Understanding inspiration: Insights into how designers discover inspirational stimuli using an AI-enabled platform

Elisa Kwon, Vivek Rao and *Kosa Goucher-Lambert*, Department of Mechanical Engineering, University of California, Berkeley, USA

Throughout the design process, designers encounter diverse stimuli that influence their work. This influence is particularly notable during idea generation processes that are augmented by novel design support tools that assist in inspiration discovery. However, fundamental questions remain regarding why and how interactions afforded by these tools impact design behaviors. This work explores how designers search for inspirational stimuli using an AI-enabled multi-modal search platform, which supports queries by text and non-text-based inputs. Student and professional designers completed a think-aloud design exploration task using this platform to search for stimuli to inspire idea generation. We identify expertise and search modality as factors influencing design exploration, including the frequency and framing of searches, and the evaluation and utility of search results.

Keywords: design tools, design behavior, creativity, protocol analysis, design inspiration

In design and other creative domains, becoming inspired may be associated with experiencing a serendipitous encounter. For designers, inspiration is important for assisting with the generation of creative solutions. One definition of inspiration proposed by Gonçalves et al. (2016) references the role of an external stimulus in altering the creative process by influencing problem framing or solution generation. Significant effort has been made to describe and understand inspiration more formally, such as through an exploration of the influence of features of inspirational stimuli on ideation and design outcomes (e.g., by Chan et al., 2011; Fu et al., 2013b; Goucher-Lambert, Gyory, Kotovsky, & Cagan, 2020), the cognitive processes underlying designers' search processes (Gonçalves et al., 2013, 2016), and the methods and systems used to derive and retrieve inspirational stimuli using, e.g., data-driven techniques (Jiang et al., 2022).

Corresponding author:
Kosa Goucher-Lambert
kosa@berkeley.edu

In the present work, designers engage with a new AI (Artificial Intelligence)-enabled search platform to discover inspirational stimuli to aid solution

www.elsevier.com/locate/destud
0142-694X *Design Studies* **88** (2023) 101202
https://doi.org/10.1016/j.destud.2023.101202

generation to a design task. Search by novel interaction modalities, including by non-text-based search inputs, are made available in the developed platform, which is described in prior work (Kwon et al., 2022). Due to the possibility that the modes of search presented in our search platform are less familiar, the role of expertise when engaging with these search inputs is also studied. The aim of this work is to extend upon knowledge regarding processes employed by designers to search for inspirational stimuli, especially when facilitated by design support tools using new interaction mediums. Specific research questions guiding this work include the following.

- RQ1: How does input modality in an AI-enabled platform impact search for inspiration?
- RQ2: How do students and professional designers compare in their search for inspiration using an AI-enabled platform?
- RQ3: What rationale do designers provide for their evaluation and selection of inspirational stimuli?

In Figure 1, the approach taken to answer these research questions, **RQ1**-**RQ3**, is presented. First, participants completed a design task using our search platform from which we collected their platform interactions and think-aloud descriptions of their search processes. This experimental data is used to describe how designers search for inspirational stimuli in terms of search activities, behaviors, and pathways, as defined and outlined in Sec. 2.3. The developed framework is used to code experimental data into search behaviors, including how searches were defined and how the retrieved results were evaluated and selected. Search pathways then explore the relationships between search behaviors, such as how designers' selections of platform-retrieved stimuli are related to their evaluations of the same stimuli. Quantitative comparisons between search activities, behaviors, and pathways made using the available search modalities (keyword, part, and workspace, as defined in Sec. 2.1) by student vs. professional designers are detailed throughout Sec. 3.1, addressing **RQ1** and **RQ2**. As a final contribution of this work, answering **RQ3**, rationale and motivations for following specific pathways are discussed in Sec. 3.2 through select examples. The presented examples demonstrate how the search platform both accomplishes and influences designers' search goals. These results can be helpful for the further development and use of design tools, including search interfaces, by leveraging insight gained into the cognitive processes underlying the search for, evaluation, and selection of inspirational stimuli.

1 Background

To deepen our understanding of how designers search for inspiration, we consider three main components influencing this process. First, insights from past work are reviewed to motivate why designers should be exposed

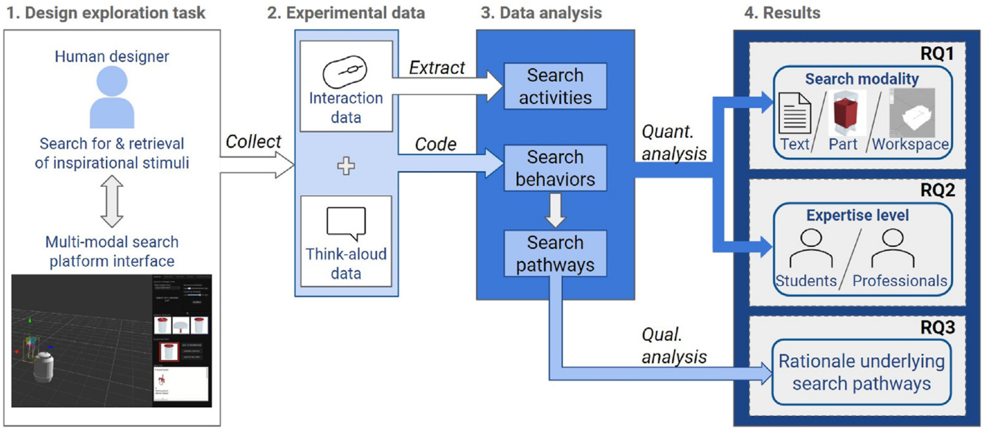

Figure 1 ***Paper overview:*** *Alignment of research questions to (**1**) design exploration task conducted (**2**) data collected (**3**) analysis approach, and (**4**) results presented*

to external stimuli during the design process. Second, cognitive processes and preferences underlying designers' search for inspiration are explored. Third, methods to support designers' search for and retrieval of inspirational stimuli, including various AI-enabled methods, are reviewed. This background is relevant to the work presented in the current paper, which investigates how designers search for inspirational stimuli when using an AI-enabled multi-modal search platform.

1.1 Impact of inspirational stimuli on design

Inspiration is discussed in this work as a process where a stimulus influences the thought process used towards problem framing or solution generation (Gonçalves et al., 2016). Accordingly, *inspirational stimuli* is used to describe external stimuli providing inspiration. Inspirational stimuli play a key role at many points across the design process: Lucero (2012) found that inspirational stimuli manifested in moodboards helped designers frame, align, abstract, and direct their work across various design activities. Inspirational stimuli can importantly aid designers by triggering idea generation and providing an anchor for mental representations of designs (Eckert & Stacey, 2000), but can also negatively lead to design fixation, where designers unconsciously focus on particular aspects of an object or task, resulting in limited idea generation (Jansson & Smith, 1991). Across many controlled experiments, the influence of external stimuli on design ideation has been studied to identify characteristics that make them useful or beneficial to designers, while aiming to avoid such fixation effects.

One significant area of prior work on the role of inspirational stimuli on design has focused on stimuli promoting analogical reasoning, defined as the process where a mapping association is made based on relations between a source and target (Gentner, 1983). Analogies are one form of external design stimuli suggested to be beneficial for creativity by encouraging new inference formation and problem construal (Gentner & Markman, 1997). Various features of analogical stimuli have been investigated, notably analogical distance, referring to the proximity of domain of the given stimulus to the designer's current problem. Far-field stimuli, for example, have been shown to lead to idea novelty (Chan et al., 2011; Goucher-Lambert & Cagan, 2019), compared to near-field stimuli, which can improve feasibility, relevance, and idea quantity (Chan et al., 2015; Goucher-Lambert et al., 2019, Goucher-Lambert, Gyory, Kotovsky, & Cagan, 2020). Fu et al. propose a "sweet spot" of analogical distance, discounting examples that are "too near" or "too far" to be beneficial to designers to apply analogical reasoning (Fu et al., 2013b).

Several factors of inspirational stimuli other than analogical distance can also impact design outcomes. The timing of when the stimulus is presented to the designer is important: it is more effective to provide once a designer has started to generate ideas for a design task than before idea generation has begun (Tseng, Moss, Cagan, & Kotovsky, 2008). The current ideation state of the designer is also relevant, where stimuli received when the designer is stuck can help produce more ideas, than when provided at predefined intervals (Siangliulue et al., 2015). In prior work, the level of detail or concreteness of the stimulus is another explored feature. Descriptions of design stimuli can be more general vs. domain-specific (Linsey et al., 2008) or constitute concrete design examples vs. abstract system properties (Vasconcelos, Cardoso, Sääksjärvi, Chen, & Crilly, 2017). While concept-level design stimuli (e.g., keywords extracted from patents) can provide more rapid inspiration, more comprehensive stimuli (e.g., patent documents) can provide rich engineering design details (Luo et al., 2021).

The modality in which the stimulus is represented to the designer is also considered. The impact of visual stimuli compared to physical stimuli (Toh & Miller, 2014), or in combination with textual stimuli (Borgianni, Rotini, & Tomassini, 2017; Han et al., 2018; Malaga, 2000), or other images (Hua et al., 2019), are examples of how representation modalities have been explored in prior work. Designers are found to tend to prefer visual information (Gonçalves et al., 2014; Linsey et al., 2011), which can lead to increased idea novelty (Linsey et al., 2008). When combined with unrelated semantic elements, images can promote creative idea generation (Han et al., 2018), especially when compared to words presented alone (Malaga, 2000). Sketches represent one specific form of visual 2D stimuli. Students have been found to seek and be most influenced by highly resolved sketch stimuli rather than rough sketches (Wallace et al., 2020). Experts may value sketch stimuli for their contextual content, while students value sketch stimuli for their real-life resemblance and direct connection to the task in question (Cai, Do, & Zimring, 2010).

Visual stimuli can also be represented in 3D, such as in 3D modelling. When comparing the use of 2D and 3D stimuli, further differences in designers' expertise level are found: Gonçalves et al. (2014) demonstrated that professional designers valued 3D object- and 2D image-based stimuli equally for inspiration, while student designers valued image-based stimuli more than other modalities. One key factor in motivating this difference is professionals' valuation of the amount of information object stimuli present to them. Their valuation of this information is reflected by their work on 'real' design solutions as opposed students' work on conceptual design solutions. Our previous work presented 3D-model parts to designers as stimuli based on chosen input modalities and analogical distance parameters (Kwon et al., 2022). In this work, we found that the modality used to *search for* inspirational stimuli affects what is discovered and how it is used. The present work extends upon these results by further examining the role of expertise when using various search modalities.

The impact of various features of inspirational stimuli on design outcomes are reviewed to motivate the present study of designers' search for stimuli to inspire idea generation. While much is known regarding how inspirational stimuli can impact the design process, the search behaviors employed by designers, as well as the methods enabling these processes, are less understood. In the present work, designers' use of an AI-enabled search platform is investigated, providing insight into designers' search for inspiration. The cognitive processes underlying these behaviors, and the design tools used to support them, are next reviewed.

1.2 Cognitive perspectives of search for inspiration

Sio et al. (2015) describe designing as a process of searching for task-relevant concepts and integrating these concepts into a design solution. Gonçalves et al. (2016) further define the search for inspiration process as initiated by a specific intention and goal, often expressed by keyword or other search input. To select keywords to initiate the search process, they discovered that designers search for closely related terms to the design problem earlier in the task and more distantly related terms later in the task. These search strategies are supported by related research on analogical stimuli that suggests the importance of both analogically near and far stimuli on promoting beneficial design outcomes (Fu et al., 2013b).

However, when the goal of a designer is not well defined, how is the search process initiated? Two search processes are proposed by Gonçalves et al. (2013, 2016): active search, which is an intentional process driven by specific goals, and passive search involving an accidental, non-deliberate discovery of relevant inspiration sources. Passive search is attributed to the random discovery of unexpected results, which can provide beneficial sources of inspiration (Gonçalves et al., 2016; Herring et al., 2009). Similar to the dichotomy between active and passive search, information retrieval theory differently defines lookup vs. exploratory search behaviors (Sutcliffe & Ennis, 1998). Exploratory search promotes knowledge acquisition and supports evolving needs, compared to lookup search activities which are used to meet precise search goals (Marchionini, 2006). Exploratory search is related to the examination of more results than lookup search (Athukorala et al., 2016). Passive and exploratory search strategies may be used when task constraints are low. Biskjaer et al. (2020) investigate the effect of task constraint on inspiration search strategies, finding that low task constrainedness was associated with more frequent and divergent search. When searching for inspiration, both active and passive search strategies are relevant. Designers are expected to find relevant inspirational stimuli through expressing specific search intent as well as through passive encounters with inspirational stimuli when search goals are not as clearly defined or unexpected search results are encountered. This intentional search for and passive discovery of inspirational stimuli can be facilitated by design-support tools, such as the search platform presented in this work and others reviewed in the next section.

1.3 Design support tools for inspirational stimuli retrieval

The discovery of inspirational stimuli is a process that can be supported by design support tools, including those that rely on AI. The interactions enabled by these systems and used by designers are important to consider towards understanding design behaviors, such as search for information and inspiration. Different computational and AI-enabled methods and tools have been proposed to provide inspiration to designers through external stimuli, applied in contexts like biologically inspired design (Vattam, Wiltgen, Helms, Goel, & Yen, 2011; Goel, Vattam, Wiltgen, & Helms, 2012; Nagel & Stone, 2012; Sartori et al., 2010), and using sources of designs such as patent databases (Murphy et al., 2014; Fu et al., 2013a, 2013b) or crowd-sourced solutions (Goucher-Lambert & Cagan, 2019; Kittur et al., 2019). Different from these studies, the present work focuses on the search for and retrieval of inspirational design stimuli, rather than on the stimuli provided by these systems. The use of multi-modal inputs is specifically studied to understand how they can support inspirational search. Various methods have also been developed that utilize non-text inputs, such as through image or sketch-based inputs.

Sketch-based retrieval of visually similar examples can importantly support visual analogy (Zhang & Jin, 2020, 2021). Image-based search using visual similarity can also extract relevant examples from sources such as patent documents (Jiang, Luo, Ruiz-Pava, Hu, & Magee, 2020, 2021). DreamSketch is an example of a sketch-based user interface that provides designers with 3D-modeled design solutions based on early stage 2D-sketch-based designs (Kazi, Grossman, Cheong, Hashemi, & Fitzmaurice, 2017). SketchSoup inputs rough sketches and generates new sets of sketches, which can inspire further concept generation (Arora et al., 2017). 3D-represented design ideas can be recognized by tools such as the InspireMe interface, which provides suggestions for new components to add to a designer's initial 3D model (Chaudhuri & Koltun, 2010). Design support tools that recognize these inputs can be beneficial since sketching itself is a process that can assist idea formation (Botella, Zenasni, & Lubart, 2018). In general, interactions with visual stimuli can help trigger new mental images and thus new ideas for design (Menezes & Lawson, 2006). By recognizing a designer's sketch as it is developing, the system can also provide relevant computational aid when it is advantageous to the designer during the design process (Do, 2005).

These examples suggest that multi-modal inputs may be used to more effectively recognize the idea or query expressed by a designer, and support the further search and exploration of the design space. The present work extends on these examples by directly assessing how these modalities are used to search for inspirational stimuli. We aim to describe the behaviors that interactions within these systems represent and to understand the cognitive processes involved in how designers search.

2 Experimental approach

To support the main aims of this research, we conducted a study facilitated by the use of a multi-modal search platform to investigate how designers search for inspirational stimuli. The study was conducted using Zoom, where participants' progress was screen and audio recorded. Screen recordings were used to capture how participants engaged with the AI-enabled design tool provided. In this section, the details of the search platform used, participants, and the design exploration task they completed are described. The methods and approach taken to analyze the results presented in this paper are also introduced.

2.1 AI-enabled multi-modal search platform

The design tool, a multi-modal search platform, relies on a deep-learning approach to efficiently retrieve relevant 3D-model parts based on the user's input 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 platform is extensively described in our prior work (Kwon et al., 2022). The search platform supports search for parts in the dataset using three types of input. The first search type is keyword-based, where parts with related text labels are returned. The second and third search types are part-based and workspace-based, where new parts are retrieved using visual snapshots taken of a selected 3D-model part or the participant's current workspace (composed of 3D-model parts), respectively. In part and workspace searches, sliders in the user interface also specify how similar the desired results are from the inputs by visual and functional similarity. For each search made, three parts are retrieved and shown in the user interface. Examples of keyword and part searches and results in the interface are shown in Figure 2a, b.

The interface also allows three additional actions to further interact with the retrieved results. Parts can be added to and modified in the user's 3D workspace using an 'Add to Workspace' button. Workspace-based searches are made with snapshots of the entire workspace with parts added to the workspace using this action. Since all results are retrieved from the PartNet dataset, which contains information on neighboring parts in the same assembly of a given result, this information may also be viewed using a 'View in Context' button. For a selected part, this action allows further understanding of the retrieved part's placement in its original context. Uses of these features for a keyword search result for "container" are also shown in Figure 2c, d. Finally, parts can be added to a gallery of collected 3D parts using an 'Add to gallery' button. During the design task, the gallery was available for participants to access and select parts from at any point. For any given search made, none to all actions can be performed, in any order.

Interactions afforded by this platform were investigated in our prior work. Using this search platform and the same design prompt provided in the present study (described in Sec. 2.2.2), a controlled experiment was conducted ($n = 21$) in which keyword, part, and workspace searches were engaged separately in three subtasks (Kwon et al., 2022). Participants were instructed to conduct a minimum of five searches using each input, and to save a minimum of three parts to their gallery of parts. The goal of this prior study was to analyze participants' interactions in the platform and relate these actions to strategies involved in searching for inspirational examples. Understanding how each modality was used and interacted with was the main aim of this study, instead of how designers may have naturally used them to achieve specific design outcomes. Distinct outcomes using each search modality were found, including the most frequent use of the part-based search, but low engagement with the returned parts (e.g., by viewing related parts in the same object assemblies or adding them to the 3D workspace). We speculated that increased part-based search but decreased engagement may have been due to the task requirement to continue to search until desired results were obtained. Based on these findings, we aim to further understand in the present

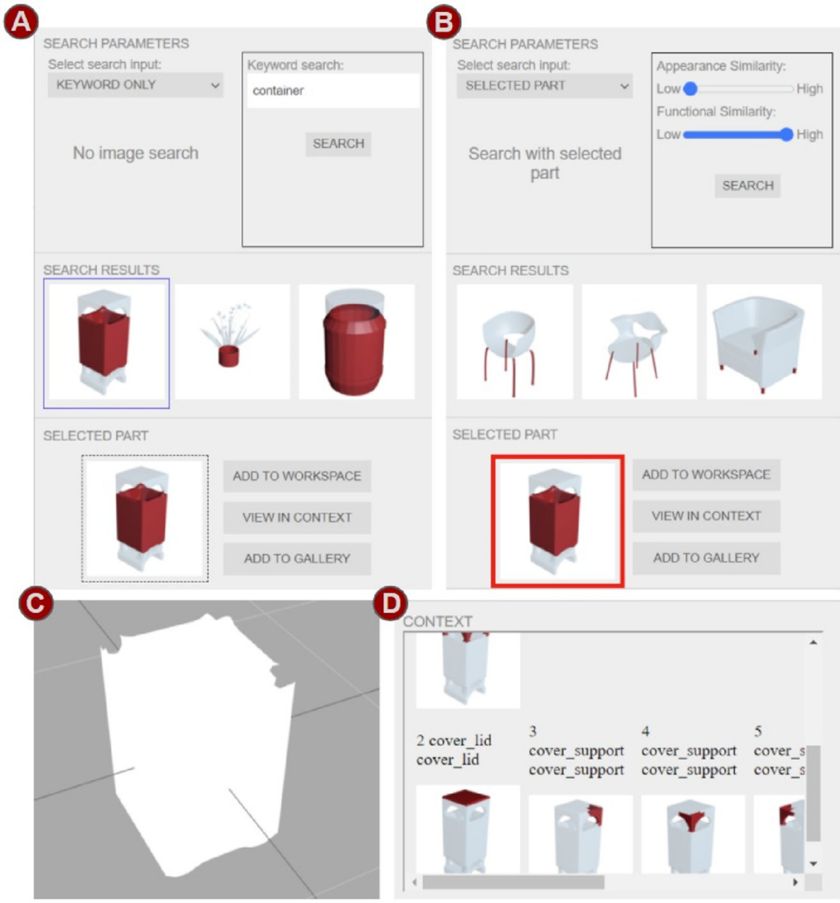

Figure 2 ***Features of multi-modal search platform:*** ***(a)*** *Keyword search and results for "container";* ***(b)*** *Part search with selected container result;* ***(c)*** *Container added to 3D workspace;* ***(d)*** *Container viewed in context*

study how each search modality supports designers' search goals when used freely in the same task, and to elucidate their intentions and discoveries by introducing a think-aloud protocol.

2.2 *Design exploration task and think-aloud protocol*

2.2.1 *Participants*

Participants were recruited for the study via email solicitation among graduate students at the University of California, Berkeley, and industry professionals. All participants were required to meet the minimum eligibility of having at least one year of Computer-Aided Design (CAD) experience. Fifteen participants volunteered for the study, including eight professionals recruited from industry and seven students recruited from the university. Self-reported experience with CAD tools of students (three males, four females) and professionals (seven males, one female) is summarized in Table 1. Students consisted of six Ph.D. students in Mechanical Engineering and one Master of Design student. Professionals included five designers and three engineers by job title, across organizations ranging from <10 to >10 000 employees. Participants were offered $20 compensation for their participation in the 1-h study, detailed below. This study was approved by the Institutional Review Board (IRB) at the University of California, Berkeley.

2.2.2 Study objective and instructions

The study objective presented to designers was to use the multi-modal search platform to search for parts that inspire solutions to the design for "a multi-compartment disposal unit for household waste". No additional design requirements or specifications on the relationship between the searched for parts to the design problem were provided. Participants completed the task in <30 min., including approx. 15 min. learning how to use the interface through a guided tutorial embedded in a Qualtrics link accessed at the start of the study. Participants read descriptions and viewed videos of the interface in use and followed instructions for completing example searches in the interface. Instructions for following a think-aloud protocol directed participants to explain their interactions aloud, with particular attention to: (1) why the specified search type and input were used before executing a search and (2) whether the returned result was what was expected, or not, after executing a search. Based on prior work in which the same task was completed without think-aloud instructions, these prompts were specified to elucidate motivations behind previously observed search behavior during the task. Designers were provided with the suggestion to conduct five of each search type (keyword, part, and workspace). These guidelines were not strictly enforced during the task to allow designers to freely use the search types in any order.

2.3 Analysis of design exploration task and think-aloud data

The main approach taken to analyze results from the design exploration task is to examine three levels of search: activities, behaviors, and pathways. Further elaborating on Figure 1, the relationships between the task data and these search levels are summarized in Figure 3. These search levels are defined to understand designers' search processes through interactions with the search platform and transcriptions of think-aloud data. Search activities describe how designers conducted multi-modal searches. Search behaviors are extracted from both platform interactions and accompanying think-aloud data before and after executing searches. Search pathways are then used to discuss how search behaviors are related.

Firstly, **search activities** are studied, related to the frequency of use of the multi-modal inputs in the search platform. Task data captured by the search platform was extracted, including individual button presses to conduct

Table 1 CAD experience of student and professional designers

CAD experience (years)				
Participant type	*1–2*	*3–5*	*6–9*	*>10*
Students	5	0	2	0
Professionals	0	2	3	3

searches, view parts in context, save parts to the gallery, add parts to the workspace, and all individual part data. The frequencies of searches made using each input type are specifically explored in this work.

Secondly, to abstract and classify **search behaviors** from platform interactions and think-aloud data, a framework was developed. This framework is an extension from Gonçalves et al.'s description of the inspirational search process, which outlines the formulation of search inputs, the (successful or unsuccessful) search for and selection of a stimulus, assessment of its correspondence to the designer's expectations, and finally the designer's choice to incorporate and adapt the stimulus to the problem at hand (2013). In the present work, the behaviors identified include: how designers defined searches (whether new or continued searches for results were made), evaluated search results (whether results were expected or unexpected), and selected search results (whether results were accepted or rejected from their design). This framework is further detailed in Table 2. For each behavior (search definition, evaluation, and selection), two possible levels were assigned by following the listed criteria, shown in Table 2. Representative examples of quotes from the think-aloud data associated with each search behavior are also provided.

Two coders, each with at least three years of postgraduate design research experience, assessed the data using the framework. Coder 1 manually transcribed think-aloud data from screen and audio recordings of the design task sessions. Coder 1 identified user interaction behavior and think-aloud quotations pertaining to the three defined behaviors (definitions, evaluations, selections). A total of 235 search actions were identified, an average of 15.7 searches per participant. To validate the framework, Coders 1 and 2 independently applied framework codes to 15% of the dataset. A minimum of 84% interrater reliability for search definition codes was determined using percentage agreement, and 0.69 using Cohen's Kappa, indicating substantial agreement (Stemler, 2004). This suggests that the developed coding framework was relatively consistent across coders.

However, exceptions emerged to the defined criteria when codes for search definitions and evaluations were assigned. An example of an exception to the defined criteria is when a 'new search' followed a 'rejected' outcome, e.g., when a participant made a new search for a "lid" without accepting results for their previous search for a "handle". Based on the criteria defined, this

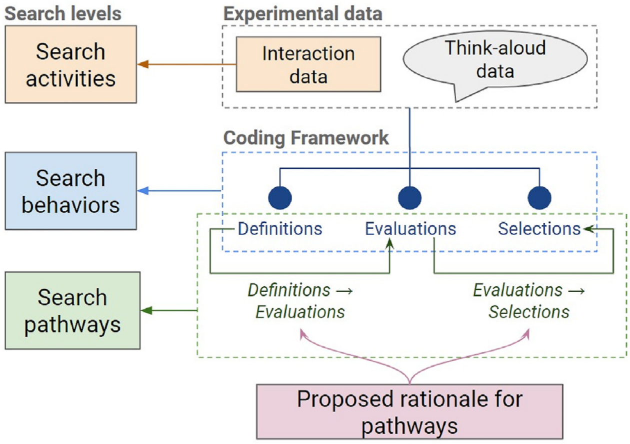

Figure 3 ***Overview of relationships between three levels of search examined in results:*** *activities describing interactions, behaviors, coded from experimental data with the developed framework, and pathways discussing relationships between behaviors. Rationale for select pathways are discussed*

Table 2 Search behavior framework: Classification scheme for search behaviors from task and think-aloud data

Behavior: *Description*	*Classification criteria*	*Representative example of associated quote*
Search Definition		
New: Beginning of a new search for a result	Follows an 'accept' outcome of a previous search (see below)	*"I want to see a disposal unit" (**P8**)*
Continuing: Continuation of a search for a result	Follows a 'reject' outcome of a previous search (see below)	*"Maybe instead of cylinder, some kind of rectangular cube" (**P7**)*
Search Evaluation		
Expected: Results match designer's expectation	Explicit acknowledgement that the result is what was searched for or preceding an 'accept' outcome, if no accompanying verbal statement	*"Yes, I like these features. This is providing what I'm looking for" (**P10**)*
Unexpected: Results do not match designer's expectation	Explicit acknowledgement that the result is not what was searched for/is unexpected or preceding a 'reject' outcome, if no accompanying verbal statement	*"This is not what I was expecting - I was expecting to see more lids, whereas these are table tops" (**P4**)*
Search Selection		
Accept: Results are accepted by designer	Result is added to the designer's developing design in the 3D workspace or saved to their gallery of parts	*"This is a shape that could possibly be used in my design. So I'm going to add it to my gallery." (**P12**)*
Reject: Results are rejected by designer	Result is not added to the designer's developing design in the 3D workspace or saved to their gallery of parts. Designer continues to search again.	*"This is not what I was thinking, but this is a trashcan, for sure."* [makes continued search] *"I'm maybe more looking for a cabinet" (**P5**)*

search should be labelled as a continuation of a prior search, but is clearly indicated by the designer to be a new search for a different part. By identifying these characteristics of designers' search behavior, the relationships between what designers search for and what they actually find useful can be explored. Coder 1 coded the entire dataset accounting for these exceptions.

Linking related search behaviors, **search pathways** are the third level of search explored in the present analysis. For a given search, designers follow pathways between defining and evaluating searches and evaluating and selecting parts to incorporate into designs. Illustrative examples from the study of various search pathways can be found in Table 3. Investigating the link between search definitions and evaluations can help uncover if designers have different expectations regarding search results they have repeatedly searched for, or are searching for, for the first time. By studying search evaluation—selection pathways, the influence of encountering unexpected search results on stimuli selection can be examined. Designers may be inspired positively or become negatively fixated on parts they are originally intending to find. These pathways are studied since stimuli selection is known to depend upon how a search is defined and the goal associated with the search (Gonçalves et al., 2016).

3 Results

Following the analysis approach introduced, results detailing participants' search activities, behaviors, and pathways are presented and discussed in this section. In Sec. 3.1, quantitative analyses of each level of search are conducted to examine differences between searches made using keyword, part, and workspace inputs and made by students and professionals, addressing **RQ1** and **RQ2**, respectively. **Search activities** describe how designers used the different search modalities in the platform in terms of frequencies of use. Using the classification scheme established in Table 2, **search behaviors** are investigated. **Search pathways** provide further insight into the relationship between search behaviors, linking search definitions with evaluations, and evaluations with selections. Finally, in Sec. 3.2 an exploration of various search pathways is also made to address **RQ3**, revealing insights into the rationale designers express for defining, evaluating, and selecting inspirational stimuli.

3.1 Quantitative analyses of search activities, behaviors, and pathways

3.1.1 Search activities: designers' use of keyword, part, and workspace searches

The frequency of use of each search modality (keyword, part, workspace) by designers of each level of expertise (student, professional) are first compared. A Poisson regression model, which is used to model count variables, was selected to analyze these differences. A mixed effects model was constructed

Table 3 Illustrative examples of search pathways linking search behaviors

#	*Search pathway*	*Group*	*Type*	*Associated quote/action*
1	New → Unexpected	Student	Workspace	*"I can search for something like. I can use the current workspace … maybe 50% appearance and full functionality to find some other stuff.* ***These are all irrelevant****"*
2	Expected → Rejected	Professional	Part	*"Ahh, yes that's good, I'm seeing kind of like very close matches … I'm going to keep playing around with sliders till I* ***get something closer****"*
3	Expected → Rejected	Student	Keyword	*"I'm going to look for a 'lid' … Ok, yes,* ***I'm looking for something like this****, something square and flat …* ***I want it to be flat*** *and cover [the bin] completely.*" [Searches again]
4	Unexpected → Accepted	Student	Workspace	*"I'm looking for something similar to this waste bin so that it can look for the top of the waste bin … Well* ***that's kind of funny****"* [referring to wheel results]. *"Now we can* ***add wheels*** *to this and make it mobile, which is good!"*

using R in RStudio, leveraging the lme4 package to incorporate both fixed (modality, expertise) and random (participant) effects using Laplace Approximation. The model predicts the effects of modality and expertise on the log of frequency of searches made by participants using each search type (N = 45, 15 participants x 3 modalities). Results of the Poisson regression are summarized in Table 4.

Model estimates (β) define the change in the log of frequency associated with each predictor compared to the specified reference (i.e., part or workspace search compared to keyword search and student compared to professional designer). To analogously describe the change in expected search frequency (rather than the change in log of frequency) given the predictor compared to the reference, incidence rate ratios with 95% confidence intervals are also reported. In the context of Poisson regression models, incidence rate ratios are equivalent to e^{β}. The average number of searches made by student (blue) and professional (red) designers using keyword, part, and workspace searches are visually presented in Figure 4.

R1.1. Search activities: most searches are made by keyword. The first comparison made between designers' use of keyword, part, and workspace inputs when searching is in the frequencies of searches conducted using each search type. Significant differences were found in the expected frequency of searches made using part and workspace, compared to keyword searches. Search frequencies for part and workspace searches are 0.39 ($p < 0.001$) and 0.19 ($p < 0.001$) times the search frequency of keyword searches, respectively. Workspace searches represent the most comparatively novel feature offered by the tool, while keyword searches are likely the most familiar input to designers. These results present an important consideration in the design of

Table 4 Poisson regression model predicting search frequency using each modality (n = 45)

Outcome variable	*Predictor*	*Level*	β	p	*Incidence rate ratio* (e^{β})	*95% C.I.*
Search frequency	**Modality**	*Keyword*	(Ref)	(Ref)	(Ref)	(Ref)
		Part	−0.94	**<0.001**	0.39	(0.29, 0.52)
		Workspace	−1.7	**<0.001**	0.19	(0.12, 0.28)
	Expertise	*Professional*	(Ref)	(Ref)	(Ref)	(Ref)
		Student	0.15	0.40	1.16	(0.80, 1.7)

multi-modal inspirational search tools for engineering design: designers, regardless of experience level, more readily use familiar search modalities in their search process.

R1.2. Search activities: Professionals and students do not differ by frequency of search type use. No significant difference was found between participant groups in the frequencies of searches made ($\beta = -0.15$, $p = 0.40$). Student and professional designers therefore do not appear to differ in the modality of search for inspiration they engage when using the multi-modal platform. Adding to Result **R1.1**, both students and professionals used keyword searches the most and workspace searches the least.

3.1.2 Search behaviors: designers' definition, evaluation, and selection of search results

The second level of search examined are behaviors, including how designers define searches and evaluate and select search results. The average proportions across participants of search behavior outcomes made using keyword, part, or workspace searches and by professional or student designers are summarized in Table 5.

To determine the impacts of search modality and designer expertise on search behavior outcomes, mixed effects binary logistic regression models are used. Three models were constructed to demonstrate whether modality and expertise are significant predictors for whether a search was new (vs. continuing), and its result was evaluated as expected (vs. unexpected) and accepted (vs. rejected). Mixed effects logistic regression models were also constructed in R using the lme4 package in RStudio, and incorporated both fixed (modality, expertise) and random (participant) effects using Laplace Approximation.

The results from each regression model are summarized in Table 6, where search definitions (as new), evaluations (as expected), and selections (as accepted) are analyzed as separate outcome variables. Model estimates (β), significance values (p), odds ratios (e^{β}) and their corresponding 95% confidence intervals are reported in Table 6. Estimates for modality are in reference to keyword searches, and for expertise in reference to professionals. Findings

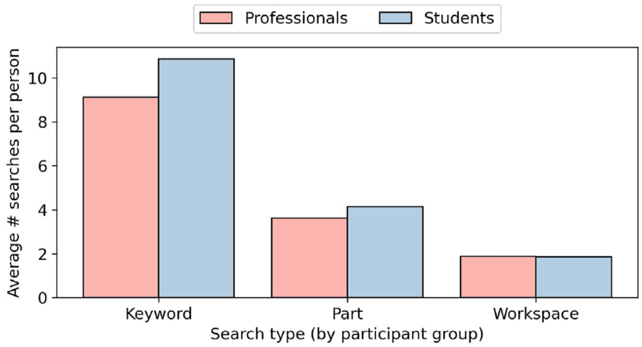

Figure 4 ***Average (per person) frequency of search type use:*** *Comparison between search types (keyword, part, workspace) and participant groups (professionals ($n = 8$), students ($n = 7$))*

across these models are discussed further in this subsection in terms of search modality and designer expertise, separately. To aid with the interpretation of these results, Figure 5 visualizes the odds ratios of each estimate compared to the indicated references for selection and evaluation outcomes. Odds ratios < 1 with confidence intervals that do not cross odds $= 1$ represent that the predictor is significantly less likely than the reference to result in the behavior. Odds ratios > 1 would indicate that the predictor is more likely to result in the behavior than the reference.

R2.1. More keyword search results are expected and accepted. Considering the impact of search modality on the generation of new vs. continued searches, no significant differences between keyword and part or workspace searches were found. Designers are known to rely on "random active search processes" to discover inspiring stimuli when they have a search intention, but do not have a keyword in mind to conduct the search (Gonçalves et al., 2016). Designers' use of part and workspace inputs to formulate new searches demonstrates that these modalities may help achieve the gap between intentional search and uncertainty of what to search for.

However, workspace searches are significantly less likely by 0.25 times than keyword searches to result in an expected evaluation ($p = 0.015$). In other words, workspace search results are 4 times more likely be unexpected than keyword search results. In total, 156/235 (66.4%) searches retrieved results that were identified as unexpected. As shown in Table 5, this high proportion of unexpected search results is disproportionately true for searches made with workspace inputs (24/28, 85.7%) in comparison to keyword searches (91/149, 61.1%). This finding may reflect that designers did not know what to expect

Table 5 Average proportions (%) of search behaviors across search types and participant groups

		Search types			*Participant group*	
Search behavior		*Keyword*	*Part*	*Workspace*	*Professional*	*Student*
Definition	New	40.94%	32.76%	53.57%	45.30%	35.59%
	Continuing	59.06%	67.24%	46.43%	54.70%	64.41%
Evaluation	Expected	38.93%	29.31%	14.29%	40.17%	27.12%
	Unexpected	61.07%	70.69%	85.71%	59.83%	72.88%
Selection	Accept	40.94%	25.86%	35.71%	43.59%	29.6%
	Reject	59.06%	74.14%	64.29%	56.41%	70.34%

when engaging workspace searches. One student designer noted: *"If I want the same functionality in the entire workspace in one part, I don't quite know what that means in this context"*. This example can help to explain results in Figure 4, and why workspace searches were less frequently used: designers often had different expectations of what such searches would yield, than what was actually returned. Beyond the designer's ability to interpret these results, also reflected is the computational difficulty of retrieving relevant and expected parts using visual and functional features. This suggests the need for further work to improve the effectiveness of this search modality to better meet designers' expectations.

A significant difference in the acceptance of part and keyword searches was found, where part searches were 0.49 times less likely to be accepted ($p = 0.041$). On average, designers accepted results from only 25.7% of part searches, while 40.9% of keywords search results and 35.71% of workspace search results were accepted (Table 5). This low likelihood of acceptance corresponds to insights from our prior study, as described in Sec. 2.1, where part

Table 6 Binary logistic regression models predicting search behavior outcomes (n = 235)

Outcome variable	*Predictor*	*Level*	β	p	*Odds ratio* (e^{β})	*95% C.I.*
Definition:	**Modality**	*Keyword*	(Ref)	(Ref)	(Ref)	(Ref)
New = 1, Continued = 0		Part	−0.36	0.27	0.70	(0.36, 1.3)
		Workspace	0.50	0.23	1.64	(0.73, 3.8)
	Expertise	*Professional*	(Ref)	(Ref)	(Ref)	(Ref)
		Student	−0.40	0.14	0.67	(0.39, 1.1)
Evaluation:	**Modality**	*Keyword*	(Ref)	(Ref)	(Ref)	(Ref)
Expected = 1, Unexpected = 0		Part	−0.49	0.17	0.61	(0.30, 1.2)
		Workspace	−1.4	**0.015**	0.25	(0.068, 0.69)
	Expertise	*Professional*	(Ref)	(Ref)	(Ref)	(Ref)
		Student	−0.63	**0.044**	0.53	(0.27, 1.0)
Selection:	**Modality**	*Keyword*	(Ref)	(Ref)	(Ref)	(Ref)
Accepted = 1, Rejected = 0		Part	−0.71	**0.041**	0.49	(0.24, 0.96)
		Workspace	−0.26	0.56	0.77	(0.32, 1.8)
	Expertise	*Professional*	(Ref)	(Ref)	(Ref)	(Ref)
		Student	−0.62	**0.025**	0.54	(0.31, 0.92)

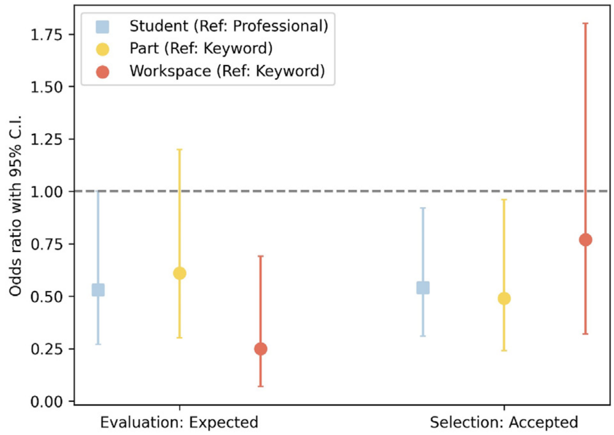

Figure 5 Odds ratios with 95% confidence intervals for predictors of evaluation and selection outcomes. Odds are computed with respect to the indicated reference

searches were most frequently used. Participants may have conducted many part searches because they did not immediately find desirable results, prompting further search.

R2.2. Students exhibit narrower search behaviors than professionals. The impact of expertise on the definition of searches was not found to be significant, but professionals and students did differ by how searches were evaluated and selected. Students, when compared to professionals, were 0.53 ($p = 0.044$) times less likely to evaluate results as expected, and were 0.54 ($p = 0.025$) times less likely to accept parts into their final designs. These behaviors can be linked broadly to narrower search processes and design fixation, where instead of fixating on aspects of an external solution, an adherence to their initial ideas and internally imagined parts may occur.

3.1.3 Search pathways: linking prior behaviors with subsequent outcomes

The relationship between search behaviors is further analyzed through **search pathways**. A similar approach as used in Sec. 3.1.1 and 3.1.2 is used to determine how modality and expertise influences pathway outcomes, such as how new vs. continued searches were evaluated and how expected vs. unexpected were selected. Additional mixed effects binary logistic regression models were constructed to model whether modality and expertise differently predict how new (N = 95) and continued (N = 140) searches were evaluated and expected (N = 79) and unexpected (N = 156) search results were selected. Across these four models, modality and expertise are only found to significantly impact the evaluation of new searches. Results of the model predicting the evaluation of new searches are summarized in Table 7. Observations regarding all definition-evaluation and evaluation−selection pathways are discussed further in this subsection.

R3.1 Search modality impacts the evaluation of new searches. The relationship between search behaviors is analyzed through search pathways related to searches made with keyword, part, and workspace inputs. As represented in Sankey diagrams shown in Figure 6, (A) definition-evaluation and (B) evaluation−selection pathways are displayed. These diagrams visually depict the average number of searches made in each pathway per designer. Associated pathway frequencies combined across all participants are shown in Table 8.

Differences between the evaluation of new vs. continued keyword, part, and workspace searches are shown in Figure 6a. New workspace compared to keyword searches were 0.91 times less likely to be evaluated as expected ($p = 0.028$). This finding is driven by the observation that only one new workspace search was evaluated as expected (Table 8). By contrast, a higher proportion of new keyword ($26/61 = 42.6\%$) and part ($7/26 = 26.9\%$) searches were evaluated as expected. As stated previously (**R2.1**), more workspace than keyword searches were evaluated as unexpected, across designers, possibly attributable to the limitations in the system's ability to retrieve expected results and the designer's ability to anticipate and understand how the system is conducting non-text-based searches.

Using workspace searches without having a clearly defined search goal may influence why the results are then evaluated as irrelevant. For instance, Example 1 in Table 3 presents an example of a new workspace search made with a vaguely expressed intent. In addition to highlighting limitations of the system discussed previously, these findings suggest that for non-text searches to be more aligned with designer expectations, further support, curation, or instruction may be necessary. This is an important result for the design of future inspirational search systems, which may leverage diverse media beyond text for queries. To understand how to encourage designers to evaluate more AI-provided results as expected and acceptable, designer rationale for following these pathways are explored in Sec. 3.2.

Once a search is made and the returned parts are evaluated as expected or unexpected, results may then either be accepted (incorporated into the participant's current design) or rejected. No significant differences were found between workspace and part searches compared to keyword searches in the evaluation of expected or unexpected results. While modality was found to affect how designers evaluate search results, it does not appear to affect how the expected results are then selected. In other words, if a search result was expected or unexpected, whether the search was made using a keyword, part, or workspace search did not significantly influence designers' acceptance or

Table 7 Binary logistic regression model predicting evaluation of new searches (n = 95)

Outcome variable	*Predictor*	*Level*	β	p	*Odds ratio* (e^{β})	*95% C.I.*
Evaluation: Expected = 1, Unexpected = 0	**Modality**	*Keyword*	(Ref)	(Ref)	(Ref)	(Ref)
		Part	−0.14	0.81	0.87	(0.28, 2.6)
		Workspace	−2.4	**0.028**	0.094	(0.005, 0.53)
	Expertise	*Professional*	(Ref)	(Ref)	(Ref)	(Ref)
		Student	−1.0	**0.033**	0.37	(0.14, 0.90)

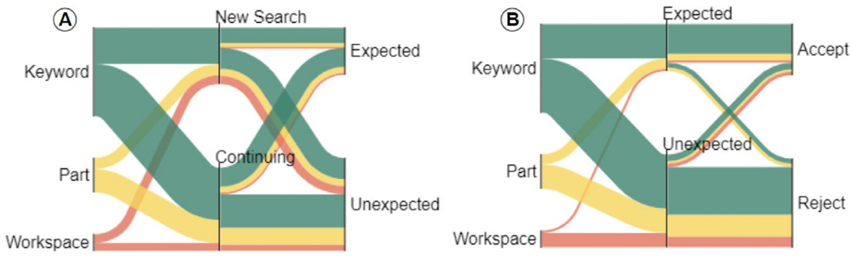

Figure 6 ***Search pathways compared across*** *keyword* ***(green), part (yellow), and workspace (orange) searches*** *linking* ***(a)*** *definition and evaluation behaviors and* ***(b)*** *evaluation and selection behaviors.*

Table 8 Summary of search pathways made using keyword, part, and workspace search inputs

Search behavior		*Search type*			*Total*
Definition	*Evaluation*	*Keyword*	*Part*	*Workspace*	*# of searches*
New	Expected	26	7	1	34
	Unexpected	35	12	14	61
Continuing	Expected	32	10	3	45
	Unexpected	56	29	10	95
Evaluation	*Selection*	*Keyword*	*Part*	*Workspace*	*# of searches*
Expected	Accept	50	11	4	65
	Reject	8	6	0	14
Unexpected	Accept	11	4	6	21
	Reject	80	37	18	135

rejection of results. The relative proportions of expected and unexpected keyword, part, and workspace searches that are accepted and rejected are shown in Figure 6b.

More surprisingly, two additional evaluation−selection pathways are notable. A small proportion of searches made with each search input that are expected are rejected, and that are unexpected are accepted. Table 8 shows that, across all participants, 8/58 (13.8%) keyword and 6/17 (35.3%) part search results evaluated as expected were rejected. Examples 2 and 3 in Table 3 illustrate these behaviors, where designers reference looking for a closer match than what has already been found. Expected search results may encourage designers to search further, as they may consider themselves ‘on the right track’. The use of slider repositioning when defining part and workspace searches can further aid this process. Another less explored and less intuitive pathway is the acceptance of unexpected stimuli, including 11/91 (12.1%) keyword, 4/37 (10.8%) part, and 6/24 (25.0%) workspace search results. Example 4 in Table 3 shows how a result from a workspace search that does not match the designer's original intention can be nonetheless useful for, e.g., introducing a design feature such as wheels to add mobility to a waste bin. These findings suggest that cognitive behaviors exist when searching that challenge designers' fixation on a given objective, and are explored further in Sec. 3.2.

R3.2 Expertise impacts the evaluation of new searches. Next, comparing definition evaluation pathways followed by students and professionals, the Sankey diagram in Figure 7a represents the average number of searches made in each pathway per designer in each group. Corresponding pathway frequencies are summarized in Table 9. The binary logistic regression model for new searches demonstrated that new searches made by students compared to professionals were 0.63 times less likely to be evaluated as expected ($p = 0.033$). Figure 7a emphasizes that professionals find more new searches provide expected results than students. On average per participant, professionals evaluated 3.0 new searches as expected, compared to 1.4 by students (see Table 9). Expressed differently, professionals evaluate, on average, 45.3% of new searches as expected, compared to 23.8% by students. No significant results are found regarding the evaluation of continuing searches.

While professionals and students do differ by the proportion of searches that are evaluated as expected and accepted (Result **R2.2**), their selection of expected and unexpected search results do not differ significantly. These relative frequencies of pathways can be compared visually in Figure 7b. Intuitively, across participants, a high proportion of results that are evaluated as expected are accepted, and unexpected results are rejected. For professionals, 41.0% of searches are evaluated as expected, 80.9% of which are accepted. Students evaluate fewer searches as expected (27.1%), but accept a relatively high proportion of these results (84.4%). Both professionals and students reject a similar percentage of searches evaluated as unexpected (81.4% and 90.7%, respectively). Therefore, although students and professionals exhibit different search evaluation and selection behaviors, they similarly evaluate expected and unexpected search results.

As noted when comparing evaluation–selection pathways across search modalities, both students and professionals also reject expected results and accept unexpected results. Only a small proportion of searches made by both participant groups are represented in these pathways. To understand why unexpected results may be accepted, examples are presented in Sec. 3.2 to

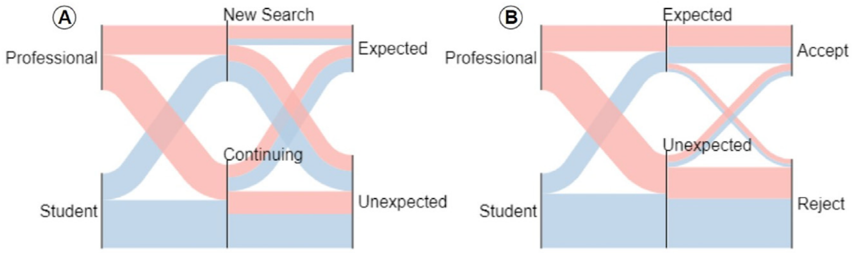

Figure 7 ***Search pathways compared across professionals (red) and students (blue)*** *linking* ***(a)*** *definition and evaluation behaviors and* ***(b)*** *evaluation and selection behaviors.*

Table 9 Summary of search pathways by professional and student designers

Search behavior		*Participant group*		*Total*
Definition	*Evaluation*	*Professional (n = 8)*	*Student (n = 7)*	*# of searches*
New	Expected	24	10	34
	Unexpected	29	32	61
Continuing	Expected	23	22	45
	Unexpected	41	54	95
Evaluation	*Selection*	*Professional (n = 8)*	*Student (n = 7)*	*# of searches*
Expected	Accept	38	27	65
	Reject	9	5	14
Unexpected	Accept	13	8	21
	Reject	57	78	135

uncover rationale for following this particular pathway. This pathway, in addition to the evaluation of new search results as expected, represent desirable behaviors to better understand and encourage regarding the use of design support tools.

3.2 Designer rationale motivating search pathway outcomes

Finally, to gain further insight into specific search pathways followed by designers, the rationale provided for their evaluation and selection of search results are explored. To identify rationale, a mixed-methods approach is used where quantitative analyses of interaction and think-aloud data first enabled the isolation of individual search pathways, as fully described in Sec. 3.1.3. Qualitative insights from think-aloud data are now used to describe rationale underlying three search pathways. Two pathways with desirable outcomes are considered: when search results from a new search are evaluated as expected and when unexpected search results are accepted. Both pathways represent less explored, but desirable outcomes from interacting with the search platform. A third pathway is discussed, constituting a more frequent, but potentially less desirable outcome: the rejection of unexpected results.

3.2.1 New search results that meet designers' expectations

The first pathway of interest involves a new search for a part, for which the system retrieves results that the designer evaluates as expected. This pathway constitutes 34/235 of all searches, across participant groups and search modalities (see Tables 8 and 9). Examples to characterize this pathway are presented to understand why some searches lead to parts that do or do not match expectations to an initial search goal. We propose that both the platform's performance as well as the designer's ability to adapt their expectations to the presented stimuli are key factors enabling this process.

R4.1.1. Evaluation influenced by perception of platform performance. The first way that designers acknowledged that the search results retrieved by the platform matched their expectations was to refer to the search itself as good (e.g., "*I think the search is good*" or "*it kind of works*"), which can be linked to an assessment of the platform's performance. By contrast, their evaluation could be motivated by an assessment of the specific results returned, which might be "*the kind of thing I was looking for*", be something they liked (e.g., "*Oh, there's a lamp shade I like*"), or have particular desirable features such as the shape or size. The 'goodness' of parts can also be attributable to features of the design problem or the designer's current idea, such as a part being able to fit inside a kitchen counter, referencing the household context of the design prompt. These examples demonstrate how designers expressed their evaluation of search results as matching their expectations using rationale around platform performance and specific features and relevance of results.

R4.1.2. Designers may adapt expectations to search results. Another way that designers evaluated search results as matching their expectations was to first *adapt* their initial expectations to the parts returned, which may have appeared in a different form or context than originally searched for. This scenario differs from the evaluation of a result as unexpected, which would involve a search outcome that was incorrect, according to the designer's expectations (e.g., a flat tabletop instead of a rectangular can). Instead, these examples demonstrate scenarios where the retrieved part was 'correct' and the designer could understand why it was returned, but also identified unsuitable or irrelevant features. This pathway is explored to understand how designers rationalized overcoming these features to apply the retrieved results to their current design context. To represent this scenario with an example, two different participants conducted a new search by keyword for a "hinge", for which various hinges were returned. After one participant (P15) initially identified "*these are hinges for these* ***doors on the cabinets***", they adapted their expectations for a more contextually relevant hinge (e.g., attaching a lid to a container) to conclude "*I'm guessing that would work*". Similarly, another participant (P4) verified "*this is a hinge*", but then noted "***it's quite small … it's more of a cabinet hinge***", before conceding that they would "*take it*". In a third example, a result from the search term "trashcan" retrieved something that "*might be a bit large for a household*" but that the participant (P3) could still "*probably work with*". Across these examples, even though the parts were what they expected (i.e., a hinge part returned for the search for "hinge"), specific features such as the size and original context of the part presented initial barriers to their acceptance. However, these examples demonstrate that designers are importantly able to overcome this initial fixation and adapt their expectations.

3.2.2 Designers' acceptance of unexpected stimuli

The second pathway for which we explore designer rationale is the selection of unexpected inspirational stimuli, corresponding to 21/235 of all searches. As we showcase through qualitative insights from the following examples, there is an opportunity for unexpected stimuli to introduce exciting and beneficial design features during ideation. Several reasons for accepting an unexpected result were found including: (1) it introduced a desirable, but unanticipated design feature, (2) it fulfilled a searched for purpose, in a different way, and (3) the designer satisfied for a result, even though it did not meet their expectations.

R4.2.1. Unexpected stimuli introduce potentially desirable features. The first way designers expressed rationale for selecting an unexpected result retrieved by the search platform was that it introduced a desirable, but previously unanticipated feature to their concept. In two cases, designers were inspired to add wheels to their designs, though this is not what they initially sought from their search. Participant P8, looking for different forms of containers through a part-based search with high functional similarity and low appearance similarity to a container lid, received parts including the set of wheels shown in Figure 8a. These were returned by the search tool because lids and wheels are visually dissimilar but share a common functional context in object assemblies including containers. Discovering the wheels, participant P8 noted: "*Well now that I see it, I think it may be a good idea to have the unit movable, so I think castors would be something useful*". The resulting influence on their design can be seen in Figure 8b, displaying that the wheels were subsequently added to the base of their disposal unit.

In a second instance, participant P7, when looking for "*something similar to this drawer*" using a workspace-based search, was returned chair wheels (Figure 9a). The search tool, recognizing visual similarity of the drawer to the seat in the chair assembly, returned chair wheels due to their shared context with the seat. After first remarking, "*well that's kind of funny*", the chair wheels were added to their design (Figure 9b) after acknowledging, similar to P8: "*Now we can add wheels to this and make it mobile, which is good!*"

In both examples, retrieved wheels introduced an unanticipated feature to their designs, i.e., mobility. In the first example, wheels from an analogically "near-field" (as defined by Fu et al. (2013b)) object assembly (a different kind of container) were added, which may represent a more obvious transfer of unexpected stimuli to the design. The second example is striking as it demonstrates how even unintentional stimuli from a "far-field" domain (a chair) can be effectively applied towards introducing a desirable, but unanticipated feature to the design. The use of contextually unrelated stimuli is also relevant to the next rationale discussed.

R4.2.2. Unexpected stimuli differently fulfill the same searched for purpose. The second rationale designers provided for using an unexpected stimulus was that it fulfilled the same purpose originally intended, but in a different way. Participant P4, upon retrieving three tabletop results (e.g., Figure 10a) when searching for a lid to place on a rectangular trashcan found that "*Nonetheless, it's actually fitting what I'm looking for exactly*". In this example, although the object did not match what was searched for, its visual form suited the designer's needs for a cover they could scale to the size of their trashcan. In a similar example, Participant P7 searched for a "can" and was given a round base of a candle holder, as shown in Figure 10b. While expressing that this is not what they were looking for, and that it was at the incorrect scale, they also stated, "*This one is maybe promising, I can maybe make it bigger … this looks like it has an opening*". Despite the size of the result, an acknowledged ability to scale it to the correct size made it useable to the designer. Finally, when looking for cylindrical shapes, Participant P14 was returned a chair seat (e.g., Figure 10c). This result was identified as being potentially useful because reorientation could be used such that, "*worst case, I can flip it … if I don't find anything, I can work with this shape which is resembling something that I might be looking for*." Object transformations, including rescaling and reorientation, were thus identified as methods enabling the use of unexpected parts to fulfill designers' intended purposes.

R4.2.3. Designers satisfied for unexpected stimuli. A final reason designers expressed for accepting unexpected stimuli was as a result of satisficing for a part. Two distinct scenarios were observed: in the first, designers' search results included previously rejected parts. Encountering these may have strengthened the belief that a more relevant match did not exist in the database. Secondly, even when acknowledging that a result is "*not quite what I was looking for*" (P15), the result was accepted. These examples suggest that designers can tolerate an acceptable threshold of accuracy when using inspiration-retrieval tools.

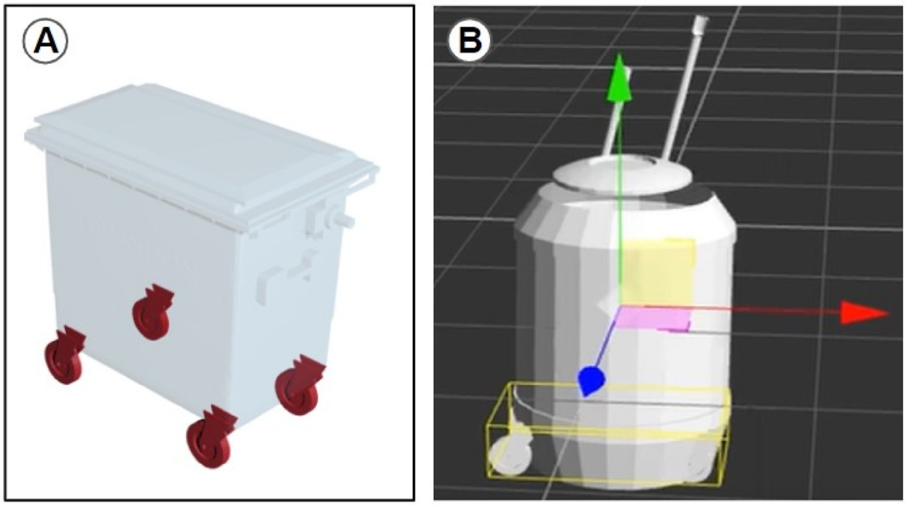

Figure 8 ***Example of unexpected results introducing an unanticipated desirable feature (P8)****:* ***(a)*** *Unexpected wheel results returned by search platform and* ***(b)*** *addition of part to P8's design*

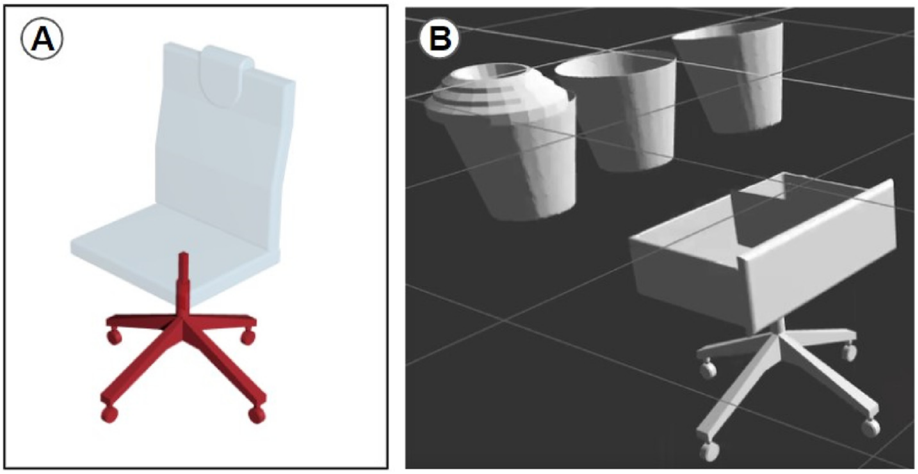

Figure 9 ***Example of unexpected results introducing an unanticipated desirable feature (P7)****:* ***(a)*** *Unexpected wheel results returned by search platform and* ***(b)*** *addition of part to P7's design*

3.2.3 Designers' rejection of unexpected results

The most frequent pathway designers followed was the rejection of unexpected search results, accounting for 134/235 searches. While beneficial outcomes of unexpected stimuli were observed, it is desirable for more results to meet expectations and be accepted, and thus important to uncover rationale for this pathway. Of these searches, 59 results were not evaluated with accompanying verbal data, but classified as unexpected if results were then rejected (as defined

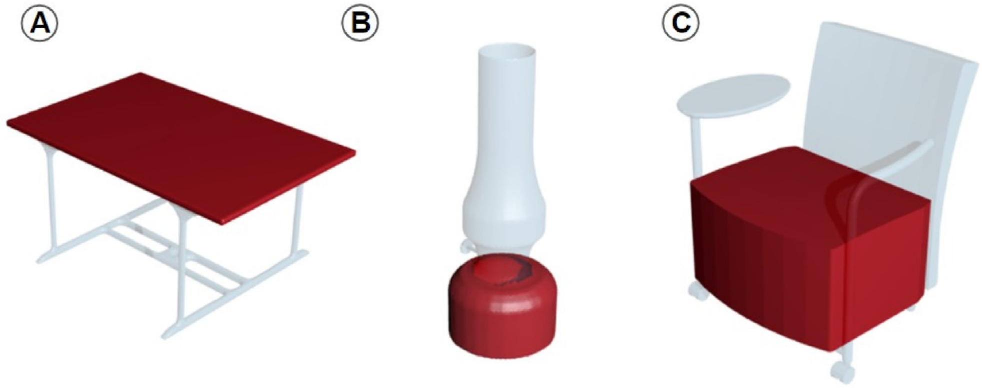

Figure 10 ***Examples of unexpected results that fulfill purposes of intentionally searched for parts****: **(a)** Tabletop scaled down to fit top of trashcan **(b)** Candle holder base scaled up to serve as can, and **(c)** Chair seat reoriented to container*

in Table 2). Of the remaining 75 searches, designers stated or described why the results did not meet expectations before not engaging with results further. When describing why results were unexpected and then rejected, two main reasons emerged, which can help improve AI-based support systems.

R4.3.*1. *Designers anticipated specific results in mind. Designers provided rationale for their evaluation of results as unexpected and rejection of results by indicating that their initial intention was not met. Most results were evaluated as not meeting the specific intention of the designer by being either "wrong" or "close", both prompting additional searches. In one notable example, when searching by keyword for a "trashcan", participant P5 stated "*Ok, it's not what I was thinking, but that is a trashcan, for sure*". Thus, even if the search provided a correct outcome, if a designer's goal is specific in their mind, results may still be rejected. This specificity of imagined results may influence the selection of results since, accounting for Result **R4.2.3**, designers were also observed to satisfice for and accept less desirable results.

R4.3.*2. *Limitations of platform and its expected use. While expectedness of results could be attributed to good platform performance (Result **R4.1.1**), unexpectedness could result from not understanding how the platform operates. Participant P8, for example, stated "*I can't really figure out how this is functionally similar or how the software determines that*" or for a different search, "*I'm trying to figure out why that might have happened*". Evaluation of retrieved results is connected to understanding how the platform functions and can impact how the examples provided are perceived and used. This finding is especially relevant when engaging with novel AI-based systems, which may not be familiar to users. Other reasons expressed by the designers in our study refer to specific features and limitations of the platform used, which may not be as generalizable. These include the platform's tendency to retrieve the same results multiple times (when previously rejected) or the missing support for general shapes and forms as opposed to specific objects.

4 Discussion

This paper investigates how designers search for inspirational stimuli when using an AI-enabled multi-modal search platform. In the design exploration task conducted, participants with either novice (graduate students) or expert (working professionals) levels of design experience searched for 3D-model parts using three modalities of search to inspire solutions to a given design challenge. By eliciting think-aloud descriptions of their interactions with the search platform, further insight into their definition, evaluation, and selection of the retrieved stimuli, and the rationale underlying these behaviors, are studied. Revisiting the research questions initially posed to introduce the aims of the present work, the main contributions made are summarized and discussed in this section.

4.1 Search input modalities result in different search outcomes

The first comparison made in this work is of the use of different search modalities to support search activities, behaviors, and pathways. Search activity was found to differ across designers, where keyword search was associated with significantly higher frequency than part and workspace searches. Differences in how designers evaluated search results can help explain the lower frequency of workspace searches made: across designers, workspace compared to keyword searches had a higher likelihood of being evaluated as unexpected. This difference can be ascribed to limitations in the search platform in recognizing the designer's search intent, as well as the designer's ability to define and expect what they were looking for when using a less intuitive search modality. In early observations about example or image-based search, Hearst (2009) identified a limitation in the searcher being required to know about the visual properties of the image searched for, which can limit search for new images. Similarly, searching with workspace inputs that rely on appearance similarity measures may produce results that are difficult to anticipate.

Through an examination of search pathways, we further demonstrate how the evaluation of workspace search results as unexpected is especially true for new searches. When continuing to search for a desired part, the same effect of modality on evaluation of results was not observed, such that neither continuing part nor workspace searches were significantly more likely to be unexpected. Continuing a search with any input may be useful during search. Sarkar and Chakrabarti discuss how stimuli referred to as "triggers" can influence designers' search of the solution space (Sarkar & Chakrabarti, 2008). Referencing O'Day and Jeffries (O'Day & Jeffries, 1993), one trigger that may motivate a switch in search strategy is the encounter with something that introduces a new way of thinking about the problem at hand Continued search using any input can facilitate encounters with stimuli that “trigger” new searches.

4.2 Expertise impacts designers’ search for inspirational stimuli

Secondly, we examined how expertise level may influence how designers search. While professionals and students were not found to differ by search activity, i.e., the frequency of use of keyword, part, and workspace searches, they did differ by search behaviors followed. Expertise is suggested not to affect how often search modalities are used, but how search results are evaluated and selected. Notably, students were found to be more likely to evaluate results as unexpected, and to ultimately reject more results from inclusion in their designs. These behaviors suggest that students may fixate more on finding their originally intended results and demonstrate less openness to incorporating unexpected parts into their design ideas. Students are expected to have less experience with design and working with AI-assisted design tools, which may make them more prone to relying on their own experience and internal stimuli (Gonçalves et al., 2016). Less experience also affects novice designers’ tendency to reflect on how inspiration sources can impact their designs, thereby limiting the adaption of unexpected stimuli to their designs (Gonçalves et al., 2013). These findings also reinforce Gonçalves et al.’s results on expert designers’ greater ability to absorb and adapt detailed information from stimuli compared to novices (2014), and Cross’s argument that experts more readily seek a diversity of information to support their design process (2004).

Through investigating specific search pathways, such as the relationship between how new vs. continuing searches were evaluated, professionals were found to evaluate more new search results as expected than students. This can be attributed to professional designers exhibiting broader expectations for parts, allowing them to consider more results as expected without continued search and exploration. This interpretation supports previous work by Gonçalves et al. (2014), Cross (2004), and Cai et al. (Cai, Do, & Zimring, 2010) that professional designers seek to extract detailed information from diverse inspirational sources. Thus, a relationship between their initial search inputs and the retrieved results may have been more immediately inferred. Our findings contrast professional designers’ broad expectations with novice designers’ relatively narrower expectations. Relatedly, Cai et al.’s findings suggest that novice designers found value in stimuli for their connection to familiar knowledge. If search results did not immediately meet expectations, designers’ ability to recognize the connection between retrieved results to their initial search input may have been limited. Students thus proceeded to conduct more continued searches, on average. While the aim of this work was to specifically investigate search processes, these findings can be more broadly applied to the role of expertise on the ability to use and extract meaning from inspirational design stimuli.

4.3 Rationale underlying less explored search pathways

An interesting finding in this paper was the uncovering of search results that were evaluated by designers as expected or unexpected. Think-aloud transcription data was examined to understand the rationale behind the evaluation of search results and the uses of unexpected stimuli. The evaluation of new search results as expected was linked to a positive assessment of the performance of the search platform itself or of specific features of the retrieved results. As Cascini et al. (2010) propose, the consideration of expected behavior of products is needed from both the perspectives of the product user and designer. As discovered in Result **R4.1.2**, initial fixation to specific part features or object contexts could importantly be overcome by adapting expectations. This may be especially true when working in a CAD environment, in contrast to a physical environment, where parts may be easily adjusted in scale and isolated from their original context.

Several examples from this study challenge whether the aim of the search platform should be to support the retrieval of inspirational stimuli that users interacting with it expect. Indeed, desirable design outcomes, such as the introduction of new design features during idea generation, can occur as a result of the discovery of initially unintended search results. Given the large proportion of results that were not what designers expected (156/235), 135 of which were rejected and unused towards continued idea generation, one area for further exploration is how to encourage designers to similarly leverage information when derived unexpectedly. Through examples underlying Result **R4.2.2**, object transformations were found to assist designers' ability to discover usefulness from unexpected sources of inspiration. Reorientation has specifically been proposed in prior research as a strategy to aid creative object reuse (Olteteanu & Shu, 2018). Damen and Toh (Damen & Toh, 2019) have found that information designers evaluate as helpful is not necessarily used during idea generation. They additionally suggest that designers are able to effectuate readily available information sources (i.e., make use of existing resources), even those that may not evidently influence an outcome (Damen & Toh, 2021). These strategies may help overcome the motivations designers expressed for rejecting unexpected results, explored in Sec. 3.2.3, by overcoming design tool limitations and specific expectations held in mind. These findings recommend that, while continuing to improve computational definitions of similarity relationships according to designers' needs and expectations is important, methods to promote designers' adaptation of expectations and ready use of available stimuli can also be beneficial.

4.4 Limitations and future work

This paper presents the results of a design exploration task in which participants, consisting of designers with a range of design experience, interacted with a multi-modal search platform. Methodologically, three main limitations and opportunities for future work exist. Firstly, across two studies (the first described in prior work (Kwon et al., 2022) and the second in the present), participants of both novice and expert level design experience found the search platform's novel modalities difficult to use. Despite some observed benefits of encountering unexpected results, continued work in the development of this and other search platforms can be done towards improving retrieval accuracy. This may be achieved through the exploration of different sets of inspirational stimuli and definitions of appearance and function-based similarity that are more intuitive to designers. More generally, the results presented in this paper, especially regarding search activities and behaviors, may be heavily influenced by features of the search platform used and the design stimuli returned. Despite this limitation, we present findings that can be adaptable to use of other design tools, such as comparisons between novice and expert designers. Through investigation of pathways, we also explore how search results are engaged irrespective of their content. Secondly, in the design exploration task completed, approx. 15 min. were allotted to search for parts. While most participants reached an impasse in their search and design activity by this time, prior work by Moss et al. (2011) has shown how incidental information provided at the point of impasse can be beneficial for problem solving. Continued design ideation after receiving new stimuli following an impasse can therefore be studied. Finally, participants were tasked with searching for parts to inspire solutions to the given design problem. These instructions were specified to promote search activity, which was the focus of the present work, rather than to encourage and assess idea generation. Thus, the extent to which designers worked on developing a single or multiple final design ideas varied, limiting our ability to assess the impact of stimuli on design activity. Future work can link how the stimuli discovered as a result of different search processes and modalities can contribute to specific design outcomes. For instance, unexpected search results may lead to more novel design features.

5 Conclusion

The main contribution made by this work is to deepen an understanding of how designers search for inspirational stimuli. This aim was achieved through a think-aloud design exploration task where designers used an AI-enabled multi-modal search platform developed for this task. Search modality and designer expertise were factors found to influence the process of searching for design inspiration. By contrasting the uses of a more familiar mode of search (by keyword) with more novel modes of search (by 3D-model part and 3D-modeling workspace inputs), we found that modality affected how designers interacted with retrieved results. When searching by keyword, more results were expected than workspace search results, and accepted than part search results. While these differences can be partially attributable to limitations of the current system, we suggest that designers may have difficulty defining their search intent and forming expectations for results when searching based on visual and functional relationships. Improved understanding of how designers perceive and seek inspiration in terms of these less explored modalities can help support the further development of multi-modal design tools. The role of expertise was also examined by comparing behaviors of student and professional designers. Professionals generally had broader expectations for search outcomes than students, who tended to reject and evaluate more results as not meeting their initial expectations. Increased design expertise was associated with greater openness to potential sources of inspiration and reduced fixation to intended results. This difference reveals both how expertise influences the use of increasingly prevalent AI-enabled design tools as well as how the process of becoming inspired may engage prior experience. Search modality and expertise were factors found to impact design behavior when engaging with an AI-enabled platform for inspiration discovery. Our study supports continued research to understand and improve designers' interactions with AI-based design tools and the relationship between the inspiration designers seek and effectively use.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

This work was supported by the National Science Foundation under grant 2145432 – CAREER. The authors would like to thank Dr. Forrest Huang for his contribution to the multi-modal search platform employed in this work.

References

Arora, R., Darolia, I., Namboodiri, V. P., Singh, K., & Bousseau, A. (2017). SketchSoup: Exploratory ideation using design sketches. *Computer Graphics Forum, 36*, 302–312.

Athukorala, K., Głowacka, D., Jacucci, G., Oulasvirta, A., & Vreeken, J. (2016). Is exploratory search different? A comparison of information search behavior for exploratory and lookup task. *J. the Association for Information Science and Technology, 67*, 2645–2651.

Biskjaer, M. M., Christensen, B. T., Friis-Olivarius, M., Sille, J., Abildgaard, J., Lundqvist, C., et al. (2020). Fixation or inspiration? A meta-analytic review of the role of examples on design processes. *International Journal of Technology and Design Education, 30*, 101–125.

Borgianni, Y., Rotini, F., & Tomassini, M. (2017). Fostering ideation in the very early design phases: How textual, pictorial and combined stimuli affect creativity. *Proc. of the 21st International Conference on Engineering Design, ICED17*, 139–148.
Botella, M., Zenasni, F., & Lubart, T. (2018). What are the stages of the creative process? What visual art students are saying. *Frontiers in Psychology, 9*.
Cai, H., Do, E. Y-L., & Zimring, C. M. (2010). Extended linkography and distance graph in design evaluation: An empirical study of the dual effects of inspiration sources in creative design. *Design Studies, 31*, 146–168.
Cascini, G., Del Frate, L., Fantoni, G., & Montagna, F. (2010). Beyond the design perspective of gero's FBS framework. In J. S. Gero (Ed.), *Design Computing and Cognition '10* (pp. 77–96), Springer.
Chan, J., Dow, S. P., & Schunn, C. (2015). Do the best design ideas (really) come from conceptually distant sources of inspiration? *Design Studies, 36*, 31–58.
Chan, J., Fu, K., Schunn, C., Cagan, J., Wood, K., & Kotovsky, K. (2011). On the benefits and pitfalls of analogies for innovative design: Ideation performance based on analogical distance, commonness, and modality of examples. *Journal of Mechanical Design, 133*, 081004.
Chaudhuri, S., & Koltun, V. (2010). Data-driven suggestions for creativity support in 3D modeling. *ACM Transactions on Graphics, 29*, 1–10.
Cross, N. (2004). Expertise in design: An overview. *Design Studies, 25*, 427–441.
Damen, N., & Toh, C. (2019). Looking for inspiration: Understanding the information evaluation and seeking behavior of novice designers during creative idea generation. *Proc. of the Design Society: International Conference on Engineering Design, 1(1)*, 1793–1802.
Damen, N., & Toh, C. (2021). Reflections on designing in the wild: How theories of design information manifest in practice. In *Proc. ASME 2021 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, Virtual, Online. Aug. 17–19* V006T06A041.
Do, E. Y-L (2005). Design sketches and sketch design tools. *Knowledge-Based Systems, 18*, 383–405.
Eckert, C., & Stacey, M. (2000). Sources of inspiration: A language of design. *Design Studies, 21*, 523–538.
Fu, K., Cagan, J., Kotovsky, K., & Wood, K. (2013a). Discovering structure in design databases through functional and surface based mapping. *Journal of Mechanical Design, 135*, 031006.
Fu, K., Chan, J., Cagan, J., Kotovsky, K., Schunn, C., & Wood, K. (2013b). The meaning of "Near" and "Far": The impact of structuring design databases and the effect of distance of analogy on design output. *Journal of Mechanical Design, 135*, 021007.
Gentner, D. (1983). Structure-mapping: A theoretical framework for analogy. *Cognitive Science, 7*, 155–170.
Gentner, D., & Markman, A. B. (1997). Structure mapping in analogy and similarity. *American Psychologist, 52*, 45–56.
Goel, A. K., Vattam, S., Wiltgen, B., & Helms, M. (2012). Cognitive, collaborative, conceptual and creative — four characteristics of the next generation of knowledge-based CAD systems: A study in biologically inspired design. *Computer-Aided Design, 44*, 879–900.
Gonçalves, M., Cardoso, C., & Badke-Schaub, P. (2013). Through the looking glass of inspiration: Case studies on inspirational search processes of novice designers. In *Proc. of the IASDR conference 2013, Tokyo, Japan, Aug. 26-30*.

Gonçalves, M., Cardoso, C., & Badke-Schaub, P. (2014). What inspires designers? Preferences on inspirational approaches during idea generation. *Design Studies, 35*, 29–53.

Gonçalves, M., Cardoso, C., & Badke-Schaub, P. (2016). Inspiration choices that matter: The selection of external stimuli during ideation. *Design Science, 2*.

Goucher-Lambert, K., & Cagan, J. (2019). Crowdsourcing inspiration: Using crowd generated inspirational stimuli to support designer ideation. *Design Studies, 61*, 1–29.

Goucher-Lambert, K., Gyory, J. T., Kotovsky, K., & Cagan, J. (2020). Adaptive inspirational design stimuli: Using design output to computationally search for stimuli that impact concept generation. *Journal of Mechanical Design, 142*, 091401.

Goucher-Lambert, K., Moss, J., & Cagan, J. (2019). A neuroimaging investigation of design ideation with and without inspirational stimuli—understanding the meaning of near and far stimuli. *Design Studies, 60*, 1–38.

Han, J., Shi, F., Chen, L., & Childs, P. R. (2018). "The combinator–A computer-based tool for creative idea generation based on a simulation approach". *Design Science, 4*.

Hearst, M. (2009). *Search user interfaces*. Cambridge University Press.

Herring, S. R., Chang, C. C., Krantzler, J., & Bailey, B. P. (2009). "Getting inspired! Understanding how and why examples are used in creative design practice". In *Proc. Of SIGCHI Conference on human Factors in computing systems, CHI'09* (pp. 87–96). New York, NY, USA: Association for Computing Machinery.

Hua, M., Han, J., Ma, X., & Childs, P. (2019). "Exploring the effect of combinational pictorial stimuli on creative design performance". *Proc. of the Design Society: International Conference on Engineering Design, 1*(1), 1763–1772.

Jansson, D., & Smith, S. (1991). Design fixation. *Design Studies, 12*, 3–11.

Jiang, S., Hu, J., Wood, K. L., & Luo, J. (2022). Data-driven design-by-analogy: State-of-the-Art and future directions. *Journal of Mechanical Design, 144*, 020801.

Jiang, S., Luo, J., Ruiz-Pava, G., Hu, J., Christopher, L., & Magee. (2021). Deriving design feature vectors for patent images using convolutional neural networks. *Journal of Mechanical Design, 143*, 061405.

Jiang, S., Luo, J., Ruiz-Pava, G., Hu, J., & Magee, C. L. (2020). A convolutional neural network-based patent image retrieval method for design ideation. In *Proc. ASME 2020 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, Virtual, Online. Aug. 17–19* V009T09A039.

Kazi, R. H., Grossman, T., Cheong, H., Hashemi, A., & Fitzmaurice, G. (2017). DreamSketch: Early stage 3D design explorations with sketching and generative design. In *Proc. Of the 30th annual ACM symposium on user interface software and technology, UIST '17* (pp. 401–414). New York, NY, USA: Association for Computing Machinery.

Kittur, A., Yu, L., Hope, T., Chan, J., Lifshitz-Assaf, H., Gilon, K., et al. (2019). Scaling up analogical innovation with crowds and AI. *Proceedings of the National Academy of Sciences, 116*, 1870–1877.

Kwon, E., Huang, F., & Goucher-Lambert, K. (2022). Enabling multi-modal search for inspirational design stimuli using deep learning. *Artificial Intelligence for Engineering Design, Analysis and Manufacturing, 36*, E22.

Linsey, J. S., Clauss, E. F., Kurtoglu, T., Murphy, J. T., Wood, K. L., & Markman, A. B. (2011). An experimental study of group idea generation

techniques: Understanding the roles of idea representation and viewing methods. *Journal of Mechanical Design, 133*, 031008.
Linsey, J. S., Wood, K. L., & Markman, A. B. (2008). Modality and representation in analogy. *Artificial Intelligence for Engineering Design, Analysis and Manufacturing, 22*, 85–100.
Lucero, A. (2012). Framing, aligning, paradoxing, abstracting, and directing: How design mood boards work. Proc. of the designing interactive. In *systems conference, DIS'12* (pp. 438–447). New York, NY, USA: Association for Computing Machinery.
Luo, J., Sarica, S., & Wood, K. L. (2021). Guiding data-driven design ideation by knowledge distance. *Knowledge-Based Systems, 218*, 106873.
Malaga, R. A. (2000). The effect of stimulus modes and associative distance in individual creativity support systems. *Decision Support Systems, 29*, 125–141.
Marchionini, G. (2006). "Exploratory search: From finding to understanding". *Communications of the ACM, 49*, 41–46.
Menezes, A., & Lawson, B. R. (2006). How designers perceive sketches. *Design Studies, 27*, 571–585.
Moss, J., Kotovsky, K., & Cagan, J. (2011). "The effect of incidental hints when problems are suspended before, during, or after an impasse". *Journal of Experimental Psychology: Learning, Memory, and Cognition, 37*, 140–148.
Murphy, J., Fu, K., Otto, K., Yang, M., Jensen, D., & Wood, K. (2014). "Function based design-by-analogy: A functional vector approach to analogical search.". *Journal of Mechanical Design, 136*, 101102.
Nagel, J. K., & Stone, R. B. (2012). A computational approach to biologically inspired design. *Artificial Intelligence for Engineering Design, Analysis and Manufacturing, 26*, 161–176.
O'Day, V. L., & Jeffries, R. (1993). Orienteering in an information landscape: How information seekers get from here to there. In *Proceedings of the INTERACT '93 and CHI '93 Conference on Human Factors in Computing Systems, CHI '93* (pp. 438–445). Association for Computing Machinery.
Olteteanu, A. M., & Shu, L. H. (2018). Object reorientation and creative performance. *Journal of Mechanical Design, 140*, 031102.
Sarkar, P., & Chakrabarti, A. (2008). The effect of representation of triggers on design outcomes. *Artificial Intelligence for Engineering Design, Analysis and Manufacturing, 22*, 101–116.
Sartori, J., Pal, U., & Chakrabarti, A. (2010). A methodology for supporting 'transfer' in biomimetic design. *Artificial Intelligence for Engineering Design, Analysis and Manufacturing, 24*, 483–506.
Siangliulue, P., Chan, J., Gajos, K. Z., & Dow, S. P. (2015). Providing timely examples improves the quantity and quality of generated ideas. In *In Proc. of the 2015 ACM SIGCHI Conference on Creativity and Cognition, C&C '15* (pp. 83–92). Association for Computing Machinery.
Sio, U. N., Kotovsky, K., & Cagan, J. (2015). Fixation or inspiration? A metaanalytic review of the role of examples on design processes. *Design Studies, 39*, 70–99.
Stemler, S. E. (2004). A comparison of consensus, consistency, and measurement approaches to estimating interrater reliability. *Practical Assessment, Research and Evaluation, 9*, 4.
Sutcliffe, A., & Ennis, M. (1998). Towards a cognitive theory of information retrieval. *Interacting with Computers, 10*, 321–351.
Toh, C. A., & Miller, S. R.. (2014). The impact of example modality and physical interactions on design creativity. *Journal of Mechanical Design, 136*, 091004.

Tseng, I., Moss, J., Cagan, J., & Kotovsky, K. (2008). The role of timing and analogical similarity in the stimulation of idea generation in design. *Design Studies, 29*, 203–221.

Vasconcelos, L. A., Cardoso, C. C., Sääksjärvi, M., Chen, C-C., & Crilly, N. (2017). Inspiration and fixation: The influences of example designs and system properties in idea generation. *Journal of Mechanical Design, 139*, 031101.

Wallace, S., Le, B., Leiva, L. A., Haq, A., Kintisch, A., Bufrem, G., et al. (2020). *"Sketchy: Drawing Inspiration from the Crowd." Proc. of the ACM on Human-Computer Interaction, 4*, 1–27.

Zhang, Z., & Jin, Y. (2020). An unsupervised deep learning model to discover visual Similarity Between Sketches for Visual Analogy Support. In *Proc. ASME 2020 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, Virtual, Online. Aug. 17–19* V008T08A003.

Zhang, Z., & Jin, Y. (2021). Toward computer aided visual analogy support (CAVAS): Augment designers through deep learning. In *Proc. ASME 2021 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, Virtual, Online. Aug. 7–19* V006T06A057.

Vattam, S., Wiltgen, B., Helms, M. E., Goel, A. K., & Yen, J. (2011). DANE: Fostering creativity in and through biologically inspired design. In T. Taura, & Y. Nagai (Eds.), *Design creativity 2010* (pp. 115–122). London: Springer.