"Like a Moodboard, But More Interactive": The Role of Expertise in Designers' Mental Models and Speculations on an Intelligent Design Assistant

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The successful adoption of artificial intelligence (AI)-enabled tools in engineering design requires an understanding of designers' mental models of such tools. This work explores how professional and student engineering designers (1) develop mental models of a novel AI-driven engineering design tool and (2) speculate AI-enabled functionalities that can aid them. Student (N = 7) and professional (N = 8) designers completed a task using an AI-enabled tool, and were interviewed to uncover their mental model of the tool and speculations on future AI-enabled functionalities. Both professional and student designers developed accurate mental models of the AI tool, and speculated functionalities that were similarly "near" and "far" in terms of analogical distance from the AI tool's functionality. These findings suggest that mental models and cross-application of AI tool functionality are readily accessible to designers, offering several implications for widespread adoption of AI-enabled design tools.

Introduction

Teaming between humans and artificial intelligence (AI) has been widely explored in engineering design research [1]. Studies have described how AI can learn from human designer behavior [2], how human designers' performance improves with the assistance of AI [3], and the negative impacts of poorly-contextualized AI assistance on human design teams [4]. Common across these studies is the fact that, when applied carefully, AI systems create the most value when partnered with humans in teams [5]. This value is not limited to the team itself: human-AI teaming broadly promises to enhance the value and impact of design in *organizations* as well [6].

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J. S Gero (ed.), *Design Computing and Cognition'22*,
https://doi.org/10.1007/978-3-031-20418-0_44

To unlock the power of human-AI teams, however, human team members must first willingly adopt and integrate AI into their work, requisite for broader integration of new technologies into organizations' practices [7].

Critical to effective adoption of AI tools are the *mental models* a designer has of what an AI tool is and does [8]. Norman, exploring end-user interaction with products, defined a mental model, or conceptual model, as an individual's "explanation of how something works" that is "often inferred from the device itself" [9]. Individuals with 'sound' mental models of an intelligent tool appear to achieve more better outcomes from it [10].

Engineering designers, however, must not only *adopt* AI, but *adapt* it to the kinds of complex and uncertain challenges they encounter in their work. From this perspective, two cognitive strategies outlined by Ball and Christensen are relevant: *analogical reasoning,* which describes "transferring previously acquired knowledge … to support current problem solving" and *mental simulation*, which describes a designer's use of imagination "to test out ideas and validate solution concepts" [11]. Here, we combine our examination of both analogical reasoning and mental simulation under the umbrella of *speculation* about AI tools, to reflect our focus on understanding novel applications of AI that may emerge in engineering design contexts. In this work, *speculation* describes a designer's ideation and narration of how AI-enabled functionalities could address current challenges or opportunities the designer faces, combining elements of analogical reasoning and mental simulation.

Despite their importance, few studies have examined how engineering designers develop mental models about AI tools, or how they speculate AI applications in their domain of practice. Similarly, while mental models, analogical reasoning, and mental simulation have shown to depend on a designer's expertise [12]–[15], little is known about how expertise informs these behaviors in the context of intelligent design tools. Addressing these knowledge gaps is essential to ensure researchers and leaders can best support designers in adopting and adapting AI tools as they further permeate engineering design practice.

In this work, we seek to develop a preliminary understanding of designers' mental models of AI-enabled design tools, designers' speculations on AI-enabled functionalities, and the relationship of both to designers' expertise. We present insights from semi-structured interviews with student (N = 7) and professional (N = 8) designers following their completion of a task involving a novel AI-enabled design tool developed by our team. We address two research questions, each of which we examine and understand with a specific consideration of designers' expertise:

1. What mental models do engineering designers develop of a novel AI-enabled engineering design tool?
2. What speculations about AI functionalities in their own domain do designers envision?

The main contributions of this study are twofold. First, we describe mental models and speculation immediately following engineering designers' engagement with intelligent tools. Second, we explore preliminary evidence of similarities and distinctions in the mental models and speculations that novice and professional designers develop.

Related Work

In this section, we briefly review five relevant areas of engineering design research to contextualize our work. First, we consider foundational and recent examples of AI-enabled functionalities in engineering design. Second, we consider relevant work on human-AI teaming. Third, we explore literature describing users' mental models of intelligent agents. Fourth, we briefly describe relevant work on analogical reasoning and speculation in engineering design. Finally, we briefly describe pertinent findings related to the distinctions between novice and expert designers regarding mental models and analogical reasoning.

AI-Enabled Functionalities in Engineering Design

AI methods have increasingly been used to assist humans with engineering design. In early considerations of the role of AI in supporting creativity, Boden described AI as potentially useful for novel combinations of familiar ideas (i.e., analogies) and exploration and transformation of the conceptual design space [16]. Recent work in engineering design has used AI to advance engineering design capability by enhancing conceptual design, accelerating design processes, and reducing and eliminating iterative design processes [1]; AI has been shown to be effective at various stages of the design process. Understanding user needs can be accomplished by AI through natural language processing (NLP) on product reviews [17]. AI can additionally use NLP to facilitate concept selection and evaluation based on user product reviews [18] or machine-learned ratings of design concepts [19]. Various AI-driven approaches utilizing NLP or latent semantic analysis (LSA) are useful for retrieving and representing design ideas from large datasets of text-based stimuli such as patents [20, 21], or crowd-sourced designs [22]; more general semantic networks, e.g. TechNet, broadly support engineering design activities [23]. Beyond sourcing design ideas from text-based data, deep-learning, neural-network-based approaches can be leveraged to also extract visual information from design examples from e.g., sketches, patent databases, or 3D-model data [24].

Our work extends on the AI design-support tool developed by Kwon et. al [24], but rather than present the design outcomes achieved when interacting with this system, we consider how AI is used and understood by designers. Accordingly, our contribution aims to improve how we can support the adoption and adaption of future AI-enabled engineering design tools.

Human-AI and Human–Machine Teaming in Engineering Design

Models of how humans and AI or machines should 'team' to achieve desirable design goals are widespread [25]. Recent research by Zhang et al. memorably highlighted that humans expected AI teammates to be an "ideal human" [26]. However, many AI systems function more as 'tools' rather than 'teammates,' a distinction that can be often arbitrarily perceived by the end-user interacting with the agent. In a large-scale study, Lyons et al. discovered that more than two-thirds of over 600 surveyed workers viewed intelligent systems they interacted with to be tools, rather than teammates, because the workers perceived a lack of decision authority and richness of communication [27]. Despite the heavy influence of perception on the distinction between teammate and tool, frameworks such as *autonomous agent teammate-likeness* establish guidelines for various types of representation of team members [28]. However, as software systems shape new workflows for the individuals using them [29], so does the introduction of AI tools. Describing the first CAD tools, and how such tools transformed designers' workflows, Ozkaya argues: "We will likely observe similar task shifts… through the development and use of AI-enabled systems" [30].

In this work, we present a relatively tool-like AI assistant into an open-ended task in a workflow familiar to engineering designers: 3D CAD design. Extending from Ozkaya's framing, we seek to understand how the functionality enabled by AI in our assistant invites different workflows for our participants, and connect such workflows to the mental models participants develop about our tools. We explore how an AI tool may—or may not—inspire designers' envisioning of new functionalities enabled by AI.

Mental Models in Engineering Tasks Related to AI

Mental models are how individuals make sense of systems they interact with: they are an individual's beliefs about a system and represent functionalities of the system perceived by them [9, 31]. Mental models can be inaccurate, and inaccurate mental models may lead to the *gulf of execution,* or a mismatch between the user's expectation of a system's function and its actual function [32], which may lead to poor adoption and less effective use of such systems. We note that in design research discourse, a *mental model* can be thought of as somewhat distinct from a *shared mental model* or a *team mental model;* these latter constructs describe a team's convergence on shared understanding and knowledge in their work [33] and have also been used to describe engineering design team behavior [34].

Several studies have explored how end-users develop mental models of AI while executing complex tasks, like design. These are primarily focused on how a user develops a mental model of trusting AI [35]. Tenhundfled et al. identified that users developed no consistent mental model of voice-controlled personal assistants despite similar interactions [36]. Tomsett et al. argued that rather than an immersive experience with an AI tool, users could create a mental model quickly if the systems offered interpretability and estimates of uncertainty [37]. Riveiro and Thill critically identified the importance of a user's *expectations* of an AI system in shaping their mental model, alongside the functional output of such a system [38]. Most pertinently among recent studies is Bansal et al.'s work examining the mental models that users of AI-based systems create while interacting with a decision-recommendation AI tool [8]. The authors focused on a specific dimension of the user's mental model, that is, the user's perception of the likelihood of error of the AI agent, the error boundary, in an experimental study of how users engage with an intelligent agent. Finally, as Wang et al. illustrated, users' mental models of AI assistants evolve over a period of usage and exposure, suggesting that mental models are not just experiential, but temporal, as well [39].

In this work, we extend on the idea of ascertaining a user's mental model of an AI system to understand *what* beliefs end-users hold about an AI system in a complex design task. While many of the leading studies such as Bansal et al.'s have focused on mental models grounded in error and trust, we focus on surfacing users' mental models related to the AI system's purpose, leveraging the Function-Behavior-Structure (FBS) framework [40]. Furthermore, we explore questions of mental models in AI systems in an engineering design CAD context, not an HCI context. We note that this work considers mental models at a single instant—immediately after interaction—as our interest is in *perception and adoption* of AI systems, rather than longitudinal evolution, which would invite further study.

Analogical Reasoning and Speculation in Engineering Design

Analogical reasoning, mental simulation, and their relation to design cognition and metacognition have been reviewed elsewhere [41]. Here, our review focuses on relevant background in *spontaneous*, *self-generated* analogizing pertaining to transfer *within* and *between* domains in engineering design. Then, we review mental simulation in engineering design.

Self-generated analogies are a crucial component of the design process. Christensen and Schunn [42] revealed that 'near' analogies—those that are *within* the domain of the target—were more frequently employed to identify a problem in design, but 'far' analogies—those that connect *between* an outside domain and the target domain—were more frequent during explanation in design. Further work by Ball and Christensen, and later Wiltsching et al., suggested that self-generated analogies reduce subjective uncertainty in design [11, 43]. Mental simulation is a "cognitive mechanism that enables reasoning about how physical systems might behave without the need actually to construct such systems" [44, 45]. Mental simulation allows designers to envision, explore, and evaluate possible concepts or solutions, and has been shown, like self-generated analogy, to play a key role in reducing uncertainty in the design process [11, 42].

In this work, we extend on previous work in analogical distance and mental simulation to examine (1) what types of analogies engineering designers employ when explaining an intelligent agent and (2) how mental simulation affords designers' speculation on AI functionalities, and the relationship of speculated functionalities to the intelligent agent they engaged with. In this study, elements of analogical reasoning and mental simulation are described by *speculation* in the context of designers' ideation of AI functionalities applied to next engineering design contexts.

Experience in Designers' Mental Models and Speculation

We focus our review on observed differences in mental models and analogical reasoning based on designers' experience. Only one study examining the differences in designers' mental models based on experience could be found. Fish et. al, in studying the differences in mental models of products (a hair dryer, leaf blower, and clothes dryer) between sophomore and senior engineering design students, found no significant difference between mental models despite a difference in experience [15]. The authors ascribed this to differences in curricula the students were exposed to.

Several studies have explored differences in analogical reasoning in engineering design based on experience. Ahmed et al. found that novice engineering designers tended to develop analogies based on explicit geometric information in a given part, while experienced designers used analogy for more abstract tasks of problem identification and problem solving [13, 14]. Studying architectural designers, Ozkan and Dogan found that experts made analogical 'mental hops,' connections to near-source domains. 'Hops' were typically grounded in structural similarity and led to incremental innovation. In contrast, first-year students made 'mental leaps,' connections to distant domains. 'Leaps' were typically grounded in surface similarity and led to more original solutions [12].

In this work, we extend Fish's work to explicitly explore the role of experience in mental models of AI agents. Rather than take a quantitative approach, we use interviews to ascertain users' perceptions of the AI tool's FBS to deconstruct their mental model of it. We similarly build on Ahmed and Ozkan and Dogan's results, by seeking to understand how the experience level shapes users' ability to speculate and transfer their experience with AI into novel domains.

Methods

In this section, we present background on the research study methodology: participants, the engineering design tool and task we developed, and the interview study. An overview of the methodology employed is in Fig. 1.

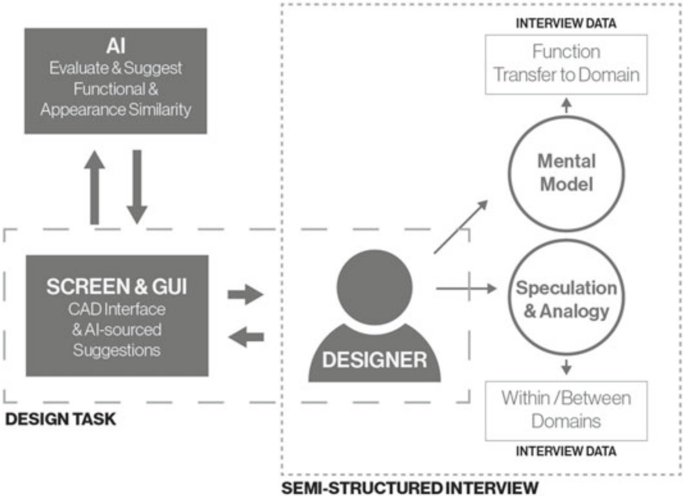

Fig. 1 Overview of methodology. A CAD interface is coupled to an AI backend, providing suggestions of 3D models that are similar to user-selected parts. After a 30-min design task, a 30-min semi-structured interview, the focus of this paper, elucidates the designer's mental model and speculation on future AI tools. Interviews are examined based on FBS and analogical reasoning frameworks

Participant Information

Participants were recruited via email solicitation among graduate students at the University of California, Berkeley, and professional networks in industry. All participants were required to meet the minimum eligibility of having at least 1 year Computer-aided design (CAD) experience. Fifteen participants volunteered for the study, including eight professionals (Table 1) and seven students. Students (3 males and 4 females) had self-reported experience with CAD tools ranging from <1 year to 9 years, and professionals (7 male and 1 female) had 3 to >10 years of professional design experience, also self-reported. Participants were offered $20 compensation for their participation in the 1-h study. Interviews were conducted via Zoom, using screenshare and audio transcription. This study was approved by the university's institutional review board.

Engineering Design Tool and Design Task

In this study, engineering designers completed an approximately 30-min design task using an AI-enabled tool we developed for multi-modal search for 3D parts. The objective of the design task was to use the tool to search for 3D parts to inspire solutions to a given design challenge. Our design tool relies on a deep-learning approach to efficiently retrieve relevant 3D-model parts based on the user's input

Table 1 Details on professional participants

Identifier	Role	Engineering design experience	Size of organization
P-1	Designer	10+ Years	>10,000
P-2	Designer	6–9 Years	>10,000
P-3	Designer	10+ Years	>10,000
P-4	Engineer	6–9 Years	>10,000
P-5	Designer	10+ Years	>10,000
P-6	Engineer	3–5 Years	<10
P-7	Designer	3–5 Years	1000–10,000
P-8	Engineer	6–9 Years	>10,000

query. Deep neural networks are used to model similarities between various 3D-model parts from the PartNet dataset, consisting of 24 object categories and 26,671 3D-model assemblies. The tool is further described in Kwon et al. [24] (Fig. 2).

The study objective presented to designers was to use the AI-enabled search interface to conduct multi-modal searches for 3D parts as they sought to design a compartmentalized waste bin. To search for parts, the available input modalities include (1) by text-based query, (2) based on another 3D-model part, and (3) based on the user's current 3D-modeling workspace, composed of previously retrieved parts. In the second and third search modalities, sliders in the user interface could also

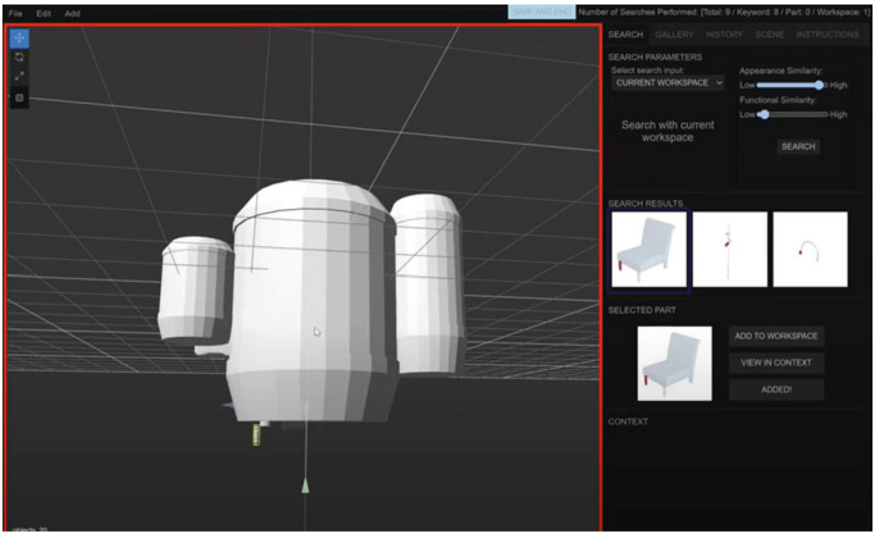

Fig. 2 Design task in progress, with functionality allowing the user to search with the AI-enabled tool. Here, three results have been returned from the workspace-based search input for parts with high appearance similarity. The selected chair leg result has been added to the developing design in the user's workspace

specify how similar the desired results were from the selected part and workspace inputs, respectively, by visual and functional similarity. For each search made, three parts are retrieved and shown in the user interface. Results of the design task are not explicitly discussed in this paper; our focus is on the mental models and speculations that designers expressed following the design task.

Interview Study Protocol and Analysis

Immediately following the completion of the design task, participants were engaged in a semi-structured interview. Questions explored the key themes of the interview study: mental models of the AI tool engaged with in the design task, and speculation and analogy around future AI functionalities (Table 2). Interviews were recorded and de-identified. Two researchers with at least two years of design research experience and two peer-reviewed papers authored proceeded to double-code various portions of the interview, resolving disagreements to reach a 100% inter-rater agreement. A single coder tabulated analogies and named systems.

First, participant-reported assessments of the tool’s function (question F1) were coded for the level of abstraction. Level of abstraction was described as whether the function described was *abstract* (meaning the described function was generalizable to many design activities and tasks); *concrete* (meaning the described function was specific to the particular use-case illustrated in the AI design tool); or *hybrid abstract-concrete* (meaning the described function included elements that were both generalizable and specific). This set of codes highlights whether the participant’s mental model was tied to the use case illustrated by the tool or not. Given the scope of this exploratory work, we do not consider *behavior* and *structure* in the FBS construct, instead exclusively focusing on *function.* Second, transfer of the illustrated AI functionality to the participant’s own domain (question F2) was reviewed

Table 2 Interview protocol: exploration topics, themes, and questions

Exploration	Theme	Question
Mental model of the encountered AI tool	Function	**(F1)** How would you describe what the tool you just worked with does, or, in other words, the tool’s function? Why? **(F2)** How important is this function in your work?
Analogical reasoning and speculation about AI functionalities	Key Functionalities	**(K1)** How would you like AI to support you in engineering design? What would the specific functionalities be? **(K2)** How would they help you in your work?

and coded for whether the designer was able to articulate why, or why not, the illustrated functionality was relevant to their work. *Successful transfer* was indicated by a clear and specific rationale for why (or why not) the illustrated functionality could support the type of work the individual pursues. *Unsuccessful transfer* was indicated by a poor or non-specific rationale for why (or why not) the illustrated functionality could support the type of work the individual pursues. Third, participant speculation on AI functionalities was reviewed (question K1 & K2) and coded for whether the proposed functionalities were, relative to the original AI search tool, *within-domain* or *between-domain,* drawing on Christensen and Schunn's work [42]. Coders determined whether the speculated application was 'within' the domain of the original functionality of a search design task, or 'between' the original functionality and another, very different functionality. Fourth, a single researcher identified (1) analogies and (2) named systems from a designer's experience and practice that were important to their mental model of the AI tool or their speculation on future functionalities.

Results & Discussion

Mental Models and Perceived Function of AI Tools

We first describe the mental models participants developed of the AI tool by examining the level of abstraction of the *function* they described. Nearly all participants were able to clearly articulate the function of the tool they engaged with (question F1). In many cases, these assessments were quite close to the actual purpose of the tool as defined by the researchers. Participant responses varied in terms of the level of abstraction, that is, whether they concretized the purpose in a specific function, or abstracted it to a more generally applicable statement of function (Table 3).

These results suggest that both students and professional designers are able to construct mental models that soundly represent the function of the AI tool. This is promising for future AI tools in design, as designers are able to quickly grasp the function of an intelligent tool, a prerequisite to *adoption* of such tools. In terms of ability to construct these mental models, there appears to be no meaningful difference between the two groups, reinforcing Fish et al.'s findings [15]. Further research could explore the apparent result, although not significant, that professionals more often interpreted the functionality of the tool abstractly than students did. This suggests a greater readiness to transfer the tool's functionality and principle to another context than that presented, which will be discussed in the next section.

Table 3 Mental model level of abstraction examples

Mental model level of abstraction	# of responses		Example quote	Participant code
	P	S		
Abstract	4	3	*“Quickly visualize a form or function, not in detail not in nuance, but enough to capture the functionality of what I’m trying to do.”*	P-2
Concrete	4	4	*“… develop simplified 3D CAD files. I like the functionality that allowed us to search for pieces that might not normally come up in mind.”*	*S-1*
Hybrid Abstract-Concrete	1	0	*“[the tool’s function is to] … help me find mechanical components that might be relevant to my design either for inspiration or directly incorporating into the design, or a small part that could be reused.”*	*P-8*

Transfer to the Participant’s Domain

Next, we examine if participants were able to transfer the perceived function of the AI tool into their own domain of expertise. All participants, regardless of experience level, demonstrated successful transfer, even if that transfer meant no fruitful application (question F2). A professional described process-oriented benefits of the tool:

> *[It] helps me get through my thinking faster. Simplifies my thought process on where to start .. to think about what to type to search it helps me think about the bigger picture of where my product is going.* **(P-3)**

A student, not finding a functional benefit for their own work, said:

> *In my work I don’t have liberties to make changes. But it makes me inspired, I really like that the search function didn’t give me what I was expecting.* **(S-8)**

These findings suggest that participants of all experience levels could transfer the principles and functionalities illustrated in the design task to their own responsibilities. This is a promising finding for design researchers exploring AI tools, as it underlines designers’ ability to take a specific example of an AI tool and *adapt* it to their work, essential for wider application of AI tools in design and the discovery of new applications.

Analogy and Connections to Named Tools

Next, we examine the analogies and named systems participants invoked in their description of the AI tool to understand differing conceptualizations of the tool. We observed that professionals and students appeared to differ in the number of analogies and references to specific, named design tools they invoked. In responses to questions F1, F2, K1, and K2, professional designers used a total of nine analogies and seven named tools. Student designers, in contrast, used a total of one analogy and eighteen named tools.

One professional analogized the function of the AI tool to a moodboard:

> *Like a moodboard, but more interactive than a moodboard … you can immediately see your design in 3D, scale it, etc.* **(P-6)**

One example of an invocation of a 'named tool' was this professional designer, who referenced McMaster-Carr when describing a future functionality they envisioned based on AI tools:

> *… [I] go to McMaster and see what's out there. It's nice being able to quickly find the components, using McMaster's search tool and working through catalog pages and stuff.* **(P-8)**

Despite the apparent difference in the usage of analogies and named tools, Wilcoxon Signed-rank tests examining the differences between the number of student and professional *analogies* ($W = 42.5$, $p = 0.0646$) and the differences between the number of student and professional *references to named systems* ($W = 15$, $p = 0.1147$) revealed no significant difference between the groups. We do note that both differences are nearly significant at a confidence level of $p < 0.10$, suggesting that further studies with larger sample sizes could statistically reinforce these findings.

Examining analogies (Table 4), we observe the one student analogy, 'toolbox,' is invoked by professionals. Examining the most frequently named systems (Table 5), three of the systems most frequently named by students are CAD tools. In contrast, none of the professionals named CAD tools during the specified questions, but frequently invoked McMaster-Carr, a popular catalog of components used in engineering design.

Nonetheless, professionals' apparently greater use of analogies points to relatively immediate and specific contextualization of an AI tool into their context. Professionals appear to be able to analogize to a range of concepts, from film ('Mad Max') to anthropomorphic interactions ('Smart Assistant'), than students do. We note

Table 4 Analogies invoked by participants

	Analogy	% of Total
Professional (7 total)	Personal Assistant (1), Lego (1), Database (1), Smart Assistant (1), Library (1), Moodboard (1), Toolbox (1), Mad Max (1)	14 (each)
Student (1 total)	Toolbox (1)	100

Table 5 Top Three most frequent named systems invoked by participants

Professional (9 total)		Student (18 total)	
Named system	*% of total*	*Named system*	*% of total*
McMaster-Carr (6)	67	Solidworks (8)	44
Google (1) Amazon (1) Netflix (1)	11 (each)	Google (4)	22
–	–	AutoCAD (2) Fusion360 (2)	11 (each)

that these analogies were self-generated and explanatory analogies. Students, on the other hand, may have less design practice experience to readily generate analogies, and instead appear to more readily reference specific named systems, particularly CAD tools, in order to articulate their ideas about AI-based tools in design. This is striking as the AI example may evoke the need to ground in well-understood *tools* for description. In contrast, professionals' use of named systems centers on engineering *resources*. This suggests that less experienced designers may look for direct tool analogues in establishing mental models and speculations about AI tools, whereas professionals may be able more immediately envision how AI tools relate to their existing workflows. We caveat this result by acknowledging that these results are not specific AI tools, and may apply to differences between professional and notice designers generally.

Speculation and Exploration of AI Functionalities in Design

Lastly, we examine the AI-enabled functionalities each participant speculated, and evaluated if these functionalities were 'within' or 'between' the functional domain of the presented tool. We found that when asked to speculate on AI functionalities (question K1 & K2), professionals and students were indistinguishable by whether their functionalities were determined to be 'within' the functional domain of the example AI system—retrieving 3D parts—or 'between' functional domains –beyond search and retrieval. Professionals reported four functionalities that were 'between,' with four 'within.' Students reported four functionalities that were 'between,' with three 'within.' One professional described an envisioned functionality, considered 'between' from the example functionality and another domain:

> *In the library if you ran FEA on each component—and then you applied that to the disposal unit. Having known what the loading capacity is, it could understand the context supporting whatever you were trying to do. It might ask you to expand the scale of the foot, or to match the simulation.* **(P-4)**

Another professional described a functionality that was considered within the example functionality's domain:

> *[there is a] difference between appearance and functional similarity … here, I didn't really care what the part was. The AI could make it much faster.* **(P-1)**

These findings suggest that when pursuing mental simulation and speculating on future AI tools, student and professional designers leverage similar modes of analogical reasoning. This finding is in contrast with Ozkan and Dogan's findings that expert designers often executed 'mental hops' in analogical reasoning, or 'within' analogical reasoning, resulting in incremental innovation, while student designers executed 'mental leaps,' or 'between' analogical reasoning, resulting in more originality [12]. We believe this finding offers an extension upon the previous work: that experience plays less of a distinguishing role when it comes to analogical reasoning during speculation. In design problem-solving, there may exist a difference between experienced and novice designers; however, in the differing cognitive mode of constrained speculation on emerging technologies, analogical reasoning that distinguishes less based on experience could occur.

Implications for Design Research and Practice

These findings present two points of departure for design research and practice. For design researchers, this work offers three areas for further investigation. First, our finding that professional and student designers pursue 'between' and 'within' speculation at similar rates could extend on Ozkan and Dogan's findings on the effect of experience on mental "hops" and "leaps" in design [12]. Notably, while their work studied architects in design problem-solving, our work examines engineering designers in speculating on future applications, suggesting that Ozkan and Dogan's conclusions about design cognition may invite nuance in different design problem-solving modes. Further research is necessary to explore *why* professionals and students both pursue similar patterns of speculation in our context—rather than associated with a design task, after all, participant replies came in the context of pure speculation. Second, this work explores the concept of mental models in the context of engineering designers' engagement with AI tools. Subsequent research is needed to explore how to further reconcile behavior and structure from the FBS framework with mental models in the context of AI tools, as this work was only able to examine function. Finally, this work hints at a high level of mental model soundness achieved in a short trial of an AI tool. Further exploration into the nexus between human-AI teaming, mental models, and experiential encounters are necessary to elucidate their interplay in engineering design.

For design practitioners and managers, this work provides preliminary indications of how to best strategize and rollout new AI functionalities into design teams. Perhaps most encouraging is the suggestion that professional designers are adept at *adapting* and *generalizing* a new tool to their work, and are readily able to envision somewhat related functionalities. This latter quality is promising to facilitate high-impact opportunities for AI tools within engineering design and design-driven organizations: it appears design professionals are particularly prepared to help realize this.

Limitations

This work had several key limitations that invite further study. First, the statistical power of our findings was limited by a small sample size, ultimately limiting the generalizability of our findings. Second, ascertaining mental models is a well-known challenge in design research, and use of FBS and our corresponding interview questions warrants further validation and study. In particular, we do not consider *behavior* and *structure* among the FBS construct, which invites further research. Third, our focus on self-generated, spontaneous analogies and named references means that participants predisposed to using analogies and references may have a large influence on our findings.

Conclusions

In this work, we examined how professional (N = 8) and student designers (N = 7) perceived the function of an AI-enabled tool they interacted with, and what kinds of future AI-enabled functionalities they could envision. Three key preliminary findings emerged. First, designers, regardless of experience, were able to construct relatively sound mental models of the AI-enabled tool that represented the function of the tool, and could transfer its functionality to their work responsibilities. Second, professional designers appeared to speculate on AI functionalities 'within' the example AI tool's functionality, while student designers speculated on functionalities that were 'between' from the tool's functionality and other domains. Lastly, professional designers appeared to more often draw analogies in describing the AI tool than students, while students invoked specific design tools than professionals in their descriptions of the AI tool.

Acknowledgements The authors thank Forrest Huang for AI tool development.

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