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AI as a Team Member: Enhancing Interdisciplinary Collaboration in Design Thinking

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Abstract

This thesis investigates how artificial intelligence (AI) can be meaningfully integrated into interdisciplinary design thinking teams as a quasi-team member, focusing on the roles and functions it can perform in collaborative innovation settings. The central research question guiding this study is: *How can AI be integrated into interdisciplinary design thinking teams as a quasi-team member, and what roles or functions can it perform within the team?* The research objective is to explore and conceptualize the dynamics of human-AI co-creation, and to identify practices that enhance or hinder AI-supported teamwork in design contexts. To ground this inquiry, the study analyzes the European "Prompt-a-Thon on AI and the Future of Higher Education" held at Luiss Guido Carli University in May 2025, where student teams engaged in a design thinking challenge supported by ChatGPT as a collaborative partner. Using qualitative methods including participant interviews and post-event reflections, the thesis captures how human participants perceived and interacted with the AI during each stage of the design thinking process. Findings highlight both the potential and the limitations of AI integration, including its contributions to idea generation and information synthesis, as well as challenges related to trust, proactivity, and role clarity. The study offers practical insights for educators and managers aiming to build hybrid teams that leverage AI's capabilities without undermining human creativity and agency.

Table of Contents

1. Introduction

1.1 Real-World Context and Relevance

Can an artificial intelligence brainstorm creative solutions alongside humans as if it were just another team member? This provocative question, once confined to science fiction, is increasingly relevant in today's innovation teams. Across industries, organizations are experimenting with "human-AI collaboration" in pursuit of competitive advantage. Business leaders even speak of "superteams"- human groups augmented by AI capabilities as a key to future performance (Mallon et al., 2020). In one recent case, a European innovation challenge formally included an AI system (OpenAI's ChatGPT) as a participant in student design teams, blurring the line between tool and teammate. Such examples reflect a broader trend: artificial intelligence is moving beyond automating routine tasks to taking on collaborative roles in creative, knowledge-intensive work. The pressing question for companies and society is how to harness AI as a positive force in team-based innovation processes, rather than as a threat or mere novelty.

The rise of AI in teamwork is driven by urgent technological and managerial forces. A majority of organizations recognize that integrating AI into work is critical, for instance, 70% of enterprises were exploring AI solutions by 2020 (Mallon et al., 2020). However, doing so is difficult. Only 16% of executives in one global survey said their companies were actively redesigning work by building human-machine hybrid teams (Mallon et al., 2020). This gap between aspiration and readiness underscores a pressing managerial problem. Leaders see immense potential in AI-augmented teams, yet many struggle with how to integrate AI agents into collaborative workflows. At the same time, innovation remains a top priority across sectors, and today's problems from digital transformation to climate change- are so complex that they demand interdisciplinary teamwork.

Design thinking has emerged as a popular framework for tackling such "wicked" problems with creativity and user-centric focus. It emphasizes iterative ideation and prototyping, typically by diverse teams that blend engineering, design, business, and other disciplines (Bender-Salazar, 2023). Interdisciplinary collaboration is widely recognized as crucial for breakthrough innovation, as mixing perspectives can spark more creative solutions (Edmondson & Harvey, 2017). Yet traditional human teams have limits: cognitive biases, groupthink, and knowledge silos can hinder their performance. This creates a tantalizing opportunity and a societal challenge: Could AI systems, with their vast information access and analytical power, become team members that enhance human creativity and problem-solving?

1.2 Academic Framing and Research Gap

Early evidence suggests that thoughtfully integrating AI can boost team outcomes under the right conditions. Advanced AI systems today are capable of generating ideas, learning from interactions, and even exhibiting surprising creativity in niche domains (Creely et al., 2023). For example, in the arts and design, people are increasingly collaborating with generative AI tools to co-produce paintings, stories, and product prototypes. In one experimental study, human writers working interactively with an AI were able to maintain or even enhance their creative performance, compared to those simply editing an AI's output (McGuire et al., 2024). This indicates that when humans treat AI as a co-creator rather than just an automated assistant, the partnership can yield synergistic benefits. Similarly, high-stakes domains like aerospace already see AI "cognitive assistants" supporting astronauts by analyzing data and making recommendations much like a human colleague (Onnasch et al., 2013).

These developments have prompted scholars to conceptualize new models of teamwork that include AI agents. The notion of AI as a team member represents a qualitative shift. Instead of being a passive tool, the AI takes on active roles in communication, ideation, and decision-making within the group (Tummala et al., 2025). Recent literature on human-AI teaming has begun exploring how classic team constructs (e.g., shared mental models, team trust, coordination processes) translate to mixed human/AI teams, and what design principles can facilitate effective collaboration. However, much of this research is still nascent. As one review noted, organizations still lack clear frameworks for adaptive human-AI teamwork, and empirical studies of AI in real team settings remain limited. In short, both academics and practitioners are only starting to understand how best to incorporate AI into collaborative creative work.

This thesis tackles that knowledge gap by investigating how AI can function as a bona fide team member in an interdisciplinary design thinking process. While prior studies have examined human-AI interaction in labs or for specific tasks, there is scant research on AI's role in end-to-end team-based innovation challenges. To address this, the present study asks: *How can AI be integrated into interdisciplinary design thinking teams as a quasi-"team member", and what roles or functions can it perform within the team?* The focus is on the dynamics between human team members and the AI, and whether the AI's participation can improve the team's creative problem-solving without undermining human agency.

1.3 Research Design, Contributions, and Thesis Structure

Importantly, rather than treating this as a purely theoretical question, the research is grounded in a real-world case. It centers on a recent educational experiment- the European Prompt-a-Thon on AI and the Future of Higher Education (Luiss Guido Carli University, May 2025) which served as a testbed for involving an AI (specifically, ChatGPT) as a collaborative partner in student design challenges. In this event, multidisciplinary student teams were tasked with developing innovative solutions in the higher education domain, following a design thinking approach. Uniquely, each team had access to ChatGPT as a team "member" that could contribute ideas, answer questions, and help generate content.

Methodologically, the study adopts a qualitative case study approach centered on the Prompt-a-Thon. As the researcher was not physically present at the workshop, data collection focused on semi-structured interviews and post-event surveys with participants who had engaged directly with AI-supported teamwork during the event. These participants- master's students, PhD candidates, and early-career researchers shared their perceptions of working with ChatGPT as a team member during the design thinking process. Their reflections, supplemented by contextual knowledge provided by the organizing team, offer valuable insight into how generative AI was integrated into interdisciplinary collaboration. This approach enables the study to examine emergent patterns in human-AI interaction from the viewpoint of active participants, without direct observation.

The findings of this research yield several important contributions. Academically, the thesis adds to the emerging body of literature on human-AI collaboration and teamwork in three ways. First, it provides empirical evidence from a naturalistic setting, demonstrating how an AI teammate can influence interdisciplinary team dynamics, creativity, and outcomes. This extends prior work which has mostly been conceptual or lab-based by showing what AI integration looks like in practice during a complex, multi-phase design thinking challenge. Second, the study proposes a preliminary framework for understanding AI's role in design thinking teams. Key factors such as the AI's level of proactivity, the team's trust in the AI, and the facilitation techniques used to involve the AI are identified as determinants of success. This framework connects socio technical context (e.g. organizational support, team training) with micro-level collaboration practices, thereby laying groundwork for future research and theory-building on mixed human-AI teams. Third, the thesis contributes to design thinking scholarship by re-contextualizing its core principles (empathy, ideation, iteration) in light of AI participation. It explores how AI can support tasks like user research (through rapid information retrieval or idea generation) and what limitations exist (for example, AI's lack of real-world empathy). Practically, the insights from this study can guide managers, educators, and team facilitators in leveraging AI as a collaborator. The results suggest that simply providing an AI tool is not enough. Teams need the right mindset and protocols to treat the AI as a team member whose suggestions are valued yet critically evaluated. For instance, one practical lesson is the importance of team preparation and training: participants who were briefed on effective prompt techniques and the AI's capabilities tended to integrate ChatGPT more successfully into their discussions. Additionally, this research highlights potential benefits such as increased ideation volume and cross-disciplinary learning, as well as pitfalls like over-reliance on the AI or biases in AI-generated content. By addressing these, organizations can better capture AI's augmentation power. In an era where 77% of employers plan to upskill their people for collaboration with AI by 2030 (Ai Group Centre for Education and Training, 2025), the thesis offers timely guidance on how to build human-AI "superteams" that are more creative and productive than either humans or AI alone. Educators can also draw on these findings to design curriculum and teamwork exercises that prepare students for future workplaces where working alongside AI will be commonplace.

In summary, this introduction has outlined the background and importance of studying AI as a team member in design thinking, highlighted the gap in current knowledge, and defined the focus of the research. The chapters that follow will elaborate and substantiate these points. Chapter 2 (Literature Review) situates the study in scholarly context, reviewing recent research on human-AI collaboration, design thinking methodology, and interdisciplinary team innovation. It also identifies theoretical lenses used to frame the role of AI in teams. Chapter 3 (Methodology) describes the research design in detail, including the case setting of the Prompt-a-Thon, data collection methods, and the analytical approach. Chapter 4 (Findings) presents the results of the case study, describing how teams interacted with the AI and what outcomes were found. Chapter 5 (Discussion) interprets these findings, discussing implications for theory and practice, and how the results answer the central research question. Finally, Chapter 6 (Conclusion) summarizes the study's contributions to knowledge, acknowledges its limitations, and offers recommendations for future research and practical implementation of AI in team-based innovation. Through this journey, the thesis aims to demonstrate how "AI as a Team Member" is not just a theoretical concept but a tangible development with significant potential to enhance interdisciplinary collaboration in design thinking.

2. Literature Review

2.1 The Rise of AI as a Collaborative Agent

2.1.1 From Tool to Teammate: Defining the Shift

Artificial intelligence (AI) has traditionally been viewed as a sophisticated tool- a set of technologies that humans use to perform tasks more efficiently rather than as an active participant in teams. However, recent advancements in AI capabilities have spurred a paradigm shift: researchers now contemplate AI "machines as teammates" rather than mere tools (Seeber et al., 2019). In essence, this shift implies moving from AI as support (e.g. an algorithm quietly aiding a human decision-maker) to AI as a partner that collaborates with humans toward shared goals. Human-AI teaming is typically defined as at least one human working together with at least one autonomous agent that has a degree of self-governance (e.g. the ability to make decisions or adapt actions) while pursuing a common objective (Schmutz et al., 2024). Such AI teammates are expected to exhibit some of the attributes of human teammates, for example, contributing ideas, adjusting to team needs, and engaging in two-way communication rather than functioning only under direct human command. This new conceptualization has given rise to an interdisciplinary research focus on human-AI teams (HATs) (Schmutz et al., 2024), spanning computer science, psychology, and organizational studies.

A core debate in this emerging field is to what extent an AI can or should be treated as a “full-fledged” team member. Some scholars are cautious, noting fundamental differences (e.g. AI lacks consciousness or accountability) and warning against over-anthropomorphizing machines (Schmutz et al., 2024). Others argue that as AI systems become more autonomous and interactive, they will increasingly embody teammate characteristics such as proactivity, learning, and adaptation-blurring the line between tool and collaborator (Schmutz et al., 2024). Seeber et al. (2019) illustrate this shift with a hypothetical scenario: an emergency response team includes an AI agent whose “insightful suggestions” help save lives by rapidly recalling regulations, tracking resources, and evaluating complex trade-offs in real time (Seeber et al., 2019). Notably, team members in the scenario do not merely use the AI. They interact with it like a knowledgeable colleague. This example underscores the potential for AI to participate in complex problem-solving steps, defining problems, proposing solutions, making decisions, and learning from team feedback which historically only human teammates performed (Seeber et al., 2019).

Reflecting this vision, a consortium of 65 collaboration scientists formulated a research agenda on “machines as teammates” to explore its benefits and risks (Seeber et al., 2019). The literature began framing AI as a teammate around 2019, aligning with practical developments in AI (e.g. advanced language models and interactive agents) that can engage in rich communication. The shift is also driven by early successes of human-AI partnerships, such as “centaur” teams in chess where a human plus AI together outperform either alone (Schmutz et al., 2024). The central idea is that human intelligence and AI capabilities can complement each other: AI offers speed, precision, and vast knowledge, while humans contribute intuition, ethics, and contextual understanding. As organizations and domains like design, healthcare, and creative industries experiment with AI as a collaborator, defining the nature of this human AI relationship becomes crucial. In summary, the field is transitioning from viewing AI as an instrument to exploring AI as a co-worker. This subsection has outlined how scholars define that transition. The next step is to examine what AI teammates can actually do in practice, and where they fall short, as a foundation for understanding their role in interdisciplinary teamwork (including design thinking contexts).

2.1.2 AI in Teamwork: Capabilities, Applications, and Limitations

AI's growing competencies have enabled a range of applications in teamwork. Modern AI agents can process information and remember details at a scale far beyond human capacity, contributing data-driven insights to group work. For example, in Seeber et al. 's (2019) scenario, the AI teammate recalled legal rules, resource locations, and procedural steps instantaneously, providing the team with comprehensive situational awareness (Seeber et al., 2019). Such capabilities illustrate how AI can serve as a knowledge repository and analytical aide in teams. In real-world domains, AI systems have demonstrated complementary strengths: in medicine, combining human expertise with AI diagnostic systems yields more accurate results than either alone (Schmutz et al., 2024), and in creative fields, generative AI tools can supply novel ideas or design alternatives that spark human creativity (as early studies in design collaboration suggest). Recent research is also beginning to identify team roles that AI agents can fulfill. For instance, a multi-method study by Siemon et al. (2022) derived four archetypal roles for AI teammates- Coordinator (organizing and managing tasks), Creator (generating ideas or content), Perfectionist (ensuring quality and consistency), and Doer (efficiently executing routine tasks) (Siemon, 2022). These roles mirror classic human team roles, indicating that AI can contribute to teamwork in diverse ways, from leadership functions to creative brainstorming.

Despite these promising capabilities, current literature also documents significant limitations and challenges when AI joins human teams. Notably, many experimental "AI teammates" are still relatively narrow AI applications, often functioning more like advanced tools than truly autonomous collaborators (Schmutz et al., 2024). Fully realizing the "teammate" potential thus remains an ongoing endeavor. Empirical findings show that human AI teams (HATs) do not automatically outperform all-human teams; in fact, they frequently underperform in highly interdependent tasks due to coordination and communication breakdowns (Schmutz et al., 2024). Schmutz et al. (2024) review several studies and conclude that when humans and AI must closely interact (e.g. sharing decision-making or brainstorming together), the teams often suffer process losses. Common issues include: misaligned team cognition (humans and AI failing to develop a shared understanding of goals or each other's intentions), reduced communication quality, and trust deficits between human and AI members (Schmutz et al., 2024). For example, one recent review noted that HATs usually show worse team communication and mutual coordination than human-only teams, which in turn leads to lower overall performance outcomes (Schmutz et al., 2024). In other words, plugging an AI into a team can disrupt well-tuned human interaction patterns, at least under current conditions.

Several technical and social limitations of today's AI systems help explain these outcomes. First, AI agents often lack a robust theory of mind for teamwork, they have difficulty interpreting nuanced human behaviors or updating their actions based on unspoken social cues. As Schmutz et al. (2024) observe, contemporary AI "might not yet be fully equipped to function as effective team members, lacking an adequate Machine Theory of Mind", which leads to misaligned actions and coordination issues. An AI, for instance, might rigidly follow its algorithmic objective in a way that inadvertently contradicts a teammate's intent or the group's implicit norms. Secondly, humans working with AI may not understand the AI's decision processes or capabilities, resulting in miscommunication. If the AI cannot explain its suggestions or if its role is unclear, team members might ignore its inputs or misuse them. These factors contribute to a vicious cycle: poor AI performance or opaque reasoning erodes human trust, while humans' uncertainty about the AI leads to suboptimal integration of the AI's contributions (Schmutz et al., 2024). Researchers have also pointed out that current studies often involve artificial settings where AI performance is either much higher or lower than human performance, which can distort teamwork dynamics (e.g. humans either over-rely on a “superior” AI or completely distrust a faulty one) (Schmutz et al., 2024).

Despite these limitations, the consensus in recent literature is that the capabilities of AI in teams are steadily improving, and many limitations are surmountable with better design and human-AI training. Table 2.1 summarizes some of the key capabilities that AI brings to teamwork, alongside the corresponding challenges that researchers have identified:

AI Capabilities in Teamwork	Limitations and Challenges
Real-time data synthesis and recall	Poor theory of mind / contextual awareness
Idea generation and creative prompting	Limited alignment with human goals or intent
Task execution at speed and scale	Opaque decision processes (black-box systems)
Support for decision-making via pattern recognition	Vulnerability to bias in training data
Automated coordination and scheduling	Trust and role ambiguity within teams

Table 2.1. Illustrative AI contributions to teamwork vs. current limitations. AI’s strengths (left) are often mirrored by social-technical challenges (right) that limit its effectiveness as a team member. For each capability or limitation, examples from recent research are provided (Schmutz et al., 2024).

In summary, AI systems today can significantly augment team capabilities by handling large-scale data, generating creative options, or performing routine tasks with speed and precision. But they also introduce new coordination costs and uncertainties. These trade-offs must be carefully managed. The next subsection will delve into the human factors that underlie many of these challenges, namely issues of trust, ethics, and acceptance in human-AI collaboration.

2.1.3 Ethical, Trust, and Acceptance Challenges in Human-AI Collaboration

Treating AI as a team member raises important ethical and socio-technical questions. One set of concerns revolves around trust: Can humans trust AI partners, and under what conditions? Research since 2020 indicates that trust in AI teammates is often fragile and dependent on performance. For example, Schmutz et al. (2024) found that teams tend to trust a new human teammate more than a new AI teammate, all else being equal. Moreover, if an AI makes errors or performs poorly, human trust in it deteriorates quickly more so than trust toward a human who falters (Schmutz et al., 2024). This aligns with broader findings that initial trust in technology can be high due to optimism, but trust in AI often declines over time as people recalibrate their expectations (especially if early expectations were inflated) (Schmutz et al., 2024). On the flip side, when an AI system demonstrates clear reliability and superior capability in a domain (for instance, a chess AI known to be far stronger than any human player), humans may over-trust the AI's suggestions (Schmutz et al., 2024). The challenge is achieving the right balance of trust sometimes called trust calibration, so that human team members neither disregard helpful AI input nor follow AI advice blindly. Studies highlight several factors that improve human trust in AI teammates, including the AI's transparency and explainability, its track record of reliability, and even its interactive behavior (e.g. an AI that communicates its uncertainties or adapts to team preferences tends to be trusted more) (Schmutz et al., 2024). Designing AI systems with these qualities (sometimes termed human-centered AI design) is therefore a key research direction to support effective collaboration.

Beyond trust, ethical and accountability issues loom large. Unlike human teammates, AI agents do not bear legal or moral responsibility for their actions, raising the question of who is accountable when an AI teammate's decision leads to harm or error. Recent literature flags this ambiguity: if a machine teammate misguides the team, "who is legally responsible for a machine teammate's actions?" (Seeber et al., 2019). Organizations deploying AI collaborators must establish clear accountability frameworks (e.g. the human supervisor is ultimately responsible, or certain decisions are left to human final approval) to address this issue. Relatedly, scholars are debating what moral code or ethical principles AI team agents should follow (Seeber et al., 2019). In high-stakes domains, an AI might face ethical dilemmas (analogous to a "trolley problem"), and it is non-trivial to encode consistent values or decision rules. The literature calls for embedding ethical reasoning capabilities in AI (and transparency about those ethics) so that human teammates can understand and predict the AI's choices (Seeber et al., 2019). There is also concern about AI bias and fairness in team settings: if an AI is trained on biased data, its recommendations might systematically disadvantage certain groups or perspectives. Such biases can undermine team decision quality and create ethical conflicts. Ensuring algorithmic fairness and mitigating hidden biases is therefore part of the ethical integration of AI into teams (recent reviews of AI acceptance emphasize fairness and transparency as key determinants of people's willingness to work with AI) (Schmutz et al., 2024).

A further challenge is team acceptance and role definition for AI members. Introducing an AI into a team can disrupt established roles and norms, potentially causing role ambiguity. Human team members may be uncertain whether the AI is supposed to lead, advise, or merely automate tasks, especially if the AI's role isn't clearly defined by design or by the team leader. This ambiguity can breed confusion or conflict, for instance, who has final say if the AI's opinion contradicts a human member's? Establishing team protocols and social norms for human-AI interaction is therefore critical (Seeber et al., 2019). Some researchers suggest developing "social conventions for how to deal with robot teammates" analogous to etiquette for human coworkers (Seeber et al., 2019). Acceptance of AI also varies widely among individuals. User adoption models in recent studies show that factors like technology literacy, prior experience with AI, and organizational culture influence how readily people embrace an AI collaborator (Schmutz et al., 2024). Cardon and Marshall (2024), for example, report that people with greater AI literacy and positive past experiences are more comfortable assigning AI into human-like team roles, whereas those unfamiliar or who have experienced failures remain skeptical (Cardon & Marshall, 2024). This suggests a need for training and change management when integrating AI into teams: humans may need to learn new skills (such as interpreting AI outputs) and overcome biases or fears about AI (e.g. fear of job displacement or mistrust of algorithms). Conversely, AI systems may need to be designed with awareness of human teamwork practices, for instance, by explaining their reasoning or by adapting to team feedback, so that humans feel the AI is a trustworthy and understandable collaborator rather than a black box.

In summary, the rise of AI as a collaborative agent brings not only technical integration challenges but also profound human and ethical considerations. Building trust is paramount, without trust, human-AI teams will underperform due to cooperation breakdowns. Ensuring ethical AI behavior and clear accountability is equally crucial to gain team members' confidence and avoid adverse outcomes. Finally, achieving widespread acceptance of AI teammates will require addressing human concerns (through transparency, training, and inclusive design) and clearly defining the AI's role within the team. These themes in the literature set the stage for investigating how AI can effectively become a co-member of interdisciplinary teams. In the context of design thinking, where creativity and human insight are key, these challenges and debates inform how teams approach AI as a potential team member to enhance (rather than hinder) collaborative innovation.

2.2 Foundations of Interdisciplinary Team Collaboration

Effective innovation in design-driven projects often hinges on the interdisciplinary collaboration of team members from diverse fields. Interdisciplinary teams consist of individuals with different disciplinary expertise who work together towards a shared goal, integrating their varied knowledge to address complex problems that no single field could solve alone (Gesing et al., 2024). By combining perspectives from multiple domains, such teams can achieve a more comprehensive understanding of multifaceted challenges and generate more holistic solutions (Horn et al., 2023). This section reviews the characteristics and benefits of such interdisciplinary teams, examines common collaboration barriers (communication difficulties, integration obstacles, and cognitive distance), and discusses key team processes and conditions that enable effective cross-disciplinary work. These foundations will inform later discussions on integrating novel collaborators (like AI systems) into team-based innovation.

2.2.1 Characteristics and Benefits of Interdisciplinary Teams

Interdisciplinary teams are characterized foremost by their diversity of expertise. Members hail from different professional or academic backgrounds, bringing specialized knowledge and skills unique to their discipline. This diversity means that team members must share and integrate disparate knowledge bases, often bridging distinct terminologies and problem-solving approaches. A unifying feature is that interdisciplinary collaborators commit to a common overarching goal, for example, designing an innovative product or solving a complex societal problem that transcends the scope of any one discipline (Gesing et al., 2024). Such teams typically adopt a collaborative mindset in which disciplinary boundaries are porous: members actively learn from each other and adapt their perspectives in light of others' insights.

This dynamic interplay of different viewpoints is a hallmark of interdisciplinary teamwork and underpins its key benefits.

Interdisciplinary collaboration offers several compelling benefits for team-based innovation:

● Enhanced Creativity and Innovation: Bringing together diverse perspectives can significantly enhance a team's creativity, as members stimulate each other to generate more novel and innovative ideas (S. Chen et al., 2024). Multiple studies indicate that when people with different backgrounds collaborate, their varied knowledge sparks creative thinking that would not arise in a homogeneous group (S. Chen et al., 2024). In practice, interdisciplinary design teams often produce more innovative solutions because they can combine creative techniques from art and design with analytical methods from engineering or data science, for example. This synergy of perspectives helps "yield transformative results" on complex problems that single-discipline teams might struggle with (Brown et al., 2023).

● Improved Problem Solving and Decision Quality: Heterogeneous teams tend to make better decisions and solve problems more effectively, especially for complex tasks. Research shows that groups composed of members from different fields outperform uniform groups in decision-making exercises (Yamashita et al., 2021). In one study, student teams with mixed disciplines achieved exceptional decision outcomes far more frequently than teams drawn from only one discipline (Yamashita et al., 2021). The variety of viewpoints allows interdisciplinary teams to scrutinize a problem from multiple angles, reducing blind spots and avoiding groupthink. This leads to more robust problem analysis and creative problem-solving, which is crucial in design thinking and innovation contexts.

● Higher Productivity and Impact: Interdisciplinary research teams have been found to achieve greater productivity and scientific impact compared to more homogeneous teams (Gesing et al., 2024). Diverse teams tend to produce more publications and high-impact outputs, likely because they can tackle novel questions at the intersection of fields. By integrating knowledge, an interdisciplinary team may unlock solutions and insights that push project outcomes beyond conventional boundaries. Over the long term, organizations have recognized that leveraging interdisciplinary teams can be a source of competitive advantage, as these teams drive innovation and knowledge creation in ways that siloed teams cannot (Zhang, 2023).

● Comprehensive, Holistic Solutions: Because they integrate multiple knowledge domains, interdisciplinary teams are well-suited to address complex, "wicked" problems that span fields (e.g. sustainability challenges, healthcare system design). Such problems require looking at the "big picture". Teams that unite engineers, psychologists, business experts, and designers, for instance, can create solutions that are technically sound, user-friendly, and commercially viable all at once. The incorporation of varied conceptual and methodological approaches yields more layered and holistic outcomes (Brown et al., 2023). In essence, interdisciplinary teams can bridge knowledge gaps between fields, leading to solutions that are both innovative and broadly informed.

Overall, the blend of disciplinary viewpoints in an interdisciplinary team provides a fertile ground for knowledge integration, creative thinking, and high-impact results. Studies have documented that when such teams effectively collaborate, they not only solve problems more creatively but also often outperform single-discipline teams on key metrics like decision quality, research output, and solution novelty (Gesing et al., 2024). These benefits underscore why interdisciplinary teamwork has become a cornerstone of modern innovation practices (including design thinking): it expands the team's collective intelligence and ability to innovate beyond the limits of any one specialty (S. Chen et al., 2024).

2.2.2 Collaboration Barriers: Communication, Integration, and Cognitive Distance

Despite their advantages, interdisciplinary teams face distinct challenges that can hinder collaboration. Key barriers reported in the literature include difficulties in communication, obstacles to integrating diverse knowledge, and issues stemming from "cognitive distance" between team members. If not managed, these factors can impede a team's ability to fully capitalize on its diversity. Below is the examination of each barrier and its impact on cross-disciplinary collaboration:

● Communication Barriers: Differences in disciplinary language and communication style are a common source of friction in interdisciplinary teams. Each field develops its own jargon, conceptual frameworks, and even norms for expressing ideas. When team members use field-specific terminology or implicit assumptions, misunderstandings easily arise. For example, an engineer and a psychologist might use the term “model” very differently. Without effort to establish a common vocabulary, team members can struggle to convey ideas clearly across disciplinary lines (S. Chen et al., 2024). Moreover, specialists may unintentionally talk “past” each other and physicians might focus on clinical specifics while sociologists emphasize systemic context, for instance. Such communication gaps often lead to confusion, frustrate collaboration, and can erode trust if team members feel they are not being heard or understood. Cultural differences between disciplines (academic vs. industry mindsets, or design vs. technical cultures) further complicate communication. All these factors make concerted communication skills and active mutual translation of concepts a necessity in interdisciplinary work (S. Chen et al., 2024).

- Knowledge Integration Challenges: A well-known barrier to successful interdisciplinary work is the difficulty of integrating knowledge across disparate domains. Team members not only bring different information, but also different approaches to reasoning and solving problems. Aligning these diverse contributions into a coherent outcome is non-trivial. Disciplinary differences and even prejudices can inhibit team members from interacting smoothly, sometimes leading to friction or reluctance to accept ideas from outside one’s own field (Zhang, 2023). In practice, it can be challenging to synthesize, say, qualitative insights with quantitative data, or to meld creative design ideas with engineering constraints. The process may incur high coordination costs: extra time and effort are needed for team members to explain background concepts to each other and develop a shared understanding. Without explicit strategies for knowledge integration, teams may default to working in parallel “silos” or default to the dominant discipline’s approach undermining the very interdisciplinary nature of the project. Thus, lack of integrative mechanisms is a major obstacle: simply gathering experts together does not guarantee their knowledge will truly combine in a synergistic way (Pennington, 2015). Successful integration requires overcoming disciplinary boundaries, but ingrained habits and mono-disciplinary mindsets can make this a slow, delicate process.

- Cognitive Distance: The very diversity that gives interdisciplinary teams their strength can also create cognitive distance, meaning the gap in understanding between members with very different knowledge bases. While some degree of cognitive difference is beneficial for creativity, too large a gap can hinder collaboration. If team members' expertise and worldviews are extremely far apart, they may struggle even to find common points of reference or to appreciate each other's ideas (Sonnenberg-Klein & Coyle, 2024). For instance, a team composed of a theoretical physicist and a graphic designer spans a greater cognitive distance than a team of, say, a civil engineer and a mechanical engineer (Sonnenberg-Klein & Coyle, 2024). When cognitive distance is high, members are more likely to experience miscommunication, misalignment of expectations, and even interpersonal conflict. Research on team diversity finds that extensive disciplinary disparity can lead to the formation of sub-groups (each subgroup sharing a common background) and increase the risk of relationship conflicts (X. Chen et al., 2019). In other words, if not carefully managed, cognitive diversity may cause the team to splinter or to have persistent friction, as individuals gravitate toward those who "speak their language" and discount others. This can reduce trust and information sharing, negating the benefits of having diversity in the first place. The challenge for interdisciplinary teams is finding the optimal distance difference enough to spur novel thinking, but not so much that the team cannot establish mutual understanding.

These barriers often interact. For example, greater cognitive distance tends to exacerbate communication difficulties, and poor communication in turn makes knowledge integration even harder. A recent ethnographic study of interdisciplinary student teams vividly illustrated how these dynamics can unfold: teams that avoided addressing their disciplinary differences ("conformative" behavior) or failed to admit knowledge gaps ("performative" behavior) ended up impairing true knowledge integration in the group (Horn et al., 2023). In such cases, the team superficially cooperates but does not fully leverage each member's expertise effectively missing the point of interdisciplinary work. Recognizing these pitfalls is the first step. Interdisciplinary teams must deliberately counteract these barriers through supportive processes and team conditions, as discussed next.

2.2.3 Team Processes and Conditions for Effective Cross-Disciplinary Work

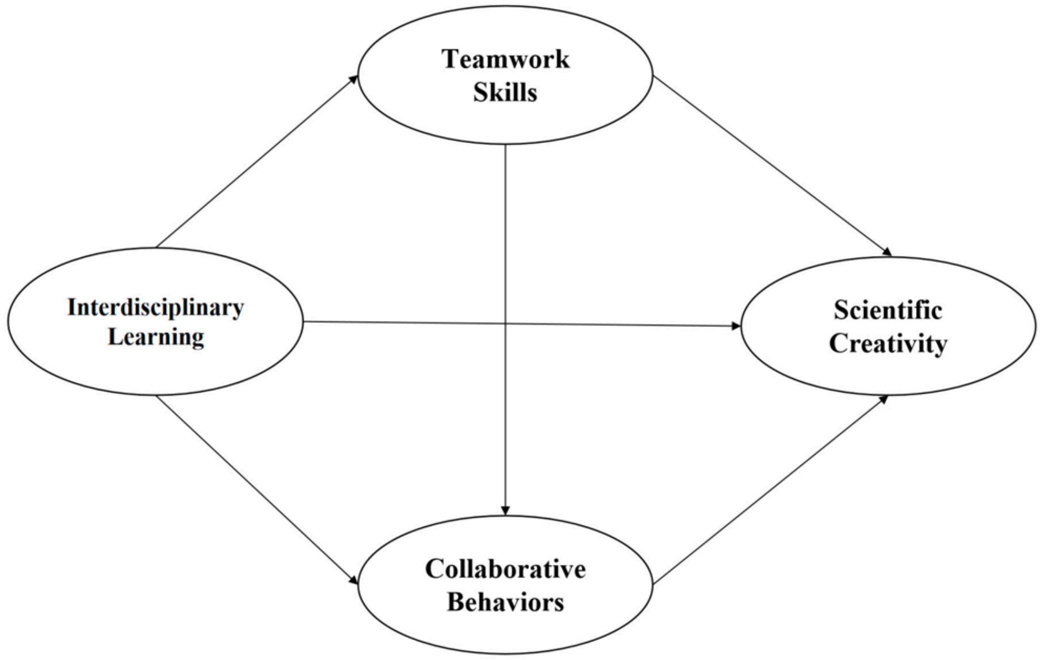

Figure 1: The hypothesized framework (S. Chen et al., 2024).

Figure 1 illustrates the conceptual model of how team processes enable interdisciplinary outcomes. In this framework, engaging in effective collaborative behaviors and developing teamwork skills mediates the link between interdisciplinary input and high team performance (e.g. creative outputs) (S. Chen et al., 2024). In other words, simply assembling experts from different fields is not enough. Teams also need the right internal processes (communication, coordination, mutual learning) to transform diverse knowledge into innovative results.

To harness the benefits of cross-disciplinary teams, research emphasizes creating supportive team processes and conditions that allow members to collaborate fluidly. Several key factors repeatedly emerge as critical for effective interdisciplinary teamwork:

- Open Communication and Knowledge Sharing: High-performing interdisciplinary teams establish open channels for frequent, transparent communication. They often develop shared communication norms or even a common “language” over time. Regular check-ins, debriefs, and the use of visual aids or boundary objects (like sketches, prototypes, diagrams) can help align understanding across disciplines. Moreover, effective teams actively practice knowledge sharing, members take time to explain their thought process and domain concepts to others. One useful mechanism is the development of a transactive memory system, where the team as a whole becomes aware of "who knows what" in the group ("Theories of Team Cognition", 2013). This way, a design specialist knows that the data analyst has certain information, and vice versa, so they can efficiently route questions and integrate expertise. Research shows that teams with well-developed transactive memory systems and communication routines coordinate more implicitly and perform better than those without ("Theories of Team Cognition", 2013). In essence, investing in communication up front (through cross-training, glossaries of key terms, etc.) builds a foundation for seamless collaboration when the pressure is on.

- Shared Goals and Team Identity: A clear, compelling shared goal is vital to unify an interdisciplinary team. When all members are committed to the same overarching objective (for example, "design a user-friendly healthcare app that improves patient outcomes"), disciplinary differences become secondary to this common mission. Effective teams take time at the outset to clarify their mission, jointly define success criteria, and agree on a work plan creating a shared mental model of what they aim to achieve. This shared purpose aligns efforts and provides a basis for resolving disputes (the question becomes "What choice best serves our goal?" rather than one discipline's preference). Alongside goals, cultivating a sense of team identity helps break down the "us vs. them" mentality between disciplines. When members see themselves as part of one integrated team (rather than as representatives of separate departments), they are more likely to trust each other and collaborate freely. Setting team norms that value every perspective and rotating leadership or roles on tasks can reinforce a unified team identity. A clear goal and team ethos act as a compass that keeps the group moving in the same direction, even when disciplinary approaches differ.
- Mutual Trust and Psychological Safety: Perhaps the most crucial condition for cross-disciplinary success is a climate of trust and psychological safety. Trust in this context means team members have confidence in one another's intentions and expertise. They believe that each person is contributing in good faith and is competent

in their domain. Trust allows members to rely on each other's knowledge without constant hesitation or second-guessing. Psychological safety, a related concept, is the shared belief that the team is a safe space for interpersonal risk-taking (Rødsjø et al., 2024). In a psychologically safe team, individuals feel secure to speak up with ideas or concerns, admit mistakes, and ask naive questions without fear of ridicule or retribution. This is especially important in interdisciplinary groups, where power dynamics or expertise disparities might otherwise silence members from outside the dominant discipline. Research confirms that interdisciplinary problem-solving relies on psychologically safe teamwork, where members feel confident to voice unique viewpoints or uncertainties (Rødsjø et al., 2024). When psychological safety is high, a biologist can admit to the computer scientist that she doesn't understand a technical term and vice versa, leading to clarification and learning rather than embarrassment. Studies of successful teams consistently highlight mutual respect as well (Brown et al., 2023). Each discipline's contributions must be respected as different but equally valid. Building trust and safety may involve team-building activities, explicit norms against blaming or dismissiveness, and leaders modeling openness. With trust and safety in place, an interdisciplinary team can fully tap into its members' expertise: people are willing to share bold ideas and constructively critique each other, which drives creativity and integration.

- Supportive Leadership and Team Learning Culture: Another important enabling condition is team leadership that facilitates collaboration rather than dominating it. In interdisciplinary teams, a hierarchical, discipline-centric leadership style can stifle open exchange. Effective leaders (or facilitators) of such teams instead act as integrators, they encourage input from all members, help translate jargon, and resolve conflicts even-handedly. They also pay attention to process, ensuring that meetings allow for cross-pollination of ideas and that quieter voices (often junior or from less represented disciplines) are heard. In some cases, teams benefit from a facilitator or coach who is explicitly tasked with bridging disciplines (for example, a project manager who understands enough of each field to connect the dots). Additionally, fostering a team learning culture is essential. This means the team values continuous improvement of how they work together. Practices like team reflexivity (periodically reflecting on team processes and outcomes) enable the group to adapt and find better ways to integrate their knowledge. For instance, after a design sprint, the team might discuss what communication hurdles occurred and adjust their strategy for next time. Embracing a learning mindset also implies tolerance for failure or iteration seeing unsuccessful prototypes or rejected ideas as learning opportunities rather than setbacks. Such a culture encourages risk-taking and openness, which have been identified as antecedents of creative collaboration (Tang, 2019). In summary, supportive leadership and a learning-oriented team climate create the conditions for interdisciplinary teams to experiment, bond, and ultimately excel in innovation.

- Organizational and Environmental Support: Finally, conditions external to the team can influence its effectiveness. Adequate resources (time, funding) are often necessary because interdisciplinary work can be more time-intensive and teams may need extra time for discussion and alignment. Training opportunities (such as workshops on communication or conflict resolution for diverse teams) can build the soft skills needed for collaboration (El-Awaisi et al., 2024). Organizational recognition and reward for team-based achievements (rather than solely individual accomplishments) also motivate members to fully engage in interdisciplinary efforts. In educational or research contexts, institutional support for interdisciplinary initiatives (through grants, interdisciplinary labs, etc.) sends a message that such collaboration is valued. Though these factors lie beyond the team's day-to-day interactions, they form a supportive ecosystem that can greatly enhance a team's ability to function cross-disciplinarily.

In combination, the processes and conditions above create a synergistic environment where interdisciplinary teams can thrive. When teams communicate openly, trust each other, share a clear purpose, and feel safe to contribute, they can truly integrate their diverse knowledge into cohesive, creative outputs. Empirical evidence reinforces that it is this social infrastructure, effective teamwork skills, mutual respect, and aligned goals that determines whether a multidisciplinary group's potential is realized (S. Chen et al., 2024). By deliberately cultivating these team processes and norms, organizations can overcome the barriers discussed earlier (communication gaps, integration woes, cognitive conflicts) and unlock the full innovative power of interdisciplinary collaboration.

These theoretical foundations of interdisciplinary teamwork are not only crucial for human teams but also highly relevant as teams begin to incorporate AI systems as collaborators. As later sections will explore, introducing an AI "team member" into design thinking teams will similarly require clear communication channels, shared goals, and psychological safety around the technology. In essence, the same conditions that foster effective human-human interdisciplinary collaboration will underpin effective human-AI collaboration. Establishing a robust collaborative climate and process is therefore a prerequisite before teams can successfully integrate AI into team-based innovation. The next section will build on this foundation, examining how design thinking teams are incorporating AI and what new dynamics emerge when an artificial agent joins an interdisciplinary human team (Brown et al., 2023).

2.3 Design Thinking as a Team-Based Innovation Framework

2.3.1 Principles and Process of Design Thinking

Design Thinking (DT) is widely recognized as a human-centered, iterative approach to innovation that prioritizes uncovering and addressing user needs (Mayer & Schwemmle, 2024). At its core, DT involves empathy with users, creative ideation, and rapid prototyping to solve ill-defined problems in innovative ways (Mayer & Schwemmle, 2024). A foundational definition describes DT as "a human-centered approach to innovation that puts the observation and discovery of often highly nuanced, even tacit, human needs right at the forefront of the innovation process" (Gruber, De Leon, George, & Thompson, 2015, p. 1). This philosophy underpins the basic structure of the design thinking process, which consistently entails exploring a problem space (to understand and empathize with stakeholders' needs) and a solution space (to iteratively generate and test solutions) (Mayer & Schwemmle, 2024). In practice, teams alternate between divergent thinking (expanding the space of possible insights or ideas) and convergent thinking (synthesizing and narrowing down options) during these phases (Mayer & Schwemmle, 2024). This oscillation of broad idea generation and focused refinement is often visualized by the "double diamond" model of design, illustrating two diamonds for the problem definition and solution development stages (each with divergent and convergent phases) (Mayer & Schwemmle, 2024). Essentially, regardless of the specific model used, DT encourages teams to first discover and define the right problem, then develop and deliver solutions through prototyping and feedback, rather than jumping straight to solutions (El-Sattar et al., 2024).

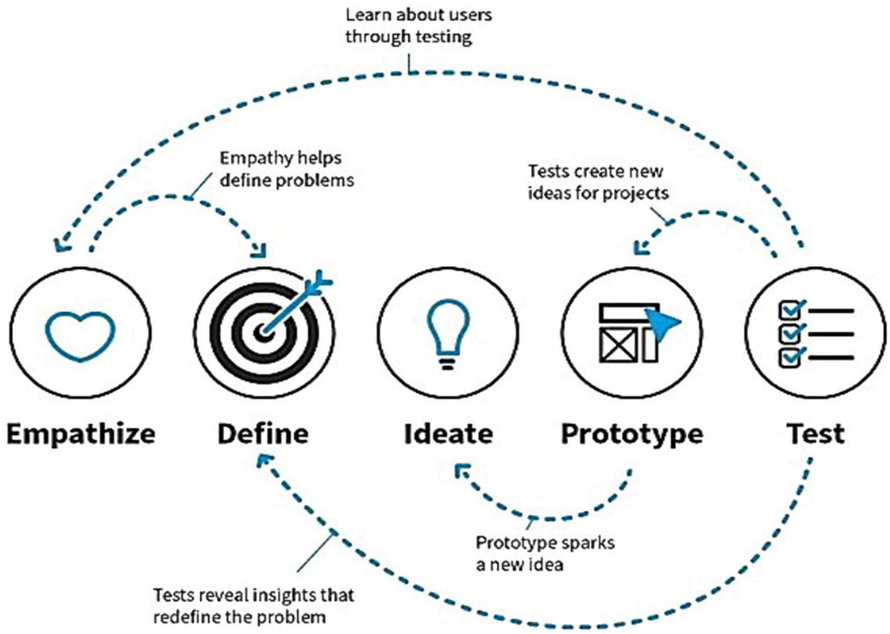

Figure 2: The 5-step empathize-define-ideate-prototype-test (EDIPT) DT process (El-Sattar et al., 2024).

A commonly used five-stage model of the design thinking process: Empathize, Define, Ideate, Prototype, Test emphasizing its iterative, non-linear nature. In practice, teams may loop through these stages multiple times; for example, testing a prototype can reveal new user insights that redefine the problem, and prototyping itself can spark fresh ideas (El-Sattar et al., 2024).

Multiple frameworks articulate the DT process in 3, 4, or 5 steps, but all share these human-centered and iterative principles (El-Sattar et al., 2024). One popular schema is the five-stage DT model developed at Stanford's d.school, comprising: Empathize (research users' needs), Define (formulate a clear problem statement), Ideate (generate a range of ideas), Prototype (build tangible representations of ideas), and Test (evaluate solutions with users) (El-Sattar et al., 2024). As shown in Figure 2, this process is not strictly linear. Testing can lead back to redefining the problem, and insights from any stage can prompt revisiting earlier steps (Mayer & Schwemmle, 2024). The emphasis on empathy ensures design thinkers deeply understand the user context before defining problems, while prototyping and testing embody the principle of learning by doing and failing fast to refine ideas (Mayer & Schwemmle, 2024). Scholars generally agree that identifying genuine user needs, engaging in creative ideation, and iterative prototyping are indispensable elements of DT (Mayer & Schwemmle, 2024). Moreover, a recent review of the literature identified a set of key mindsets and attributes associated with effective design thinking. These include abilities like abductive reasoning and visualization, a blend of analytical and intuitive thinking, tolerance for ambiguity and failure, and a predisposition toward interdisciplinary collaboration and experimentation (Mayer & Schwemmle, 2024). Such attributes highlight that DT is not only a process but also a mindset, a "bundle of attitudes, tools, and approaches" that practitioners adopt to drive innovation (Mayer & Schwemmle, 2024).

One distinguishing hallmark of design thinking is its integrative approach: it combines methods and perspectives that are often separated in more traditional problem-solving approaches (Mayer & Schwemmle, 2024). For example, DT brings together ethnographic need-finding techniques with creative solution generation, and marries the creation of physical artifacts with consideration of emotional user experiences in parallel (Mayer & Schwemmle, 2024). Rather than relying solely on analytical reduction, design thinking embraces abductive reasoning generating plausible new solutions from incomplete information and continually iterates between thinking and making. This approach stands in contrast to linear problem-solving methodologies, and it has proven especially adept at tackling "wicked" problems (ill-defined or complex challenges with no obvious solutions) by keeping human values and feedback in the loop (Dragičević et al., 2023). Thanks to these strengths, design thinking has gained traction across domains: it originated in design and engineering fields, but is now extensively applied in business innovation, social entrepreneurship, and public sector problem-solving (Dragičević et al., 2023). In recent years, it has also been increasingly adopted in education, both as a teaching strategy to foster students' creative problem-solving skills and as a framework for educators to redesign learning experiences. Universities and schools have embedded design thinking in their curricula to help learners develop capabilities for dealing with complex, real-world problems and uncertainty (Dragičević et al., 2023). Even with occasional critiques (e.g. that DT can appear too practitioner-oriented or lacking a unifying theory), the consensus is that its human-centered, iterative ethos offers a valuable antidote to “fossilized” traditional methods in the face of rapid, disruptive change (Dragičević et al., 2023). In summary, the principles of design thinking, empathy for users, collaborative ideation, prototyping experimentation, and iterative learning form a robust framework that drives innovation in both professional practice and educational settings. These principles naturally rely on teamwork and diverse perspectives, as discussed next.

2.3.2 Collaborative Roles and Structures in Design Teams

By its very nature, design thinking is a team-based endeavor. Complex innovation challenges benefit from the collective intelligence of interdisciplinary teams, where each member contributes unique expertise and viewpoints. In fact, interdisciplinary collaboration is identified as a core attribute of design thinking methods (Mayer & Schwemmle, 2024). This means that DT teams are typically composed of individuals from diverse backgrounds, for example, a single project might involve a product designer, an engineer, a marketing specialist, a user-researcher, and other domain experts working in concert. Bringing together these different perspectives is believed to spur more creative outcomes and ensure solutions are viable from multiple angles (human, technical, business, etc.). Design thinking’s emphasis on empathy and holistic problem framing creates an environment where everyone’s input is valued, encouraging team members to look beyond their own disciplinary silos. Collaboration in such teams is not merely about dividing labor; it is about integrating insights to co-create better solutions. As one design education study notes, effective collaboration requires “embracing diverse perspectives, leveraging collective expertise, and co-creating solutions” to address real-world challenges (Wu & Liu, 2024). In educational settings, students are deliberately placed in design thinking teams to practice these skills, learning how to negotiate different viewpoints and work jointly on open-ended problems- a preparation for the interdisciplinary teamwork expected in modern innovation practice (Wu & Liu, 2024).

Team roles in design thinking tend to be fluid and can rotate as needed, but certain structural roles commonly emerge to support the process. A frequently observed role is the facilitator or design thinking coach, who guides the team through the DT process (ensuring time is allocated to empathizing with users, fostering brainstorming sessions, managing prototype tests, etc.). The facilitator helps maintain the human-centered focus and keeps the team aligned with DT principles and timelines. Meanwhile, other team members may take on functional roles aligned with their expertise. For instance, one member might focus on user research (leading efforts in the Empathize phase), another might drive prototyping due to engineering skills, and another might specialize in evaluating concepts against business criteria. Importantly, however, design thinking teams are generally non-hierarchical compared to traditional teams. They operate with a spirit of equality where ideas are judged on merit rather than seniority. This flat structure encourages open communication and psychological safety, so that even junior or non-expert members feel comfortable contributing wild ideas or voicing concerns. Studies have shown that such psychological safety, the belief that the team environment is safe for interpersonal risk-taking- is critical for innovation. It allows teams to critique ideas and iterate candidly without fear of embarrassment, which is essential when navigating the ambiguity and occasional failures inherent in design thinking (Heldal, 2023).

At the same time, recent research suggests that some degree of team structure and discipline can enhance design thinking outcomes. In a study of 51 design student teams, Heldal (2023) found that the highest-performing teams exhibited more “authority-based” behaviors (clear leadership or decision-making authority) and fewer purely supportive behaviors, compared to lower-performing teams (Heldal, 2023). In other words, teams that treated design thinking not just as a free-form brainstorming exercise but as a disciplined process with roles or individuals enforcing process steps and decisions achieved better innovative performance (Heldal, 2023). These well-structured teams were better at moving through divergent and convergent phases in a timely way, suggesting that coordination and leadership help prevent design thinking activities from getting stuck or veering off-course (Heldal, 2023). Interestingly, the same study noted that these high-performing teams managed to pair a disciplined approach with high psychological safety: they used authority to keep the process on track, but still fostered an environment of open dialogue and team reflexivity (i.e. collectively reflecting on ideas and feedback) (Heldal, 2023). This combination allowed them to converge on decisions without stifling creativity, members felt safe to voice opinions, yet the team could critically evaluate and cull ideas when needed. These findings illustrate that effective DT teams often strike a balance between creative freedom and structured coordination. It reinforces the notion that having a designated facilitator or a clear process plan can improve team focus, as long as the team culture remains collaborative and trusting.

In terms of team composition and diversity, evidence indicates that design thinking can positively influence how teams leverage their diversity. A recent systematic review by Schlott (2024) synthesized numerous studies and concluded that design thinking has diverse impacts on team dynamics and performance, including improving team interactions, enhancing team members' skills and mindsets, and even shaping team composition and structure (Schlott, 2024). Several studies in the review reported that engaging in design thinking led teams to adopt more effective coordination structures and value a mix of personalities and backgrounds on the team (Schlott, 2024). For instance, DT workshops often prompt teams to recognize the benefit of including members with different thinking styles (analytical vs. creative, novice vs. expert, etc.), thereby encouraging heterogeneous team makeup. In one case, teams noted that the method helped surface each member's creative contribution, thereby increasing individuals' sense of inclusion and personal creativity within the group (Schlott, 2024). Notably, none of the studies in that review found negative effects of DT on teamwork when properly facilitated, DT practices tended to either improve or have neutral impact on team cohesion and effectiveness (Schlott, 2024). This aligns with the broader view that design thinking can act as a social technology that transforms team culture: it infuses values of empathy, experimentation, and user-focus into the team's way of working, which can lead to more open-minded communication and a shift away from siloed or adversarial team behaviors (Schlott, 2024). In organizational contexts, adopting design thinking has even been linked to broader cultural changes, teams become more innovation-oriented, willing to take risks and learn from failure, which can gradually influence the larger organization's norms and climate (Schlott, 2024).

In summary, successful design thinking teams are intentionally structured to maximize collaborative creativity. They thrive on diversity of expertise, rely on clear yet flexible roles (with facilitative leadership to guide the process), and cultivate an atmosphere of trust and open exchange. In educational environments, instructors often simulate this by assigning students to cross-disciplinary teams and rotating roles so that they learn both leadership and collaboration (Wu & Liu, 2024). The practical implication is that any organization or project implementing design thinking should invest in team-building and possibly training of facilitators, to ensure that the team dynamic supports the methodology. Good team setup (mix of skills, clarity of process) is a prerequisite to reap the full benefits of DT in producing innovative outcomes (Schlott, 2024). Having established the importance of team collaboration and structure in design thinking, further literature review turns to how the design thinking framework is evolving in the modern context, in particular, how digital tools and artificial intelligence are transforming the way design teams collaborate.

2.3.3 The Digital Turn: Hybrid and AI-Enhanced Design Thinking Environments

In recent years, design thinking practices have undergone a significant digital transformation, shifting from sticky notes on co-located workshop walls to shared online whiteboards and AI-powered collaborative tools. This “digital turn” has been accelerated by factors such as the globalization of teams and the COVID-19 pandemic, which forced many design sessions to go fully remote. As a result, modern design thinking often unfolds in hybrid environments. Some team members might be in the same room while others join via videoconference, or all members collaborate through digital platforms despite being physically apart. These changes have fundamentally altered how design teams communicate and innovate, bringing both opportunities and new challenges. On the one hand, advanced online collaboration tools have made it easier to involve diverse participants regardless of location, enabling broader stakeholder input and continuous collaboration beyond the constraints of scheduled in-person meetings. For example, platforms like Miro, Mural, or Figma (along with communication channels like Slack or Microsoft Teams) allow teams to brainstorm, sketch, and prototype on a virtual canvas in real time. A recent study in design education demonstrated that a blended use of such online tools can enhance team engagement and collaboration, effectively overcoming traditional barriers of distance and time zones (Wu & Liu, 2024). By integrating Slack for communication, Figma for co-design, and virtual whiteboards for ideation, student design teams in the study were able to maintain high levels of interaction and co-creativity even when not physically co-present (Wu & Liu, 2024). The researchers found that this approach improved students' collaboration skills and project outcomes, suggesting that digital platforms can successfully augment the collaborative capacity of design teams when used thoughtfully (Wu & Liu, 2024). Indeed, online tools provide persistent spaces where ideas can be asynchronously developed and documented, and they broaden participation by allowing input from team members who might be less vocal in a live setting.

On the other hand, virtual and hybrid design thinking require deliberate effort to replicate the spontaneous interactions and shared understanding that come naturally in person. Effective remote collaboration hinges on clear communication and maintaining team cohesion through digital channels. Recent research has begun to delve into the dynamics of remote design teams. For instance, Lee and Ostwald (2025) investigated how collective design thinking unfolds via videoconference meetings, analyzing both the cognitive process and language used by teams working entirely online (Lee & Ostwald, 2025). Their study revealed nuanced links between communication patterns and team effectiveness in digital environments. Notably, they found that when remote teams had explicit task allocation (i.e. clarity on who is doing what), it correlated with more substantive cognitive processing likely because clear roles reduced confusion and allowed deeper focus on the design problem (Lee & Ostwald, 2025). Moreover, the analysis highlighted the importance of Language Style Matching (LSM) among team members: teams whose members subconsciously adopted similar linguistic styles during chat and discussion tended to have higher cohesion and more synchronized thinking (Lee & Ostwald, 2025). In short, communication alignment can serve as a proxy for shared understanding in virtual teams. These findings underscore that while digital tools provide the infrastructure, teams must also establish new norms (like explicit turn-taking, over-communication of intent, and regular check-ins) to ensure everyone remains on the same page. When done well, remote design collaboration can approach the efficacy of in-person teamwork, and in some respects even improve it, for example, digital brainstorming can generate a higher quantity of ideas since participants can contribute in parallel, and records of discussions are automatically kept. However, teams and facilitators need to be mindful of issues like “Zoom fatigue”, reduced spontaneity, or the loss of rich nonverbal cues. Researchers are actively seeking ways to enhance online design collaboration, focusing on how to fuse cognitive processes with new communication modalities to keep creativity flowing in virtual settings (Lee & Ostwald, 2025). The hybrid model (where some members are co-located and others remote) adds another layer of complexity, requiring careful facilitation so that remote participants are not marginalized in discussions. Overall, the digital turn has expanded the reach and flexibility of design thinking, but it requires an updated skill set, digital facilitation techniques, fluency with collaboration software, and an emphasis on communication strategies to fully leverage these new environments.

Perhaps the most groundbreaking aspect of the digital evolution of design thinking is the emergence of artificial intelligence (AI) as a collaborator in the creative process. Increasingly, AI tools and systems are being integrated into design thinking activities to support and amplify human ingenuity. This ranges from relatively simple applications (using AI-based research tools to gather user data or identify patterns during the Empathize phase) to more sophisticated ones (employing generative AI to propose novel ideas, or machine learning algorithms to test thousands of prototype variations virtually). The incorporation of AI aligns with design thinking’s experimental ethos: teams treat AI systems as sources of inspiration, rapid simulation, or even as quasi-team members that contribute alongside humans. For example, an AI language model like ChatGPT might be used during ideation to generate a large variety of concept prompts, functioning as a creative “sparring partner” that suggests ideas the team might not have considered. Visual AI tools (such as generative image models) can produce quick sketches or storyboards from text descriptions, accelerating the prototyping of experience concepts. Early studies indicate that these AI contributions can enhance the creativity and efficiency of design teams. In a 2024 mixed-method study of UK design agencies, Altaie and Taqa found that a higher level of AI integration in the design thinking process was associated with significantly improved innovation outcomes for the team's projects (East Bridge University & Altaie, 2024). Design professionals reported that AI tools were successfully adopted for activities like exploring user trends and visualizing data insights, as well as speeding up aspects of brainstorming and experimentation (East Bridge University & Altaie, 2024). In essence, AI augmented the teams' capabilities handling certain tedious or complex tasks quickly which freed human designers to focus on higher-level creative and strategic thinking. The study concluded unequivocally that AI tools, when properly implemented, "enhance creativity and efficiency in design thinking and foster innovation in organizations". (East Bridge University & Altaie, 2024). This positive impact is echoed in educational contexts as well: a survey of instructional designers revealed a broad belief that AI can improve the design thinking process by providing on-demand information, suggesting personalized solutions, or automating parts of prototyping (Al-Zahrani, 2024). Respondents in that study indicated that with adequate training and awareness, AI's role could shift from a mere tool to a co-creator in the design workflow, assisting with idea generation and decision support.

However, along with optimism about AI's potential, researchers also caution about the challenges and evolving team dynamics that AI integration brings. One immediate challenge is ensuring that human team members understand the AI's contributions and limitations, in other words, maintaining a human-centered approach even as AI is woven into the process. If designers treat AI outputs uncritically or as black boxes, the human-centered spirit of DT could be undermined. It's therefore crucial that teams approach AI as a collaborative aid whose suggestions are scrutinized and refined through human judgment (just as one would respectfully critique a human teammate's idea). Additionally, issues of data privacy, solution bias, and ethical use of AI have been noted as concerns when introducing AI into creative teamwork (East Bridge University & Altaie, 2024). For instance, using an AI that relies on large datasets might inadvertently introduce biases in the concepts it generates, or raise questions about the ownership of AI-generated design outputs. Organizational support in the form of training and clear guidelines is needed to navigate these issues (East Bridge University & Altaie, 2024). Another consideration is the team's perception of AI: will team members accept AI as an equal participant?

Al-Zahrani (2024) found factors like an individual’s experience with AI and general tech-savviness affected how they perceived AI’s impact on design thinking (Al-Zahrani, 2024). Teams might need time and positive experiences to build trust in AI tools. Encouragingly, when the context is set up right (e.g., leadership champions AI experimentation and makes it clear that the AI is there to assist, not replace, human creativity), teams are more likely to integrate AI effectively into their workflow. In fact, preliminary evidence from a design education case suggests that when students used generative AI tools in a co-design challenge, they viewed the AI as a helpful support rather than an all-knowing oracle, indicating that with proper framing AI can be seen as a partner that provides ideas to build upon. This points toward a future model of design teamwork where AI is an accepted part of the multidisciplinary team, sometimes referred to as “AI as a team member”. In such a model, an AI agent might take on specialized roles analogous to a human team member. For example, an AI could function as an “information specialist” on the team, quickly retrieving user data or relevant research to inform the Empathize and Define stages. Later in the process, the AI might act as a “creative provocateur” during Ideation by generating outside-the-box prompts or combinations of ideas to inspire the human team. During prototyping, AI tools could rapidly test variations or even generate code/graphics, serving as an ever-ready “technical assistant”. The theoretical and practical implications of this AI-enhanced design thinking are profound: it suggests teams could tackle more complex problems faster, explore a wider solution space, and make data-informed design decisions with greater confidence. Nonetheless, it also raises new research questions (and is indeed the focus of Section 2.4 of this thesis): how do we best integrate AI into each phase of design thinking? What frameworks ensure that AI’s involvement remains human-centered and ethical? And how do team processes and outcomes change when an AI is actively collaborating in the creative mix?

In conclusion, the digital turn in design thinking has expanded the framework into new terrains both the virtual collaboration space and the frontier of human-AI co-creation. Hybrid and online environments have made design teams more distributed and technology-reliant, demanding new collaboration skills but also offering new opportunities for inclusive and continuous teamwork. Simultaneously, the advent of AI in design thinking is beginning to redefine team roles and possibilities, positioning AI not just as a tool but as an intelligent collaborator that can augment human creativity. These developments reinforce the adaptability and relevance of design thinking as an innovation methodology: its core principles of empathy, iteration, and collaboration are being reinterpreted and applied in novel ways through technology. As organizations and educational programs adopt AI-enhanced design thinking, they stand to benefit from greater efficiency and creativity, but must also be mindful of maintaining the human-centered ethos that is the hallmark of design thinking (Dragičević et al., 2023). The next sections of this thesis (Section 2.4) will delve deeper into how AI's integration into design thinking is being researched, including specific contributions, case examples, and remaining challenges in making AI a true team member in design. Here, it suffices to recognize that design thinking, as a team-based innovation framework, is entering a new era that remains grounded in its collaborative, interdisciplinary foundations while embracing the digital tools and AI partners that can elevate creative problem-solving to new heights.

2.4 Integrating AI into Interdisciplinary Design Thinking

Building on the foundations laid in Sections 2.1-2.3, this section examines how AI can be woven into the fabric of interdisciplinary design thinking. Prior discussions have underscored the human-centered, collaborative nature of design thinking and the growing presence of AI in creative work. Now the focus is on the convergence of these threads, exploring what AI contributes across each phase of the design thinking process, how practitioners in both educational and corporate team contexts are beginning to integrate AI, and what challenges and open questions remain. In doing so, Section 2.4 sets the stage for subsequent analysis of AI as a collaborative team member in design, highlighting both its promise and the sociotechnical complexities it introduces.

2.4.1 Potential Contributions of AI Across the Design Thinking Phases

Artificial intelligence offers a range of potential contributions that align with the Empathize, Define, Ideate, Prototype, and Test phases of the design thinking cycle. By leveraging machine learning, natural language processing, and generative algorithms, AI systems can augment human capabilities in each stage:

- Empathize: In the initial user research phase, AI can help designers gather and analyze vast amounts of qualitative and quantitative user data. For example, AI language models are able to summarize user interview transcripts and perform sentiment analysis on open-ended feedback, uncovering patterns in user needs and emotions that a human might overlook (Saeidnia & Ausloos, 2024). Such AI-driven analysis can deepen empathy by efficiently extracting "profound insights into user behaviors and preferences", thereby enhancing human understanding of the problem space (Saeidnia & Ausloos, 2024). This aligns with recent studies highlighting AI's affordance for supporting analytical tasks in design-AI tools can quickly identify trends or pain points in large data sets, giving designers a richer evidence base for defining the problem (Polster et al., 2024).
- Define: During the problem framing stage, AI can assist in synthesizing research findings and clarifying design challenges. Pattern-recognition algorithms can sort through complex user data to help define key problem statements or user personas. For instance, an AI might cluster user stories or usage data to reveal latent needs, which designers can then articulate as problem definitions. By identifying correlations and anomalies in data, AI supports designers in distilling a clear and data-informed problem scope (Polster et al., 2024). Additionally, AI-powered tools can conduct rapid market research or competitor analysis, providing context that shapes how the design problem is understood (Saeidnia & Ausloos, 2024). In essence, AI acts as a research partner, combing through information and highlighting insights that inform the design brief.
- Ideate: Perhaps the most celebrated contribution of AI is in the ideation phase, where generative AI systems can stimulate creative thinking. AI can generate a wide variety of concepts or suggest novel combinations that spark human inspiration. For example, transformer-based language models (like GPT-3/GPT-4) are capable of producing hundreds of brainstorming ideas or design alternatives in response to a prompt, vastly expanding the idea pool (IDEO, n.d.). Empirical research confirms that AI can enhance creativity in design teams by providing divergent options and unexpected perspectives (Polster et al., 2024). In design thinking workshops observed by Polster et al. (2024), professionals reported that AI-based ideation tools accelerated

their creative process and helped overcome "blank page" paralysis by facilitating task initiation (Polster et al., 2024). Generative AI visual tools (e.g. DALL·E, Midjourney) can similarly produce quick concept sketches or storyboards, which designers then refine. By augmenting human imagination with machine-generated suggestions, AI enables teams to explore larger solution spaces with relatively little cost or time (Bouschery et al., 2023). This breadth of ideation can improve innovation performance by ensuring more alternatives are considered in early stages (Bouschery et al., 2023). It should be noted, however, that human judgment remains crucial in curating and building on AI-generated ideas- a point to which will be found in Section 2.4.3 when discussing potential downsides.

● Prototype: In the prototyping phase, AI tools can streamline the creation of tangible design artifacts. Generative design algorithms can automatically produce prototype variations (for instance, 3D models or UI wireframes) based on specified constraints and requirements. This automation allows design teams to quickly iterate on concepts (Saeidnia & Ausloos, 2024). Rather than building each prototype from scratch, designers can leverage AI to generate draft models or simulations, then adjust parameters to explore different configurations. For example, an AI system might generate dozens of layout alternatives for a product interface or physical component, optimizing for factors like ergonomics or structural strength. Such AI-assisted prototyping not only saves time but can also reveal non-intuitive solutions that a team might not have envisioned on their own. Moreover, AI-driven simulation tools enable rapid testing of prototypes: designers can use machine-learning models to predict how users might interact with a design or to identify failure points, allowing for early refinement before committing to costly physical mockups (Saeidnia & Ausloos, 2024). Overall, AI contributes to prototyping by accelerating the cycle of build-test-learn, helping interdisciplinary teams converge on effective solutions more efficiently.

● Test: In the testing and evaluation phase, AI can assist in gathering and analyzing feedback to inform iterative improvements. For instance, AI-based analytics platforms can monitor user interactions with a prototype (in a usability test or field pilot) and automatically highlight patterns which features attract attention, where users encounter difficulties, etc. (Saeidnia & Ausloos, 2024). Natural language processing can be used to analyze open-ended survey responses or social media comments about a new design, extracting common sentiments and points of confusion. Additionally, AI enables more robust experimental testing: A/B testing of design alternatives can be partially automated with AI algorithms that detect statistically significant differences in user preferences or behavior, guiding designers toward the most effective solution (Saeidnia & Ausloos, 2024). Some researchers even explore “digital twin” users or agent-based simulations using AI, essentially testing design concepts on virtual user models to predict real-world reactions. While such approaches are nascent, they illustrate how AI might scale up the testing phase by providing rapid, data-driven feedback. By iterating with AI-generated insights, design teams can more quickly converge on user-centered solutions, thus shortening the design cycle without sacrificing rigor (Saeidnia & Ausloos, 2024).

In summary, AI technologies have the potential to streamline and enhance each stage of design thinking. They can bolster the empathetic understanding of users through data analysis, sharpen problem definitions via pattern recognition, supercharge ideation with prolific idea generation, expedite prototyping through automation and simulation, and refine testing by extracting actionable insights from complex feedback data. These contributions promise a more efficient and expansive design process: teams can explore broader problem-solution spaces in less time and ground their decisions in richer evidence (Bouschery et al., 2023). Importantly, the benefits of AI are not limited to raw efficiency; they also include qualitative improvements such as uncovering hidden user needs and provoking more creative thinking in teams (Polster et al., 2024). The next subsection (2.4.2) will illustrate how these theoretical contributions are beginning to manifest in practice within real design teams. At the same time, it must be acknowledged that integrating AI is not without challenges as subsection 2.4.3 will discuss. The introduction of AI brings forth new questions about collaboration, trust, and creativity that the field has yet to fully resolve.

2.4.2 Emerging Practices and Case Examples of AI in Design Teams

AI integration into design thinking is no longer just speculative. Recent years have seen a proliferation of real-world attempts to bring AI into both educational and corporate design team settings. Interdisciplinary design teams (combining expertise from fields like engineering, design, business, etc.) are experimenting with AI tools to support their innovation processes. This subsection reviews emerging practices and illustrative cases, highlighting how design teams are actually using AI on the ground. Notably, the contexts span education-based teams (e.g. university design courses, academic hackathons) as well as industry teams (corporate innovation departments, design agencies), reflecting a broad interest in leveraging AI for collaborative design work.

In educational design environments, instructors and students have begun to treat AI as a new kind of design collaborator. One prominent example comes from a recent academic makeathon (a time-bounded design challenge) at the Shenkar Design Factory in Israel, which explicitly incorporated generative AI tools into a design thinking curriculum. David et al. (2023) report on a week-long "Jamweek" event with 705 undergraduate participants from both design and engineering programs, tasked with following a Double Diamond Design Thinking (DDDT) process while using AI tools for assistance (David et al., 2023). The findings from this case are illuminating: over 80% of the students made use of generative AI (GAI) tools such as ChatGPT (text-based) and Midjourney or DALL·E 2 (image-based) during their design process (David et al., 2023). Students predominantly perceived these AI tools as supportive aides rather than as solution providers, indicating that they used AI to assist their own creative work instead of expecting the AI to solve the problem outright (David et al., 2023). For instance, many teams used ChatGPT akin to a smart research assistant querying it for quick facts, brainstorming prompts, or initial idea generation effectively treating it "as [a] search engine" to gather inspiration and information in the Empathize and Ideate stages (David et al., 2023). Visual generative tools were used to create storyboards or mockups in the Prototype stage, helping teams visualize concepts rapidly (David et al., 2023). An interesting observation was the difference in approach and trust between design vs. engineering students: design students tended to use AI more for sparking creativity (and were slightly more skeptical of AI's factual outputs), whereas engineering students more readily trusted AI-generated suggestions for problem-solving and technical research (David et al., 2023). Despite these differences, a strong majority of both groups (around 85%) saw the AI tools as beneficial “assistants” that helped them achieve outcomes faster or explore more ideas (David et al., 2023). Crucially, however, the students did not fully tap into AI’s capabilities, the study notes that many participants stuck to basic uses (e.g. asking ChatGPT simple questions) without exploring more advanced or creative functionalities of the tools (David et al., 2023). This underscores a learning curve in how to co-create with AI: even digital-native students need guidance to move beyond treating AI as a fancy search box toward using it for deeper design collaboration. Educational design programs are beginning to respond by updating curricula, for example, some architecture and product design courses have started integrating AI-based modules where students practice co-designing with generative models (Longo & Albano, 2025). These early experiments in academia suggest that, when guided appropriately, AI can be a valuable addition to interdisciplinary student design teams, enhancing the learning experience by extending the range of research and creative exploration available to novices. At the same time, educators are observing the need to teach new skills (such as prompt engineering, critical evaluation of AI output, and cross-disciplinary communication around AI findings) to fully realize AI’s potential in design education.

In professional and corporate design teams, AI integration is also gaining momentum. Businesses are increasingly investing in AI to drive innovation. Design thinking widely adopted in industry as a framework for user-centered innovation- is a natural arena for applying these tools. Recent surveys and case studies indicate that organizations see AI as a means to augment human innovation teams, not replace them (Bouschery et al., 2023). For example, Bouschery et al. (2023) describe how some new product development teams have piloted using transformer-based AI (like GPT-3) during their innovation projects. By embedding AI into an “AI-augmented Double Diamond” process, these teams allowed AI to assist with tasks such as scanning customer reviews to identify unmet needs (Empathize), summarizing technological trends for problem definition (Define), and generating alternative solution concepts (Ideate) (Bouschery et al., 2023). Early reports from such pilots are promising: teams were able to explore larger problem and solution spaces than before, ultimately reaching more novel ideas and potentially higher innovation performance (Bouschery et al., 2023). In essence, AI gave them a kind of superpower to canvass more information and permutations, which is especially valuable in interdisciplinary teams where relevant data and solution approaches may span diverse fields. Outside of formal studies, anecdotal evidence from industry also abounds. Design consultancies have begun to use AI image generators to produce mood boards or concept art for clients in a fraction of the time traditionally required. UX design teams at tech companies leverage AI-assisted prototyping tools to quickly visualize interface ideas and iterate with users.

Notably, emerging practice is not uniform. Different teams adopt AI differently. Polster et al. (2024) observed several archetypes of human-AI interaction in a series of design thinking workshops with experienced professionals. In these trials, teams were tasked with using ChatGPT alongside their usual design methods. Some teams took an “AI-first” approach, allowing the AI to generate initial ideas or research summaries which the humans then built upon. Other teams preferred a “human-guided” approach, using AI only after they had framed the problem or generated concepts themselves, to avoid overly constraining their thinking. One striking archetype identified was the “AI-only” approach for speed: occasionally teams deferred entirely to the AI for certain subtasks (like rapidly drafting a user persona or generating a list of possible features) when they prioritized speed over accuracy (Polster et al., 2024). This indicates that when deadlines are tight, teams might lean on AI to do quick heavy-lifting, accepting that the results may be rough, and then swiftly improve upon them. By contrast, other teams integrated AI more iteratively, treating it as a colleague whose outputs must be questioned and refined. Across these cases, a common theme is the need to clearly define the roles of AI vis-à-vis human team members. Practitioners found that assigning appropriate roles e.g. using AI as an “ideation assistant” or “data analyst” for the team helped avoid confusion and played to the strengths of both human and machine (Polster et al., 2024). It also mitigated issues like designers feeling overshadowed by AI. When roles were defined, team members maintained ownership of final decisions, seeing AI as a support tool rather than a competitor in creativity (Polster et al., 2024). Many organizations are now developing best-practice guidelines for this sort of integration. For example, research teams at IBM have proposed design principles for using generative AI in professional design practice, emphasizing transparency, controllability, and alignment with user-centric values (David et al., 2023). These guidelines aim to ensure that AI's contributions are harnessed in ways that enhance team effectiveness without undermining human insight.

In summary, real-world practice is beginning to validate the theoretical contributions outlined in 2.4.1. In both educational and corporate spheres, interdisciplinary design teams are experimenting with AI as a new team member. It can take on data crunching, inspire fresh ideas, and speed up implementation of concepts. Early cases like the Shenkar makeathon show that even relatively novice teams can successfully incorporate AI to expand their capabilities, given the right support and mindset (David et al., 2023). In industry, forward-looking companies are piloting AI to tackle complex design challenges at scale, reporting improved exploratory breadth and efficiency gains (Bouschery et al., 2023). These emerging practices demonstrate AI's tangible value: it can reduce grunt work, inject informed creativity, and function as an ever-ready brainstorming partner or analyst within the team. However, the experiences also reveal frictions and open questions. Teams grapple with how to balance AI's contributions with human creativity, how to maintain trust in AI suggestions, and how to adapt workflows to include a non-human collaborator. The following subsection will delve into these unresolved issues and under-explored questions of human-AI co-creation, drawing on current theories to frame the challenges that must be addressed as AI becomes a fixture in interdisciplinary design teams.

2.4.3 Unresolved Issues and Under-Explored Questions in Human-AI Co-Creation

While the integration of AI into design thinking offers exciting opportunities, it also surfaces significant unresolved issues and research questions. Designing an effective human-AI partnership is a sociotechnical challenge: it requires not only technical innovation but also rethinking team dynamics, roles, and processes. Scholars argue that it is needed to shift from viewing AI as a mere tool to treating it as a team member, adopting a human-centered, socio-technical perspective on "human-AI teaming" (Berretta et al., 2023). In such hybrid teams, humans and AI would synergistically combine their capabilities to achieve shared goals, but realizing this vision demands confronting several open questions (Berretta et al., 2023). This subsection outlines key issues and under-explored areas that emerge from recent literature, which future research and practice must address to fully unlock AI's potential in collaborative design contexts. These issues are rooted in concerns about trust, creativity, agency, ethics, and the very nature of collaboration when one "teammate" is an algorithm. Below is the discussion of each in turn, framing them with relevant theoretical lenses (e.g. human-AI trust and teaming, co-agency, sociotechnical systems) and empirical observations.

- Team Trust and Communication: One central challenge is establishing appropriate trust and communication between human designers and AI systems within a team. Effective human teams rely on mutual trust, clear communication, and shared understanding. The same appears true for human-AI teams (Berretta et al., 2023). However, studies find that adding an AI "teammate" often strains these social dynamics. For instance, in collaborative design settings, initial enthusiasm for AI can give way to disappointment or mistrust once the AI makes mistakes or reveals its limitations. Schmutz et al. (2024) observed that when an AI was introduced into team problem-solving, coordination and communication among human team members tended to decrease, as some members either deferred to the AI or disengaged from tasks the AI was handling (Schmutz et al., 2024). Paradoxically, team members might overestimate the AI's capabilities at first (a form of over-trust or automation bias), only to have trust decline over time after encountering errors (Schmutz et al., 2024). This dynamic can impair collaboration e.g., humans may stop double-checking AI outputs or conversely, dismiss potentially useful AI suggestions after a failure, leading to breakdowns in human-AI synergy. Moreover, AI systems today lack the rich communication modalities humans use (tone, gesture, context-sharing), making it hard for a team to maintain a shared mental model with an AI. Design team members might not fully understand the AI's rationale or confidence in its ideas, partly because current AIs are "black boxes" in terms of how they reach conclusions. This opacity hinders the development of common ground. Researchers highlight the need for better AI explainability and transparency as a way to foster trust and understanding in human-AI co-creation (David et al., 2023). If designers can see why the AI proposes a certain design concept (e.g. which user needs or data points influenced it) and if the

AI can communicate its uncertainties, the human team members can calibrate their trust and integrate the AI's contributions more effectively. As it stands, achieving fluent communication and calibrated trust between humans and AI remains an open challenge, one that intersects with technical questions (how to design AI that can interact in human-friendly ways) and organizational questions (how to train teams to work with AI, and to intervene when trust is miscalibrated). Addressing this issue is critical, because without trust and open communication, an AI's contributions no matter how brilliant may either be ignored or, worse, lead the team astray.

- Creativity and Idea Ownership: A second unresolved issue concerns the impact of AI on team creativity and the sense of ownership over ideas. Design thinking thrives on human creativity, empathy, and insight. Introducing AI into creative workflows raises the question: does AI amplify human creativity, or might it inadvertently dampen it? Early evidence is mixed. On one hand, AI's ability to generate many ideas can indeed increase creative fluency (number of ideas) and even stimulate originality by offering surprising stimuli. On the other hand, researchers warn of "design fixation" effects, where teams fixate on AI-suggested ideas too early and prematurely converge on those concepts (David et al., 2023). Instead of exploring a problem space broadly, teams might become biased toward the AI's outputs especially if those outputs seem polished and thus overlook potentially better solutions. Van den Broek et al. (2024) noted a tendency for stakeholders to "uncritically fixate on AI input", which sometimes diminished the quality of final design outcomes. In other words, if a generative AI proposes a concept that looks plausible, the human co-creators may spend less effort imagining alternatives or critically evaluating the AI's suggestion, leading to less innovative results. This challenge is under-explored: how can teams reap the creativity boost from AI without falling into the trap of intellectual complacency or tunnel vision around the AI's ideas? The concept of co-creativity is useful here and it calls for interactive systems that encourage human creators to continually build upon and diverge from AI contributions (rather than simply accept them). Another aspect is idea ownership. Polster et al. (2024) found that designers sometimes experienced a sense of diminished ownership over AI-generated outputs (Polster et al., 2024). For example, if an AI produces a detailed prototype or a piece of code, the human team members might feel less personally invested in it, since they did not author it themselves. This could potentially reduce their motivation or the depth of refinement they apply. Ensuring that teams maintain a strong creative engagement when working with AI is an open question. Theoretical frameworks like co-agency suggest treating the human and AI as jointly responsible for creative outcomes, which may mean developing new methods for attribution, credit, and intellectual property in co-designed work. Overall, the community is still grappling with how to balance AI's creative contributions with human intuition and avoid scenarios where human creativity is either overshadowed or stifled by over-reliance on AI.

- Human Agency, Roles, and Co-Agency: A related and deeper question is how human roles and sense of agency evolve when AI becomes part of the team. Design thinking traditionally emphasizes human agency- the empowerment of designers (and users) to drive innovation. With AI generating ideas, making recommendations, or even taking autonomous actions (e.g. running user tests or iterating prototypes), the role of the human designer is inevitably shifting. Some theorists pose the provocative idea of AI as a "colleague" or team co-agent rather than a tool (Berretta et al., 2023). This raises practical and ethical questions: How do we delineate responsibilities between humans and AI in a project? Who is the "lead" on a given task- the human expert or the algorithm with superior data-processing ability? If an AI generates a successful design solution, do the human team members get credit, or is the AI a kind of inventor? Conversely, if the AI's suggestion fails or has negative consequences (e.g. a biased design that excludes certain users), how is accountability apportioned? These questions of authorship and accountability are currently under-explored in design research. Empirical studies suggest teams are improvising role allocations, but best practices are not yet established. In Polster et al.'s workshops, clear role definition was highlighted as a mitigation strategy to avoid confusion and dependency (Polster et al., 2024). For instance, a team might explicitly agree that the AI will act as a research assistant (finding facts and patterns), while humans will remain the decision-makers who vet and integrate those findings. However, as AI systems become more capable (e.g. performing higher-level creative decisions or automatically generating complete design solutions), maintaining meaningful human agency can be challenging. The notion of human-AI co-agency calls for frameworks where AI contributes autonomously but under human direction and with human values at the core. This extends into the need for sociotechnical system design: creating workflows, user interfaces, and organizational policies that keep the human in the loop and preserve human intentionality in the outcome. Until now, there is little consensus on how to achieve this balance. Many design teams are in an experimental phase, trying to avoid either extreme automation dominance (where AI dictates the design) and automation marginalization (where AI is under-utilized because humans don't trust it). Finding the sweet spot where AI is an empowering teammate and humans retain a sense of mastery and responsibility is a crucial research frontier. This also ties to educational needs: future designers must be trained not just in design skills, but in collaboration skills for working with AI, including when to lead, when to let the AI lead, and how to negotiate disagreements (e.g., if the AI's data-driven conclusion conflicts with a designer's intuition or stakeholder preference).

- Bias, Ethics, and Sociotechnical Blind Spots: Another pressing issue is the ethical dimension of AI-assisted design. AI systems come with well-documented biases and limitations. They learn from historical data that may contain societal biases, and they often lack contextual understanding of ethical or cultural nuances. When such systems are integrated into design thinking, there is a risk that they introduce or amplify biases in the resulting solutions. For example, an AI analyzing user data might overemphasize the needs of the majority user group at the expense of minorities if the data are skewed, leading the team toward solutions that inadvertently exclude certain populations. Van den Broek et al.'s (2024) review of participatory design with AI warns that stakeholders' reliance on AI can lead to "biased models" influencing design outcomes and potentially exacerbating stakeholder vulnerabilities. This points to a broader socio technical issue: who gets to have a say when AI is part of the design team? Traditional design thinking strives to include diverse human perspectives (through empathy and user involvement). If an AI mediates those perspectives, for instance, by summarizing user research, its biases could skew what the team perceives as user priorities. Moreover, accountability for ethical missteps becomes murky in a human-AI team. If a flawed design recommendation is made, was it the AI's "fault" for reflecting biased data, or the human team's fault for not catching it? Current legal and professional frameworks do not clearly address this scenario. Transparency and auditability of AI processes become essential so that teams can identify why a given suggestion was made and challenge it if needed. Yet many AI models (especially deep learning based generative models) operate as black boxes. Without improvements in AI transparency, design teams may struggle to interrogate AI outputs critically. This challenge is underlined by David et al., (2023), who found that increasing an AI system's transparency can improve users' trust and willingness to use it appropriately. For design teams, having AI that can explain its rationale or show the data it relied on would help humans spot potential biases or errors before they propagate into design decisions. There is also an educational gap here: design teams often lack members with expertise in AI ethics or data science, which can lead to blind spots when using these tools. Interdisciplinary collaboration might be part of the solution, for example, involving ethicists or AI specialists in design sprints to evaluate AI contributions. In sum, the integration of AI into design brings to the fore socio technical questions about fairness, accountability, and inclusion that remain insufficiently explored. As AI continues to evolve, researchers call for proactive approaches (guidelines, oversight mechanisms, and new participatory methods) to ensure that human-AI co-creation aligns with human values and does not inadvertently harm or exclude (Van Den Broek et al., 2024). Addressing these concerns is not only a moral imperative but also crucial for the long-term viability of human-AI design teaming. If stakeholders (clients, end-users, society at large) lose trust in AI-assisted designs due to ethical lapses, it could hinder broader adoption of these technologies in design practice.

In conclusion, integrating AI into interdisciplinary design thinking is as much about rethinking human collaboration and design methodology as it is about deploying new technology. The unresolved issues identified trust and communication barriers, the impact on creativity and ownership, the negotiation of human/AI agency, and the ethical pitfalls highlight that human-AI co-creation is a delicate balancing act. Theories of human-AI teaming and sociotechnical systems remind us that a successful partnership with AI will require joint optimization: designing both the AI tools and the social practices around them to complement each other (Berretta et al., 2023). Many of these questions are under active investigation. For instance, researchers are exploring adaptive interfaces that adjust the AI's level of autonomy based on human team members’ stress or workload, techniques for improving AI explanations to foster shared understanding, and frameworks for “calibrated trust” that dynamically tune how much the team relies on the AI’s outputs. There is also recognition that organizational culture plays a role: companies and educational programs need to create environments where experimenting with AI is encouraged but critical evaluation of AI is also standard practice. Ultimately, Section 2.4 has outlined both the potential and the perils of bringing AI into the fold of design thinking. This lays important groundwork for the thesis’s subsequent analysis, which will delve into strategies for treating AI not just as a tool but as a collaborative team member. The goal of that analysis will be to propose how interdisciplinary design teams can harness AI’s contributions while mitigating its risks ensuring that the human-AI partnership leads to more innovative, human-centered, and responsible design outcomes, rather than undermining the very principles of empathy and creativity that define design thinking. The journey toward truly integrated human-AI design teams is just beginning, and addressing the unresolved issues identified here will be crucial for its success.

2.5 Theoretical Lenses Guiding the Study

2.5.1 Sociotechnical Systems Theory: Contextual Alignment for Human-AI Integration

Sociotechnical systems (STS) theory holds that technology and social factors exist in an interdependent system, where neither can be optimized alone without regard to the other (Kudina & Van De Poel, 2024). This perspective emphasizes that AI tools deployed in organizations or teams are embedded within broader structures of people, culture, and processes. As Kudina and van de Poel (2024) note, a purely technology-centric view of AI is inadequate: fairness or effectiveness of AI depends not only on algorithms but on the “broader context” in which they operate. Human-AI integration thus requires a socio-technical approach: both the technical subsystem (AI capabilities, interfaces, data) and the social subsystem (human skills, roles, norms, organizational culture) must be jointly designed and aligned (Herrmann & Pfeiffer, 2022). In practice, this means that teams implementing AI need supportive infrastructure and policies (e.g. training, leadership support, ethical guidelines) that complement the technology (Makarius et. al., 2020).

When applied to interdisciplinary design teams, STS theory helps explain how the organizational and cultural context shapes AI adoption and use. For example, Berretta et al. (2023) argue that a socio-technical approach is needed to view AI as more than just a tool, instead seeing it as a bona fide team member. In a supportive socio-technical environment, team members receive the training and encouragement to use AI collaboratively, and resources (e.g. high-quality data and software) are available. By contrast, if the social context (training, attitudes) is misaligned with the technology, AI's potential is wasted- people may distrust or underutilize it, and it remains a passive tool rather than an active collaborator (Herrmann & Pfeiffer, 2022). This aligns with the STS notion of "joint optimization", wherein both social and technical subsystems must be tailored together for maximum performance. The STS lens thus highlights that successful AI integration requires fitting the technology to the existing organizational practices and vice versa. As Makarius et al. (2020) model, building "sociotechnical capital" involves socializing employees to the AI, blending novel AI capabilities with the scope of work so that humans and machines learn to work in tandem.

Moreover, STS theory foregrounds the mediating role of organizational structures and policies. Herrmann and Pfeiffer (2022) describe a "socio-technical extension" of human-centered AI in organizations, emphasizing that organizations must be 'kept in the loop' (e.g. through governance processes and human-in-the-loop decision points) to ensure that AI usage aligns with organizational goals. This perspective is crucial for design teams. For instance, an interdisciplinary project will succeed only if its broader institution tolerates experimentation and grants autonomy for the human-AI process. In summary, the STS lens illuminates both opportunities and barriers: on one hand, a well-aligned socio-technical context can empower teams to leverage AI (improving efficiency and innovation); on the other hand, misalignment can lead to breakdowns in trust, communication, and performance (Herrmann & Pfeiffer, 2022).

2.5.2 Co-Creation and Collaborative Creativity: Human-AI Interactions in Innovation

The co-creation lens centers on the interactive creative process between humans and AI. Rather than seeing AI as merely a computational aid, this perspective treats AI as an active co-creator in ideation and design. Z. Wu et al. (2021) propose an "AI Creativity" concept whereby humans and AI "co-create by playing to each other's strengths" to achieve innovation beyond what either could produce alone. In this model, AI tools are not just automation, but partners in a shared creative process: for example, the AI might rapidly generate a diversity of ideas, while human teammates apply contextual judgment and emotional intelligence to shape and select among them. This mixed-initiative, interactive process embodies collaborative creativity: it leverages AI's generative capabilities (e.g. exploring unusual design alternatives) while preserving human control, reflection, and final decision-making.

Empirical studies support the benefit of genuine co-creation over passive use of AI. McGuire et al. (2024) show that participants working in a "co-creator" mode (iteratively exchanging ideas with a generative AI) outperformed those who merely edited an AI's output. Specifically, they found that human creativity deficits (compared to solo work) dissipate when people co-create with AI-generated content (McGuire et al., 2024). This implies that teams realize the most creative benefit when members see AI suggestions as seeds for joint development, rather than final answers. In practice, an AI can be a creative provocateur or brainstorming partner: it might suggest novel metaphors, unexpected features, or alternative scenarios that humans might not have considered. Meanwhile, humans can critique and build on these AI-generated ideas, leading to a richer creative outcome. Co-creation thus fosters a dialogic cycle where AI augments divergent thinking and humans provide convergent judgment and contextual sense-making.

In interdisciplinary design teams, the collaborative creativity lens highlights the power of cognitive diversity. Collective creativity research finds that heterogeneous teams including members with expertise far from the core domain often generate more innovative solutions (Waddingham et al., 2022). By extension, bringing an AI "mind" with different knowledge can similarly broaden the idea pool. For example, an AI trained on thousands of datasets may surface connections that no single human team member would notice. Thus, co-creative systems can amplify the benefit of team diversity: the AI can act as a bridge among domains, translating or integrating inputs from engineering, business, and design members. However, co-creation also presents challenges. Human-AI teams can suffer from misunderstandings and trust issues if roles are unclear. Schmutz et al. (2024) caution that adding an AI teammate often reduces coordination and trust, especially if team members initially overestimate AI capabilities. In practice, teams may become confused about whether AI suggestions should be blindly accepted or carefully critiqued. To realize the creative potential, teams must explicitly adopt a mindset that sees AI as a collaborative partner: treating AI outputs as contributions to be iterated on, rather than as final solutions. In sum, the co-creation lens emphasizes the opportunity of synergistic innovation through human-AI interplay, while also alerting us to the challenge of aligning expectations, maintaining shared mental models, and sustaining creative engagement (Z. Wu et al., 2021).

2.5.3 Integrating the Lenses: A Multi-Level Framework of "AI as a Team Member"

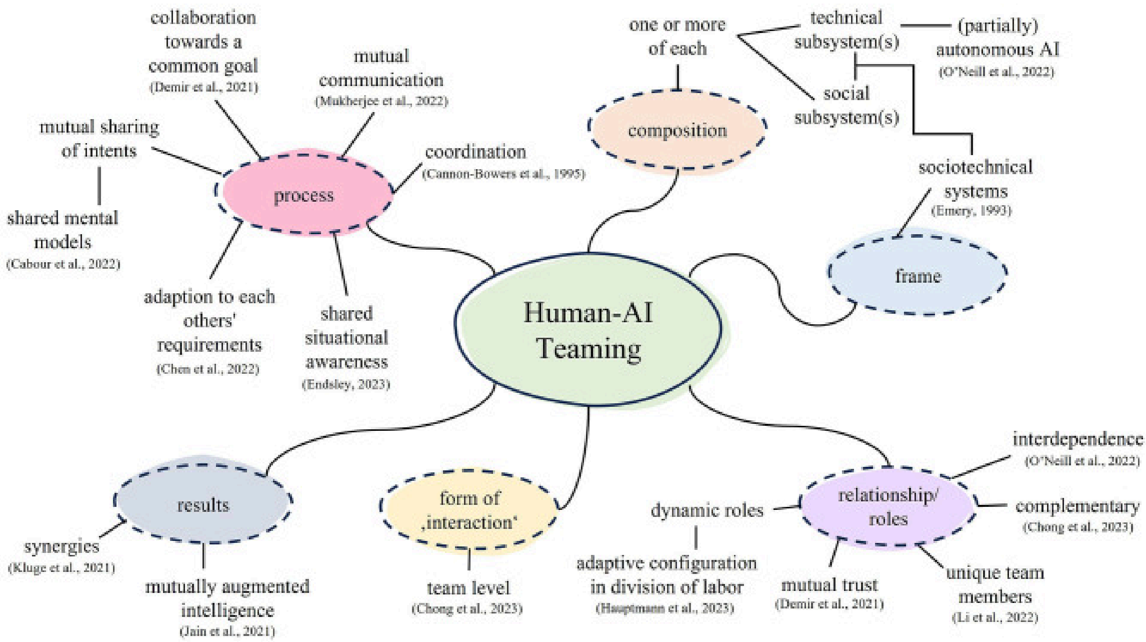

Figure 3: Key components of proposed HAIT definition (Berretta et al., 2023).

This model synthesizes the sociotechnical perspective (outer layer: context and organization) with the co-creative collaboration perspective (inner layer: human-AI team and processes). In the framework, the outer socio-technical context encompasses factors such as organizational culture, technological infrastructure, and policies (blue box), which “shape” and “empower” the inner team. The central Human-AI Team (green box) consists of diverse human experts collaborating with an AI agent, engaging through the design thinking cycle. Arrows represent their co-creative interaction (e.g. humans co-create with AI, AI assists/augments the process). Finally, the inner process leads to Outcomes (red box) like creative solutions, enhanced efficiency, and shared learning. Figure 3 illustrates that when socio-technical alignment and co-creative processes are combined (as theorized above), AI effectively functions as an integrated team member.

At the macro level, STS and co-creation complement each other by bridging context and process. The socio-technical lens reminds us that supportive context is critical: organizational practices such as training, incentives, and ethical governance condition the team’s ability to collaborate with AI (Herrmann & Pfeiffer, 2022). For instance, clear guidelines that clarify the AI’s role (as assistant, devil’s advocate, etc.) can prevent misunderstandings. The co-creation lens, meanwhile, focuses on the team’s internal dynamics: diverse human talents interacting with AI capabilities to drive innovation (Waddingham et al., 2022). At the workshop (Prompt-a-Thon by ENGAGE.EU), these perspectives interlock: a robust socio-technical environment provides the “nutrients” (resources, norms, trust) that allow the human-AI team to engage in truly collaborative creativity. Conversely, the quality of co-creative interactions feeds back into the context, as successful AI integration reinforces organizational learning and trust in the system. The theoretical complementarity is evident: while STS alerts us to the need for joint optimization of systems and people, co-creation theory prescribes the mode of interaction through which optimization yields creative benefits.

This integrated view yields a well-justified synthesis for this research core aim. It suggests that AI’s contribution to interdisciplinary design teams should be evaluated at multiple levels. For example, an AI that generates many design ideas (co-creation benefit) will only improve outcomes if the team has the capacity to incorporate them (socio-technical alignment). Wu and Zaifeng’s iSTS model similarly emphasizes human-centered joint optimization across individual, organizational, and societal levels (Wei & Zaifeng, 2025). In practice, the workshop (Prompt-a-Thon by

ENGAGE.EU) implies that researchers should examine not just what the AI tool does (e.g. generative capacity) or how individuals respond, but how the team system as a whole operates. By combining the two lenses, we see that maximizing creative outcomes depends on both enabling conditions (context, norms, training) and interaction processes (idea exchange, feedback loops, role clarity). For instance, a team might achieve breakthroughs (creative solutions) only when leaders promote an AI-friendly culture (STS) and team members actively engage with the AI's suggestions (co-creative behavior).

In conclusion, the multi-level "AI as a Team Member" framework positions AI at the center of an ecosystem of influences. It highlights that AI-integration initiatives in design teams succeed when contextual factors align with co-creative team processes (McGuire et al., 2024). This synthesis guides workshops (Prompt-a-Thon by ENGAGE.EU) by underscoring where to look for effects of human-AI teaming from organizational norms down to design activities. Ultimately, it supports the research aim by clarifying why and how AI can augment interdisciplinary creativity. When socio-technical supports and collaborative creativity practices converge, AI becomes a true partner, enabling teams to achieve outcomes that neither humans nor AI could produce alone (Z. Wu et al., 2021). Modern STS theory highlights the importance of contextual alignment for AI systems (Kudina & Van De Poel, 2024), while co-creation research shows that human-AI creative interaction boosts innovation when people act as co-creators (McGuire et al., 2024). These complementary insights justify a unified framework in which AI operates as an integrated team member.

2.6 Research Gaps and Focus of the Present Study

2.6.1 Summary of Conceptual and Empirical Gaps

Although recent literature has begun to explore intersections of artificial intelligence (AI) and design thinking, substantial gaps remain in understanding how AI can function as an integrated partner in interdisciplinary design teams. Systematic reviews note that AI can "significantly influence the design process by eliminating tedious processes, improving user-centricity, and stimulating creativity", supporting decision-making, prototyping, and ideation (Sreenivasan & Suresh, 2024). Others emphasize that combining AI's pattern-recognition power with human creativity promises more innovative, user-focused solutions (Sreenivasan & Suresh, 2024). However, these accounts are largely high-level and conceptual, highlighting AI's potential without explaining how AI actually participates in a team. Existing frameworks for human-AI collaboration (e.g. hybrid-intelligence taxonomies (Siemon, 2022) or general classifications of AI roles (Song et al., 2024)) are not specific to creative design contexts. For example, Song et al. (2024) propose a comprehensive scheme for classifying AI roles and an "AI design framework" of expected capabilities and interaction modes, but their focus is on broad engineering contexts. Rau et al. (2022) identify four abstract roles for AI teammates (coordinator, creator, perfectionist, and doer) through large-scale surveys (Siemon, 2022). These contributions are valuable, yet they do not yet specify the unique functions an AI might play during creative design activities or in the distinct phases of design thinking. In short, there is no established theory or model that situates AI as a quasi "team member" within the design thinking process, accounting for the creative, iterative, and user-centered character of design work.

Another conceptual gap concerns the nature of interdisciplinary team dynamics. Design thinking is typically conducted by interdisciplinary teams, for example, combining engineering, design, business, and social-science expertise to tackle "wicked" problems. One promising insight is that AI tools can help integrate diverse domain knowledge in such teams. Yin et al. (2023) report that a generative image tool (Midjourney) enables team members to "conserve more energy to focus on researching design inspirations" and to "integrate knowledge from various disciplines to build an understanding of key interdisciplinary… innovations". In their workshop study, teams using AI produced five times as many design iterations as those without, with members noting that AI improved communication between participants from different backgrounds (Yin et al., 2023). Similarly, Sreenivasan and Suresh (2024) emphasize that "interdisciplinary cooperation is essential to the success of AI-driven design", and that experts from domains such as neuroscience, ethics, and environmental science must collaborate to ensure AI is used "ethically and creatively" in design processes. These findings suggest that AI could reduce communication barriers and enrich creativity in interdisciplinary teams. Yet this promise is tempered by practical concerns: for example, cross-specialty misunderstanding and unequal skill levels can limit team effectiveness, and it is unclear how AI participation might alleviate or exacerbate those issues. Notably, Yin et al. (2023) found that while AI-generated assets improved shared understanding, the AI itself could not perform high-level evaluation or decision-making (requiring expert judgment). Thus, the conceptual role of AI in bridging disciplines e.g. as a translator, visualizer, or knowledge integrator remains to be more precisely defined.

A further conceptual gap is the lack of clarity about team process and roles when a nonhuman agent is involved. Research on human-AI teams (often called HATs) has begun to address factors like trust, coordination, and social cognition. For instance, Schmutz et al. (2024) observe that simply adding an AI teammate can reduce coordination, communication, and trust unless properly managed. In practice, human participants often treat AI tools not as equal peers but as assistants. Han et al. (2024) report that designers interacting with generative AI viewed the AI mainly as responsible for “content generation and laborious tasks”, while human team members “steered the direction and provided guidance” (Han et al., 2024). Likewise, in co-creative design sessions, about 30% of student designers perceived the AI as a dominant “team leader”, creating role ambiguity (Rahman et al., 2025). These studies suggest that existing teams tend to assign AI a subordinate or supportive role rather than a fully-fledged collaborator. However, there is no cohesive framework to predict what roles an AI could play, or should be allowed to play, within a creative team. For example, might AI serve as an “ideator” by proposing divergent concepts, a “critic” by evaluating ideas against criteria, or a “connector” by bringing external knowledge? The literature has not yet enumerated the possible functions of AI in design teams, nor examined how these functions align with established human roles (e.g. facilitator, subject-matter expert, user representative).

Empirically, research on AI in real-world design thinking teams is surprisingly scant. Most studies have been small-scale, exploratory, or confined to educational settings. Yin et al. (2023) conducted an interdisciplinary workshop with students using an AI image-generator. Their data showed marked efficiency gains (Yin et al., 2023), but this was a one-off experiment with young participants, not professionals. Similarly, Zhou and Nah (2024) study non-designers working with generative AI in structured exercises, developing an AI "card toolkit" to help novices in an interdisciplinary project (Zhou & Nah, 2024). Guo et al. (2023) performed an observational workshop with designers and AI and identified distinct modes of human-AI interaction (Guo, 2023), yet their focus was on designers' personal agency, not on team-wide outcomes. On the quantitative side, Rahman et al. (2025) randomly assigned students to AI-assisted or control groups on a creativity task and found that AI assistance significantly increased creative output (fluency, flexibility, originality). However, that study also uncovered issues like "fixation" on AI ideas and AI being seen as a dominant leader. These results hint at both benefits and challenges of AI in creative work, but they do not tell us how a genuine design team (with multiple professionals from different fields) would integrate an AI partner over a full design process.

In summary, despite growing attention to AI and creativity, there is a clear gap between general insights and the specific scenario of interdisciplinary design thinking teams. Prior work has identified AI's potential (e.g. speeding up prototyping (Yin et al., 2023), generating novel ideas (Sreenivasan & Suresh, 2024)) and has begun to classify abstract AI roles (Siemon, 2022). It has also documented human attitudes (e.g. distrust or role ambiguity) (Rahman et al., 2025). Yet none of this prior research explicitly treats AI as a quasi-team-member in the structured, iterative environment of design thinking. There is little empirical evidence on how AI alters team processes such as empathizing with users, defining problems, ideating solutions, and prototyping. Crucially, there is no comprehensive account of which roles or functions an AI can fulfill within a design team and how these roles affect collaboration. These conceptual and empirical gaps in AI-as-collaborator theory, in understanding team dynamics, and in real-world observations motivate the current study. In particular, they lead us to ask how AI can be meaningfully embedded in design teams.

2.6.2 Scope and Contributions of the Current Research

The present research directly addresses the central question: *"How can AI be integrated into interdisciplinary design thinking teams as a quasi-'team member,' and what roles or functions can it perform within the team?"* Specifically, the study focuses on understanding the concrete dynamics and outcomes of human-AI collaboration within the structured setting of a real-world design challenge: the European Prompt-a-Thon on AI and the Future of Higher Education, held at Luiss Guido Carli University from May 13-16, 2025. In other words, the workshop investigates AI not as a mere tool, but as an active participant in the design process of cross-functional teams. This Prompt-a-Thon brought together multidisciplinary student teams and researchers to co-develop innovative solutions using both design thinking and AI tools, particularly ChatGPT. Teams were explicitly encouraged to integrate AI as an active team member in ideation, problem framing, and prototyping activities. Structured over four days, the program included hands-on AI prompting training, iterative design challenges, and final pitching presentations

This study's contributions are both conceptual and empirical. To do so, it builds on existing human-AI teaming theories but it adapts them to the creative domain. For example, the workshop will examine whether the "creator" role corresponds to generating ideas during design ideation, or whether new roles like "inspiration catalyst", "visual communicator", or "domain integrator" emerge in practice. The outcomes will also draw on findings such as Yin et al. (2023), who showed that AI-enabled visualization can bridge disciplinary communication gaps. Thus at the workshop (Prompt-a-Thon by ENGAGE.EU) will articulate specific functions (e.g. idea generator, synthesizer, evaluator, communicator) that an AI might perform in a design team, and link these functions to stages of the design process. This framework will clarify how AI-as-teammate differs from a mere software tool, highlighting attributes like proactiveness, adaptability, and the ability to 'explain' or 'negotiate' with humans, which prior literature has only implicitly mentioned (Schmutz et al., 2024).

Empirically, the workshop will enable research to test this framework through a mixed-methods design investigation. The research plans to use workshop Prompt-a-Thon by ENGAGE.EU as a dataset, in which small interdisciplinary teams tackle realistic design challenges while using AI systems as collaborators. During these sessions, the AI will be treated analogously to a team member: for example, team members may query the AI for ideas or feedback, and the AI's outputs (e.g. images, text) will be used in group discussions. The research will have surveys and interviews with participants that will capture participants' perceptions of the AI's role in interdisciplinary teams.

In designing this methodology, the research builds on precedents such as Yin et al. (2023) who used design workshops to study human-AI co-creation. However, unlike those studies, the research's focus is explicitly on the team dynamic, not just individual behavior. The research will include diverse expertise in each team, for example, incorporating students from various social science disciplines such as law, management, finance, political science, and the intersection between management and digital technologies, fostering interdisciplinary collaboration. By combining qualitative and quantitative evidence, the research aims to give a nuanced picture of AI's actual impact on team creativity and process.

The anticipated contributions of this research are two. First, it will propose and validate a taxonomy of AI-as-teammate roles tailored to design thinking. This will fill the conceptual gap left by general AI-role taxonomies, grounding them in the specific workflow of design, for example, identification of roles like "Facilitator" (guiding ideation sessions), "Idea Generator" (provoking novel concepts), "Translator" (visualizing or explaining ideas across disciplines), and "Advisor" (providing data-driven feedback) (Yin et al., 2023). Second, it will empirically demonstrate how these roles function in practice. If, for instance, Yin et al. observed improved communication via AI images, this research will analyze whether teams explicitly credit the AI for that effect and whether similar gains occur when addressing different types of design problems.

Finally, the workshop will have methodological implications. The choice to integrate an AI into a live team setting reflects theoretical commitment to studying team dynamics. This research will situate analysis in a human-AI interdisciplinary teaming framework and adapt it to creative teams. For instance, it will examine how an AI's suggestions enter the team's cognitive process, how the team shares and debates those suggestions, and what the final outcomes are in terms of solution quality and team satisfaction. This approach is informed by prior HAIC research (Schmutz et al., 2024) but is novel in focusing on a design process in an interdisciplinary team.

In summary, by explicitly positioning an AI system as a quasi team member in interdisciplinary design-thinking teams, this study bridges the gap between design research and human-AI collaboration theory. It restates the central research question

“How can AI be integrated into interdisciplinary design thinking teams as a quasi-‘team member’, and what roles or functions can it perform within the team?” and proceeds to address it through a carefully designed workshop (Prompt-a-Thon by ENGAGE.EU). The outcome will be a coherent rationale for analyzing AI’s integration in creative teams, along with concrete findings on how such integration shapes team roles, processes, and creative performance.

3. Methodology

A convergent mixed-methods design was employed to answer the research question, drawing on both quantitative and qualitative data. This approach was chosen because integrating multiple methods can yield a more comprehensive understanding of complex phenomena (Wasti et al., 2022). In practice, the post-event survey provided quantitative measures of participants’ perceptions, while semi-structured interviews elicited rich, contextual insights into team dynamics and AI integration. Combining these data with the content of team project reports allowed methodological triangulation of findings. Such triangulation using surveys, interviews, and written reports- is recognized as improving the validity and reliability of results by minimizing single-source bias (Valencia, 2022). In other words, employing at least two different data sources (qualitative and quantitative) to address the same question is expected to give a fuller, more credible picture than any single method alone (Wasti et al., 2022).

3.1 Case Study Context: The Workshop and Its Participants

The study is based on data from the 2025 ENGAGE.EU “Prompt-a-Thon” workshop on AI and higher education (Luiss University, May 2025). Although the researcher did not attend the event, the organizers made official datasets (survey results and team project reports) available. Follow-up interviews were conducted within one week after the event. Participants were researchers, master’s and doctoral students from ENGAGE.EU partner universities, selected for the workshop via a competitive process (motivational letters and CVs) to ensure diverse interdisciplinary representation. Ultimately, 26 students completed the post-event survey. From these, 9 individuals volunteered for semi-structured interviews. This sample is purposive rather than random. The competitive selection of workshop participants and the voluntary nature of follow-up interviews introduce limitations (e.g. higher motivation or technological affinity among participants) that must be acknowledged. Despite these constraints, the sample spans engineering, social sciences, and humanities, providing a broad range of perspectives on AI in team settings.

3.2 Data Collection

Survey. A structured questionnaire was distributed electronically to all 26 workshop participants immediately after the event. It was created by the researcher to align closely with the study's research objectives. The questions were structured to probe several key themes participants' background, how ChatGPT was used during their design process, perceived impacts on the team and the challenges of integrating AI as a "team member". Likert scales were used to assess levels of perceived usefulness, while open-ended prompts encouraged participants to reflect on specific team experiences and critical moments. The survey also included questions on ethical concerns and collaboration dynamics. Responses were collected anonymously to encourage honest and reflective input. A complete copy of the questionnaire, including all sections and items, is provided in Appendix A.

Interviews. 9 volunteers participated in follow-up semi-structured interviews, conducted remotely (video calls) within one week after the workshop. An interview guide covered topics such as: how the team used AI tools, roles assumed by AI, challenges encountered, and effects on team interaction. Open-ended questions allowed participants to elaborate their experiences in their own words. Interviews lasted 25-30 minutes, were audio-recorded with consent, and transcribed verbatim. Participants were assured of confidentiality, and identifying information was removed from transcripts. This qualitative data supplements the survey by providing detailed accounts of how AI functioned in practice.

Project Reports. Each team submitted a final project report (documenting their group's AI-driven proposal) to the workshop organizers. Copies of these de-identified reports were provided to the researcher. While the researcher had no direct role in the projects, analysis of these artifacts served as a third data source for triangulation. The reports contained narratives of the team's design process, AI applications used, and final outcomes. By comparing themes from interviews and surveys with the content of the reports, the research could cross-validate interpretations. In line with methodological guidance, triangulating across these sources helped to minimize bias and enhance validity (Valencia, 2022).

3.3 Data Analysis

Quantitative Analysis. Survey data (n=26) were coded numerically and analyzed with descriptive statistics (means, frequencies, and cross-tabulations). The researcher summarized overall trends in perceived AI usefulness and integration difficulty, and explored differences across participant subgroups by cross-tabulating background variables with survey items. Given the modest sample size, no complex inferential tests were performed. The goal was to characterize general patterns rather than test hypotheses.

Qualitative Thematic Analysis. Interview transcripts and relevant excerpts from project reports were subjected to thematic analysis following Braun and Clarke's reflexive approach (Byrne, 2021). Coding was done inductively, meaning that categories emerged from the data rather than being imposed a priori. The analysis procedure included: immersing in the data (reading and re-reading transcripts), generating initial codes for notable features, collating codes into potential themes, reviewing themes against the raw data, defining and naming final thematic categories and interpreting these themes in relation to the research question. For example, if multiple participants described the AI tool as suggesting ideas or prompts, codes from those segments were grouped under a theme such as "AI as idea generator". Themes were refined through iterative review to ensure coherence and credibility. Immersion in transcripts (familiarization)

- Generation of initial inductive codes
- Collation of codes into candidate themes
- Review and refinement of theme categories
- Definition of final themes (e.g. "AI as collaborator", "AI as critic")
- Interpretation of themes in light of the research question

Each step ensured that themes accurately reflected participants' perspectives. Throughout analysis, memoing and peer debriefing were used to enhance reflexivity and to guard against premature conclusions.

Triangulation and Integration. Qualitative and quantitative findings were then integrated to build a coherent picture of AI's role in teams. The survey results provided a backdrop for interpreting the qualitative themes (for example, teams with more mixed perceptions of AI in the survey tended to describe more nuanced experiences in interviews). The final project reports offered concrete examples that illustrated or sometimes complicated the interview-based themes. By comparing data from all sources, the researcher followed a methodological triangulation strategy (Valencia, 2022). As Valencia (2022) observes, using multiple sources "improves validity and reliability" by checking for consistency across methods. In this way, convergence of evidence (e.g. both surveys and interviews highlighting "AI as idea generator") strengthened confidence in the findings, while any discrepancies were carefully examined to capture the full complexity of the case.

4. Results

This chapter presents the findings from the European Prompt-a-Thon workshop, integrating qualitative data from nine in-depth participant interviews and survey responses from 26 workshop participants. The aim is to provide a thematically structured synthesis of how AI impacted interdisciplinary team collaboration, ideation, and workflow dynamics during a design thinking sprint. The triangulated findings are organized by themes relevant to the research question and emergent sub-questions raised in literature review. Quantitative summaries (percentages, counts) are supplemented by illustrative quotes from participants.

Teams reported using AI extensively across design-thinking phases. All 26 teams used AI for data analysis/summarization (empathy/research phase), and most also used it for problem structuring (define), persona creation, and ideation (each ~80-85% of teams) (Table 1). A majority (≈70%) treated AI at least to a moderate degree as a "team member" (rated 4-5 on a 1-5 scale) rather than a mere tool (Table 1). Many noted that AI participated in brainstorming and prototyping by generating or combining ideas, summarizing research, and even drafting project documents. For example, one respondent explained, *“we did brain dumping and used AI to summarize, add and critique our ideas”,* indicating that AI contributed iteratively during ideation. Teams typically decided to use AI “on demand”, often when stuck or pressed for time (“*when we needed to be more efficient*”, one participant said) or to check assumptions. Few prescribed strict rules: one team noted *“no particular moment”* dictated AI use, while another observed *“we decided together to use AI when feeling stuck and needed to speed up the process”*. Thematically, three dimensions emerged:

Efficiency enhancer: Participants described AI as a tool that improved speed and reduced cognitive workload. P1 noted that AI helped *"go quicker, faster, and to cover more comprehensive aspects of the problem"*.

Cognitive scaffold: Several participants (P4, P7, P9) indicated that AI supported their thinking by synthesizing complex ideas or refining ambiguous team discussions into concrete outputs. For example, P9 stated, *"AI helped us find this common space between four different opinions"*.

Confidence amplifier: Teams leveraged AI to validate or challenge their ideas. As P4 recalled, *"We were unsure about a matchmaking feature until we ran it through GPT and it made us feel more confident"*.

However, a minority of participants expressed ambivalence. As P2 remarked, *"I'm not convinced it helped us work better just faster"*.

AI Usage (design phase/task)	**Participants (N=26)**
Analyze or summarize user research/data (Empathize/Define)	22
Reframe/structure the problem statement	21
Create or improve user personas	20
Generate ideas during brainstorming	20
Create or improve project documents (pitch decks, notes)	20
Search for inspiration or references	12
Decision support (pros/cons, comparisons)	8

Table 1. AI use-cases in design process (number of participants)

Participants conceptualized AI in multiple roles throughout the workshop. From the transcripts and survey open-ended questions, three dominant metaphors emerged:

- Facilitator: AI was described as helping drive group progress, particularly during brainstorming. For instance, P3 shared, *"It inspired prompts that broadened our perspective"*.
- Researcher: Many teams treated AI as an information aggregator, tasked with synthesizing web-scale data or framing stakeholder perspectives. P6 described using AI to *"frame interviews, summarize external insights, and evaluate stakeholder alignment"*.
- Assistant: In this most frequent role, AI acted as a supportive utility summarizing, formatting, generating drafts. P5 likened it to *"a slave for hard work"* and P8 highlighted how it *"validated our insights in real time"*.

Survey results reflect this distribution: 58% saw AI primarily as an assistant, 31% as a facilitator, and only 11% as a full team member.

Importantly, no participant described AI as having true autonomy or independent agency. Rather, AI's perceived identity was contingent upon human prompting, as P9 emphasized: *"It doesn't have a voice unless you give it one"*.

A consistent finding across all data sources is that AI enabled faster ideation cycles. Teams who used AI early in the process (P6, P7, P8) reported quicker convergence on problem definitions and higher confidence in chosen directions. As seen in Figure 4 below, 81% of survey respondents agreed that AI improved iteration speed.

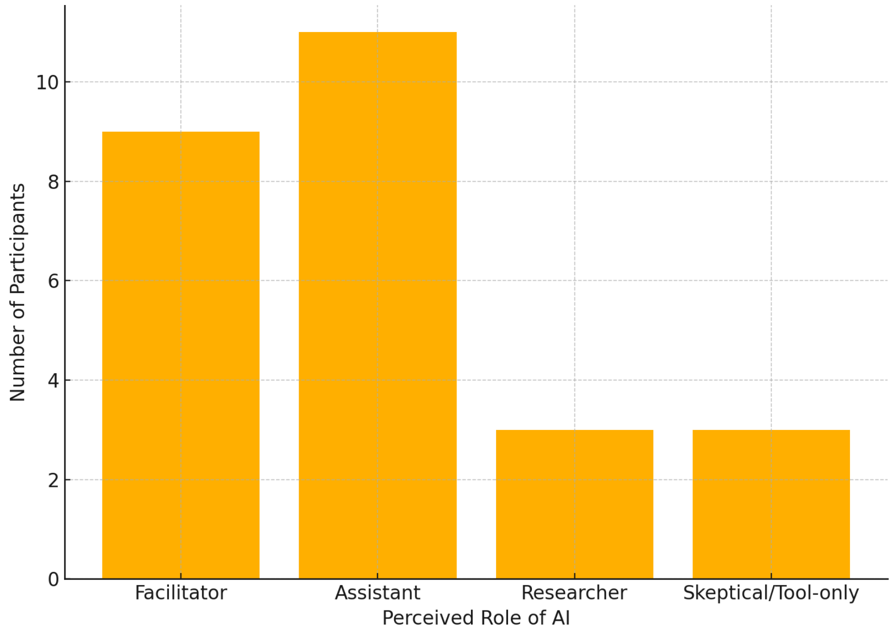

Figure 4: Participant Agreement with the Statement "AI helped us work more efficiently"

Teams used AI for:

- Iterative brainstorming (P3, P5, P7)
- Prototyping textual elements (P6, P9)
- Summarizing user interviews (P6)

Notably, speed did not always equal clarity. Several participants (P2, P4) noted that rapid generation of alternatives sometimes led to decision fatigue or diffusion of focus.

AI's influence on team dynamics was ambivalent. In several teams, especially those with high prompting transparency (P4, P6, P9), AI served as a collaborative agent that mediated consensus and encouraged inclusive discussion. As P6 explained, *"It helped us find a shared language despite our disciplinary differences".*

Conversely, in teams where AI was used unilaterally (P1), participants experienced detachment and disconnection. P1 recalled: *"One teammate would silently write prompts while the rest of us waited. It really disrupted our flow".*

Themes around AI's asynchronicity and opacity surfaced frequently. P2 and P7 both highlighted that since AI was not always present in live conversation, it couldn't participate naturally, limiting its potential to feel integrated.

These mixed results were reflected in the survey, where 38% agreed that AI improved team communication, 35% were neutral, and 27% disagreed.

Several teams reported enhanced creative breadth through AI. P3 credited the *"More-than-Human Stakeholder"* prompt with opening conceptual doors they *"would never have imagined without GPT"*. P5 described how AI-generated categories helped make sense of 100+ raw ideas. Figure 5 shows 69% of survey respondents agreed AI sparked more creative ideas.

However, the outputs were not always useful. P2 critiqued AI for offering *"crazy or lame ideas"* and described the outputs as lacking genuine innovation. Furthermore, concerns over algorithmic bias emerged. P7 observed that AI categorized ideas based on *"patterns it recognized"* raising questions about representational fairness and originality.

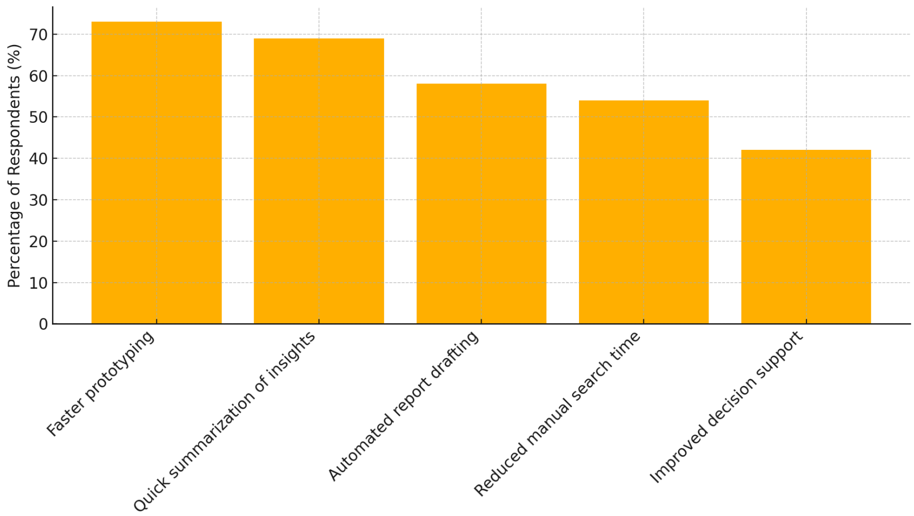

Figure 5: "AI helped us be more creative than we would have been without it"

Productivity gains were clear: most participants cited AI's utility in automating low-level tasks. P6 highlighted time savings in formatting reports; P8 noted that they accomplished in one hour what previously took five days.

Yet, several participants (P1, P4, P7) worried that these efficiencies came at the expense of human-centeredness. As P7 put it, *"GPT was fast and logical, but lacked the sense of emotional realism we needed"*.

AI's impersonal nature sometimes disrupted empathy-driven decisions, especially in user-centered design. P9 noted that AI often failed to reflect complex social nuances or ethical considerations, despite its rational outputs.

The data suggests a nuanced but overall positive role of AI in interdisciplinary design thinking contexts. Participants valued AI primarily as a productivity enhancer and ideation partner. Its perceived utility was highest in areas requiring synthesis, summarization, and rapid iteration.

However, the absence of emotional intuition and the difficulty of seamless integration into team workflows limited its potential to act as a full-fledged collaborator. Trust and usability were shaped not only by AI's outputs, but also by prompting strategy, user experience design, and team communication norms.

In short:

- AI augmented, but did not replace, human creativity and coordination.
- Its role was socially constructed and often fluctuated based on task demands.
- Teams benefited most when AI was embedded transparently and intentionally into their workflow.

These findings set the stage for the upcoming discussion chapter, which will interpret these empirical insights in light of broader literature on sociotechnical systems, collaboration theory, and human-AI interaction design.

5. Discussion

This chapter interprets the empirical findings presented in Chapter 4 within the context of the broader academic literature on design thinking, AI integration, and interdisciplinary collaboration. The discussion revisits the research questions, engages with theoretical frameworks, and explores implications for both scholarship and practice. In doing so, it emphasizes how the European Prompt-a-Thon case extends current understandings of human-AI collaboration in interdisciplinary settings.

The central research question of this thesis is: *How can AI be integrated into interdisciplinary design thinking teams as a quasi-"team member", and what roles or functions can it perform within the team?* The findings demonstrate that AI functioned as a valuable yet ambivalent partner, capable of enhancing certain cognitive and logistical aspects of teamwork (e.g., idea refinement, synthesis, information retrieval), while falling short in areas requiring contextual sensitivity, emotional intelligence, and spontaneous intersubjectivity. As discussed in results, participants appreciated AI's speed and consistency in generating structured information. However, the perception of AI as a "team member" varied widely, with many participants stressing that AI remained a tool unless guided interactively and intentionally. This supports prior research suggesting that the effectiveness of AI in collaborative settings depends on the degree of human initiative and framing (Seeber et al., 2020). Participants described AI as useful for tasks like summarizing, prompting brainstorming, and offering alternative viewpoints. Nevertheless, many teams exercised selective adoption, filtering AI outputs through their own intuition and disciplinary judgment.

Domain	Strengths	Limitations
Ideation	Volume, variety, speed	Novelty plateau, lack of disruptive ideas
Problem Framing	Perspective expansion	Surface-level interpretations
Communication	Summarization, structure	Lack of empathy, passive turn-taking
Decision-Making	Information aggregation	Absence of contextual judgment
Creativity	Prompting alternative paths	Inability to synthesize across domains

Table 2: Summary of AI Contributions and Limits in Collaborative Design Thinking

The observed human-AI collaboration aligns with several core tenets of design thinking theory, particularly the iterative nature of ideation and prototyping. AI enabled teams to quickly iterate on divergent ideas, and in some cases, accelerated convergence by surfacing patterns. Yet the design process retained its human-centered focus; empathy mapping and value-driven framing still required interpersonal deliberation, as seen in participant reflections (P3, P6).

AI tools in this study did not merely execute commands; they mediated interactions between human teammates, surfaced latent knowledge, and shaped team pacing and communication flow. As such, AI can be conceptualized as a mediating actor within sociotechnical systems rather than a passive instrument. Participants reported that AI influenced who spoke when, who took initiative, and how teams distributed cognitive labor (P2, P5, P9). For instance, when a team member silently engaged with AI for extended periods, it created disruptions in conversational flow and required re-synchronization (P1). In other cases, AI helped resolve disagreements by offering "neutral" synthesis that multiple perspectives could align with (P4, P7). This confirms calls for revisiting traditional human-centric models of teamwork in light of digital augmentation. AI's role is best understood not as an assistant or replacement, but as an agent of redistribution: redistributing attention, authority, and cognitive effort.

The Prompt-a-Thon provides a valuable case for understanding the complexities of interdisciplinary collaboration in AI-augmented settings. Disciplines vary not only in vocabulary but in epistemological assumptions, problem-solving styles, and risk appetites. AI's presence served both to bridge and sometimes exacerbate these gaps. Participants from technically oriented backgrounds (P3, P6, P8) viewed AI as an efficient partner, whereas those from social sciences (P1, P4) were more reflective, highlighting ethical and epistemological concerns. This heterogeneity reinforces the need for adaptive strategies in AI-mediated interdisciplinary teams. The findings extend recent models of interdisciplinary learning ecosystems, where cognitive diversity can become a strength when mediated by enabling technologies. AI served as a shared frame of reference, but only when teams took time to calibrate their expectations and engage critically with its outputs.

Based on empirical insights, the following best practices are recommended for future AI-enabled design sprints and collaborative workshops:

- Set expectations early: Teams benefit from explicit discussion of AI's role (P7, P9), including capabilities, boundaries, and potential misuses.
- Encourage co-prompting: Involving the whole team in crafting prompts promotes shared understanding and more accurate AI outputs (P4).

- Balance AI-driven and human-centered modes: Ensure time is allocated for non-AI ideation, empathy building, and storytelling.
- Integrate AI seamlessly into documentation: Tools like shared dashboards and collaborative prompts (as used in P5's Google Docs workflow) help bridge asynchronous and synchronous inputs.

6. Conclusions

This thesis set out to explore a central research question: *How can AI be integrated into interdisciplinary design thinking teams as a quasi-team member, and what roles or functions can it perform within the team?* Through the lens of a real-world case study the Prompt-a-Thon on AI and the Future of Higher Education. This research has shown that AI, specifically a generative language model (ChatGPT), can move beyond its traditional role as a tool and contribute meaningfully to creative team collaboration.

Chapter 1 introduced the relevance of this topic in both academic and practical contexts, highlighting the emerging interest in teams that combine human and AI capabilities in innovation settings. It identified a gap in understanding how AI can be deliberately and ethically embedded into team-based design processes. Chapter 2 situated the study within existing literature on human-AI teaming, interdisciplinary collaboration, and design thinking, identifying both conceptual opportunities and practical tensions in treating AI as a team member. Chapter 3 outlined the qualitative case study methodology, including data collection through interviews and surveys with student participants in the Prompt-a-Thon. The real-world setting provided valuable insights into how AI is used, perceived, and integrated by diverse teams engaged in design thinking.

Chapter 4 presented empirical findings that illustrate AI's multifaceted contributions to teamwork: as an ideation partner, a communication bridge across disciplines, and a support tool that helped quieter team members express ideas more confidently. These insights align with the concept of AI as a collaborative agent within sociotechnical systems. However, participants also reported limitations, including concerns about AI-generated content being generic or misaligned with context, potential distractions from interpersonal dialogue, and ethical risks such as overreliance and bias. Chapter 5 discussed these findings in relation to broader theoretical frameworks and practical implications, offering guidance on how to responsibly structure human-AI collaboration in creative teams.

In answering the research question, the study demonstrates that AI can perform valuable roles in interdisciplinary design teams such as idea generation, synthesis, and feedback when integrated with intention and supported by facilitation. However, its effectiveness depends on clear role definition, team training in prompt use and critical reflection, and the creation of ethical norms around AI participation. Rather than replacing human creativity, AI has the potential to augment it provided that human agency, judgment, and values remain central.

This thesis contributes to the growing scholarship on AI-human collaboration by providing empirical evidence from a naturalistic educational setting and proposing a framework for incorporating AI into design thinking. As teams increasingly evolve into hybrid collectives, the study calls for rethinking collaboration dynamics, authorship, and leadership models in ways that preserve the integrity of human-centered innovation.

6.1 Limitations of the Study

While this research provides novel insights into the perceived roles and collaborative potential of AI in interdisciplinary design thinking teams, its conclusions must be interpreted within the boundaries of its methodological and contextual limitations.

The study was conducted in the context of the European Prompt-a-Thon, a structured, time-bound, and mentor-guided workshop. This environment enabled intensive observation of AI-facilitated collaboration under artificially accelerated conditions. However, this also created a constrained ecological setting where participants were not operating under typical workplace or academic pressures. As such, while the design sprint environment encouraged creativity and innovation, it may not have captured the full complexity or realism of longer-term collaborative dynamics with AI (Participant 4).

Furthermore, the workshop format included pre-defined stages of team formation, ideation, prototyping, and final presentations, all of which may have subtly influenced participants to use AI in certain predictable ways. Mentorship guidance and instructional framing also shaped team attitudes and behaviors, leading several participants to adopt an experimental mindset rather than an organically emergent one. Thus, findings such as the framing of AI as a “team member” might partly reflect the workshop's narrative rather than a natural conceptual evolution.

Moreover, the dominant use of generative AI tools (primarily ChatGPT) in a prototyping context makes it challenging to extend conclusions to more domain-specific AI (e.g., predictive algorithms in finance, diagnostic systems in medicine, or embedded AI in manufacturing). Participant 9 emphasized the lack of technical depth in the tools used, noting that collaboration with AI relied heavily on general language processing rather than advanced sector-specific functionalities.

6.2 Directions for Future Research

Building upon the current findings, several important avenues for future investigation can be identified to deepen our understanding of AI's collaborative role in team-based innovation environments. A key limitation of this study was its cross-sectional nature, capturing only a snapshot of AI-human collaboration during a short design sprint. Future research should investigate how AI influences team behavior, learning, and performance over longer durations. Longitudinal designs would enable scholars to observe how trust, dependency, and critical thinking evolve over time as teams repeatedly engage with AI systems. For instance, some participants (e.g., Participants 2 and 5) initially rejected AI-generated suggestions, only to later revise their stance as they grew more familiar with the tool's logic and capabilities. Studying such adaptive learning cycles over time could inform theories on co-evolution in human-AI teams and the conditions that lead to productive integration versus dependency or overreliance. The longitudinal studies could explore the trajectory of leadership distribution within hybrid teams. Does the perceived role of AI stabilize or fluctuate across iterative projects? Does it begin to shape planning and strategy beyond execution? These questions remain open. Ethical concerns emerged subtly but meaningfully in the interviews. Participant 8 reflected on the risk of teams using AI without accountability or transparency, while Participant 6 warned against blind trust in AI outputs. These concerns point to a growing need for well-defined ethical guidelines, especially as AI systems become more autonomous and integrated into decision-making.

Future studies should explore the development and application of ethical frameworks that define acceptable boundaries for AI participation in team dynamics. These may include issues such as data provenance, consent in AI-assisted ideation, transparency of AI-driven contributions, and attribution in co-authored work. The absence of governance structures in AI-mediated collaboration may undermine trust, equity, and intellectual integrity. Moreover, future research should investigate how different disciplines interpret and operationalize ethics in AI teamwork. For example, design teams may prioritize creative authorship and originality, while engineering teams may emphasize traceability and accountability. Comparative studies across domains can thus help tailor ethical guidelines to context-specific norms and values.

In summary, the European Prompt-a-Thon workshop provided a valuable foundation for examining the early-stage integration of AI in interdisciplinary teamwork. However, to fully realize the potential of AI as a constructive partner in team-based innovation, future studies must extend both temporally and normatively probing how AI collaboration matures over time and how ethical, responsible practices are embedded into collaborative routines.

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Appendix A: Survey Questionnaire

This appendix contains the entire post-workshop survey developed by the researcher to evaluate participants' experiences of integrating AI into interdisciplinary design thinking teams.

Section 1: Background Information

1. What is your academic background or primary field of study? *(Open-ended)*
2. How frequently have you used AI tools (e.g., ChatGPT, Midjourney) before this workshop? *Linear scale: 1 (Never) to 5 (Very frequently)*

Section 2: Integration of AI into the Team

3. How was AI (e.g., ChatGPT) used during your team's design process? *(Select all that apply)*

☐ *To analyze or summarize user research/data*

☐ *To create or improve user personas*

☐ *To structure or reframe the problem statement*

☐ *To generate ideas during brainstorming*

☐ *To challenge ideas (e.g., playing devil's advocate or offering alternative viewpoints)*

☐ *To search for inspiration, trends, or references*

☐ *To help with decision-making (e.g., pros/cons, comparisons)*

☐ *To prototype solutions (e.g., generating content, interface suggestions, mockups)*

☐ *To write or edit project documents, such as pitch decks or team notes*

☐ *We did not use AI during the project*

☐ *Other (please specify):* __________

4. To what extent did your team treat AI as a "team member" rather than a tool? *Linear scale: 1 (Pure tool) to 5 (Fully integrated team member)*
5. Who in your team mostly interacted with the AI tool(s)? *(Open-ended)*
6. Describe in a few sentences how your team decided when and how to use AI. *(Open-ended)*

7. Can you describe a specific moment where AI changed the way your team thought about a problem or a solution? *(Open-ended)*

Section 3: Collaboration and Outcomes

8. Did the use of AI affect how your team collaborated? *Likert scale: 1 (Not at all) to 5 (Very significantly)*

9. To what extent do you think AI improved the quality of your team's final solution or prototype? *Linear scale: 1 (Strongly worsened it) to 5 (Strongly improved it)*

10. To what extent do you agree with the statement: "AI helped us generate more innovative ideas than we would have without it". *Likert scale: 1 (Strongly disagree) to 5 (Strongly agree)*

Section 4: Challenges and Enablers

11. What challenges did your team face while using AI in your design thinking process? *(Select all that apply)*

☐ *Lack of technical skills or experience with AI prompting*

☐ *Confusing or irrelevant AI outputs*

☐ *Difficulty interpreting or applying AI suggestions*

☐ *Over-reliance on or uncritical trust in AI*

☐ *Lack of originality or depth in AI content*

☐ *Ethical concerns (e.g., bias, fairness)*

☐ *Disagreements on AI usage*

☐ *AI lacked contextual understanding*

☐ *Time pressure limited AI integration*

☐ *No significant challenges*

☐ *Other (please specify):* ___________

12. What factors helped your team use AI successfully? *(Select all that apply)*

☐ *Preliminary training or onboarding at the start of the program*

☐ *Having an AI-savvy team member who guided the process*

☐ *Clear internal agreements or rules on when and how to use AI*

☐ *Mentor or facilitator support during the design process*

☐ *Iterative experimentation with prompts and AI outputs*

☐ *Using AI to complement team strengths (e.g., writing, analysis, ideation)*

☐ *Open communication and shared reflection on AI use*

☐ *Trust in the AI tool's usefulness, based on previous experience*

☐ *We did not find any specific practice helpful*

☐ *Other (please specify):* __________

13. Did the presence of AI affect team trust, communication, or roles? If yes, how? *(Open-ended)*

14. Would you use AI again in a similar teamwork or innovation setting? Why or why not? *(Open-ended)*

Section 5: Final Reflections

15. What is one insight or takeaway you gained about working with AI in interdisciplinary teams? *(Open-ended)*

16. Is there any specific aspect related to the use of AI in this collaboration experience that you think hasn't been mentioned yet but is particularly important? *(Open-ended)*

17. Would you be open to participating in a follow-up interview regarding your experience with AI in this Prompt-a-Thon? If yes, please provide an email address where you can be contacted. *(Open-ended)*

Appendix B: Interview Questions

This appendix contains the entire interview questions developed by the researcher to explore participants' in-depth experiences, reflections, and narratives about collaborating with AI during the Prompt-a-Thon.

Section 1: Introductory Context (Warm-Up)

1. Could you briefly describe your background and your role during the Prompt-a-Thon? *Aim: Establish their disciplinary lens and how they contributed to the team.*

2. What was your previous experience (if any) with AI tools before this event? *Aim: Understand how their expectations were shaped before entering the challenge.*

Section 2: Exploring AI Integration in Practice

3. When in the design process did your team choose to involve AI, and how did that decision happen? *Aim: Investigate the team's reasoning and decision-making strategy around AI use.*

4. Did the AI contribute actively to shaping your team's direction or ideas? If so, how? *Aim: Explore AI's influence on design evolution, not just task output.*

5. Can you describe a specific moment where AI changed the way your team thought about a problem or a solution? *Aim: Collect rich, illustrative cases for the thesis discussion.*

Section 3: Collaboration and Team Dynamics

6. How would you describe the team's interaction style, did the inclusion of AI change how you communicated or made decisions? *Aim: Examine effects on participation, listening, turn-taking, and authority.*

7. Were there any moments where you felt the AI acted like a true "team member"? What made it feel that way or not?

8. In terms of creativity and outcomes, do you feel AI helped your team do something you could not have done otherwise? *Aim: Explore added value or stretch in ideation and solution-building.*

Section 4: Emotional, Cognitive, and Ethical Reflections

9. How did it feel to work with an AI during an intense, creative challenge like this? *Aim: Capture emotions like frustration, relief, confusion, or confidence.*

10. Did you or your team struggle with when to follow AI's suggestions versus your own intuition? Can you give an example? *Aim: Explore tensions between machine and human judgment.*

11. Were there any ethical or reflective conversations in your team about the role of AI in shaping your solution?

Section 5: Looking Ahead

12. Based on your experience, how would you change the way teams use AI in future design sprints or academic settings? *Aim: Gather suggestions that can shape practical recommendations.*

13. What advice would you give to future students or teams about integrating AI into teamwork? *Aim: Elicit participant wisdom and forward-looking reflections.*