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INVESTIGATING THE ROLES OF EXPERTISE AND MODALITY IN DESIGNERS' SEARCH FOR INSPIRATIONAL STIMULI

Elisa Kwon
Dept. of Mechanical Engineering
University of California, Berkeley
Berkeley, CA, USA
Email: elisa.kwon@berkeley.edu

Vivek Rao
Dept. of Mechanical Engineering
University of California, Berkeley
Berkeley, CA, USA
Email: vivek.rao@berkeley.edu

Kosa Goucher-Lambert
Dept. of Mechanical Engineering
University of California, Berkeley
Berkeley, CA, USA
Email: kosa@berkeley.edu

ABSTRACT

Designers can benefit from inspirational stimuli when presented during the design process. Encountering external stimuli can also lead designers to negative design outcomes by limiting exploration of the design space and idea generation. Prior work has investigated how specific features of inspirational stimuli can be beneficial or harmful to designers. However, the processes designers use to search for and discover inspirational stimuli leading to these outcomes are less known. The objective of this work is thus to better understand how designers search for inspirational design stimuli. Specifically, we investigate how factors such as designer expertise and search modality (e.g., text vs. visual-based) impact both explicit and implicit features during the search for design stimuli. A cognitive study was completed by novice and expert designers (seven students and eight professionals), who searched for design stimuli using a novel multi-modal search platform while following a think-aloud protocol. The multi-modal search platform enabled search using text and non-text inputs, and provided design stimuli in the form of 3D-model parts. This work presents methods to describe search processes in terms of three levels: activities, behaviors, and pathways, as defined in this paper. Our findings determine that design expertise and search modality influence search behavior. Illustrative examples are presented and discussed of search processes leading designers to both negative and beneficial outcomes, such as designers fixating on specific results or benefiting unexpectedly from unintentional inspirational stimuli. Overall, this work contributes to an improved understanding of how designers search for inspiration, and key factors influencing these behaviors.

1 INTRODUCTION

Designers rely on becoming inspired to formulate creative ideas for a given design problem. Inspiration has been defined as the process where a stimulus influences the thought process used towards problem framing or solution generation [1]. Inspirational design stimuli have been demonstrated to assist designers with developing design solutions with improved characteristics such as greater novelty, feasibility, or innovativeness [2–4]. While external stimuli can be beneficial for idea generation, they can also contribute to a more constrained exploration of the design space. They can lead, for instance, to design fixation, where designers unconsciously focus on particular aspects of an object or task, limiting their idea generation [5]. It is therefore important to understand what determines whether a given stimulus leads a designer to beneficial or harmful design outcomes.

While this question has been explored from the perspective of features of inspirational stimuli, it is also relevant to consider what designers actively search for to further their designs, and how they are inspired by the external stimuli encountered. The main aim of this paper is to study how designers search for inspirational design stimuli, through the following research questions:

1. RQ1: How can designers' inspirational search processes be understood in terms of discrete actions?
2. RQ2: How does experience level shape how designers seek inspiration?
3. RQ3: How does designers' use of various search modalities shape their search for inspiration?

This work examines the roles of expertise and search modality on search for inspirational stimuli through a cognitive study. In this study, novice and expert designers (seven students, eight professionals) interacted with a multi-modal search platform to complete a design task while following a think-aloud protocol. Addressing **RQ1**, these interactions are explored using a framework developed to classify search behavior. This framework describes inspirational search in terms of discrete actions, including how designers (1) define new and continued searches, (2) evaluate search results as meeting their expectations, or not and (3) select search results to be accepted into or rejected from their designs. Search behaviors related to designers' expertise level and use of search modalities are identified to answer **RQ2** and **RQ3**. To preface the experimental design and results of this study, prior work is reviewed on inspirational design stimuli, relevant design support tools, and cognition underlying search behavior.

1.1 Inspirational design stimuli

An understanding of the characteristics of external stimuli that make them useful for designers can provide insight into why, when, and how certain stimuli are actively searched for during the design process. Prior work has identified many features of external stimuli as impactful on design outcomes including analogical distance, representation modality, timing of delivery, and level of detail or concreteness (e.g., [2, 6–8]). First, analogical distance, referring to the proximity of the given stimulus to the designer's current problem or design space, is one factor that can be influential on design ideation. For example, far-field stimuli can lead to idea novelty [2, 9], compared to near-field stimuli that have been shown to improve feasibility, relevance, and idea quantity [4, 10, 11].

A second factor is the representation modality of inspirational stimuli as presented to designers. Explored in past work are the impact of visual stimuli compared to physical stimuli [12], or in combination with textual stimuli [13], or other images [14]. Combining visual stimuli with semantic elements has been found to help designers generate creative ideas [15] and increase idea novelty [6]. Our previous work presented 3D-model parts to designers as stimuli based on chosen input modalities and analogical distance parameters [16]. The results of this work suggested that the modality used to search for inspirational stimuli affects what is discovered and how it is used. Stimuli modality has been shown to vary in effectiveness based on designers' experience levels: Goncalves et al. 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 [17]. The authors argue that 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.

A third factor influencing the impact of inspirational stimuli on design ideation is when in the design process it is presented to the designer. Once a designer has started to generate ideas for a design task, inspirational stimuli is known to be more effective, than if provided before ideation [7]. The current state of the designer is also important to consider, since stimuli received when they are stuck, as opposed to at predefined intervals, can help produce more ideas [18].

A final factor to consider is the level of detail or concreteness of the stimulus. Descriptions of design stimuli can be more general vs. domain-specific [6] or constitute concrete design examples vs. abstract system properties [19]. 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 [8].

These factors including analogical distance, representation modality, timing, and detail, demonstrate how external stimuli can be differently effective on the design process. However, different from many prior studies on inspirational design stimuli, identifying how features of these examples influence design outcomes is not the main focus of this work. Instead, the behaviors and processes employed by designers to search for inspirational stimuli is studied. Search behavior will be investigated in the present work by observing designers' use of an AI-enabled search platform. Thus, the development of and interactions with design support tools in prior work is next reviewed.

1.2 Design support tools for inspirational stimuli retrieval

The discovery of inspirational stimuli is a process that can be supported by AI-enabled design support tools. 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 AI-enabled methods and tools have been proposed to provide inspiration to designers through external stimuli, applied in contexts like biologically inspired design [20–23], and using sources of designs such as patent databases [3, 24, 25] or crowd-sourced solutions [9, 26]. 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 multimodal 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 [27, 28]. Image-based search using visual similarity can also extract relevant examples from sources such as patent documents [29, 30]. 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 [31]. SketchSoup inputs rough sketches and generates new sets of sketches, which can inspire further concept generation [32]. 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 [33]. Design support tools that recognize these inputs can be beneficial since sketching itself is a process that can assist idea formation [34]. In general, interactions with visual stimuli can help trigger new mental images and thus new ideas for design [35]. 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 [36].

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 design stimuli. Towards designing these tools and interpreting the behaviors that interactions within these systems represent, the cognitive processes involved in how designers search also need to be better understood.

1.3 Cognitive processes used in inspiration search

To gain insight into how designers search for stimuli to support their design idea generation, search behavior and cognitive processes involved when searching for inspiration are reviewed. Especially relevant are the roles of active and passive search processes when looking for inspiration [1]. The intentional search for a stimulus to fulfill a specific goal is referred to as active search, while passive search is a process used when the search goal is not clearly defined [37]. Passive search is attributed to the random discovery of unexpected results, which can provide beneficial sources of inspiration [38]. Information retrieval theory differently defines exploratory and lookup behaviors [39]. Exploratory search promotes knowledge acquisition and supports evolving needs, compared to lookup search activities which are used to meet precise search goals [40]. Exploratory search is related to the examination of more results than lookup search [41]. 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.

Another factor shaping cognitive processes in design is the experience level of the designer, which has implications for inspirational search. Goncalves et al., drawing on Cross's work, suggested that while novices lack a clear structure to guide their design activities, experienced designers are able to analyze a problem in detail and seek a diversity of information that might support their process [17,42]. While this is not explicitly linked to inspirational search, Cross's assessment applies across design activities broadly. Wallace et al., in examining students' desire for inspiration during a design sketching exercise, found that students sought and were influenced by sketches that were near-finished, highly detailed, and carefully drawn [43]. Cai et al. found that novices and experts valued sketch stimuli, but for different reasons: a novice designer valued sketch stimuli for their real-life resemblance and connection to familiar knowledge, while experienced designers found value in the contextual information offered by sketches that allowed them to shift focus [44].

This work extends on prior research in two ways. First, a tool is presented that affords active (intentional) search strategies for inspirational 3D-model stimuli, but offers discovery of unexpected results enabled by AI, representing elements of passive search. Extending from Goncalves et. al, then, this work offers deeper insight into the *process* by which designers assess and adopt inspirational search results in an engineering design context. Second, extending on Cross, Wallace et. al's, and Cai et al.'s work, this work examines differences in inspirational search and adoption between professional and novice designers, here using 3D-model parts as the inspirational medium.

2 METHODS

In this study, participants completed a design task using a multi-modal search tool. In this section, the details of the participants who completed the task, the design tool used in the task, and the design task conducted are described. The approach taken to analyze the results presented in this paper is also introduced.

2.1 Participant information

Participants were recruited 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 1 year 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-hour study, detailed below. This study was approved by the Institutional Review Board (IRB) at the University of California, Berkeley.

TABLE 1. **CAD experience of student and professional designers**

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

2.2 AI-enabled multi-modal search platform

The study was facilitated using Zoom, which enabled screen and audio recording of participants' progress. Screen recordings were used to capture how participants engaged with an AI-enabled design tool. 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 26671 3D-model assemblies. The platform is further described in prior work by Kwon et al. [16].

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 selected part and workspace inputs, respectively, by visual and functional similarity. For each search made, three parts are retrieved and shown in the user interface. Examples of keyword and part searches and results in the interface are shown in **Fig. 1a, b**.

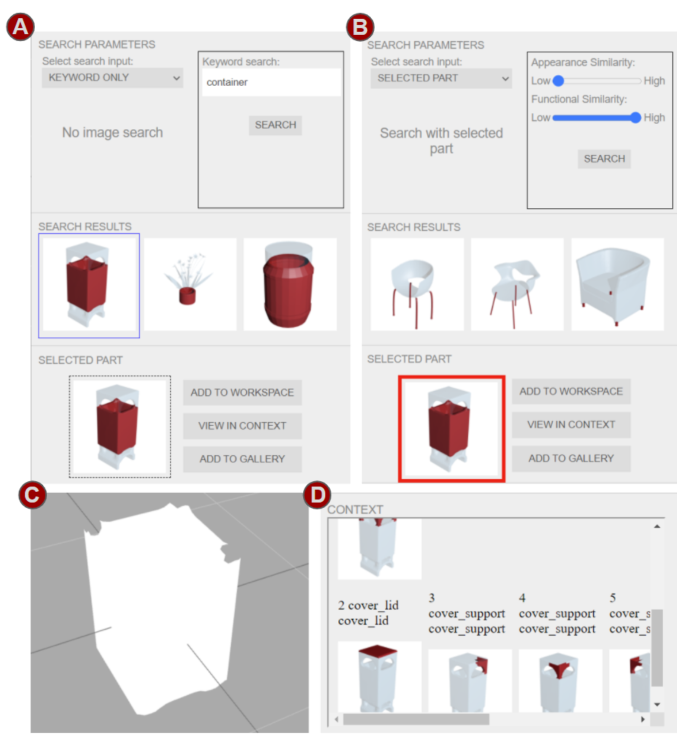

FIGURE 1. **Features of multi-modal search platform:** **(a)** Keyword search and results for "container"; **(b)** Part search with selected container result; **(c)** Container added to 3D workspace; **(d)** Container viewed in context

The interface also enables 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. Use of these features for a keyword search result for "container" is also shown in **Fig. 1c, 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 is available to access and select parts from at any point. For any given search result, none to all actions can be performed, in any order.

2.3 Design task and think-aloud protocol instructions

The study objective presented to designers was to use the multi-modal search interface 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 design task was completed without think-aloud instructions, these prompts were specified to elucidate motivations behind previously observed search behavior during the task. In the following 30 min., participants engaged in a semi-structured interview regarding their experience using AI-enabled technologies. These results are not explicitly discussed in this work, which focuses on the results of the design task.

2.4 Analysis of design task and think-aloud data

The main approach taken to analyze results from this study is to examine three levels of search: activities, behaviors, and pathways. The relationships between these search levels are summarized in **Fig. 2**. Search activities describe how designers conducted multi-modal searches. Search behaviors are extracted from design task data, including the use of the multi-modal search platform and accompanying think-aloud data. Search pathways are used to discuss how search behaviors are related and lead to specific design outcomes.

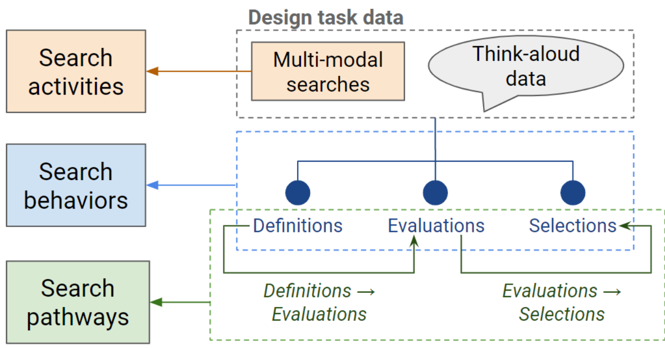

FIGURE 2. Overview of relationships between three levels of search examined in results: activities, behaviors, and pathways.

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

Secondly, to abstract and classify search behaviors from discrete task and think-aloud data, a framework was developed. This framework is an extension from Goncalves et al.'s description of the inspirational 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 [45]. 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 the 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, suggesting that the developed coding framework was relatively consistent across coders.

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: Result matches 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: Result does 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: Result is 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: Result is 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)***

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 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.

Lastly, search pathways are explored in the present analysis to link related search behaviors. For a given search, designers follow pathways between defining and evaluating searches and evaluating and selecting parts to incorporate into designs. 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 [1].

3 RESULTS AND DISCUSSION

In this section, the results of the design task are presented and discussed. Addressing the research questions posed initially, these results focus on:

1. Describing search for inspiration in terms of search activities, behaviors, and pathways
2. Comparing how designers with different levels of design expertise search for inspiration
3. Comparing the influence of text and non-text search modalities on search for inspiration.

Following the approach detailed in the previous section, results related to search activities, behaviors, and pathways are next presented. For each search level, findings are discussed in terms of differences between how expert compared to novice designers search for inspiration using text and non-text search modalities. Insights gained from the present work and proposed future work are presented.

3.1 Search activities: Overview of how designers use multi-modal search inputs

To describe how designers used the search platform throughout the task, frequencies of use of each search type are first computed. Designers were provided with guidelines to conduct five of each search type (keyword, part, and workspace), which were not strictly enforced during the task to allow designers to freely use the search types in any order.

Professionals and students do not differ by use of search types. As demonstrated in **Fig. 3**, Mann-Whitney U test results reveal no significant difference between the proportions of keyword (U=24.0, p=0.34), part (U=28.0, p=0.48), and workspace (U=27.0, p=0.48) searches made by professionals and students.

Most searches are made by keyword. **Figure 3** also shows that search frequency differs by type (χ^2 (2, N=235) = 101.37, $p < 0.001$), irregardless of experience level. In total, more keyword (149) than part (58) and workspace (28) searches were made across designers.

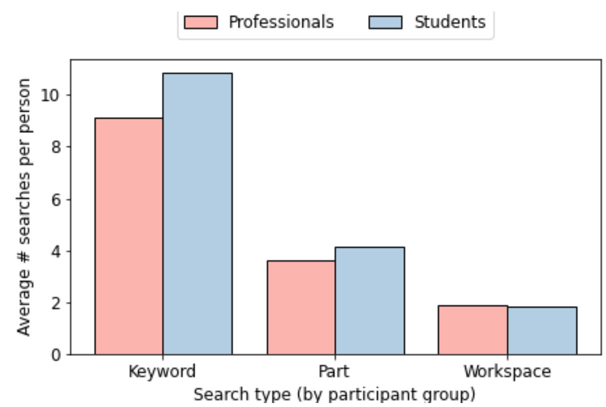

FIGURE 3. **Average (per person) frequency of search type use: Comparison between professionals (n=8) and students (n=7)**

These results suggest that student and professional designers do not significantly differ in the modality of search for inspiration they engage when using the search platform. Interestingly, both students and professionals used workspace searches the least, despite the workspace search being the most comparatively novel feature of the tool. This may suggest that when intentionally searching for inspiration, designers of all experience levels more readily use familiar search modalities to begin their search process. This presents an important consideration in the design of multi-modal inspirational search tools for engineering design. In the next section, search behaviors of professionals and students are investigated, as well as how they are related to the use of text and non-text search types.

3.2 Search behaviors: Examination of designers' search definitions, evaluations, and selections

Using the classification scheme for search behaviors established in **Table 2**, differences between how professionals and students define, evaluate, and select searches are first investigated. The relative proportions of searches made by each designer that were new vs. continuing, and returned results that were evaluated as expected vs. unexpected, and accepted vs. rejected were computed. Average values of individual proportions of search behaviors across participant groups are presented in **Table 3**.

TABLE 3. **Comparison of average proportions (%) of search behaviors by professionals vs. students:** Mann-Whitney U test results

	Participants		U-test result	
Behavior (level)	Professionals	Students	U	p
Definition (New)	45.30%	35.59%	13.0	**0.047**
Evaluation (Expected)	41.03%	27.12%	12.5	**0.040**
Selection (Accept)	43.59%	29.6%	8.0	**0.012**

Professionals and students use different search behaviors. To assess whether there are differences in proportions of each behavior between groups, Mann-Whitney U tests were conducted. Professionals and students are observed to differ by how searches were defined (U=13.0, p=0.047), evaluated (U=12.5, p=0.040), and selected (U=8.0, p=0.012). Students, when compared to professionals, conducted more consecutive continued searches for parts, evaluated more results as unexpected, and rejected more results from their final designs. These behaviors can be linked broadly to design fixation, but instead of fixating on aspects of an external solution, an adherence to their initial ideas and internally imagined parts may occur. 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 [1]. 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 [45]. These findings also reinforce Goncalves et al.'s results on expert designers' greater ability to absorb and adapt detailed information from stimuli compared to novices [17], and Cross's argument that experts more readily seek a diversity of information to support their process [17, 42].

To compare how text and non-text (part and workspace) search types are related to each search behavior, a similar analysis was performed. **Table 4** reports the average proportion of text and non-text searches made by designers that were new, and resulted in expected and accepted results.

More non-text searches were unexpected. When comparing the use of text and non-text search inputs, no significant difference is observed when used to define new vs. continued searches (U=110.5, p=0.48) or in returning results that were accepted or rejected (U=87.5, p=0.15). Searches made using text and non-text inputs do differ by whether designers evaluated the returned results as expected or not, where more non-text results were considered unexpected (U=67.5, p=0.032). Across participant groups, results returned using non-text compared to text searches were more likely not to match their expectations.

It is notable that no difference between new search definition was found between text and non-text searches. Designers are known to rely on random active search processes to discover inspiring stimuli when a search intention exists, but a keyword

TABLE 4. **Comparison of average proportions (%) of search behaviors from text vs. non-text searches:** Mann-Whitney U test results

	Search types		U-test result	
Behavior (level)	Text	Non-text	U	p
Definition (New)	40.94%	39.53 %	110.5	0.48
Evaluation (Expected)	39.60%	24.42%	67.5	**0.032**
Selection (Accept)	40.94%	29.07%	87.5	0.15

to conduct the search does not [1]. Designers' use of non-text inputs to formulate new searches demonstrates that this modality may help achieve the gap between intentional search and uncertainty of what to search for. The finding that more non-text search results were unexpected may reflect that designers did not know what to expect. 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 finding may potentially explain results in **Fig. 3**, 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 these search modalities to better meet designers' expectations.

3.3 Search pathways: Qualitative exploration of relationships between search behaviors

To further understand how search definitions, evaluations, and selections are related, a qualitative exploration of pathways between search behaviors is presented. The pathways described in this section link search definitions with evaluations and evaluations with selections. Sankey diagrams in **Fig. 4** are used to demonstrate the proportion of searches related to each pathway.

In **Fig. 4a, c**, the average number of searches per designer in each group is depicted, to account for group size differences. **Figure 4b, d** shows the total number of searches made using text and non-text inputs. These results are supported by illustrative examples from the design task, shown in **Table 5**. Comparisons are made between search pathways followed by professionals vs. students and that involve searches with text vs. non-text inputs.

Professionals evaluate more new search results as expected than students. First examining the role of expertise in definition-evaluation pathways, new and continuing searches are differently made and evaluated by professionals and students. Shown in **Fig. 4a**, two results are salient. First, a higher proportion of searches by students are continuing than new. Second, **Fig. 4a** emphasizes that professionals find that more new searches provide expected results than students. On average per participant, professionals evaluated 3.4 new searches as expected, compared to 1.25 by students.

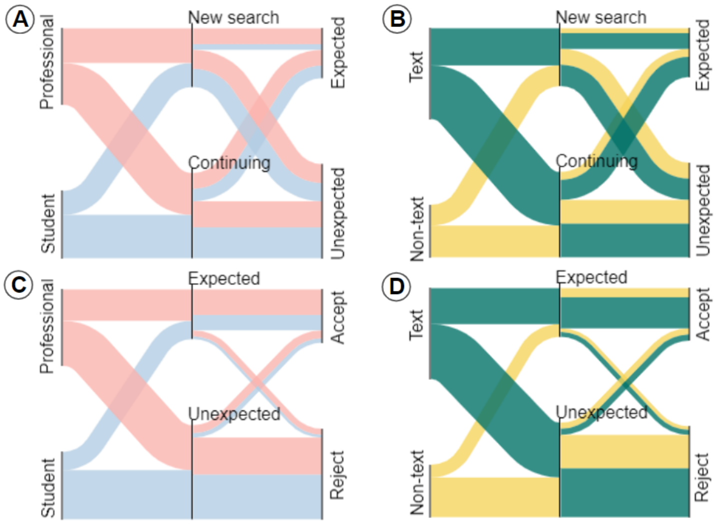

FIGURE 4. **Search pathways linking search behaviors**: Search *definition-evaluation* pathways are compared across **(a)** professionals (red) and students (blue) and **(b)** text (green) and non-text (yellow) searches. Search *evaluation-selection* pathways are compared across **(c)** professionals and students, and **(d)** text and non-text searches.

The apparent result that professional designers have broader expectations of their searches - and thus, evaluate fewer searches as 'unexpected' - supports previous work by Goncalves et al, Cross, and Cai et al., that professional designers seek to extract detailed information from diverse inspirational sources [17,42,44]. Our findings contrast professional designers' broad expectations with novice designers' relatively narrower expectations, echoing Cai et al.'s findings that novice designers found value in stimuli for their connection to familiar knowledge.

More new non-text searches are unexpected than expected. The role of search type on how new vs. continued searches are evaluated is demonstrated in **Fig. 4b**. While a similar number of new text searches are unexpected (35) and expected (26), many more new non-text searches are unexpected (26) than expected (8).

As suggested by results above, more non-text than text search results were unexpected, but this finding highlights that this is especially true when a new search for a part begins. Limitations to both the system's ability to effectively retrieve expected results using non-text search inputs as well as the designer's ability to anticipate and understand what the system may retrieve can provide insight into these results. Notably, continuing non-text searches are similarly split between being evaluated as unexpected and expected, suggesting that even persisting with non-text searches does not align search results with designer expectations. Furthermore, Example 1 in **Table 5** presents an example of searching with a vague search intent. Not having a clearly defined search goal may influence why the results are then evaluated as irrelevant. 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.

Professionals and students reject expected results and accept unexpected results. Once a search is made and the returned parts are evaluated as expected or unexpected, results may either be accepted (incorporated into the participant's current design) or rejected. The average frequencies of these pathways, compared across professionals and students, are summarized in **Fig. 4c**. Students evaluate more results as unexpected than professionals, as previously reported. Intuitively, across participants, a high proportion of results that are evaluated as expected are accepted, and unexpected results are rejected. However, less intuitive are the processes involving the rejection of expected results and acceptance of unexpected results.

TABLE 5. **Illustrative examples of search pathways linking search behaviors**

#	Search pathway	Group	Type	Associated quote/action
1	New → Unexpected	Student	Non-text	*"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	Non-text	*"Ahh, yes that's good, I'm seeing kind of like very very close matches... I'm going to keep playing around with sliders till I **get something closer**"*
3	Expected → Rejected	Student	Text	*"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	Non-text	*"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!"*

As exhibited by both participant groups, 9/15 participants (5/8 professionals and 4/7 students) rejected results from 14 out of 79 searches that matched their expectations. Examples 2 and 3 in **Table 5** illustrate these behaviors. A motivation for this behavior may be to discover an even closer match in aesthetics or features to what is being searched for than what has already been provided. In this way, expected search results may encourage designers to search further, as they may consider themselves 'on the right track.' Another surprising observation is when participants accept results that are unexpected, as done by 9/15 participants (4/8 professionals and 5/7 students) who accepted results from 21 out of 156 searches. Motivations for accepting unexpected results may be that they introduced a useful, but unintended, design feature. For example, wheels unexpectedly retrieved by the search platform were subsequently added to two participants' designs. Further motivations for and examples of accepting unexpected search results are discussed in our continued work [46].

More unexpected non-text search results are accepted. Unexpected non-text vs. text search results are also disproportionately accepted, as shown in **Fig. 4d**. Despite the higher overall frequency of text (149) to non-text (86) searches, an equal number of unexpected results (10) are accepted. Example 4 in **Table 5** shows that a result from a non-text search that does not match the designer's original intention can be nonetheless useful. The system's retrieval of wheels when a waste bin top was sought using a non-text search, points again to the difficulty designers experience when anticipating results from novel modalities. Nonetheless, leveraging unexpected results can beneficially allow for the integration of more, and more novel, design features. These findings suggest that cognitive behaviors exist in search processes to challenge designers' fixation on a given objective. However, further investigation is necessary to understand why this behavior occurs.

3.4 Key insights gained regarding search for inspirational stimuli

To introduce the aims of this work, three research questions were posed. Responding to **RQ1**, *How can designers' inspirational search processes be understood in terms of discrete actions?*, three distinct levels of search were defined (search activities, behaviors, and pathways), as summarized in **Fig. 2**. Search activities described designers' interactions with the multi-modal search platform. Search behaviors were classified using the framework described in **Table 2** into how designers: (1) define new and continued searches, (2) evaluate search results as expected or unexpected, and (3) select search results that are accepted into or rejected from the designer's final solution. Finally, search pathways linking search definitions with evaluations and evaluations with selections were discussed to understand how search behaviors are related with different design outcomes.

Analyses related to each search level were conducted to firstly explore differences between professionals and students, addressing **RQ2**, *How does experience level shape how designers seek inspiration?* While professionals and students did not differ by **search activity**, i.e., the frequency of use of keyword, part, and workspace searches, they did differ by **search behaviors**. Notably, students were found to make more continued searches for the same part, evaluate more results as unexpected, and ultimately reject more results from inclusion in their designs. These behaviors suggest that, in general, students fixate more on finding their originally intended results and demonstrate less openness to incorporating unexpected parts into their designs. Through an investigation of 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. Professional designers generally exhibited broader expectations for parts, allowing them to consider more results as expected without continued search and exploration. By examining how designers selected results based on how they were evaluated, both professionals and students were found, surprisingly, to reject expected results and accept unexpected results. It is important to note that professionals and students did not differ by search activities, but did differ by search behaviors, suggesting that expertise does not affect how often search types are used, but what they are used for and when.

Finally, search activities, behaviors, and pathways were also compared between searches made using text and non-text search inputs to address **RQ3**, *How does designers' use of various search modalities shape their search for inspiration?*. Search activity differed across designers, where more text than non-text searches were made. Differences in search behaviors related to text and non-text searches were found in how designers evaluated search results. More non-text than text search results appear to be unexpected, which may 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 through a less intuitive search modality. This is especially true for new compared to continuing non-text searches, as found in an examination of search pathways between how searches were defined and evaluated and how designers evaluated and selected search results. When making an initial search for a part using a non-text modality, designers may be missing a clear idea of what to expect from the system. Also true is that more unexpected non-text search results are accepted, which indicates that the use of a search modality that retrieves unexpected results does not prevent designers from selecting these results to use in their designs. The ability to define non-text searches without a well-defined input or expectation may be an advantageous pathway to discovering relevant inspirational stimuli.

3.5 Future work and limitations

Results from this study present many opportunities for future work. While the current study examined how designers search for inspirational stimuli, future work can additionally consider how stimuli discovered as a result of different search processes contribute to specific design outcomes. For instance, unexpected search results may lead to more novel design features. In this study, designers exhibited interesting design behaviors, such as instances of succumbing to and overcoming fixation on prior search results and design ideas. These findings are alluded to in the present work, but further exploration is needed into understanding how encountered stimuli influence design behaviour and outcomes. The role of timing of stimulus discovery can also be better understood in future work. In the task completed, approx. 15 min. were allotted for stimuli search. While most participants reached an impasse in their search and design activity by this time, prior work by Moss et al. has shown how incidental information provided at the point of impasse can be beneficial for problem solving [47]. Continued design ideation after receiving new stimuli following an impasse can therefore be studied. Finally, future work is also encouraged to investigate how designers interact with design stimuli in different modalities to improve the development of design tools supporting multi-modal inspirational search and retrieval.

4 CONCLUSION

In this work, a cognitive study was conducted where designers searched for inspirational design stimuli to develop a solution to a given design task while following a think-aloud protocol. To complete the task, designers engaged with a novel multimodal search platform that enables text and non-text search inputs. The results of this work present an approach to describing how designers search and investigate the roles of designer expertise and search modality on inspirational search processes. These findings contribute to a deeper understanding of the relationship between the stimuli designers actively search for and the stimuli that are used in their designs. Different from prior work that has investigated how inspirational stimuli affects design outcomes, this work reveals that how designers discover these stimuli, whether intentionally or not, is important to consider. Overall, these results provide avenues for future work to explore including the study of design stimuli, processes leading to inspiration, and the improved design of tools to support the search for and discovery of relevant design stimuli.

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REFERENCES

[1] Goncalves, M., Cardoso, C., and Badke-Schaub, P., 2016. "Inspiration Choices that Matter: The Selection of External Stimuli During Ideation". *Design Science*, ***2***(10).

[2] Chan, J., Fu, K., Schunn, C., Cagan, J., Wood, K., and Kotovsky, K., 2011. "On the Benefits and Pitfalls of Analogies for Innovative Design: Ideation Performance Based on Analogical Distance, Commonness, and Modality of Examples". *J. Mech. Des.*, ***133***(8), p. 081004.

[3] Fu, K., Chan, J., Cagan, J., Kotovsky, K., Schunn, C., and Wood, K., 2013. "The Meaning of "Near" and "Far": The Impact of Structuring Design Databases and the Effect of Distance of Analogy on Design Output". *J. Mech. Des.*, ***135***(2), p. 021007.

[4] Goucher-Lambert, K., Gyory, J. T., Kotovsky, K., and Cagan, J., 2020. "Adaptive Inspirational Design Stimuli: Using Design Output to Computationally Search for Stimuli that Impact Concept Generation". *J. Mech. Des.*, ***142***(9), p. 091401.

[5] Jansson, D., and Smith, S., 1991. "Design fixation". *Design Studies*, ***12***(21), pp. 3–11.

[6] Linsey, J., Wood, K., and Markman, A., 2008. "Modality and Representation in Analogy". *AI EDAM*, ***22***(2), p. 85–100.

[7] Tseng, I., Moss, J., Cagan, J., and Kotovsky, K., 2008. "The Role of Timing and Analogical Similarity in the Stimulation of Idea Generation in Design". *Design Studies*, ***29***(3), pp. 203–221.

[8] Luo, J., Sarica, S., and Wood, K. L., 2021. "Guiding Data-Driven Design Ideation by Knowledge Distance". *Knowledge-Based Systems*, ***218***, p. 106873.

[9] Goucher-Lambert, K., and Cagan, J., 2019. "Crowdsourcing Inspiration: Using Crowd Generated Inspirational Stimuli to Support Designer Ideation". *Design Studies*, ***61***, pp. 1–29.

[10] Chan, J., Dow, S. P., and Schunn, C., 2015. "Do the Best Design Ideas (Really) Come from Conceptually Distant Sources of Inspiration?". *Design Studies*, ***36***, pp. 31–58.

[11] Goucher-Lambert, K., Moss, J., and 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***, pp. 1–38.

[12] Toh, C. A., and Miller, S. R., 2014. "The Impact of Example Modality and Physical Interactions on Design Creativity". *J. Mech. Des.*, ***136***(9), p. 091004.

[13] Borgianni, Y., Rotini, F., and Tomassini, M., 2017. "Fostering Ideation in the Very Early Design Phases: How Textual, Pictorial and Combined Stimuli Affect Creativity". In Proc. of the 21st International Conference on Engineering Design, ICED17, The Design Society, pp. 139–148.

[14] Hua, M., Han, J., Ma, X., and Childs, P., 2019. "Exploring the Effect of Combinational Pictorial Stimuli on Cre-

ative Design Performance". *Proc. of the Design Society: International Conference on Engineering Design,* ***1***(1), p. 1763–1772.
[15] Han, J., Shi, F., Chen, L., and Childs, P. R., 2018. "The Combinator–A Computer-Based Tool for Creative Idea Generation Based on a Simulation Approach". *Design Science,* ***4***(11).
[16] Kwon, E., Huang, F., and Goucher-Lambert, K., 2021. "Multi-Modal Search for Inspirational Examples in Design". In Proc. ASME 2021 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, Virtual, Online. Aug. 17-29, p. V006T06A020.
[17] Gonçalves, M., Cardoso, C., and Badke-Schaub, P., 2014. "What Inspires Designers? Preferences on Inspirational Approaches During Idea Generation". *Design studies,* ***35***(1), pp. 29–53.
[18] Siangliulue, P., Chan, J., Gajos, K. Z., and Dow, S. P., 2015. "Providing Timely Examples Improves the Quantity and Quality of Generated Ideas". In Proc. of the 2015 ACM SIGCHI Conference on Creativity and Cognition, C&C '15, Association for Computing Machinery, p. 83–92.
[19] Vasconcelos, L. A., Cardoso, C. C., Sääksjärvi, M., Chen, C.-C., and Crilly, N., 2017. "Inspiration and Fixation: The Influences of Example Designs and System Properties in Idea Generation". *J. Mech. Des.,* ***139***(3), p. 031101.
[20] Vattam, S., Wiltgen, B., Helms, M. E., Goel, A. K., and Yen, J., 2011. "DANE: Fostering Creativity in and through Biologically Inspired Design". In Design Creativity 2010, Springer, pp. 115–122.
[21] Goel, A. K., Vattam, S., Wiltgen, B., and 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***(10), pp. 879–900.
[22] Nagel, J. K., and Stone, R. B., 2012. "A Computational Approach to Biologically Inspired Design". *AI EDAM,* ***26***(2), pp. 161–176.
[23] Sartori, J., Pal, U., and Chakrabarti, A., 2010. "A Methodology for Supporting 'Transfer' in Biomimetic Design". *AI EDAM,* ***24***(4), pp. 483–506.
[24] Murphy, J., Fu, K., Otto, K., Yang, M., Jensen, D., and Wood, K., 2014. "Function Based Design-by-Analogy: A Functional Vector Approach to Analogical Search". *J. Mech. Des.,* ***136***(10), p. 101102.
[25] Fu, K., Cagan, J., Kotovsky, K., and Wood, K., 2013. "Discovering Structure in Design Databases Through Functional and Surface Based Mapping". *J. Mech. Des.,* ***135***(3), p. 031006.
[26] Kittur, A., Yu, L., Hope, T., Chan, J., Lifshitz-Assaf, H., Gilon, K., Ng, F., Kraut, R. E., and Shahaf, D., 2019. "Scaling Up Analogical Innovation with Crowds and AI". *Proc. of the National Academy of Sciences,* ***116***(6), pp. 1870–1877.
[27] Zhang, Z., and 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, p. V008T08A003.
[28] Zhang, Z., and 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. 17-19, p. V006T06A057.
[29] Jiang, S., Luo, J., Ruiz-Pava, G., Hu, J., and 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, p. V009T09A039.
[30] Jiang, S., Luo, J., Ruiz-Pava, G., Hu, J., and Magee, C. L., 2021. "Deriving Design Feature Vectors for Patent Images Using Convolutional Neural Networks". *J. Mech. Des.,* ***143***(6), p. 061405.
[31] Kazi, R. H., Grossman, T., Cheong, H., Hashemi, A., and 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, Association for Computing Machinery, p. 401–414.
[32] Arora, R., Darolia, I., Namboodiri, V. P., Singh, K., and Bousseau, A., 2017. "SketchSoup: Exploratory Ideation Using Design Sketches". *Computer Graphics Forum,* ***36***(8), pp. 302–312.
[33] Chaudhuri, S., and Koltun, V., 2010. "Data-Driven Suggestions for Creativity Support in 3D Modeling". *ACM Transactions on Graphics,* ***29***(6), pp. 1–10.
[34] Botella, M., Zenasni, F., and Lubart, T., 2018. "What are the Stages of the Creative Process? What Visual Art Students are Saying". *Front. Psychol.,* ***9***(2266).
[35] Menezes, A., and Lawson, B. R., 2006. "How Designers Perceive Sketches". *Design Studies,* ***27***(5), pp. 571–585.
[36] Do, E. Y.-L., 2005. "Design Sketches and Sketch Design Tools". *Knowledge-Based Systems,* ***18***(2005), pp. 383–405.
[37] Eckert, C., and Stacey, M., 2003. "Sources of Inspiration in Industrial Practice: the Case of Knitwear Design". *J. Design Research,* ***3***(1).
[38] Herring, S. R., Chang, C. C., Krantzler, J., and 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, Association for Computing Machinery, pp. 87–96.

[39] Sutcliffe, A., and Ennis, M., 1998. "Towards a Cognitive Theory of Information Retrieval". *Interacting with Computers,* ***10***, pp. 321–351.

[40] Marchionini, G., 2006. "Exploratory Search: From Finding to Understanding". *Communications of the ACM,* ***49***(4), pp. 41–46.

[41] Athukorala, K., Głowacka, D., Jacucci, G., Oulasvirta, A., and 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***(11), pp. 2645–2651.

[42] Cross, N., 2004. "Expertise in Design: An Overview". *Design studies,* ***25***(5), pp. 427–441.

[43] Wallace, S., Le, B., Leiva, L. A., Haq, A., Kintisch, A., Bufrem, G., Chang, L., and Huang, J., 2020. "Sketchy: Drawing Inspiration from the Crowd". *Proc. of the ACM on Human-Computer Interaction,* ***4***(172), pp. 1–27.

[44] Cai, H., Do, E. Y.-L., and 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***(2), pp. 146–168.

[45] Goncalves, M., Cardoso, C., and Badke-Schaub, P., 2013. "Through the Looking Glass of Inspiration: Case Studies on Inspirational Search Processes of Novice Designers". In Proc. of the International Association of Societies of Design Research, IASDR 2013, Tokyo, Japan.

[46] Kwon, E., Rao, V., and Goucher-Lambert, K., 2022. "Exploring Designers' Encounters with Unexpected Inspirational Stimuli". *Design Computing and Cognition'22 (Accepted)*, pp. 1–12.

[47] Moss, J., Kotovsky, K., and 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***(2), pp. 140–148.