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HUMAN-AI COLLABORATION AMONG ENGINEERING AND DESIGN PROFESSIONALS: THREE STRATEGIES OF GENERATIVE AI USE

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ABSTRACT

Designers are increasingly using Generative Artificial Intelligence (GenAI) in design processes; however, knowing how designers use GenAI–especially in professional design practice–is under-explored. This paper presents an ethnographic study of an early-stage design team at NASA that explores the natural variation of GenAI use across team members during a speculative design workflow. We aimed to uncover when, how, and why GenAI tools were or were not employed using ethnographic observations to map the team's speculative design process and follow-up interviews to provide deeper insights into team members' interactions (or lackthereof) with GenAI. Through inductive qualitative coding, our analysis revealed three strategies of GenAI use observed among professional engineers and designers–intimate co-design with GenAI, selective delegation to GenAI, and minimal use of GenAI–as well as factors that appeared to influence their decisions whether or not to use GenAI. This study proposes new theory in human-AI collaboration that sheds light on the strategies, rationale, and circumstances under which design professionals do and do not use GenAI. These strategies and factors tied to GenAI use offer insights into when, how, and why professionals use GenAI in design and how GenAI could be built to better accommodate designers.

1 Introduction

As generative AI (GenAI) tools, such as large language models (LLMs), spread across industries, their integration into the design process is also expected to grow, raising questions regarding the influence of AI on both the designer and the resultant design outcomes. Numerous studies have explored this topic, focusing on the impact of AI on various factors, such as designers' trust and confidence in AI to support them in a variety of design tasks [1–6]. However, many of these studies are done in the context of specific design tasks within controlled environments that lack real-world context and application. Notably, there is a scarcity of research on how design teams in real-world settings employ AI to tackle complex, real-world challenges.

In this paper, we follow a design team at the National Aeronautics and Space Administration (NASA) who was engaged in

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addressing the wicked problem of envisioning the future of environmentally sustainable airports. The team used a speculative design (a.k.a. strategic foresight and scenario building) workflow. Over a six-week period, the team aimed to develop multiple scenarios of net-zero carbon hub-scale airports in the year 2075. These would be used in subsequent work to "backcast" and identify near-term actionable R&D projects that build towards the envisioned futures. Their speculative design process encompassed several stages: alignment, stakeholder research, benchmarking, problem statement definition, subject matter expert inputs, concept generation, user persona and journey creation, and the synthesis of all this information into envisioned future scenarios of sustainable airports in 2075. During this process, the designers were encouraged to utilize GenAI tools, such as Microsoft CoPilot, to aid in completing specific design tasks and activities.

Our research primarily aimed to explore the human-AI interaction within this context, focusing on the impact of GenAI on the designers' work. As our inductive analysis process progressed, strategies of GenAI use and factors influencing its use emerged which led us to more specific research questions (RQs):

RQ1: When did individual professional design team members use GenAI for support during a speculative futures design process?
RQ2: How did design team members use GenAI in their design process?
RQ3: What factors appear to explain variation in team members' use of GenAI?

To address these questions, we conducted ethnographic observations of team meetings and wrote fields notes during the NASA team's speculative design workflow, identifying varying levels of convergent and divergent thinking at each stage. We visualized this in a journey map, highlighting activities and tasks assigned to individual designers and their use or non-use of GenAI for each task. Through a survey, we found that team members spanned the spectrum from low/medium to very high AI literacy. We conducted follow-up interviews to enrich our observations and inductively coded these qualitative data. Our analysis revealed three key strategies of GenAI use observed among design professionals: *intimate co-design* with GenAI, *selective delegation* to GenAI, and *minimal use* of GenAI. We also found a preliminary set of factors that appeared to influence designers' decisions to use GenAI. These were categorized into negative factors – such as lack of GenAI familiarity or workflows, perceived poor quality of GenAI responses, and perceived unintended consequences of GenAI use – and positive factors – such as familiarity with GenAI or GenAI-adjacent technologies, perceived increase in productivity, and ability to discern strengths and weaknesses of GenAI. Our findings propose new theory on the strategies, rationale, and circumstances under which professional designers use GenAI, thus providing insight into the nuanced role of GenAI in the design process.

2 Background

2.1 Speculative Design Process

Speculative design is a methodology within the design field that diverges from traditional product-oriented design methodologies that are predominantly aimed at addressing current issues and fulfilling immediate needs [7, 8]. Speculative design is future-oriented and involves crafting speculative scenarios and artifacts that serve to ignite critical dialogue around the potential impacts that design challenges and potential solutions may have decades into the future [7]. However, since engineering design tends to be oriented around present-oriented needs and problems, one might ask the question: is it not more important to design with the near-future in mind so we can tackle the real-world challenges facing humanity today? It is essential to recognize that designed artifacts are not merely technical entities but also possess political, societal, and economical dimensions that are embedded with specific forms of power and authorities [9]. Therefore, speculative design extends the horizon of design thinking into the future in order to foster critical dialogue and reflection on the ethical and societal consequences that future design decisions may entail [7].

In addition, the utility of speculative design also extends beyond theoretical discourse and has been practically applied to the realm of engineering design as well. It has been demonstrated to facilitate design ideation by offering a novel perspective during the early stages of the design process [10], and it has also been used as a means of framing the initial problem for highly complex design problems [11]. Speculative design–and the related approaches of strategic foresight and scenario building–are being used in a variety of industries and organizations, ranging from Shell to Ford to growBot Garden [12–14]. Although terminologically distinct, strategic foresight shares the core objective of speculative design: to craft plausible, coherent visions that inform stakeholders of the future, which may come in the form of crafting future scenarios [15, 16]. These visions and scenarios act as boundary objects, bridging diverse stakeholder perspectives to facilitate dialogue and debate [17–19]. In both strategic foresight and speculative design, resulting future scenarios are considered to be thought experiments aimed at aiding the framing and reframing of a design problem. This is particularly valuable in the context of wicked problems, where framing the problem is particularly challenging and crucial [20].

In our study, we observed a NASA design team engaged in a series of strategic foresight activities aimed at envisioning the future of net-zero carbon hub-scale airports in 2075 (see Section 3.2 for more information on the process). The team's efforts culminated in the development of scenarios that were intended to provoke discussion and reflection on the long-term future of sustainable aviation infrastructure and facilitate backcasting to identify an actionable R&D roadmap towards these futures. Ultimately, the primary objective of the team is to produce opportunity concept reports, which are to be presented to government

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officials and business executives responsible for the allocation of funding and resources. The challenge addressed by the NASA design team may be considered a wicked problem due to its complex, multifaceted, cross-sector nature with high degrees of societal, political, economical, and environmental considerations.

It is important to note that during the speculative design tasks, one of the team leaders frequently encouraged members of the team to utilize GenAI to support them in their individual tasks. The means by which they were to use it was not specified, and when they were supposed to use it was not enforced. Thus, our analysis aimed to uncover the timing, manner, and rationale behind when specific designers utilized GenAI tools throughout their speculative design workflow. By mapping the speculative design process, highlighting instances of GenAI use, and following up to understand how and why they were used, we sought to gain insights into the role of GenAI in helping designers work through speculative design tasks.

2.2 Using GenAI to Aid in the Design Process

GenAI has been recognized for its capability to produce text, images, and other forms of data through the use of pre-trained generative models. In particular, the recent advances in AI architectures, such as those of in the form of transformers, has led to powerful pre-trained LLMs and text-to-image models such as ChatGPT and DALL-E [21, 22]. This has naturally led to an increased use of these tools by designers, which has prompted questions on how and when designers are integrating these tools into their workflow. Previous studies have revealed that designers are quite capable of customizing GenAI tools for their specific needs, which leads to creative and unique ways of adapting the tools to support their design activities [3]. It has also been theorized that GenAI can help designers by enabling them to focus on higher-level decision-making because they will be able to delegate more routine tasks to the AI, leading the designer to serve as a manager of the generated results [23]. Moreover, GenAI has shown to be able to facilitate divergent thinking by generating a vast array of inspirational stimuli that can be leveraged by designers to support them during the early stages of the design process [24, 25]. In addition, GenAI has also been shown to be capable of supporting designers for convergent thinking by allowing the designers to explore the design space more broadly and guide them to making better decisions [4, 26]. Building upon this foundation, our research extends on previous work by examining when and how professional designers leverage GenAI to support them during the speculative design process. We aimed to identify the strategies and rationales that design professionals employed when integrating GenAI into their design process.

2.3 Factors that Impact AI Use in Design

Previous studies have indicated an association between a designer's confidence and their receptiveness to AI-generated suggestions, with the level of confidence in AI being closely related to its successful incorporation into a designer's workflow [6]. Moreover, there has been a divergence in findings from various research efforts, with one indicating that AI support might detract from team performance [5], while another posits that it could enhance team effectiveness and adaptability [4]. Additional research has also revealed that rigid AI systems may elevate stress levels among humans, which could negatively impact the utilization of AI in complex engineering tasks; however, despite this, individuals have demonstrated the capability to adapt to the limitations presented by an inflexible AI collaborator [1]. In addition, past research has shown some conflicting evidence that while team members regard the input from both AI and human managers as comparably valuable and pertinent [27], designers still tend to favor responses by humans over those from AI [2]. In summary, there exists a substantial body of research investigating a variety of factors that could influence the incorporation of AI into a designer's workflow. Our review of the prior work has shown that the designer's self-confidence, stress level, and perception of the AI tool are important factors that influence the designer's ability to integrate AI into their design workflow. In addition, we also noted from prior work by *Gyory et. al.* [1] that demonstrates these factors lead to designers to adapt to the AI tool differently, which leads to them developing new strategies to cope with the AI tool's limitation. Our paper aims to expand on this research by providing additional insights into these identified factors. Furthermore, we uncovered three emergent strategies that arise as the designers adapted to the different mechanisms of the GenAI tool they used.

3 Methods

3.1 Field Site: NASA Convergent Aeronautics Solutions

We followed a professional design team in the Convergent Aeronautics Solutions (CAS) project at NASA. CAS aims to accelerate the future of aviation by developing transformative solutions to complex sociotechnical challenges like accelerating electrified flight, enhancing wildfire fighting, enabling access to healthcare, and supporting rural community resilience. The team included participants from engineering, design, and other professional backgrounds working together on the goal of *"envisioning an ideal sustainable future airport 50 years from now, and then later backcasting the developments that would be needed to achieve this. Given the time frame of the sprint, these results are preliminary and meant to generally frame the problems and the questions involved in such an activity."* Microsoft Teams was used as a communication platform for working sessions three to five times per week over the course of 6 weeks. Mural was used as a collaboration platform for documentation in real-time and asynchronously throughout the design sprint. A brief demo of Microsoft Co-Pilot was provided by the team facilitator, although

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other GenAI tools were available to use at team members' discretion.

The following seven sections provide context for each phases of the NASA team's design sprint through the design facilitator's descriptions (see quotes at beginning of each section) and concise accounts of the design sprint activities pieced together from the research team's field notes. A journey map of the design sprint was constructed to illustrate these seven phases, activities engaged with at each step, and a determination for the kind of tasks (divergent, convergent, or a combination of the two) that the team engaged in for each activity along the journey (see Figure 1).

3.1.1 Phase 1: Kickoff and Alignment

"What are our first impression of airports today?"

Ultimately, this phase involved team members introductions and establishing team agreements. The team member introductions involved unpacking personal travel experiences and establishing team agreements, which involved curating, reviewing, and confirming a list of approximately 10 agreements to move forward with throughout this design sprint (see checkpoints #1 and #2 in Figure 1). This involved each team member creating a personal profile that communicated their general affinity for travel, gripes or likes about travel, airport experience, preference for urban vs rural environments, and technological use at home.

3.1.2 Phase 2: Stakeholder Research

"Airports are central to economies, communities, and often our lives. There are a large number of stakeholder with often diverging interests. In the future, the stakeholders may be very different. In later Sprints, we plan to look more into present and future stakeholders, but for now we worked for a basic understanding of some of the stakeholders involved."

Anchored by "Industry", "Society", and "Policy" as themes, the team was tasked with generating and mapping an exhaustive collection of stakeholders within airport contexts. Next, the team was instructed to sort through and refine the collection of stakeholders to identify subthemes and relationships. Finally, the team was tasked with generating a list of future uncertainties related to the operations of sustainable airports. Checkpoints #3, #4, and #5 in Figure 1 represent the tasks for this phase.

3.1.3 Phase 3: Benchmarking Research

"Ordering some of these stakeholders into groups we investigated their values. Their interests and concerns depended on the stakeholder and were often conflicting. . . Our objective was to try to understand some of the core questions impacting each group and understand technology drivers that may impact society in the coming decades."

During this phase, the team was tasked with scouring literature and other reliable sources to identify benchmarks for technologies and other operational features relevant to sustainable airports. Next, the benchmarks were to be sorted according to their respective time periods: past, present, and future. Checkpoints #6 and #7 in Figure 1 represent the tasks for this phase.

3.1.4 Phase 4: Research to Define Problem States

"To understand what might be the future state, we examined the past present, and what we thinking we know so far about the future. . . Before 2001, factors such as deregulation, changing technology and economics, and evolving societal views influenced air travel. . . . Today, there are a number of pain points in play. For the near future, much is already established by existing infrastructure, economics and increasing travel needs. However, we are on the cusp of major changes in air travel driven by, for example, new technology and climate change. A common theme is the poor regard the public has for airports. . . . 'We developed a list of top uncertainties for the future. One issue is that if we want to change how we travel, we will need more power.' Key question [problem statement] is, 'How will we acquire the level of power needed?' "

During this phase, the team was tasked with generating key factors related to the functioning of past airports and problem statements that represent significant challenges to address for current and future airports. Checkpoints #8 and #9 in Figure 1 represent the tasks for this phase.

3.1.5 Phase 5: Expert Feedback on Stakeholders

"We revisited Stakeholders and got input from Subject Matter Experts. We interviewed leaders who have designed airports. Our top findings include: define values, communicate across teams, and leverage new tools."

During this phase, the team was to engage in conversations with subject matter experts (SMEs) related to airplanes and airport operations. Later, discussion facilitated the synthesis of knowledge gained from SME conversations, which also informed the refining of problem statements crafted earlier. Checkpoints #10 and #11 in Figure 1 represent the tasks for this phase.

3.1.6 Phase 6: Idealize Future States (User Journey Construction)

"Our next step was to imagine the future airport. This started with what we learned from the past, present, and possible future as well as what is not viewed favorably today. From there, suggestions were made as to how to address these challenges. . . . We practiced envisioning the future airport by tracking the journy of different travelers 50 years from now. What works, what doesn't, and what are some of the details involved – including technology used to make things work – were identified."

During this phase, the team was tasked with creating user

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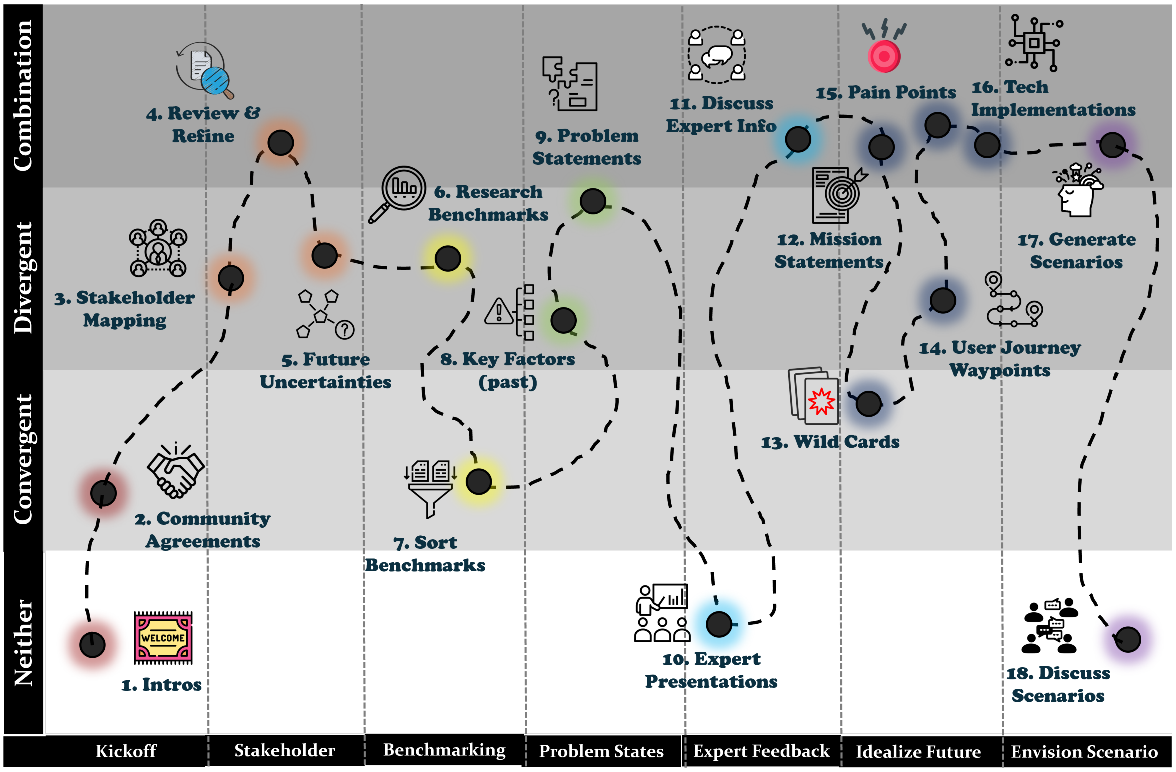

FIGURE 1: Journey Map illustrating the NASA Convergent Aeronautics Solutions team's design sprint to generate future scenarios of sustainable airports

journeys, which were based on user personas that were generated by the facilitators, that supported the narrative construction of future scenarios in sustainable airports. This included constructing several mission statements based on each user persona, selecting 'wild card' events to feature in each user journey, curating and assembling the journey way points (or steps in the journey), identifying appropriate places to acknowledge pain points in the user journey, and implementing technologies used to address these pain points throughout the user journey. Checkpoints #12, #13, #14, #15, and #16 in Figure 1 represent the tasks for this phase.

3.1.7 Phase 7: Envision Scenarios

"This work is by no means done yet. But two preliminary examples [are provided] of what a airport/transport infrastructure 50 years from now could look like: distributed and central. These depend on how much energy can be provided as well as host other pivot points. Significantly, if one wants both sustainable energy usage and highly advanced capabilities, the extent of the infrastructure established is dependent on the power available."

During this phase, the team was tasked with creating future scenarios based on all of the previous activities in the future scenario. Once future scenarios were created, the team took some time to reflect and discuss the generated future scenarios. Checkpoints #17 and #18 in Figure 1 represent the tasks for this phase.

3.2 Data Collection

We collected multiple forms of primarily qualitative data from the design team, including responses to a survey, ethnographic field notes and/or recordings of 10 team meetings, transcripts of six semi-structured interviews with team members. The survey was designed to gather information on team member demographics, professional background, and AI literacy. Participation in the survey was entirely optional and team members on the design sprint were free to abstain if they wished. The survey included a 5-item Likert scale aimed at evaluating team member's understanding of AI capabilities and limitations, drawing on prompts from the Meta AI Literacy Scale [28]. Responses to the Likert scale were documented as ratings from 1 to 5: (1) "Strongly disagree," (2) "disagree," (3) "neither agree nor disagree," (4) "agree," and (5) "strongly agree." The specific Likert scale prompts are provided below:

> "I can meaningfully use artificial intelligence to achieve my everyday goals."

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TABLE 1: Design Team Member Demographics

Participant	Gender	Years of Experience at NASA	Years of Experience Outside of NASA	Highest Level of Education	Average AI Literacy	Consent to Interview
P1	Male	2-4 Years	25+ Years	Masters	4.6	Yes
P2	Male	5-9 Years	25+ Years	Masters	3.6	Yes
P3	Male	25+ Years	1-4 Years	Masters	2.8	Yes
P4	Male	5-9 Years	1-4 Years	Masters	4.6	Yes
P5	Male	15-19 Years	1-4 Years	PhD	4.8	Yes
P6	Male	0-1 Years	None	Bachelors	3	Yes
P7	Male	25+ Years	1-4 Years	PhD	3.8	No

"I can assess the limitations and opportunities of using an AI too."
"I can think of new uses for AI."
"I can distinguish if I interact with an AI or a 'real human."
"I can weigh the societal consequences of using AI."

In addition, the survey asked about duration of tenure at NASA and outside organizations, highest level of education attained, field of study, and gender. Finally, we asked for details pertaining to work roles, their prior industry experience, age, racial/ethnic background, but we opted to omit this information as it was deemed unnecessary or too revealing of the participant's identity. Out of the ten individuals involved in the design sprint, seven elected to complete the survey. Their responses are shown in Table 1. All seven participants identified as men, and we will refer to them using "he/him/his" pronouns.

After the design sprint was completed, we reached out to participants who completed the survey to conduct interviews informed by our ethnographic observations and survey data. Of the seven survey respondents, we conducted 45-60 minute semi-structured interviews with six team members, whom we have named P1 through P7. Based on our observations of variation in GenAI use across team members and variation in AI literacy shown in the survey data (see Figure 2), we targeted interview questions around when and why each team member did or did not use GenAI. Our interview guide was semi-structured and asked interviewees to give an overview of their team's approach, inquired about their personal use of GenAI at various stages in the process, and prompted for detailed explanations of how they used GenAI and why they used or did not use GenAI at each stage. Questions were intentionally open-ended and interviewers followed the interviewee's lead as new ideas arose. The interviews were conducted by the first, second, and last authors using Microsoft Teams and were video recorded with each participant's permission. During interviews, some team members showed us parts of their team's online whiteboard or examples of their LLM prompts when describing their use of GenAI. All interviews adhered to our approved Institutional Review Board's guidelines, which includes the assurance of anonymity for all participants.

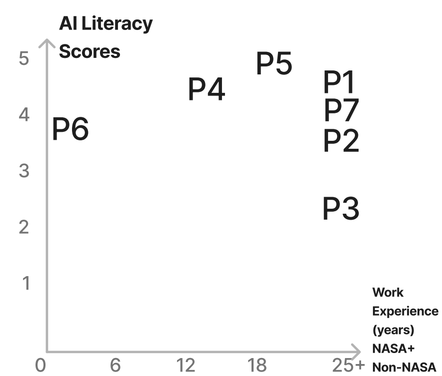

FIGURE 2: 2x2 plot with AI literacy on the y-axis and work experience on the x-axis ranging from low, medium, and high as labelled in the plot. This plot is intended to serve as a visual representation of where the participants lay across these two spectrum.

3.3 Data Analysis

We took a modified grounded theory approach in analyzing our data [29]. Over the course of data collection period, the first, second, and last authors engaged in iterative analysis of the data which then informed subsequent data collection. For example, we reviewed the survey results and held recurring field note reflection discussions after observing team meetings which informed subsequent observations and our interview questions.

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As the interviews progressed, three authors on this paper inductively coded the interview transcripts. We started off with open coding where we reviewed each unit of meaning in the interview data [30]. This led to a large set of codes and the first iteration of our codebook. These codes ranged from "attitudes toward AI-skepticism" or "attitudes toward AI-optimism" to various uses of AI such as "using AI for search or synthesis". We then re-coded these original codes and organized them into major categories and later subcodes and tertiary codes. We continued coding and iteratively refining the codebook until a point of saturation was reached, indicating a consensus among the codes. Our final codebook has two major codes–(1) strategies of GenAI use and (2) factors influencing GenAI use–and three subcodes each that emerged inductively from our data as described in Section 4. These correspond to RQ2 and RQ3. Our future step involves axially coding the data to draw linkages between these different strategies and factors [30].

3.4 Addressing Validity

Because we relied on ethnographic methods and qualitative data embedded in a single engineering organization, we strove for internal not external validity. In pursuing internal validity, we followed recommended practices for analyzing qualitative data [31], including triangulation using multiple data sources (live observations, recordings, interviews, surveys, and collection of artifacts), debate of interpretations and results among a team of multiple researchers, and establishing theoretical foundations that build upon relevant prior work. Future studies may examine the external validity of our findings by testing them across multiple organizations and contexts.

4 Emergent Findings

In the context of a speculative futures design process, our findings show where professional engineers used GenAI, how they used it, and factors that appeared to influence their use. We identify three strategies of GenAI use in design, two of which align with nascent theory of GenAI practices from the field of organization studies [32].

4.1 GenAI Use During a Speculative Design Process

To address RQ1, we used feedback from semi structured interviews to document where participants used GenAI in their speculative design process. Table 2 provides an account of where each participant used GenAI based on each speculative design process task.

To provide context around the use of GenAI, the research team categorized each step in the speculative design process by thinking task: convergent, divergent, both, or neither. Informed by creative problem solving literature [33–35], we crafted the following definitions for convergent and divergent activities involved in this speculative design process. Convergent activities involve tasks that require judgement, decision making, down selection, and re-purposing of current knowledge to new needs. Divergent activities involve tasks that require generation of innovative problems, opportunities, concepts, ideas, or artifacts.

A key takeaway illustrated in Table 2 highlights participants that seldomly used GenAI in their design process (such as P2 and P4). Here we notice that the task type in which these participants used GenAI always included some form of divergent thinking.

4.2 Strategies of Generative AI Use in Design

To address RQ2, we conducted interviews with participants to explore how they incorporated GenAI into their design workflow. During these interviews, participants discussed how and why they did or did not opt to incorporate GenAI into specific parts of the workflow. By employing a modified grounded theory approach as described in Section 3.3, we iteratively refined our qualitative codes until we identified three emergent strategies of GenAI use: *intimate co-design* with GenAI, *selective delegation* to GenAI, and *minimal use* of GenAI (Figure 3). We show that, while each designer tended toward a primary strategy of GenAI use, individual designers employed multiple strategies over time. These findings offer insight into how designers might be expected to interact with GenAI tools, variation of GenAI use within design teams, and the user strategies that GenAI tools may cater to. We begin with the first strategy—designers intimately co-designing with generative AI.

Strategy 1: *Intimate Co-design* with GenAI. *Intimate co-design* involved close and recurring integration between designers and GenAI. P1 often embodied this strategy and noted during an interview: *"I think I've used AI in every single step that I've been involved with."* He went on to describe creating a user persona of a airport traveler in 2075: *"I can't even say how much of it really is me authoring it. How much am I editing, and how much is the AI authoring? 50/50. I am not typing the output, but in terms of the content that is there, I steered it."* In another example, P5 described using GenAI to identify references and summarize the power generation capacity of various energy sources (coal, solar, fission, etc.) and energy densities of various fuels (conventional jet fuel, H2, methane, etc.). He shared: *"I used AI to come up with sources to get me the information [...and then used] various prompts saying, give me resources that talk about this stuff. Then I had to verify it so, you know, read it quickly. And once verified, I'll just say OK, give me a bulleted list of all these things, with this format, and I got [the output] from there."* P5 asked GenAI to synthesize a large body of knowledge and then relied on his own engineering knowledge to verify and refine it until the outputs met his needs. When using an *intimate co-design* strategy, designers did not employ a clear division of labor between GenAI and themselves but intimately intertwined

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TABLE 2: Participant use of GenAI across Speculative Design Process phases and activities

Phase		Kickoff		Stakeholder			Benchmarking		Problem States		Expert Feedback		Idealize Future					Envision Scenario	
Task #		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
Task Type		-	>	<	<>	<	<>	<>	<	<	-	<>	<>	>	<	<>	<>	<>	-
Design Team Members	P1	Used	Used	Used	Used	Used	Used	Used	Used	Used	Used	Used	Used	Not used	Not used	Not used	Not used	Used	Not used
	P2			Used	Not used		Used	Not used		Not used	Not used	Not used	Not used	Not used	Not used	Not used	Not used		Not used
	P3												Not used	Not used	Not used	Not used	Not used		Not used
	P4	Not used	Not used	Not used	Not used	Not used	Not used	Not used	Used	Used	Not used	Not used	Not used	Not used	Not used	Not used	Not used		Not used
	P5	Used	Used	Used	Used	Used	Used	Used	Used	Used	Used	Used	Used	Used	Used	Used	Used		Used
	P6	Not used	Not used	Not used	Not used	Not used	Not used	Not used	Not used	Not used	Not used	Not used	Not used	Not used	Not used	Not used	Not used		Not used
	P7	Not used	Not used	Not used	Not used	Not used	Not used	Not used	Not used	Not used	Not used	Not used	Not used	Not used	Not used	Not used	Not used	Not used	Not used

Key

- Used GenAI to support this task
- Did not use GenAI to support this task
- Did not participate in task
- < Divergent Task
- > Convergent Task
- <> Divergent & Convergent Task
- \- Neither Divergent nor Convergent Task

their efforts. The human-AI workflows were tightly coupled, and the ultimate outputs were co-produced.

Strategy 2: *Selective Delegation* to GenAI. *Selective delegation* involves a strategic division of labor between designers and GenAI, with designers conducting tasks themselves or delegating tasks to GenAI based on their and GenAI's strengths and weaknesses. In an interview, P2 described the following distinction: *"I like being able to refine my thinking through it [GenAI], but I would not want to rely on it for original thought."* He later shared an example of turning to GenAI for help learning about nuclear fusion: *"it was a matter of, OK, providing the citations, checking the citations, and reading the paper which further helped me to have an understanding of the state of nuclear fusion. So it is almost like I am using AI as kind of an adjunct, a learning tool for myself."* We found that P1, P2, P4, and P5 each employed a *selective delegation* strategy at different points in time. P5 described an example of using GenAI to generate waypoints for a user journey through a future airport provided a set of inputs he had curated. He shared: *"What I found very useful was the waypoints. [...] Given this persona, uh in 2075, and you'd have to give it trends in such way, so 2075,[...] there's climate change, the world has gone to 2C or whatever, and nuclear fusion is available, and there's a solar storm coming, blah blah blah, and you can just get a sketch of here's the different things a user might do to go through this journey. Those are the kinds of things I found CoPilot [GenAI] was good at."* While P5 found that generating user journey waypoints was a task well suited to GenAI, he described situations where the outputs were not fine grained enough. In those cases he preferred him or his colleagues to do it because, *"that's a highly connected, integrative task that just from the knowledge that we have in our minds over the years of studying these things, it's easier for us to just pull that together. That's specialized knowledge, and I don't think CoPilot [GenAI] is as good at doing that stuff."* When using a *selective delegation* strategy, designers discern which tasks are well suited and can be trusted to GenAI versus those that require a higher degree of specialized knowledge, trust, or traceability.

Strategy 3: *Minimal Use* of GenAI. *Minimal use* involves limited or no use of GenAI and designers choosing to rely on traditional engineering tools or their own expertise instead of turning to GenAI for support. P2 expressed an example of this during an interview: *"I have a 30 year background in aviation at airports, so I understand what is happening. So all of this stuff is from my knowledge of aviation. I did not use AI tools here."* Similarly, P3 expressed: *"I don't think I used AI at all. This was just coming straight out of the mind."* He later elaborated his concerns around integrating GenAI into his job and engineering design more broadly: *"For me, I am always worried in the sense that when people say, 'hey we can use AI to do this,' the system engineering side of me is always kicking and says how do*

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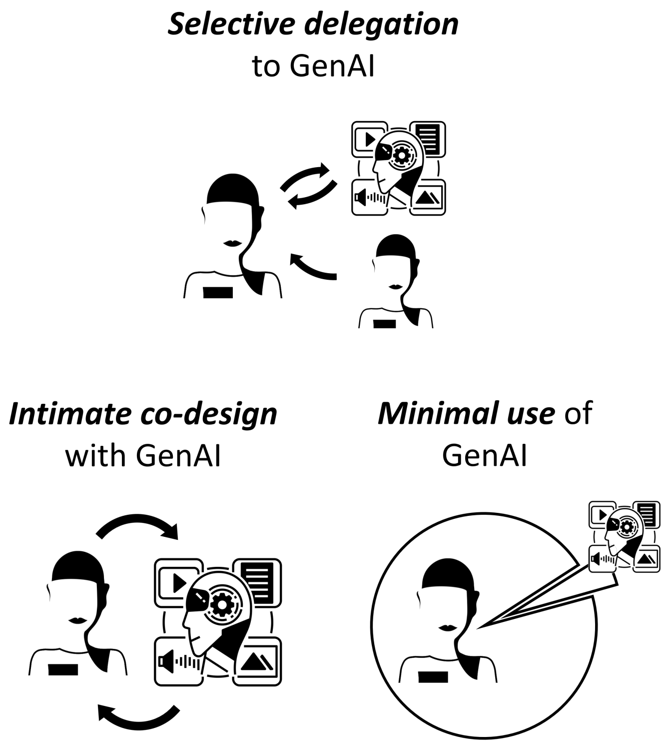

FIGURE 3: Three strategies of generative AI use in design.

you do verification and validation of the answer you get? And repeatability? Would it give you the same answer every time or not? [...] Not knowing all the inner workings [...] or even if the data has been updated, you know in real time, that can impact the results it gives you, right?" Those who used the *minimal use* strategy, like P2 and P3, acknowledged some uses for GenAI in searching *"obscure corners of the Internet"* and *"synthesizing non-specialized information"*, but always treated GenAI outputs with caution, looking to verify their outputs or assess their uncertainty. To help explain the variation within and across designers employing different strategies of GenAI use, we now turn a set of emergent factors influencing GenAI use.

4.3 Factors Influencing GenAI Use in Design

In addressing RQ3, we employed a methodology similar to the one done in Section 4.2. We divided our factors into two major categories that contribute to the variance in team members' use of GenAI during the speculative design workflow: *factors that negatively inflence GenAI use among designers* and *factors that positively influence GenAI use among designers*. Each overarching category contained factors. For the category *factors that negatively influence GenAI use among designers*, the factors include: *lack of GenAI familiarity or workflows*, *perceived poor quality of GenAI responses*, and *perceived unintended consequences of GenAI use*. Conversely, for the category *factors that positively influence GenAI use among designers*, the factors are: *familiarity with GenAI and GenAI-adjacent technologies and workflows*, *perceived increase in productivity*, and *ability to discern strengths and weaknesses of GenAI.*

4.3.1 Factors that Negatively Influenced GenAI Use Among Designers

In this section, we detail a preliminary set of factors that appeared to influence why designers opted not to use GenAI in various situations.

Factor 1: Lack of GenAI Familiarity or Workflows. This negative factor involves designers who have limited familiarity, comfort, or workflows using GenAI. Generally, these participants expressed not having time to "play with" GenAI tools thereby learning how to quickly derive meaningful outputs from them. Some held limited perspectives on how GenAI might be useful in the design process and others rarely even considered using GenAI. For example, P3 hesitated to use GenAI because *"right now for us to get something useful and meaningful out of it (GenAI), we have to retrain ourselves to think like what the AI is at the moment. So if I get to that stage where I am comfortable with how to create the system, I will probably use it more, but right now it is demanding more of my time."* He further explained, *"I really do not play with ChatGPT or any AI system. Just cause if I am outside of work, in my free time, I would rather not deal with any systems completely. But when I am at work, my other duties take a lot of time, so I do not have time to play with ChatGPT."* This led to P3 not feeling *"comfortable with using ChatGPT [...] to query whatever (he) needed to do."* Similarly, when asked whether or not he used GenAI, P4 stated, *"No, I like to create worlds [...] How the process of how you go about that is instrumental in how we are doing this."* When asked whether he would use AI to create the user journey if he could re-do it, he said, *"It would be interesting [...] but once you plug it [persona] into AI [to create a user journey], what do you ask? [...] So using AI, would it have been helpful? I guess in a way to get beyond writers' block."* P5, one of the team leads, suspected that the hesitation among some team members to use GenAI stemmed from a *"trust issue"*, which arises from a *"a lack of familiarity"*.

Factor 2: Perceived Poor Quality of GenAI Responses. This negative factor involves designers' perceptions of GenAI responses as being generic or "cookie-cutter"; being too outlandish to be acceptable to other engineers; being of poor quality and lacking the desired level of detail or nuance; being useful only when guided by a designer with relevant subject matter expertise; or lacking traceability regarding the source of information from which they are derived. For instance, P1 chose not to present some of the results from GenAI because results like *"self-replicating nanobots"* were deemed too *"insane"* to present despite being *"completely defensible."* Additionally, when using an image generation tool like MidJourney, P1 re-

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ported *"a real authority conflict"*, stating that he spent *"like 6 hours with a prompt"* but could not *"capture the detail that (he) needed."* Similarly, P2 and P4 expressed reservations about using GenAI in many parts of the design workflow, citing the output as generic or lacking the necessary detail needed to be useful. P2 noted, *"at least at this stage, and as far as AI, I think right now [AI] lacks the depth and breadth of the nuance unless you have an operator who has the understanding of the industry sufficient to tease out those threads."*. P4 added, *"my biggest gripe with AI is I never really see it come up with anything particularly engaging. I was like, if I asked it who are the main stakeholders in an airport, it'd go read ten articles and spit out 20 answers that are pretty cookie cutter. I would say very rarely does it come up with something, and I think, 'wow I never thought about that.' "* Ultimately, P5 highlighted a cultural barrier, stating that *"the NASA subject matter experts [...] [are] inherently [going to be] skeptical about everyone else's research. Which is a good thing in the scientific process [...] but in cases like this [speculative design workflow], there's a need to summarize everything and everyone has to understand it. And if you think about what [Microsoft] Co-Pilot is doing, the whole explainability part of it is not evident [...] you still have to trust that it summarized the article or the video without you having watched the whole one hour thing."* P5 argues that the skepticism amongst engineers and designers in NASA towards information that is not explainable or referenced in a traceable manner can lead to the perception of the information as poor quality, thereby negatively impacting the level of GenAI use amongst these participants.

Factor 3: Perceived Unintended Consequences of GenAI Use. The final negative factor we found involves designers' concerns regarding the potential unintended and undesirable consequences associated with using GenAI in the design process. Some of these risks include introducing or amplifying bias through AI generated content; limiting valuable human-to-human design interactions; or weakening designers' knowledge, skills, or abilities to execute design tasks without GenAI. P1 exhibited this factor most prominently when he stated, *"I have a rule [...] that there is not a sentence that I share with the group that I have not read and reviewed myself because that enfeeblement problem that's there."* P1 was concerned about the potential for GenAI to lead to his own complacency and the risk of *"self-enfeeblement"*. P1 also shared a different example, *"When I am talking with people [in a design team meeting], I don't want to be typing to a chatbot at the same time."* This participant did not want using an LLM to limit the potential for valuable human-to-human design interactions. This factor also aligns with literature on bias in AI in that AI-based systems can yield unintended consequences for groups of people who are minorities in training datasets, e.g., in healthcare [36].

4.3.2 Factors that Positively Influenced GenAI Use Among Designers

We now turn to factors that appeared to influenced designers' choice to use GenAI in their speculative design process.

Factor 1: Familiarity with GenAI and GenAI-adjacent Technologies and Workflows. This factor is countervailing to Factor 1 from Section 4.3.1. It involves designers who possess familiarity and established workflows using GenAI or GenAI-adjacent digital technologies. Participants P2 and P5 demonstrated these characteristics most prominently. P2 mentioned that although he used GenAI sparingly in the design workflow, he has begun to *"use it more to refine my thinking and also my writing."* Similarly, P5 stated that *"if you are familiar with this, just kind of being immersed in getting information from technology whether that's really low level or not..., the barrier to using AI tools might be lower."* He described how his workflow of spending *"hours per day"* listening to future-oriented ideas on YouTube, reading blogs, papers, etc. has made him more open to using *"CoPilot"* in his design process in a manner comparable to using *"Google or Google Trends."*

Factor 2: Perceived Increase in Productivity. Designers described this positive factor as a belief that GenAI enhances their productivity by accelerating their research and design processes, thereby increasing their overall work output and improving their work-life balance. Both P1 and P5 viewed GenAI as a significant boost to their productivity. For instance, P1 stated, *"I think I am a solid user [of GenAI], and I would say that I am able to double my productivity if not more [with the use of GenAI]."* He further added that GenAI has *"made my life better. While there may have been radical imaginations that I would have had without using these tools, but now I have time to [get good enough output], and spend time with my son."* Similarly, P5 remarked, *"I look at it [GenAI] as in the given time that is available, you can do more research."*

Factor 3: Ability to Discern Strengths and Weaknesses of GenAI. This was the most dominant positive factor in our data as it was observed amongst nearly all participants interviewed. This positive factor involves possessing an understanding of the strengths and weaknesses of various GenAI models, including being able to discern when and and when not to use GenAI and its various models. It also includes comprehending how datasets and prompts can be engineered to positively direct GenAI responses and yield quality results. For instance, P1 expressed confidence in some of the results generated by GenAI, noting that they can be *"logically justified based on historical research."* Additionally, when P2 was asked whether he would use GenAI to create personas, he mentioned that he would need to *"start with a framework. Then it would be the context that the human would be living in... [then talked about the framework he would build explicitly]. So, yeah I would use it."* Similarly, since P4 was less familiar with the process of creating a user journey during the design process, he indicated that he would have used GenAI

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to assist with the user journey process as it would have allowed him to *"come up with something and have something to start with."* Finally, P5 stated that once individuals are able to discern whether results generated by GenAI are good or not, in a manner similar to discerning the quality of results from Google, *"the barrier of using AI tools might be lower."*

5 Discussion

Here we explore the implications of our findings, discuss the limitations of our paper and propose directions for future work.

5.1 Emergent Strategies of GenAI Use–Contributions to Theory in Alignment with Prior Literature

Our exploratory study of AI use in a professional engineering setting uncovered three strategies of generative AI use in design. Two of these strategies align with existing literature, namely a study by *Dell'Acqua et al.* conducted with the Boston Consulting Group that examined the adoption of GenAI among 758 consultants. They found two emergent strategies of GenAI use amongst their consultants [32]–what they termed *centaur practices* and *cyborg practices*. *Centaur practices* involved behaviors of dividing and allocating specific tasks between themselves and AI, a concept that parallels the *selective delegation* strategy we observed among NASA engineers and designers.*Cyborg practices* involved consultants completely integrating GenAI into their workflow, a strategy closely aligned with the *intimiate co-design* strategy we observed in the NASA team. In addition, our study contributes another strategy–*minimal use*– which was predominantly adopted by designers with limited GenAI experience. When using this strategy, used GenAI as little as possible, preferring to rely on personal expertise, colleagues, or traditional engineering tools with a strong emphasis on output verification and validation. These proposed categories and preliminary and exploratory. Moving forward, we aim to observe and conduct interviews with a broader group of designers, both within the same design sprint team and across other teams at NASA, to uncover additional emergent strategies employed by engineering designers.

5.2 Emergent Factors Influencing GenAI Use–Implications for Human-AI Collaboration

Our study also unveiled emergent factors that played a role in the designers' decision on whether or not to integrate GenAI into the design process. In past studies, the incorporation of LLMs into the design workflow was a subject of interest, and a large chunk of these studies focused on how LLMs can be utilized in divergent thinking tasks [25, 26, 37–39]. Naturally this should imply that designers should prefer using LLMs for divergent thinking tasks because of LLMs capabilities to generate a diverse range of solutions for inspiration; however, in Table 2, we observed that there is no definitive correlation between the use of LLMs for either convergent or divergent tasks. Instead, the designer's decision to employ LLMs appeared to be more significantly influenced by considerations such as familiarity with GenAI and GenAI-adjacent technologies and workflows; perceived quality of GenAI responses; perceived increase in productivity, and the designer's ability to discern strengths and weaknesses of GenAI.

These factors emerged as themes from the qualitative data, and they often displayed a high interrelation between each other. For example, P1 and P5 demonstrated greater familiarity and comfort with GenAI tools, which appeared tied to them having higher perceived increase in productivity with these tools since they were well versed with the utility of GenAI. Thus, they ended up applying them into their design workflow more often, and this extensive experience reinforced their ability to discern the strengths and weaknesses of GenAI in their workflow. On the other hand, P2 and P4, exhibited lower familiarity and comfort with GenAI tools. They, instead, showed a preference for relying on their own skills, particularly when they felt confident in their own ability to perform a design task based on their own personal experiences. However, this does not mean they are not open to using GenAI in the future. As noted by P4, if he viewed GenAI as having a higher threshold and knowledge base than what he can offer on his own, GenAI would be an attractive option for quickly generating a starting framework for the task at hand.

The reasoning behind this difference is likely because of the knowledge barrier required to use GenAI effectively. As P5 highlighted, this barrier to GenAI adoption amongst team members was likely due to a lack of familiarity with using GenAI tools. This observation aligns with findings from *Zhang et. al.*, which emphasized the significant influence of an individual's expertise on human-AI collaboration [40], aligning with our findings that designers' expertise with using GenAI indirectly contributes to whether or not they decide to incorporate it into their design workflow.

5.3 Limitations

This study is limited in that the strategies and factors proposed are based on observations in a single design organization (NASA) and with a single team who represented a limited portion of the population (i.e., majority men with white or Asian/Pacific Islander ethnic identities based in the U.S.). In addition, the study is also limited by organizational inertia, where NASA policies introduce barriers that other organizations may not encounter, such as wariness of new tools. Designers in other cultural, organizational, or demographic contexts who identify with other gender and racial/ethnic identities or work in other organizations may not exhibit the same strategies and factors influencing GenAI use. Future work should examine the transferability of these findings to other populations, cultures, industries,

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and organizations.

While we collected and triangulated rich data across multiple sources (observations, surveys, and interviews), reached saturation in our coding process, and did so with a professional team that exhibited natural variation in team member AI literacy (a natural form of theoretical sampling), our data were limited in size and scope. Future research may extend our results by examining a larger number of participants and design teams. In addition, the strategies and factors influencing designers' use of generative AI may depend on the type of design tasks, stage, process, and more, so our findings may or may not transfer beyond the speculative design process we examined. Future work is needed to see how well these findings apply to other design processes and the later stages of design.

6 Conclusion

We followed a NASA design team on a speculative design process to understand how design team members used GenAI tools. We conducted ethnographic observations and interviewed six designers on the team who had varying levels of AI literacy and professional experience. Our focus was on understanding the instances and motivations behind individual designer's decisions to use or not use GenAI tools during their design process.

We did not find discernible patterns in when designers used GenAI across different activities in the speculative design process. However, we did uncover three emergent strategies of GenAI use among design professionals: *intimate co-design* with GenAI, where GenAI was fully integrated into the design workflow; *selective delegation* to GenAI, where designers gave specific tasks to GenAI and reserved others for themselves; and *minimal use* of GenAI, where designers used GenAI as scarcely as possible. Furthermore, our analysis identified preliminary factors that appeared to influence designers' decisions to use GenAI. These were categorized into negative factors, such as designers' lack of GenAI familiarity or workflows, perceived poor quality of GenAI responses, and perceived unintended consequences of GenAI use, and positive factors, like designers' familiarity with GenAI, perceived increase in productivity, and ability to discern the strengths and weaknesses of various GenAI.

These emergent themes align with findings from previous research and contribute new theory in the nuanced ways that design professionals engage with GenAI. Future research may examine how different factors affects which strategies of GenAI use that designers employ. This would be helpful in addressing questions like: How might design students or professionals be supported to move from a strategy of *miminal use* of GenAI to *strategic delegation* or *intimate co-design* with GenAI, or vice versa? Future work may also test the broader applicability of these proposed strategies and factors by studying a wider array of designers and design processes beyond speculative design and connecting further to existing design theories and frameworks.

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