Economic Forum's Global Skills Taxonomy (2024), a framework of skills anticipated by international experts in the future world of work to rise in employer demand in the coming years.

Table 5

CBA Construct Map

Category	Reflective Practice	Design Thinking
Skill Definition	Engaging in reflection during product design activities	Engaging in human-centered, iterative problem-solving while collaborating as a team
Joint Display Themes (Chapter 2)	- Learning and reflecting throughout design activities - Exploring new perspectives - Recognizing importance of clear communication	- Centering learner and educator needs - Balancing priorities during decision-making
Target Constructs	- Internal self-awareness - Empathy - Liaising, networking, and exchanging information	- Human-technology interaction - Building trust
CBA Tasks	- Team brainstorming session: (make a compromise; support stressed colleague; ask a question)	- Team brainstorming session: (UX research readout; product features prioritization)

Note. Reflective practice emphasizes individual reflection and communication, whereas design thinking focuses on collaboration and human-centered approaches.

After mapping the focal constructs and their subdimensions, the next step in the CBA design and development process is to design a meaningful scenario that engages learners through the simulation of real-world tasks (Zapata-Rivera et al., 2023). Qualitative insights from research participants can guide the development of such a conversational scenario. The next step in creating a CBA is to develop adaptive dialog systems that facilitate dynamic interactions with learners that can adapt to their responses (Zapata-Rivera et al., 2023). Large language models (LLMs) can support the creation of authentic conversational agents aligned with the skills being measured (Forsyth et al., 2024). Concluding with piloting and refining assessment prototypes and evaluating their effectiveness, the CBA design and development process promotes continuous improvement (Zapata-Rivera et al., 2023).

MVP Development

Developing the CBA MVP entailed bringing together innovative tools, iterative design processes, and evidence-centered methodologies to create a dynamic and engaging experience for AIEd ed tech product teams. Table 6 outlines the requirements for the development of the CBA MVP and the accompanying resource page it is accessed from.

Each MVP requirement supports the overarching goals of fostering reflective practice, design thinking, and ethical decision-making within interdisciplinary AIEd product teams. The prioritization of requirements reflects the immediate goals and long-term vision for the MVP. High priority features are essential to the MVP's core functionality and alignment with its learning and collaboration goals. These include elements like ethical scenarios, reflective prompts, and user-friendly navigation. Ethical scenarios could reflect elements of Value-Sensitive Design (VSD) (Friedman et al., 2002), a design framework that champions human-centered values in the development of new technology.

Medium priority features enhance the user experience or add value but are not critical for initial deployment with a limited group of select test users. For example, accessibility features and supplementary guides for reflective practice fall into this category. Lastly, low priority features support scalability or future iterations, such as building infrastructure to support deployment for larger audiences. This prioritization ensures that initial development efforts focus on delivering the most impactful features while leaving room for iterative improvements and scalability in future phases.

Table 6

MVP Requirements

#	Requirement Name	Description	Priority

1	Ethical Decision-Making Scenarios	Develop scenarios that engage users in reflecting on and addressing ethical dilemmas in AI product design.	High
2	Reflective Prompts	Include prompts that encourage users to reflect on their decision-making process and its downstream impacts.	High
3	Design Thinking Activities	Provide tasks that guide users through brainstorming, prototyping, and iterative problem-solving.	High
4	Interdisciplinary Realism	Ensure scenarios are authentic and applicable to real-world interdisciplinary AIEd team challenges.	High
5	Generative AI Responsiveness	Integrate generative AI to create dynamic and context-aware dialogue that adapts to user inputs.	Medium
6	User-Friendly Navigation	Design an intuitive website interface that simplifies access to scenarios, tasks, and resources.	High
7	Progress Tracking	Include functionality to track user progress and provide feedback on their performance.	Medium
8	Resource Hub Contextualization	Create a resource page explaining the purpose of the assessment, its features, and examples of real-world applications.	High
9	Inclusivity in Scenarios	Ensure diversity in characters and perspectives to promote equitable engagement with the assessment.	Medium
10	Usability Testing and Feedback	Conduct iterative usability testing to refine both the assessment tool and resource page.	High
11	Accessibility Features	Incorporate accessibility features, such as text-to-speech or adjustable font sizes, to ensure inclusivity.	Medium
12	Data Collection and Analytics	Collect meaningful data on user interactions to evaluate both process and product outcomes.	High
13	Deployment Scalability	Build the MVP on a platform that can scale for broader use beyond the initial SME evaluation.	Low
14	Reflective Practice Tutorials	Add tutorials or examples on how to incorporate reflective practice in real-world AIEd product teams.	Medium
15	Design Thinking Guides	Provide clear guides on applying design thinking principles to AIEd product team workflows.	Medium
16	Ethical Decision-Making Resources	Include supplementary materials to help users understand ethical principles in AI design.	Medium

This section describes how the conceptual framework, scenario and content design, generative AI integration, and technical architecture were brought together to build the MVP.

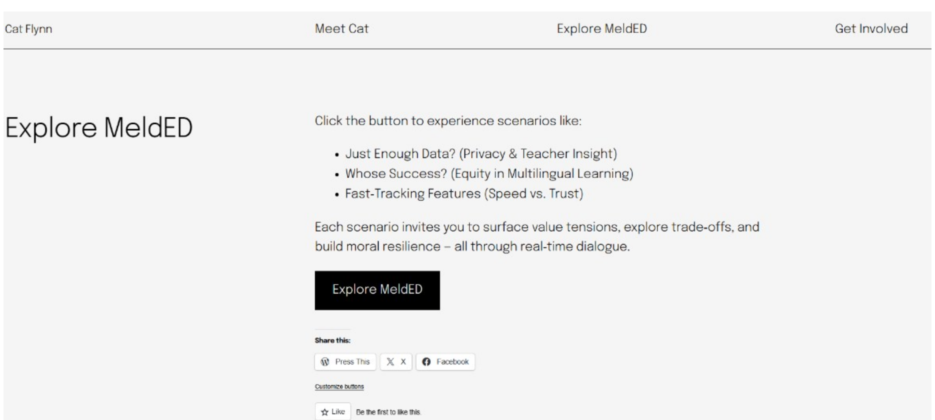
Structure and Functionality

Branded as "MeldED," the CBA platform functions as a user friendly web tool designed to help interdisciplinary ed tech teams work through realistic AI scenarios. At its core, the platform operates as a minimum viable product (MVP), a basic but functional version of a tool or service that includes enough features to be useful to users, while allowing the development team to gather feedback and improve the platform over time. For example, instead of developing a full-featured system from the start, MeldED launched with essential capabilities like role-based scenario interaction and progress tracking, enabling early testing, rapid iteration, and real-world validation.

The MeldED platform is accessible via a companion website at catflynn.net as shown in Figure 6, which supplies users with project context and a space to submit feedback. The landing page offers an overview of the platform's goals and design approach.

Figure 6

MVP Companion Website



The MVP's home page, depicted in Figure 7, serves as an entry point to the platform, introducing users to the objectives of the assessment and the interdisciplinary team responsible for AI-integrated ed tech development. Under the "Meet Your Team" section, users can explore profiles of key roles: Alex the product owner, Sarah the learning scientist, Miguel the UX designer, and Priya the data scientist. Each team member is linked to considerations from their field that inform ethical AI design decisions.

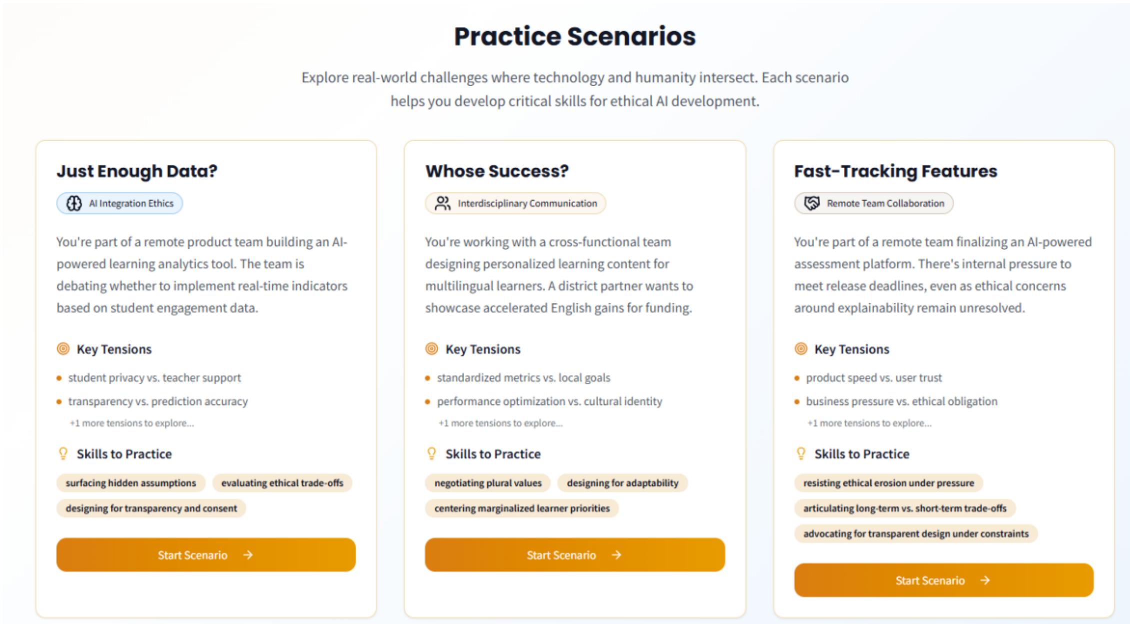
Figure 7

MeldED Home Page

The Practice Scenarios section contains interactive, case-based stories as shown in Figure 8. One such scenario known as “Just Enough Data?” asks the user to balance teacher and student needs, transparency, and accuracy while developing an AI-powered learning analytics tool. Users choose responses, see how their choices affect others’ perspectives, and reflect on the trade-offs involved.

Figure 8

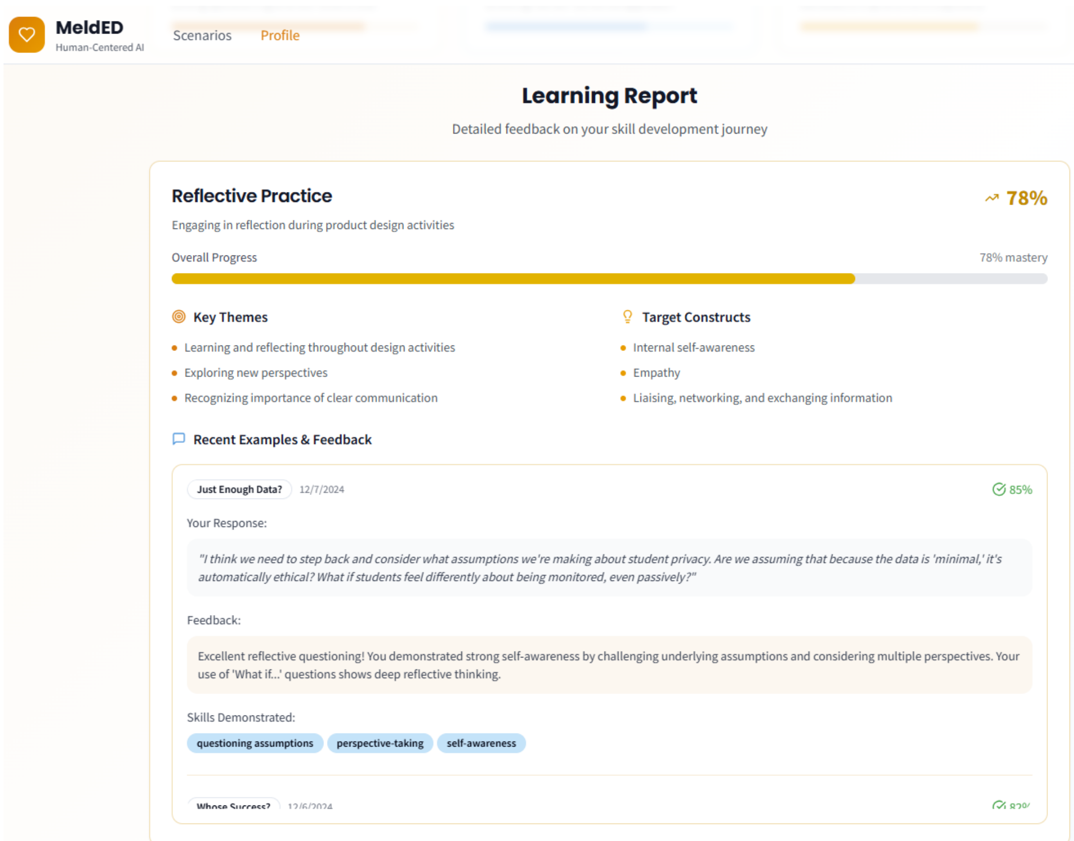
Practice Scenarios



Upon completing scenarios, users can view detailed profile pages as depicted in Figure 9, summarizing their engagement. These profiles provide visual indicators that show how each user is developing their reflective design and design thinking skills, with sample insights illustrating their approaches. These insights are intended to spark ongoing reflection for the user.

Figure 9

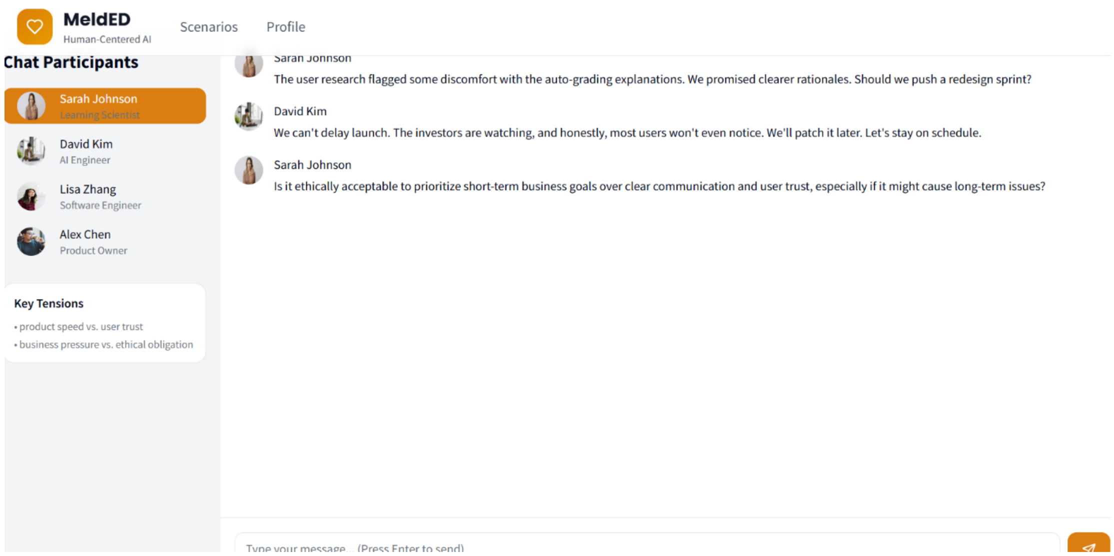
MeldED User Profile



The scenario pages form the heart of the MVP platform, offering users a structured, interactive approach to analyzing real-world challenges in AI-integrated educational technology. Each scenario presents a case-based ethical dilemma, prompting users to critically evaluate AI design choices, interdisciplinary tensions, and potential unintended consequences. For example, the "Fast-Tracking Features" scenario as shown in Figure 10 places users in the role of an AI-integrated ed tech product team navigating the challenges of remote work. The exercise encourages teams to reflect on the impact of asynchronous communication, cross-disciplinary misunderstandings, and ethical trade-offs in AI decision-making.

Figure 10

MeldED Interactive Scenario



MeldED provides a guided experience for interdisciplinary team members to engage in reflective practice and ethical decision-making. By integrating role-based analysis, scenario-driven inquiry, and interactive engagement, the MVP supports teams in enhancing moral resilience and improving collaboration in AI-integrated educational technology design. The platform’s approach aligns with research on complex adaptive systems, design thinking, and interdisciplinary shared mental models, reinforcing the importance of proactive ethical engagement in AI product development.

Conceptual Framework

Built on evidence-centered design (ECD) principles, the CBA MVP ensures the systematic collection of process and product data for evaluating participants' skills in two focal constructs: design thinking and reflective design practice. These constructs are critical for fostering interdisciplinary collaboration in AIEd, as they emphasize creative problem-solving, stakeholder perspective-taking, and iterative refinement of ideas. The ECD framework guided the identification of key evidence to measure participants' engagement with these constructs, ensuring the assessment aligns with both theoretical and practical goals.

Scenario and Content Design

The MVP's scenarios reflect authentic, real-world challenges faced by interdisciplinary teams in AIEd product development. I created these scenarios using generative AI to draft initial content, which I later refined for clarity, accuracy, and relevance. The content includes branching dialogue paths and decision-making opportunities that mimic the complexities of collaborative work, encouraging users to demonstrate critical skills in an adaptive environment. By grounding scenarios in practical challenges, the assessment bridges theoretical constructs with actionable tasks.

These scenarios reflect elements of VSD (Friedman et al., 2002). VSD is a theoretically grounded and methodologically integrative approach to technology design that explicitly accounts for human values throughout the design process. It emphasizes three types of investigations: conceptual (clarifying which values are at stake and how they relate), empirical (understanding how stakeholders perceive and prioritize those values), and technical (exploring how design features support or hinder those values). Rather than assuming neutrality or treating values as afterthoughts, VSD treats them as essential design inputs, often in tension, requiring negotiation and reflection.

VSD can inform not only the principles behind technology development but also the design of immersive, CBA scenarios that help practitioners engage with those principles in action. In this context, the CBA prototype functions as a reflective practice tool, providing simulated, ethically complex dialogues that mirror the everyday challenges faced by ed tech professionals, such as deciding whether to implement behavior-tracking features, designing adaptive content algorithms, or navigating competing stakeholder demands. These scenarios are not intended to prescribe answers, but to create space for participants to surface implicit values, examine trade-offs, and practice making design decisions that honor dignity, equity, and learner autonomy. By embedding VSD concepts into the structure of each assessment interaction, the CBA allows participants to rehearse ethical reasoning that is directly applicable to their work. In doing so, it contributes to the cultivation of moral resilience (Rushton, 2017). Rather than treating VSD as a static checklist, the CBA encourages its use as a dynamic, context-sensitive practice that evolves through dialogue and reflection.

Generative AI Integration

Generative AI played a pivotal role in the development process, enabling rapid prototyping of both website code and assessment content. Using the generative AI coding platform Vercel Vo, I employed prompt engineering techniques to generate the code for the assessment's website interface, which I then deployed using the same tool. This approach not only streamlined the technical development process but also provided an opportunity to iterate on design elements in real time. Additionally, generative AI helped draft initial assessment materials, ensuring a rapid yet thoughtful content creation process. I carefully reviewed and refined AI-generated content to meet the project’s educational and ethical standards.

Technical Architecture

The technical architecture of the MVP supports further scalability of the tool in the future if desired. I generated and deployed the website using Vercel Vo in combination with a range of generative AI tools including Anthropic’s Claude and Open AI’s ChatGPT and hosted it on my WordPress domain as part of a comprehensive resource page. This resource page provides contextual information about the assessment, shares additional project details, and supports user engagement. By combining a user-friendly front-end with back-end systems designed to collect and analyze data, the technical architecture supports both seamless user interactions and robust evidence collection aligned with the ECD framework.

MVP Evaluation

My preliminary evaluation of the CBA MVP gathered data supporting the refinement and validation of its design. This evaluation aimed to obtain feedback from a select group of AIEd professionals, cumulatively four to five past or present colleagues with expertise across key functional areas of AIEd product teams. Their insights provided valuable perspectives on the formative version of the MVP, particularly regarding its ability to foster reflective practice and design thinking: two critical skills for effective interdisciplinary collaboration.

By engaging professionals across these areas, the evaluation provided insights about how well the MVP supports practicing these constructs. Additionally, this evaluation determined areas of improvement necessary for enhancing the MVP's value for AIEd product teams.

Goals and Objectives

The primary objective of the evaluation was to explore how the formative version of the conversation-based assessment MVP aligns with the needs of AIEd product teams and supports their development of reflective practice and design thinking. Specifically, the evaluation sought to accomplish three objectives:

- Assess the MVP's ability to engage participants in authentic, meaningful scenarios relevant to their roles.
- Gather feedback on the usability and functionality of the platform, including the integration of generative AI.
- Identify areas for improvement to refine the MVP and enhance its scalability and real-world applicability.

Methodology

The evaluation followed a qualitative approach, gathering data via user feedback and interviews. Table 7 delineates the full evaluation plan. I observed participants' reactions to my demonstration of the assessment and invited feedback asynchronously to capture their reflections on the experience for purposes of improving the MVP's design in the future. ECD principles informed the data collection framework, ensuring alignment between evidence, task design, and targeted constructs. The methodology also included light pilot testing to identify technical and content-related issues prior to broader deployment.

Table 7

Evaluation Plan

Evaluation Question/Feature	Supporting User Interview Quote	Evaluation Plan	Feature Purpose
Does the CBA encourage ethical decision-making for AI in product design?	"I think that one of the big questions to ask straight up front or to establish maybe straight up front is like, you know, do we all have the same like do we know what our ethical lines are" (Participant 2)?	Will ask SMEs how effectively the scenarios prompt reflection on ethical dilemmas and decision-making strategies in AI-related challenges.	A scenario where users are asked to make decisions about an AI feature, highlighting ethical trade-offs and impacts.
Does the MVP support reflective design practice through scenario activities?	"Until you start doing it, how much of how much is it worth having that conversation with the user? And I think that like there's certain like known risks out there that you probably have to discuss, right? Like, right now we're in a space where a lot of people are concerned about" (Participant 2).	Will ask whether the SMEs found the reflective prompts engaging and realistic for fostering critical thinking about their workflows.	Prompts built into scenarios that ask users to think about the "why" behind their decisions and how they might improve.
How well does the MVP foster understanding of	"Just that openness to see that, you know, this could be leveraged in	Will ask SMEs to evaluate whether the MVP activities	A task in the tool that walks users through

design thinking principles?	this, that, but it's also extremely discovery, you know, like land and it's explorative because, you know it you may not see how it might fit into your industry or your workflow or whatever, but that doesn't mean it can't or you might need to" (Participant 1).	helped them apply design thinking concepts, like prototyping or iterative testing.	brainstorming ideas, refining them, and testing solutions in teams.
Are the scenarios realistic and applicable to interdisciplinary AIEd teams?	"So it's like, how do you work with someone to say like, OK, what is a good like you want? Like, what's a good experience for you if we're trying to do this? So that's how you might work with someone who's more on that UI side. Working with programmers is like talking very carefully about the requirements of how the systems are going to integrate" (Participant 2).	Will gather feedback on the authenticity of the scenarios and whether they reflect the dynamics of interdisciplinary collaboration.	Role-playing exercises based on real-world interdisciplinary challenges that teams face in AIEd product development.
Is the website interface user-friendly and intuitive?	"You know, we don't have unlimited development resources. We need to focus them on features that will actually help" (Participant 3).	Will gather feedback on navigation, accessibility, and usability of the interface from SMEs during the interview session.	A clean, simple website that makes it easy for users to find scenarios and complete tasks without confusion.
Does the resource page provide adequate context and value for users?	"I think knowledge is in an incredible tool of not only empowering, but also like you know, resolving maybe a fear or a trepidation around a topic or its use case" (Participant 1).	Will ask SMEs if the resource page adequately contextualizes the CBA and provides actionable insights for their work.	A resource hub with tips, explanations, and examples to help users understand the purpose of the assessment tool.

Participants

The evaluation involved a carefully selected group of subject matter experts (SMEs) who will provide formative feedback on the MVP's key aims. These participants consisted of individuals with expertise and experience in AIEd product development, capable of mentoring a new colleague entering an interdisciplinary AIEd team for the first time. Their roles spanned critical functional areas, including user experience design, instructional design, and product development, reflecting the interdisciplinary nature of real-world teams.

Participants were recruited based on specific eligibility criteria (see Table 8), ensuring that they bring relevant expertise and perspectives to the evaluation. Efforts were also made to select SMEs from diverse demographic and professional backgrounds to test the inclusivity of the assessment and ensure that the findings would be broadly applicable to the target audience of the MVP. This diverse and highly qualified group of participants offered valuable insights into how well the MVP supports reflective practice and design thinking in AIEd team collaboration.

Table 8

SME Criteria

Eligibility Criterion	Description	Rationale	Interview Quote
Functional Area	SMEs must have experience in one or more functional areas within AIEd product teams: User-Centered Design, Product Development, Learning Science and Instructional Design, or Technology Capabilities.	Ensures SMEs bring relevant expertise to evaluate the MVP's alignment with team roles and functions.	"In that multidisciplinary way of working, but also you know, 2 heads are better than one and oftentimes, some really great creative solutioning comes" (Participant 1).
Experience with Interdisciplinary Teams	SMEs should have prior experience collaborating in	Reflects the collaborative nature of AIEd	"We have people who are technical, who have learned a lot about education, we have

	interdisciplinary teams, ideally within an ed tech or AI-focused context.	teams and ensures relevant insights into team-based workflows.	people who people who started with a really more of an education background and they've learned a lot more about technology and we all talk to each other" (Participant 3).
Familiarity with Reflective Practice	SMEs should demonstrate familiarity with reflective practice, either through formal training or professional application.	Ensures SMEs can effectively evaluate how well the MVP fosters reflective practice within AIEd workflows.	"You know underbelly of, like, these postulated worlds of like, you know, AI and its use and commentary there. So I I I really like gaining from lots of different. It's like my theme gaining from like lots of different places but LinkedIn is somewhere I'm on there often" (Participant 1).
Familiarity with Design Thinking	SMEs should have knowledge or experience with design thinking methodologies, such as prototyping, brainstorming, or iterative design processes.	Ensures SMEs can assess the MVP's support for design thinking in solving complex problems.	"Of letting the teacher into the AI grading procedure so they grade a couple, and then we kind of say like, OK, this is what we've learned from you. Do you want to just let it grade the rest or do you want to keep grading and tune things? And that was part of that project" (Participant 2).
Years of Professional Experience	SMEs must have a minimum of 3–5 years of relevant experience in their respective functional area.	Provides confidence in the SME's expertise and ability to provide actionable feedback.	"In that multidisciplinary way of working, but also you know, 2 heads are better than one and oftentimes, some really great creative solutioning comes" (Participant 1).
Interest in AIEd Innovation	SMEs should express a demonstrated interest in advancing innovation and ethical practices in AIEd.	Ensures alignment with the goals of the MVP and meaningful contributions to its development.	"I think that ultimately, you know, AI is an incredible tool to be leveraged for, not just a student, but definitely a teaching professional, whether that be through, you know, curriculum development practice, activities, opportunities to leverage a student's own strengths or areas to improve

	by, you know, maybe catering" (Participant 1).

Findings

Five SMEs spanning faculty, UX research, instructional design, and product development backgrounds responded positively to the MVP, highlighting its research grounding, cross-functional relevance, and practical applications. Faculty reflected on real-world AI use among students and appreciated the tool’s alignment with reflective practice. The UX researcher emphasized contextual relevance, suggesting homepage redesigns, customizable assessments, and enhanced interdisciplinary storytelling. Instructional designers praised the simulation’s theoretical underpinnings and encouraged improved chat dynamics to support skill development in negotiation and collaboration. A product development leader was especially enthusiastic about the tool’s potential for team insight and role alignment. They noted how the responsiveness and character-driven conversation mimicked real-time team interactions and highlighted its value for interview preparation by showcasing team members' unique perspectives, priorities, and pain points.

Based on this feedback, future areas for improvement include enhancing the homepage to reflect different organizational use cases; developing features for role- or context-specific customization; and embedding clearer learning pathways that support reskilling and immersive collaboration. Additional improvements will focus on optimizing character interactions and making them more dynamic and reflective of team expertise. Future expansion could include incorporating formative feedback loops. The tool may also be adapted for use cases like interview preparation or onboarding, where gaining insight into interdisciplinary roles and team dynamics is valuable. The MVP will continue to evolve with a focus on promoting reflective design and interdisciplinary learning in AI Ed Tech and organizational contexts.

Implementation Statement

The CBA MVP, designed to foster ethical anticipatory decision-making, reflective design practice, and design thinking among interdisciplinary product development team members, is intended for implementation within ed tech organizations actively developing AI-enabled learning tools. The implementation strategy emphasizes organizational alignment, accessible training, and sustainable engagement.

The CBA MVP is an early-stage prototype designed to test the potential of structured, dialogue-driven learning interventions to support product development teams in building interdisciplinary competencies essential for ethical AI design. Specifically, the MVP targets three core skill areas identified in prior research: anticipatory decision-making, reflective design practice, and collaborative design thinking. The CBA MVP is intended for implementation within ed tech organizations actively developing AI-enabled learning tools, where the stakes of ethical and effective product design are especially high.

Implementation centers on organizational alignment, accessible training, and sustained engagement. Senior leadership plays a critical role in authorizing and championing the MVP to ensure it is prioritized across teams. Product owners coordinate program scheduling and integration into day-to-day workflows, while functional managers encourage their teams to apply the practices to ongoing product development. The primary participants, interdisciplinary product team members, are the intended beneficiaries of the intervention. Additionally, a designated facilitator (either myself or an internal lead) oversees program delivery and process evaluation.

To operationalize the MVP, only modest but strategic resources are needed. The facilitator is supported by administrative staff for scheduling and communications. Program components include: two asynchronous video modules (focused on ethical AI decision-making and reflective practice), a live synchronous team session introducing design thinking, a facilitation toolkit to support ongoing practice, and a reflective log. All resources are distributed via familiar internal platforms (e.g., SharePoint), and synchronous components are delivered using standard tools like Microsoft Teams. Data collection is integrated into the program using pre/post surveys, communication logs, and platform analytics to assess learning engagement and behavioral uptake.

The implementation spans approximately six to nine weeks. During a two-week pre-implementation phase, the facilitator secures leadership buy-in, administers participant interest surveys, and distributes initial materials. The four- to six-week active phase includes the release of asynchronous modules, the team-based training session, and continued use of the reflective log. In the final phase, evaluation data are gathered to assess participant engagement and surface areas for refinement.

Several foreseeable challenges are addressed through thoughtful design. Competing work demands are mitigated by embedding the MVP into existing workflows and emphasizing its practical relevance. Personnel turnover is addressed through asynchronous content that supports onboarding. Inconsistent leadership support is managed through continuous engagement with sponsors. To address possible technological barriers, all tools and resources are delivered via platforms already familiar to participants.

Program success is evaluated using a process evaluation framework focused on recruitment, exposure, and maintenance. Recruitment is assessed through leadership engagement and interest survey responses. Exposure is evaluated via metrics on training resource usage, participation in the team session, and perceived relevance of the materials. Maintenance focuses on participant use of the reflective logs and stated intentions to apply anticipatory decision-making, design thinking, and reflective practice in future work.

The CBA MVP is designed to contribute to three developmental phases: in the short term, participants adopt ethical and reflective practices in their daily work; in the medium term, interdisciplinary team members cohere around a shared vision and collaborative skillset; and in the long term, teams enhance product quality and performance by designing AI features that are ethically sound and instructionally effective.

Broader Implications and Cross-Sector Applications

Although this dissertation is situated in the field of AIEd, the challenges addressed are not unique to ed tech. Sectors such as healthcare, civic technology, environmental policy, and public infrastructure also rely on interdisciplinary teams navigating high-stakes decisions with far-reaching consequences. In these domains, as in AIEd, complexity arises not only from the technologies being developed but from the diversity of knowledge, values, and roles embedded in the teams who build them.

MeldED, the conversation-based reflective design MVP developed through this work, offers a flexible framework for teams to surface hidden assumptions, examine power dynamics, and collaboratively reason through ethical tradeoffs. Its structured yet conversational approach to reflection can support team learning and resilience across settings, from clinical innovation labs to city planning teams. Grounded in Complex Adaptive Systems theory, this dissertation provides both a theoretical lens and a practical toolkit for fostering integrative capacity in environments where linear solutions fall short. This work contributes to a growing body of translational research bridging learning science, systems thinking, and responsible innovation, offering practical pathways for navigating complexity across sectors.

Conclusion

Reflective design practice and design thinking combined in a CBA MVP comprise a foundation for improving the present problem of practice. Together, these approaches empower individual professionals and collective teams to research and remedy ethical implications of AI when incorporated in ed tech product design. Reflective practice promotes the habit of overturning assumptions one might otherwise take for granted or challenging a teammate to reexamine their own assumptions. This is particularly vital in interdisciplinary collaboration in which UX, learning science, or technical team members might default to their own disciplinary lens. Building upon reflective design practice, design thinking strengthens team members' exploration of possible future impacts of the designs they make together in the here and now. Creating conditions to support team decision-making and product design quality, implementing this product team design toolkit enhances team performance and overall product impact.

Reflection

Embarking on this doctoral journey has been a transformative experience, both intellectually and professionally. I began the program with an interest in lifelong learning, grounded in my experience in higher education. However, through shifts in my career and exposure to new academic lenses, my problem of practice (PoP) evolved into an examination of interdisciplinary collaboration in the development of AI-powered educational technology. This journey has deepened my understanding of how scholars and practitioners can contribute to building equitable learning technologies.

Throughout this process, I've cultivated a range of skills, including literature synthesis, critical analysis, research design, and mixed-methods data collection. These all have made me a more agile and reflexive scholar. My writing has also matured, shifting from an internally focused expression of curiosity to a more intentional, audience-aware communication style grounded in purpose and utility. One of the most profound shifts in my thinking was reframing scholarship as a service-oriented practice, where research becomes a tool not just for insight, but for creating shared understanding and meaningful change.

Research Process Insights

Each stage of the research process presented distinct challenges and opportunities. The literature review phase exposed gaps in interdisciplinary discourse, particularly the lack of unifying frameworks between AI, learning science, and user-centered design. This phase not only shaped my research questions but also taught me to recognize disciplinary silos and begin to articulate how these impact the design and implementation of AI ed tech.

The empirical study brought its own set of logistical and methodological challenges. Recruitment was difficult. This was partly due to participant hesitancy and misunderstanding about the scope of the study. But this also prompted creative solutions: refining recruitment posts, building transparency into the study process, and addressing participant discomfort. I learned the importance of empathy in research design. I came to recognize that asking professionals to reflect on their work and team dynamics can be sensitive, and that researcher positionality must be thoughtfully managed.

In hindsight, I would streamline my theoretical framing earlier and reduce the scope of my PoP to focus more sharply on power dynamics and meaning-making within interdisciplinary teams. These themes, which came into sharper focus as the study progressed, are ones I would now elevate and center more directly from the outset.

Connections Between Projects

One of the most satisfying aspects of the dissertation process has been witnessing how the different components – the literature review, empirical work, and findings – converge to provide a layered understanding of my PoP. Initially, I explored various divides in AI ed tech development, inspired by theoretical models such as Bronfenbrenner's Ecological Systems Theory and later, Complex Adaptive Systems Theory. Over time, my understanding matured: interdisciplinary collaboration was not just a logistical challenge, but a matter of epistemological negotiation and power-sharing.

My interviews confirmed and complicated insights from the literature, revealing tensions between roles, assumptions about AI, and the importance of shared reflection. The move from theoretical conception to lived experiences of practitioners brought a new level of richness to my understanding of the PoP. Themes such as boundary objects, fluid roles, and the importance of creating "holding environments" for team learning and reflection emerged as connective tissue between theory and practice.

Implications for Future Practice

This work has significantly influenced how I view my role in the ed tech space. As a learning scientist, I now see my contributions as not only grounded in theory but also instrumental in facilitating interdisciplinary understanding and ethical design. I will carry forward a commitment to fostering communication structures that promote equity, curiosity, and reflection in team settings.

Professionally, I plan to advocate for more structured team reflection practices and push for greater integration of diverse perspectives during the design process. The research has reinforced the importance of creating tools that function well and are developed through inclusive and critically aware processes. I aim to help teams build bridges. These could be conceptual, interpersonal, and/or methodological, but at the end of the day, they all support learner-centered innovation.

Broader Reflections

Ethical considerations surfaced throughout this work, particularly around bias in AI, the power dynamics within design teams, and the representation of learners in data. The notion that AI "holds up a mirror" to our societal values was a guiding insight. I became more attuned to the moral responsibility of those who design AI-driven learning experiences, especially given how easily these tools can reinforce existing inequities.

The significance of this research lies in its potential to inform how educational technology is created, not just by identifying what needs to be improved, but by outlining how teams can improve their collaborative processes to better serve learners. This reflection has reinforced my belief that ethical, interdisciplinary, and reflective collaboration must be the cornerstone of responsible AI in education.

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Appendix A

Social Media Post

How do you design AI-powered learning tools? Share your insights and join my research study. I'm a doctoral student at the Johns Hopkins University School of Education, and I'm conducting a research study on how ed tech product teams collaborate and create AI-powered learning tools. My study is titled "Interdisciplinary Collaboration in AIEd," and Dr. Laura Flores Shaw is the Principal Investigator.

If you are an ed tech product team member who works with AI or related technologies, I would love to hear from you. Your insights will help me understand how you conceptualize AI's role in education, how you integrate your disciplinary knowledge and beliefs about AI into a shared mental model, and how you make ethical decisions regarding AI's possible downstream effects during implementation.

To participate in this study, you need to meet the following criteria:

- You work in an interdisciplinary product team.
- You are employed by an assessment development organization, an educational technology company, an academic publisher, a university, or a corporation with a training department.
- You have one of the following job titles (or similar): learning scientist, instructional designer, learning experience designer, learning engineer, assessment developer, assessment specialist, curriculum designer, user experience designer, user experience researcher, impact scientist, research scientist, data scientist, AI engineer, machine learning scientist, product manager, or product owner.

Your participation will involve completing a short online survey via Qualtrics (about 15 minutes) and an optional follow-up interview (about 30 minutes). The interview will be conducted via Zoom at a time convenient for you.

By participating in this study, you will not only help me with my dissertation, but may also contribute to the advancement of knowledge and practice in our field. This is an opportunity to reflect on your own experiences and perspectives on AI and education.
If you are interested, please click on this link to access the survey and consent form:
https://jh.qualtrics.com/jfe/form/SV_eE831HUBA3Bt4rQ

Please feel free to share this post with your colleagues and network who might be eligible and interested in this study. You can also direct message me on LinkedIn with any questions.

Thank you for your time and support!

Appendix B

Internal Communication Channel Post

Hi Product Innovation and Development team,

I am writing to ask for your help with my EdD dissertation research.

As you may know, I am a doctoral student at the Johns Hopkins University School of Education, and I am studying how ed tech product teams collaborate and create AI-enabled learning tools. My study is titled "Interdisciplinary Collaboration in AIEd," and Dr. Laura Flores Shaw is the Principal Investigator.

I am interested in understanding how you conceptualize AI's role in education, how you integrate your disciplinary knowledge and beliefs about AI into a shared mental model, and how you make ethical decisions regarding AI's possible downstream effects during implementation. I would greatly appreciate it if you could participate in my research study, which consists of a short online survey (about 15 minutes) and an optional follow-up interview (about 30 minutes). Responses to the survey will be anonymized before I receive them. The interview will be conducted via Zoom at a time convenient for you outside of working hours.

Participation in the survey and / or the interview is voluntary and confidential, and you can withdraw at any time. By participating in this study, you will not only help me with my dissertation, but may also contribute to the advancement of knowledge and practice in our field.

If you are interested, please click on this link to access the survey and consent form: https://jh.qualtrics.com/jfe/form/SV_eE831HUBA3Bt4rQ

Thank you for your time and support. If you have any questions, please feel free to contact me at cflynn@ets.org.

Appendix C

Study Survey

Survey - Interdisciplinary Collaboration in AIEd Product Development

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Start of Block: Introduction and Consent

Q1.1 Thank you for considering participation in "Interdisciplinary Collaboration in AIEd Product Development," a research study being conducted by Cat Flynn, a graduate student at Johns Hopkins University.

This research study's purpose is to better understand the contributing factors related to a contextualized Problem of Practice within an educational context. The findings from this study will be used to develop an intervention that will address the educational Problem of Practice. This research is being done to fulfill requirements for a Doctorate in Education for the Johns Hopkins University School of Education, where the researcher is a student. The ultimate use of the data gathered will become part of the student researcher's dissertation research study.

Education technology companies use a method called product management to make their products stand out in a competitive market. They do this by quickly adapting to new technologies like AI in our digital world. Creating new learning tools with AI requires teamwork from different fields like data science, education, and user experience to make the most out of what new technology can offer.

To help these teams design learning tools that are ready for real-world classrooms, more research is needed. This research should focus on what conditions help teams work together to make ethical decisions that anticipate the realities of implementation.

People who are adults, not affiliated with Johns Hopkins University, and English speakers may join.

This study has been reviewed by an Institutional Review Board (IRB), a group of people that reviews human research studies. The IRB can help you if you have questions about your rights as a research participant or if you have other questions, concerns or complaints about this research study. You may contact the IRB at 410-516-6580 or hirb@jhu.edu.

If you have questions for the researcher, you may contact Cat Flynn at cflynn17@jh.edu.

By completing this survey or questionnaire, you are consenting to be in this research study. Your participation is voluntary, and you can stop at any time.

End of Block: Introduction and Consent

Start of Block: Demographic Questions

Q1.3 How old are you?

- 18-24 years old (1)
- 25-34 years old (2)
- 35-44 years old (3)
- 45-54 years old (4)
- 55-64 years old (5)
- 65+ years old (6)
- Prefer not to say (7)

Q1.4 How do you describe yourself?

- Male (1)
- Female (2)
- Non-binary / third gender (3)
- Prefer to self-describe (4) ____
- Prefer not to say (5)

Q1.5 Choose one or more races that you consider yourself to be

- ☐ White or Caucasian (1)
- ☐ Black or African American (2)
- ☐ American Indian/Native American or Alaska Native (3)
- ☐ Asian (4)
- ☐ Native Hawaiian or Other Pacific Islander (5)
- ☐ Other (6)
- ☐ Prefer not to say (7)

Q1.6 Are you of Spanish, Hispanic, or Latino origin?

- ○ Yes (1)
- ○ No (2)
- ○ Prefer not to say (3)

Q1.2 What is the highest level of education you have completed?

- ◯ Some high school or less (1)
- ◯ High school diploma or GED (2)
- ◯ Some college, but no degree (3)
- ◯ Associates or technical degree (4)
- ◯ Bachelor’s degree (5)
- ◯ Graduate or professional degree (MA, MS, MBA, PhD, JD, MD, DDS etc.) (6)
- ◯ Prefer not to say (7)

Q1.7 What best describes your employment status over the last three months?

- ◯ Working full-time (1)
- ◯ Working part-time (2)
- ◯ Unemployed and looking for work (3)
- ◯ A homemaker or stay-at-home parent (4)
- ◯ Student (5)
- ◯ Retired (6)
- ◯ Prefer not to say (7)
- ◯ Other (8)

End of Block: Demographic Questions

Start of Block: Disciplinary Perspectives

Q2.1 What is your current job title?

____

Q2.2 In 3-5 sentences, explain your job duties the same way you would to a new acquaintance. Include what types of deliverables you work on and which teammates you collaborate with most frequently.

____

Q2.3 Which functional area does your current (or most recent) role correspond to?

- ○ Research (focus on user experience design and research and product efficacy research) (1)
- ○ Learning and assessment (focus on learning science theory and research, assessment design, and instructional design) (2)
- ○ Technology (focus on AI engineering, data science, and software development) (3)
- ○ Other (please elaborate) (4) ____

Q2.4 How many years have you been working in this role?

- ◯ Less than a year (1)
- ◯ 1-3 years (2)
- ◯ 4-5 years (3)
- ◯ 6-10 years (4)
- ◯ 10-15 years (5)
- ◯ 15-20 years (6)
- ◯ 20+ years (7)

Q2.5 What is your area of professional training?

____

End of Block: Disciplinary Perspectives

Start of Block: General Attitudes Toward AI

Q3.1 We are interested in your attitudes towards Artificial Intelligence. By Artificial Intelligence we mean devices that can perform tasks that would usually require human intelligence. Please note that these can be computers, robots or other hardware devices, possibly augmented with sensors or cameras, etc. Please complete the following scale, indicating your response to each item.

	Strongly disagree (1)	Somewhat disagree (2)	Neutral (3)	Somewhat agree (4)	Strongly agree (5)
For routine transactions, I would rather interact with an artificially intelligent system than with a human. (1)	○	○	○	○	○
Artificial Intelligence can provide new economic opportunities for this country. (2)	○	○	○	○	○
Organizations use Artificial Intelligence unethically. (3)	○	○	○	○	○
Artificially intelligent systems can help people feel happier. (4)	○	○	○	○	○
I am impressed by what Artificial Intelligence can do. (5)	○	○	○	○	○
I think artificially intelligent systems make many errors. (6)	○	○	○	○	○

I am interested in using artificially intelligent systems in my daily life. (7)	○	○	○	○	○
I find Artificial Intelligence sinister. (8)	○	○	○	○	○
Artificial Intelligence might take control of people. (9)	○	○	○	○	○
I think Artificial Intelligence is dangerous. (10)	○	○	○	○	○
Artificial Intelligence can have positive impacts on people's wellbeing. (11)	○	○	○	○	○
Artificial Intelligence is exciting. (12)	○	○	○	○	○
I would be grateful if you could select agree. (13)	○	○	○	○	○
An artificially intelligent agent would be better than an employee in many routine jobs. (14)	○	○	○	○	○

There are many beneficial applications of Artificial Intelligence. (15)	○	○	○	○	○
I shiver with discomfort when I think about future uses of Artificial Intelligence. (16)	○	○	○	○	○
Artificially intelligent systems can perform better than humans. (17)	○	○	○	○	○
Much of society will benefit from a future full of Artificial Intelligence (18)	○	○	○	○	○
I would like to use Artificial Intelligence in my own job. (19)	○	○	○	○	○
People like me will suffer if Artificial Intelligence is used more and more. (20)	○	○	○	○	○
Artificial Intelligence is used to spy on people. (21)	○	○	○	○	○

End of Block: General Attitudes Toward AI

Start of Block: Sociotechnical Imaginaries

Q4.1 Consider each of the hypothetical narratives listed below. Indicate the extent to which you favor a further future development of AI systems in each vein.

	Strongly unfavorable (1)	More unfavorable than favorable (2)	More favourable than unfavorable (3)	Strongly favorable (4)
AI could revolutionize treatments and drugs to the point of living forever (1)	○	○	○	○
AI could make our daily life easier, free from the routine chores that computers can do for us (2)	○	○	○	○
AI could become our friend, to listen to us when we need it and to fulfill our desires (3)	○	○	○	○
AI could help bolster diplomacy and military with safer information and smarter weapons (4)	○	○	○	○
AI could improve our bodies to the point of becoming very similar to bionic machines (5)	○	○	○	○
AI could replace the need for real humans in work, relationships and social activities (6)	○	○	○	○

AI may respond so well to our needs that we prefer interaction with AI over human interaction (7)	○	○	○	○
AI could make computers powerful and autonomous to the point where they no longer need human control (8)	○	○	○	○

End of Block: Sociotechnical Imaginaries

Start of Block: Moral Resilience

Q5.1 In answering the following questions, please consider how you have responded to challenging ethical situations in the last three months in your professional role.

	Disagree (1)	Somewhat disagree (2)	Somewhat agre (3)	Agree (4)
I voice my ethical concerns in a way that others take seriously. (1)	o	o	o	o
No matter the situation I do what is consistent with my values. (2)	o	o	o	o
Difficult ethical situations leave me feeling powerless. (3)	o	o	o	o
I have the conviction to act in accordance with my values. (4)	o	o	o	o
I am overwhelmed by persistent ethical conflicts. (5)	o	o	o	o
I take responsibility for my choices. (6)	o	o	o	o
After facing a challenging ethical situation, lingering distress weighs me down. (7)	o	o	o	o
I have the courage to take action when others resist. (8)	o	o	o	o

When confronted with an ethical challenge, I push myself beyond what is healthy for me. (9)	○	○	○	○
When I am confronted with an ethical challenge, I can articulate the ethical conflict. (10)	○	○	○	○
I tend to be distracted by others' strong emotions when ethical conflicts occur. (11)	○	○	○	○
I am confident in my ability to reason through ethical challenges in my professional role. (12)	○	○	○	○
When others criticize my opinions, I compromise my values. (13)	○	○	○	○
I would rather avoid conflict with those who have more authority than I do than act in accordance with my values. (14)	○	○	○	○

I can think clearly when confronting an ethical challenge, even when I feel pressured. (15)	○	○	○	○
My fear can cause me to act in a way that compromises my values. (16)	○	○	○	○

End of Block: Moral Resilience

Start of Block: Attitudes Toward Agile Methodologies

Q6.1 Is your current team collocated?

○ Yes, we work in the same physical location. (1)

○ No, we all work remotely. (2)

○ No, some of us work in the same physical location and others work remotely. (3)

○ Other (please explain) (4)

____

Q6.2 Does your team use Agile methodology?

○ Yes (1)

○ No (2)

Display This Question:

If Does your team use Agile methodology? = Yes

Q6.3 How long has your current team used Agile methodology?

____

Display This Question:

If Does your team use Agile methodology? = Yes

Q6.4 Indicate the extent to which you agree with the following statements.

	Strongly disagree (1)	Disagree (2)	Neutral (3)	Agre (4)	Strongly agree (5)
Agile is working well for me. (1)	○	○	○	○	○
Agile is working well for my team. (2)	○	○	○	○	○
Agile is working well for my larger group. (3)	○	○	○	○	○
Adopting Agile methods positively impacts my team's morale. (4)	○	○	○	○	○
My team collaborates more effectively with Agile than without. (5)	○	○	○	○	○

Display This Question:

If Does your team use Agile methodology? = Yes

Q6.5 Select Agile practices used in your current team.

- ▢ User stories (1)
- ▢ Small releases (2)
- ▢ Direct interaction with users (3)
- ▢ Design improvement (4)
- ▢ Collective ownership (5)
- ▢ Acceptance testing (6)
- ▢ Whole team daily stand-up meeting (7)

End of Block: Attitudes Toward Agile Methodologies

Start of Block: Perceived Shared Mental Model

Q7.1 Consider an interdisciplinary team you have most recently collaborated with on an ed tech product incorporating AI. Rate the extent to which you agree with the following statements finishing the prompt about your team:

Team members have a similar understanding about…

	Strongly disagree (1)	Somewhat disagree (2)	Neutral (3)	Somewhat agree (4)	Strongly agree (5)
How to use other team members' equipment (13)	○	○	○	○	○
The tools needed to complete our tasks (14)	○	○	○	○	○
What equipment is important for which tasks (15)	○	○	○	○	○
The technology needed to complete our tasks (16)	○	○	○	○	○
Specific strategies for completing various tasks (17)	○	○	○	○	○
How to deal with the task (18)	○	○	○	○	○
How best to perform our tasks (19)	○	○	○	○	○
The relationships between tasks (20)	○	○	○	○	○
How to communicate with each other (1)	○	○	○	○	○
Sharing information with each other (2)	○	○	○	○	○

How we should interact with each other (3)	○	○	○	○	○
The best methods to communicate with each other (4)	○	○	○	○	○
Each other's skills for doing various team tasks (5)	○	○	○	○	○
Each other's individual strengths and weaknesses (6)	○	○	○	○	○
Each other's abilities (7)	○	○	○	○	○
Each other's knowledge (8)	○	○	○	○	○
Our deadlines (9)	○	○	○	○	○
How quickly we need to work (10)	○	○	○	○	○
Appropriately timing our work (11)	○	○	○	○	○
Coordinating the timing of our work (12)	○	○	○	○	○

End of Block: Perceived Shared Mental Model

Start of Block: Reflective Practice

Q8.1 Consider an interdisciplinary team you have most recently collaborated with on an ed tech product incorporating AI. Rate how often you engage in the following practices while working in this team.

	Not at all (1)	Slightly (2)	Somewhat (3)	Moderately (4)	Very much (5)	Extremely (6)
When reflecting with others about my work I become aware of things I had not previously considered. (1)	○	○	○	○	○	○
When reflecting with others about my work I develop new perspectives. (2)	○	○	○	○	○	○
I find that reflecting with others about my work helps me to work out problems I might be having. (3)	○	○	○	○	○	○
I gain new insights when reflecting with others about my work. (4)	○	○	○	○	○	○
Sometimes I am unsure if my planning for users is the best possible way to proceed. (5)	○	○	○	○	○	○

Sometimes I am unsure that I properly understand the needs of users. (6)	○	○	○	○	○	○

End of Block: Reflective Practice

Start of Block: Conclusion

Q9.1 Thank you for participating in this survey and for sharing your valuable insights!

A second and optional part of this study entails participating in a half-hour follow-up interview with the researcher to be conducted virtually over Zoom at your convenience. The goal of this interview is to expand upon themes from the preliminary analysis of survey results.

Please complete the survey at the following link to indicate your interest in participating in an optional follow-up interview. This survey will open in a new window. Follow Up Interview Recruitment Survey

End of Block: Conclusion

Appendix D

Follow Up Interview Recruitment Survey

Follow Up Interview Recruitment - Interdisciplinary Collaboration in AIEd Product Development

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Start of Block: Default Question Block

Q1 A second and optional part of the research study "Interdisciplinary Collaboration in AIEd" entails participating in a half-hour follow-up interview with the researcher to be conducted virtually over Zoom at your convenience. The goal of this interview is to expand upon themes from the preliminary analysis of survey results.

Please indicate if you are interested in being contacted to participate in a follow-up interview and provide contact information for the researcher to follow up with you. You may change your mind at any time.

○ Yes, I am interested in being contacted to participate in a follow-up interview at the following email address. (1) ____

○ No, I am not interested in being contacted to participate in a follow-up interview. (2)

End of Block: Default Question Block

Appendix E

Follow Up Interview Protocol

Introduction

- Review the consent statement with the participant.

Sample Questions

- What is your job title and role in your interdisciplinary AIEd product team?
- How long have you been working in this team and on this product?
- What are the main features and functions of your product that use AI or related technologies?
- How do you define AI? What do you think is its role in education?
- How do you communicate and collaborate with other team members who have different disciplinary backgrounds and perspectives on AI?
- How do you integrate your own knowledge and beliefs about AI with those of other team members into a shared mental model for your product development?
- How do you make design decisions regarding AI's possible downstream effects during implementation, such as ethical, social, or pedagogical issues?
- How do you cope with any uncertainty, ambiguity, or complexity that arises from working with AI or related technologies?
- How do you evaluate the effectiveness and impact of your product on the learners and educators who use it?
- How do you keep up with the latest developments and trends in AI and education?
- Is there anything else you would like to share about your experience and perspective on AI and education?

Conclusion

- Thank the participant for their time and valuable insights.
- Explain the next steps of the study: the researcher will analyze the data and report the findings in the dissertation and possibly other publications.
- Ask the participant if they have any questions or comments about the study or the interview.
- Remind the participant of the confidentiality and anonymity of their data and their right to withdraw at any time.
- End the interview and stop the recording.

Appendix F

Codebook

Question	Theme	Code	Quote	Interview
Conceptualization of AI's Role in Education	Time Saver	save time	Putting that or anything of that means, but more so just. Again, there's efficiency tools the same way that educators can leverage that maybe it just, you know, cuts your time in half when you're developing out some ideation around a protocol for a study or a type of design or maybe a research methodology to.	Participant 1
		support human or reduce their effort	So that's kind of like how I like to think abo student sidet. It's like if we say I want an AI to help students do X. The question underlying that is how would a human do it? And then how do we, like, support the either support the human or reduce that effort? If it's like a rote task. And I think that what is important when dealing with education is that there's a balancing act, right? You can either say I want to replace the.	Participant 2
		efficiency, time saving	Or aiding them in and what they're doing. I see AI as a tool for efficiency, time saving, you know, time to task and which enables, I think, any educator especially study.	Participant 1
		give teachers more room to do things they want to do, take things they do not want to do off their plate	Learn and replacing the work on the teacher side needs to be handled very carefully cause you want to take stuff off their plate that they don't want to do while still giving them, giving them more room to do the things that are interesting to them and giving them more support for the things that are interesting to them. So if they feel very strongly that they want to have control over grading because that's how they get feedback to the students, then it's more important for you to.	Participant 2
	Thinking Intentionally	tool	I think that ultimately, you know, AI is an incredible tool to be leveraged for, not just a student, but definitely a teaching professional, whether that be through, you know, curriculum development practice, activities, opportunities to leverage a student's own strengths or areas to improve by, you know, maybe catering.	Participant 1
		reproducing human decision making	And then thinking about like, what's the most useful goal of that AI system in terms of reproducing human decision making?	Participant 2
		Match educator questions	Find the report that best matches their question, their user story.	Participant 3
	Retaining Human Autonomy	support tasks they want to have control over instead over complete automation	Support the grading than to completely replace it with an automated system.	Participant 2

		give teachers more room to do things they want to do, take things they do not want to do off their plate	Learn and replacing the work on the teacher side needs to be handled very carefully cause you want to take stuff off their plate that they don't want to do while still giving them, giving them more room to do the things that are interesting to them and giving them more support for the things that are interesting to them. So if they feel very strongly that they want to have control over grading because that's how they get feedback to the students, then it's more important for you to.	Participant 2
		do not replace the effort students need to put in to learn	Human in this task or I want to support the human in this task and I think that a lot of educational tasks, especially in classrooms, get really tied up with student and teacher identity and you don't want to be like replacing the work on the student side.	Participant 2
Integration of Knowledge and Beliefs	Knowledge Imbalance	a lot of people are looking for AI to do something they do not know how to do	And it's really hard to kind of manage that. And so a lot of people are looking for AI to do something that they don't know how to do.	Participant 2
		disagreement about what AI should and should not be used for	UX discussion it seemed to be something where you had kind of differing point of view of like some people felt it was, you know it it you shouldn't use a tool like this to do this. We should get user human feedback and that inform the persona we create and others were very keen on leveraging something like this to be kind of that.	Participant 1
		knowing what AI is good at and what it is not	Because that's not really what AI is good at. But I can give you this piece of it.	Participant 2
		People not knowing what they mean by AI	Do you have AI? And they don't know what they mean by that and what we are trying to resist doing is thinking that we can just sprinkle A ion to our product like Magic Pixie dust and it will just make things better. That is not what happens in the real world. So.	Participant 3
		knowledge is power, trepidation can silo people	You know, in in that trepidation certainly can. Like silo people, it can. It can. It can derail. The user from something that may actually benefit them, potentially because of this unknown or fear of the unknown. I mean again like classical, just like cognitive psychology like that's.	Participant 1
	Viewing Through Multiple Lenses	branch out and reach out	One of it's like many sources and then like always trying to branch out and reach out to to see a more rounded picture.	Participant 1
		Bridges education and technology	I have an educational background, so I'm representing that to the actual developers. The technical team who are building features and explaining to them. No, we will not use generative AI to build reports because.	Participant 3
		Identifies as more technical and responsible for explaining advantages and disadvantages	We do a couple of different things. One is as one of the relatively more technical people on our team. It's my responsibility to do some exploration and explain the advantages and the limitations of the technology to other members of the product team who have a strong educational background but may not be.	Participant 3
		follows people and organizations outside of discipline	Yeah. I mean, I like in like many professionals, I would say very addicted to LinkedIn. I I love looking at many, many sources there. I follow a lot of different types of people, organizations way outside of my discipline.	Participant 1

		multidisciplinary, 2 heads are better than 1, creative solutioning	In that multidisciplinary way of working, but also you know, 2 heads are better than one and oftentimes, some really great creative solutioning comes.	Participant 1
		Team members have learned outside of their expertise - tech learning about ed and vice versa	We have people who are technical, who have learned a lot about education, we have people who people who started with a really more of an education background and they've learned a lot more about technology and we all talk to each other. And I would say that one of one of the things that helps them most at our institution and our organization is.	Participant 3
		pulling from many sources (lenses) when sharing with team	I think my kind of thought around this, even when I was having an opportunity to do some knowledge sharing and like sharing out with that UX team is this idea of like pulling from many sources, you know, not again just the one and you know it sounds like it would be common sense or very something that most would.	Participant 1
	Drawing Boundaries	defining desired results	What does a bad response look like? How do you tell the difference between the two? Because then I can take an AI and train it to tell the difference between the two, but I need to kind of know what pieces of information you're looking for, what what looks like good, what looks like bad.	Participant 2
		goals and boundaries matter	What what our goals are, what we want to achieve and what each person can do to help us achieve that goal. And that's a really kind of important process to just kind of like make sure that you've established, you know who, who can be doing what, who should be doing what, what are the boundaries of what the tech can do of the people can do of the you know.	Participant 2
		knowing what AI is good at and what it is not	Because that's not really what AI is good at. But I can give you this piece of it.	Participant 2
		mixed feelings	Perhaps like, how might we leverage a tool like AI to do this? And just among us researchers in, you know, my organization, you've got a lot of mixed feelings there because some people think there's, you know, a lot of bias baked in to AI, which I I certainly think so. And it's something that we should be.	Participant 1
	Tailoring Communication	communication matters	Everyone has different expertise. Everyone has different viewpoints and a lot of what's happening in collaboration. Is this like negotiation of responsibility, of expertise, of boundaries and things like that, and the kind of the more clearly all of those things are articulated and and and understood by the group.	Participant 2
		frame in terms of outcomes and goals	But it's it's it's a question of saying like, OK, if you want this outcome, you want the AI to grade these, you know, this speech in a certain way. The question that I need to know from your perspectives, like, what would you look for, what looks like.	Participant 2
		Not being colocated might help team collaboration	I think it might actually be helping us, that we're not colocated. But the fact that we are remote from each other means we have to write things down.And we have to be clear about communication and that could have gone either way.	Participant 3

		work with someone to understand their wants	So it's like, how do you work with someone to say like, OK, what is a good like you want? Like, what's a good experience for you if we're trying to do this? So that's how you might work with someone who's more on that UI side. Working with programmers is like talking very carefully about the requirements of how the systems are going to integrate.	Participant 2
	Learning Together	Demonstrations help people understand limitations	Generally, demonstrations what we found to be most effective in.	Participant 3
		discovery learning	Just that openness to see that, you know, this could be leveraged in this, that openness, but it's also extremely discovery, you know, like land and it's explorative because, you know it you may not see how it might fit into your industry or your workflow or whatever, but that doesn't mean it can't or you might need to.	Participant 1
		Educate people about the right tool for the right job	It can't do math, right? It's a language model, so trying to educate people about the right tool for the right job has help.	Participant 3
		Do education in both directions	So we do some education in both directions.	Participant 3
		get great insight	Out of opportunities where I may not have gotten able to expand on something, but then find that I get great insight because I spoke with an instructional designer or learning scientist or a user experience, you know, designer.	Participant 1
		trying the technology and debriefing	Of letting the teacher into the AI grading procedure so they grade a couple, and then we kind of say like, OK, this is what we've learned from you. Do you want to just let it grade the rest or do you want to keep grading and tune things? And that was part of that project.	Participant 2
		resolving a fear or trepidation around a topic or its use case	Yes, yes, I think again, you know it's a principle that I've always held for me personally. I think knowledge is in an incredible tool of not only empowering, but also like you know, resolving maybe a fear or a trepidation around a topic or its use case.	Participant 1
	Considering Business Strategy	Focus development resources on the most helpful features	You know, we don't have unlimited development resources. We need to focus them on features that will actually help.	Participant 3
		keep costs down	Because like from a strategic standpoint, you want to keep costs down as much as possible, and it's expensive to collect data. But from like an AI building standpoint, the more high quality that data is, the more accurate your process is going to be. So you know, it's a question of, like, you know, first of all, where do you get some basic data to work with? And then the second piece is like.	Participant 2
		managing scope is biggest challenge	Yeah. And you know, from the more technical side, I would say that the biggest challenge tends to be managing scope.	Participant 2
Moral Resilience	Policy Guardrails	GDPR	And so that's why it's useful to have those controls and that's where things like GDPR come into play. Say like, no, you need to give them this control.	Participant 2

			Well, the EU has GDPR. You know, Australia has a privacy act. Canada has a very strong privacy act. You know all the different regions of the world generally have very strong legislation about what you're allowed to show to a person about other people.	Participant 3
		ensuring compliance	Yeah, I'm not a a legal expert in the least, so I I know a little bit about these AI and data laws that have been floating around because it's useful for you to be aware so that I can at least like frame a question to the legal expert when I need it. Right. So like, if I'm working with someone in legal and I say like, OK, this is what we want to design, what do we need to put in place to make sure we're compliant with the laws?	Participant 2
		using policy as a guide	Right. And I think that that's where some of the policy helps a lot, because if you're crossing policy lines, then you're very likely to get in pretty big trouble. And that's a very costly endeavor. Yeah. But I think that the other side of the coin is just like keeping the user in mind, right. Like, what are the things that you think they will agree to?	Participant 2
	Anticipating User Needs and Behaviors	danger of false positives/negatives	False positives and false negatives are both really bad, so that's what we've had to, you know, explain the requirements about accuracy and the requirements about how we do calculations.	Participant 3
		speculative design	Or past disciplines, you know, definitely have played lots in the speculative design space and future and foresight strategy. So there's a lot of thought leaders I really enjoyed there and they're always, you know, thinking about this sort of like.	Participant 1
			You know underbelly of, like, these postulated worlds of like, you know, AI and its use and commentary there. So I I I really like gaining from lots of different. It's like my theme gaining from like lots of different places but LinkedIn is somewhere I'm on there often.	Participant 1
		controlling for random events	And then you know when we talk about the boundaries of the law, it can be actually pretty impactful because, like, there's all kinds of like what ifs that come into play. Like, what if someone decided in the middle of their essay to just drop their social? Now it's like, well, how do you how do you control for that? And usually, right, the task that they're being given is controlling enough. Like if you're writing an essay, you're not supposed to be just dropping.	Participant 2
		nonidentifying information can still impact privacy	How they're, you know, they're keystrokes individual keystrokes. And I think that it's actually recorded somewhere that like, you know that keystroke level data can be identified because like, it's almost like a fingerprint. The problem is you need, like, so if you have enough to compare to, then you can kind of get some pretty, pretty strong information out of it. But the question again is like, OK, if you're going to tell them that you're recording that.	Participant 2

			[B]ut the other part is like people can write really personal essays like about they're like like, what did you do last summer, right. Like that can contain a lot of identifying information you feel like well, I you know, me and my Uncle Bill went to the beach and we spent, you know, a couple days and then talk it or whatever you're like. Well, now I know a lot about you.	Participant 2
		understanding user receptiveness	If we don't know it, and you're like, but yeah, I think it it it it's it's at an organizational level. I think it's at a societal level culturally, you know. And then of course, obviously districts and admins being open to this, a lot of the research that I'm finding and speaking with.	Participant 1
	Team Decision Making	anticipating paths for team based on project decisions	Have kind of two paths forward. You can either say I'm going to spend the time doing research to figure out how to make the I do this and that will often end up pushing the boundaries of what is possible.	Participant 2
			In the tech space, right? So that's novel research, and that can take a lot of time that can take several years.	Participant 2
		establishing ethical lines for project	I think that one of the big questions to ask straight up front or to establish maybe straight up front is like, you know, do we all have the same like do we know what our ethical lines are?	Participant 2
		discovering possibilities for technology	Just that openness to see that, you know, this could be leveraged in this, that, but it's also extremely discovery, you know, like land and it's explorative because, you know it you may not see how it might fit into your industry or your workflow or whatever, but that doesn't mean it can't or you might need to.	Participant 1
		embracing complexity	One very predominant use case, but like embracing the complexity, embracing the different people we might be able to serve or.	Participant 1
	Communication	communicating about the downstream explicitly	It's going to be much more heavy on the data side depending on how you design the architecture. So you have a lot of kind of moving pieces there. And I think the best thing to do is just try and like communicate that in as straightforward a way as possible.	Participant 2
		having a conversation with the user	Until you start doing it, how much of how much is it worth having that conversation with the user? And I think that like there's certain like known risks out there that you probably have to discuss, right? Like, right now we're in a space where a lot of people are concerned about.	Participant 2
		involving AI folks in design to manage expectations	There's very few things that are in actual hard limitation, but you know, given the current technology, there's limitations on what we can do. Yeah. So it's like, do we, you know, you have to communicate that and then the then a decision has to be made and you can. This is why I think personally it's actually very important to have the AI folks in the design process, because that way you can have these back and forth before you say no, this is what the product needs to be. It can't be anything else. And then coming up against something that the AI is not going to be able to do in a reasonable amount of time.	Participant 2