Understanding How People use Search to Support their Everyday Creative Tasks

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ABSTRACT

Creativity is an essential part of people's daily life and work across a range of everyday tasks. However, little prior work has explored how people use search engines and information resources as part of their creative processes, and how systems might better support users working on creative tasks. In this paper, we conducted an online survey with 175 participants to explore how people use search engines and online resources (e.g., images, videos, and social media) to support their creative tasks. Our participants reported information seeking to support a broad range of everyday creativity including tasks in arts, writing, crafts, and technical projects. Our findings show that participants' tasks included multiple stages of creative processes (e.g., creating ideas, combining ideas, executing plans) and that participants reported using search engines along with other tools (such as images and videos) to facilitate their creative process. By using Bayesian random effects regression models, we found that different stages of the creative process influence participants' use of tools. For example, for tasks that involved creating ideas, participants were more likely to use images and social sites, and when needing to put ideas into practice they were more likely to use videos. We also found differences in users' satisfaction with using the tools for different creative stages. Based on our findings, we provide recommendations for supporting users' information seeking needs during creative tasks.

KEYWORDS

Search engines, information search, creativity, creative process

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1 INTRODUCTION

Creativity and innovation are highly valued characteristics by societies and individuals. From a societal perspective, it has been argued that creativity will become increasingly important because of increased global competitiveness, decreasing numbers of jobs that do not involve aspects of creativity, and growing demand for products of creative industries [50]. In addition to these social dimensions, creativity has been considered as a universal quality that helps individuals survive and is a component of many everyday activities. As Richards highlights, "Throughout our day, whether at home or at work, we humans adapt and innovate, improvise flexibly... Our creativity may involve anything from making breakfast to solving a major conflict with one's boss" [46, p.190].

The importance of supporting humans' creativity through the use of technologies has been recognized by scholars over the past decades. In 1999, Shneiderman [51] emphasized the significance of developing user interfaces that support creativity and highlighted opportunities to facilitate the creative process by using search engines. More recently, in the field of information retrieval, White [64, p.137] has pointed out the need for additional research to investigate ways that information systems can support creativity.

To the best of our knowledge, however, very few efforts have been made to investigate how to design search systems for supporting creativity. With this goal in mind, we must first understand what kinds of creative tasks people perform in their life and work, how they conduct the tasks, and what opportunities there are for search systems to support their needs. In this study, we are particularly interested in understanding people's *everyday creativity*, which Richards defines based on two crucial criteria: originality and meaningfulness [46]. Incorporating these two criteria in the context of information searching, we broadly define *creative tasks* as tasks in which people attempt to use information technology to create something original and meaningful. This definition has an intentionally broad scope, with the "something" being able to refer to both physical and non-physical things (e.g., an idea or a project).

To gain a better understanding of how people use search engines and information tools to support their creative process, we conducted an online survey (N=175) using the Amazon Mechanical Turk (MTurk). Our survey asked participants to think of a time recently when they were trying to create something and went online to look for useful resources or information. We asked participants to type a detailed description of their task, to indicate what computing devices they used as part of the task, what information tools they used, and to indicate which (from a list of) creative process stages (e.g., figuring out goals, creating ideas, combining ideas, etc.) were involved in their task. We also asked about their satisfaction using particular tools to support particular creative process stages.

We grounded our survey questions and analysis in prior research on creativity. One way that creativity has been studied is in terms of different *domains*. We analyzed the participants' responses using a set of everyday creativity domains developed by Jauk et al. [27]: visual arts, performing arts, music, literature/writing, arts & crafts, cooking, and science & engineering.

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Creativity is also understood to be a process that involves multiple *stages*. We used a set of creative process stages identified by Sawyer [50]: find goals, look-up information, explore, create ideas, combine ideas, select ideas, and put ideas into practice (execute).

In this paper, we present the results of our survey and address the following research questions:

- **RQ1: What kinds of creative tasks do people perform in their everyday life and work?** To address this, we analyzed participants' task descriptions and categorized them based on a set of *creativity domains* from prior work [27].
- **RQ2: How are computing devices and information tools used by people to support their creative tasks?** For devices, we report on participants' use of desktop/PCs, smartphones, tablets, and other devices to support their tasks. For information tools, we report on the use of search engines, images, videos, and social media sites.
- **RQ3: How is information search used as a part of a creative process?** We examine how seven different creative process stages (e.g., find goals, create ideas, combine ideas, etc.) identified from prior work [50] were involved in our participants' tasks, and show how different information resources and tools were used to support each stage.
- **RQ4: What are the opportunities for search engines to support the creative process?** We present Bayesian regression models to investigate: how the domain of the task influenced the creative stages involved, how the creative stages influenced the resources/tools used, and how satisfied participants' were using particular tools to support creative stages.

Based on our results, we present a set of implications about how IR systems can better support users engaged in creative tasks.

2 RELATED WORK

In this section, we review related work on creativity, information seeking, and tools to support creative tasks.

Definitions of creativity: For the past several decades, different definitions have been proposed to characterize the nature of creativity. In the *sociocultural* approach ("big–C"), scholars attempt to understand creative genius and identify which creative works might last forever [53]. Whereas the sociocultural approach ("big–C") assumes that only certain people can be creative, the *individual* approach ("little–c") looks more at everyday creativity which is seen as central to human survival and must be found in everyone [46]. In the perspective of individualists, creativity is defined as "a new mental combination that is expressed in the world" [50, p.7]. In the work presented here, we focus on everyday creativity ("little–c"). Everyday creativity has been considered along four levels: doing, adapting, making, and creating (the highest level) [48].

Creative process: Despite some disagreements on the definitions of creativity, there is a general agreement that creativity is a *process*. In 1926, Wallas [61] created one of the earliest creative process models by examining four different stages: preparation, incubation, illumination, and verification. Inspired by Wallas' work, other models emerged including Amabile's five-stage model [1], the Geneplore model [16], and Mumford's eight-stage model [42].

In a more recent work, Sawyer developed an integrated framework based on models proposed in previous studies. We used Sawyer's framework in our survey questions. This framework includes eight stages, including [50, p.90]: (1) find and format the problem, (2) acquire knowledge relevant to the problem, (3) gather a broad range of potentially related information, (4) take time off for incubation, (5) generate a large variety of ideas, (6) combine ideas in unexpected ways, (7) select the best ideas, applying relevant criteria, (8) externalize the idea using materials and representations.

There are several important aspects in Sawyer's framework. First, the creative process begins with finding a problem. Previous research on creativity has found that finding and formatting a problem is extremely important [11]. Second, gaining deep knowledge of a domain is crucial in a creative process. Third, different from the aforementioned models, Sawyer's framework considers the stage of externalizing the idea. Previous studies have shown that most creative people externalize their ideas before they are fully formed, and this often results in follow-on ideas [50]. We note that search systems have a role to play in supporting each of these stages.

Domains of creativity: A prevailing view is that people may not be creative in a universal way, but rather are creative in particular domain(s) [12]. In creativity research, many efforts have been made to quantify the domains of creativity. For example, Carson and his colleagues [8] identified three types of creativity: expressive creativity (visual arts, writing, and humor), performance creativity (dance, drama, and music), and scientific creativity (invention, science, culinary). To characterize everyday creative activities, Jauk et al. proposed eight domains, including literature, music, arts & crafts, creative cooking, sports, visual arts, performing arts, and science & engineering [27]. In our analysis, we adapted Jauk et al.'s set of eight domains of creativity (see Section 4).

Information seeking: Information seeking and searching have been explored extensively in the fields of information science (IS) and information retrieval (IR). In previous work, models of information seeking have been developed to describe an interaction cycle that starts with identifying an information need, followed by searching, examining the results, and if necessary, adjusting goals and iterating through the entire process again [38, 40, 57]. Work has also explored how a person's information seeking process and goals evolve over time [35]. Researchers have also considered different characterizations of information seeking tasks. Especially relevant to our work are *exploratory search* tasks, in which a searcher seeks to explore and learn about a topic. Exploratory searches often involve investigation and synthesis [39, 65], which can also be stages of a creative process [50]. Prior work has also examined people's everyday information seeking behaviors [49] and their information behaviors in the context of leisure activities [24, 55, 56].

Also related to our work are efforts to understand and design ways to deliberately induce *serendipity* in search systems. Toms [58] proposed several approaches to supporting serendipitous retrieval (e.g., attempting to enhance the chance of serendipity by randomness, leveraging user profiles, and using relaxed similarity measures). Several efforts have investigated tools to encourage serendipity (e.g., [4], [44]). However, some have argued that focusing on the "chance encounters" aspect of serendipity will not necessarily support creativity [2]. As André, schraefel, Teevan, and Dumais noted in their paper, "Discovery is never by chance" [2], a system could increase users' chances of encountering "dots" of information, but knowing how to connect these dots is a different story.

Information seeking and artists: In the area of library science, efforts have been made to understand artists' information seeking behaviors. For example, by interviewing four artists (a sculptor, painter, fiber artist, and metalsmith), Cobbledick [9] found that these artists had different kinds of information needs (e.g., inspiration, technical information, specific visual information, information about trends and events in the art world, and business information). Inspired by Cobbledick's work, other similar studies have been conducted to investigate the information seeking behaviors of artists [10, 18, 60] and art librarians [36, 54].

Creativity Support Tools (CST): Outside of information search, researchers in human-computer interaction and other fields have explored ways to understand creativity and to design creativity support tools (CSTs). In the past decades, several theories have been developed to inform the design of CSTs [13, 14, 52] and tools have been developed to support crowd ideation [3, 17, 22, 23, 25], to stimulate creative thinking [15, 32, 45, 63], and to support design processes [33, 37, 43].

However, as Frich and his colleagues [19] note, much of the existing creativity-related HCI research has focused on new tools, often developed by the researchers themselves, and investigated in controlled experiments. To address this issue, the authors suggest "shifting our efforts to studying in-vivo use of creativity support tools, not just the ones we build ourselves, but the ones that most creative practitioners employ in practice" [19, p. 1243]. The study presented here is an effort to better understand the types of information seeking tools and strategies that people currently use in practice when they engage in tasks that involve everyday creativity.

3 METHODOLOGY

To explore how people use search engines and online resources to support their everyday creative tasks, we conducted an online survey. In this section, we describe how we recruited our participants and give details about our survey.

3.1 Participants and Recruiting

We recruited participants to complete our survey by posting Human Intelligence Tasks (HITs) to the Amazon Mechanical Turk (MTurk) crowdsourcing platform. To encourage a diverse sample, we used several techniques. First, we posted our recruitment HITs in small batches on different days and times across a one week period. Second, when posting different batches, we included different terms in the "keywords" field of the HIT (for keyword list, see **Appendix A**). The HIT keywords are often used by MTurk workers to search for HITs to work on, so by using different terms we hoped to attract a more diverse sample of participants who were doing tasks that involved creativity. Each day, we posted five groups, each of which included nine HITs. Each group was posted using a different set of keywords, but the survey itself was identical for all participants.

We posted our HITs with the following requirements for the MTurk workers: (1) location in the United States, (2) HIT approval rate greater than or equal to 95%; and (3) age > 18. We configured MTurk and our survey software (Qualtrics) to prevent participants from taking the survey more than once. Participants who completed the survey and entered a valid completion code into the HIT were paid $1.50 USD through the MTurk platform.

3.2 Survey Design

The survey began with a brief demographic questionnaire (e.g., age, gender, education, field of employment). Then participants responded to the main part of the survey – the creative task questionnaire. At the end of the survey, we also included a creative achievement questionnaire that is not analyzed in this paper.

Creative task questionnaire: We asked participants to think of a time recently when they were trying to create something and went online to look for useful resources or information. Focused on this task, we asked participants a series of questions (for full text, see **Appendix B**):

Q.1: Describe the task – We asked participants to type a written description of the task into a textbox. Also as part of Q.1, we asked participants to categorize the domain(s) of the task they described. To make it easier for participants to identify categories, instead of showing the eight high-level domains identified by Jauk et al. [27], we showed participants a list of 18 more specific categories[1] derived based on previous research [8, 27, 28] as well as from our own pilot testing. Participants were instructed to select all categories that applied to characterize their task.

Q.2: Describe how they approached the task – Using another open-ended question, we asked participants to describe how they approached the task (e.g., how they started, what resources they used, what strategies they used to find information).

Q.3: Indicate computing devices used for the task – To gain insight about what different computing devices were involved, we asked them to indicate if they used any of the following: desktop/PC, smartphone, tablet, smart TV, voice assistant (e.g., Siri, Alexa, Google Home), or other (please specify).

Q.4: Indicate information resources/tools used – We also asked which of the following information resources were used to support their task: search engines, videos, images, social sites (e.g., Pinterest, Instagram, etc.), other (please specify).

Q.5: Creative processes stages – Based on the answers to Q.4, we created a loop in the survey that dynamically asked a set of questions to capture the relationship between each information resource and stages of the creative process outlined by Sawyer [50, p.90]:

> For which of the reasons below did you use *<option selected in Q.4>* in the task (choose all that apply, or not applicable):
> - **Find goals**: figure out my goal (what I want to create/design or which problem I want to address/solve)
> - **Look up**: look up information relevant to my goal
> - **Explore**: explore (gather a broad range of potentially related information) about my goal
> - **Create ideas**: create a large variety of ideas that may achieve my goal
> - **Combine ideas**: combine some ideas that I have already had
> - **Select ideas**: select the best ideas from all the new ideas that I have created
> - **Execute**: figure out how to put my ideas into practice to achieve my goal

For example, if in Q.4 a participant chose both search engines and social sites they would see two separate **Q.5** questions, one asking about the reasons for using search engines and another asking about

[1] Visual arts, music, dance, sports, education, architectural design, entrepreneurial ventures, creative writing, humor, inventions, scientific inquiry, theater & film, culinary arts, crafts, product design, presentation, report writing, graphic design, and other.

the reasons for using social sites. Throughout the paper, we will refer to the creative process stages as: find goals, lookup, explore, create ideas, combine ideas, select ideas, and execute.

Q.6: Satisfaction/experience with information resources for each stage – We embedded a second-level loop in the survey to investigate participants' satisfaction with each information tool used for each creative stage. For example, we asked: "How satisfied were you with using *images* to *create ideas*?" Participants were asked to evaluate a resource/tool only when they reported using it.

4 DATA ANALYSIS

Qualitative coding: In the survey, we asked participants to select from 18 domains to categorize their creative task. We thought that providing a large set of 18 domains would help participants identify relevant categories. However, in some cases there was variation in how participants interpreted and applied the categories. For our analysis, we decided to re-categorize the data using eight domains we adapted from Jauk et al. [27] (shown in Table 1). The two authors independently reviewed participants' responses to Q.1 and Q.2 and assigned one of the eight domains. After this initial round of coding, the Cohen's Kappa for inter-coder agreement was $\kappa = 65.9\%$. After this, the authors independently re-coded the 47 responses they had disagreed on in the first round. The overall inter-coder agreement after the second round was 85.2%. Following Bradley's suggestion [6], we resolved the remaining 15 cases by discussion and consensus.

Quantitative analyses: Following the call of Tetsuya Sakai [47] at SIGIR 2017 and Kay et al. [29] at CHI 2016 advocating the use of Bayesian statistics, all the statistical inferences in our study are based on Bayesian inference. In our Bayesian analysis, a No-U-Turn sampler [26] was used; in each model, we ran Stan (http://mc-stan.org/) with six chains, each of which had 8000 iterations. Details of our Bayesian analysis are provided in Appendix C.

Responses and data quality: Based on our MTurk HITs, a total of 175 participants provided responses to our survey (86 female, 86 male, 2 other, 1 no answer). The age ranges of our participants varied broadly: "18-24 years old" (n=20), "25-34 years old" (n=75), "35-44 years old" (n=48), "45-54 years old" (n=19), "55-64 years old" (n=9), and "65-74 years old" (n=3). Most of our participants were employed (n=151, 86%) and came from 22 different fields.

Before we conducted our data analysis, we checked the quality of the survey data. Our manual review showed that all participants provided thoughtful responses to Q.1 and Q.2. The total length of Q.1 and Q.2 ranged from 22 words to 624 words (M = 138.09). Across all the questions, participants spent on average 24.31 minutes completing the survey. Based on our review, participants spent sufficient effort on the survey and we did not omit any responses.

5 RESULTS

5.1 Descriptive statistics

Recall that our survey questions asked participants to describe a particular creative task they had done recently and to answer questions about the domain of the task, the devices used, the information resources/tools used, and the creative process stages that were involved. In this section, we present descriptive statistics about the participants' responses to these questions.

Table 1: Activities and domains of the creative tasks

Domains (count)	Task activities (count)
Visual arts (35)	Painting/sculpture (4), Photography design (1), Interior design/renovation (14), Graphic design (10), Character/logo design (5), Architectural design (1).
Perform arts (2)	Making movie/film (2).
Music (5)	Making music (5).
Literature (15)	Nonfiction writing (5), Fiction writing (10).
Arts and Crafts (54)	Making tools (5), Making cards (5), Making furniture (13), Making jewelry (4), Making decoration or gift (11), Clothing (8), Gardening/landscape work (4), Craft other (4).
Cooking (16)	Cooking (16)
Science & engineering (28)	Academic writing (2), Technical problem solving (14), Programming (5), Website development (4), Building a scientific product (3).
Everyday/other (20)	Learning how to do/use something (5), Non-technical problem solving (15).

Creative task domains: As shown in Table 1, in response to Q.1 and Q.2, the everyday creativity tasks that participants described were distributed across the eight domains we examined. The variety and richness of participants' task descriptions was particularly striking and illustrates the complex information seeking that is required to support everyday creative tasks.

Devices used: In Q.3, participants noted the use of (possibly multiple) computing devices in their creative tasks. Desktop/PC was the most frequently used platform (163 of 175 responses, 93%), followed by smartphones (n=70, 40%), and then tablets (n=26, 15%). Devices such as Google Home (n=3) and Smart TVs (n=2) were mentioned by only a few participants. Using Bayesian logistic regression models, we examined whether this distribution differed based on task domain and did not find any notable differences.

We also investigated different *combinations* of platforms that participants reported using. The most common scenario was that a desktop/PC was the only platform used for a task (n=92, ~53%). However, scenarios that included combinations of two and three devices were very common, being reported in 74 of the 175 responses (~42%). The frequencies included: desktop only (92), desktop + smartphone (46), desktop + smartphone + tablet (12), desktop + tablet (8), other combinations (8), smartphone only (7), tablet only (2). These results suggest that task resumption across devices and sessions [62] is an important part of supporting creative tasks.

Resources/tools used: In Q.4, participants indicated the (possibly multiple) tools and information resources (search engines, images, videos, social sites) they used to accomplish their creative tasks. Figure 1 shows how frequently each tool was used for tasks in each domain. Overall, search engines were the most frequently reported tools. Videos were also frequently used, especially in arts & crafts tasks. Images were commonly used in both visual arts and

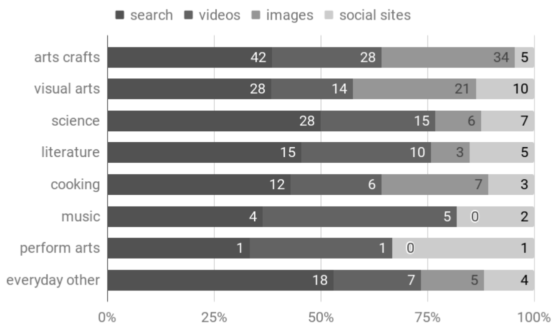

Figure 1: Use of tools across different domains.

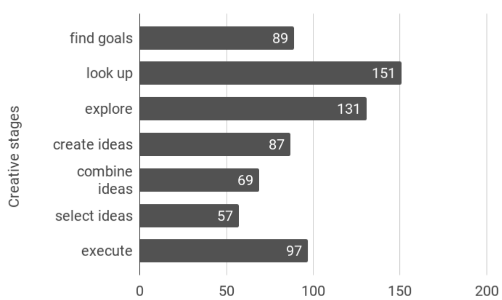

Figure 2: Creative process in creative tasks.

arts & crafts tasks. We also note that tools were used in combinations; approximately 69% of participants used at least two different tools in their creative tasks.[2]

Creative stages involved: Figure 2 shows the creative stages that participants reported as being part of their tasks (from Q.5). Among the stages, **look up** (look up information relevant to the goal, (n=151, 86%)) and **explore** (gather a broad of range of potentially related information about the goal, (n=131, 75%)) were the most frequently involved stages in our participants' creative tasks. However, all stages were commonly used, with even the least frequent (**select ideas**) being used by 33% (n=57) of our participants. These results show the complexity of creative tasks and illustrate how they may differ from fact-finding and comparative search tasks. Similar to exploratory search, the creative tasks reported by our participants involved exploration, learning, and synthesis.

Descriptive statistics summary: Our results show that participants reported tasks that involved multiple creative process stages, and that they used multiple information resources/tools and computing devices to support their tasks. These results also suggest that the participants used resources/tools differently when doing tasks in different domains. To explore these potential differences, we conducted a set of regression analyses (Section 5.2).

[2]The frequencies of tools reported included: search only (39), search + videos (32), search + images (27), search + videos + images (19), search + videos + social (14), search + videos + images (9), images only (8), videos only (7), videos + images (5), search + social (4), images + social (4), search + images + social (4), social only (2).

5.2 Relationships of Domain, Stage, and Tools

In this section, we explore relationships between the task domains, resources/tools used, and the creative stages. We present analyses of (1) how different task domains involve different creative stages, (2) how different creative stages involve the use of different resources/tools, and (3) users' satisfaction using different resources/tools to support particular stages.

5.2.1 How different task domains involve different creative stages. We wanted to investigate how different task domains (e.g., arts & crafts) might involve different creative stages (e.g., create ideas, look up). To investigate this, we developed seven Bayesian logistic regression models (see Equation 1 in Appendix C), one for each creative stage. In each model we included eight dummy variables corresponding to the task domain (e.g., visual arts, cooking, etc.) as predictors. The predicted (binary) outcome for each model was whether that particular stage was included in the task (1) or not (0).

The results of the Bayesian logistic regression analysis are shown in Table 2. Each **column** shows results for one of the models. Following Kruschke's [34] suggestion, we report the *mode* and 95% *high-density interval (HDI)* for each parameter. In Bayesian regression the *mode* indicates the log odds increase or decrease and the *HDI* provides a function similar to a confidence interval in null hypothesis testing (but must be interpreted differently; see details in **Appendix C**). In Bayesian inference, there is no *p*-value; instead, *to interpret the results, the null value (zero) of a coefficient is rejected if its 95% HDI excludes zero* [34]. In other words, when the HDI of a coefficient does not include zero, then we have high confidence that this variable has an effect on the model.

In Table 2, the domains (e.g., visual arts, cooking, etc.) that had an effect in a model are shown in bold and marked with a "*". For each model (stage), the highlighted domains are the ones that were more predictive of that stage. The estimated potential scale reduction factors ($\hat{R}$) of all the models were less than 1.1 for all the parameters, which indicates that the Bayesian models converged well [7].

Description of the results – Three of the models in Table 2 show interesting results (Models 2, 3 and 4). There is evidence that (1) the look-up stage was less likely to be included in arts & crafts tasks (log odd decreased 1.37 in Model 2); (2) the explore stage was less likely be included in everyday/other tasks (log odds decreased 1.06 in Model 3); and the creating ideas stage was more likely to be involved in tasks related to visual arts and arts & crafts (log odds increased 0.85 and 1.10, respectively in Model 4).

5.2.2 How different creative stages involve the use of different resources/tools. To understand whether the creative stages (e.g., find goals, look-up) could be used to predict the use of specific tools, we created four Bayesian random effects logistic regression models, one for each tool (search, videos, images, social sites). In each model, the predicted outcome is a binary variable that indicates whether the particular tool was used in the task. The predictor variables are seven binary variables corresponding to the seven creative stages (e.g., find goals, look-up, etc.). Also in each model, we included random effects to control for the influence of domains on the use of a tool (for instance, images might be generally more likely to be used in the domain of visual arts than in other domains).

		Model 1: Find goals	Model 2: Look up	Model 3: Explore	Model 4: Create ideas	Model 5: Combine ideas	Model 6: Select ideas	Model 7: Execute
Intercept	**Mode**	-0.02	**2.59***	**1.26***	-0.35	**-0.87***	**-1.17***	0.03
	HDI	[-0.56, 0.44]	**[1.74, 3.82]**	**[0.65, 2.19]**	[-0.91, 0.14]	**[-1.77, -0.23]**	**[-2.07, -0.55]**	[-0.48, 0.52]
Visual Arts	**Mode**	0.04	-0.80	-0.18	**0.85***	0.75	0.47	0.20
	HDI	[-0.74, 0.76]	[-2.26, 0.42]	[-1.31, 0.71]	**[0.09, 1.67]**	[-0.15, 1.76]	[-0.52, 1.44]	[-0.48, 1.01]
Cooking	**Mode**	0.08	-1.01	0.09	-0.08	0.33	0.86	-0.27
	HDI	[-0.92, 1.02]	[-2.68, 0.43]	[-1.13, 1.48]	[-1.15, 0.86]	[-0.78, 1.57]	[-0.19, 2.13]	[-1.24, 0.71]
Arts crafts	**Mode**	0.43	**-1.37***	0.02	**1.10***	0.76	0.47	0.52
	HDI	[-0.25, 1.09]	**[-2.67, -0.29]**	[-1.03, 0.89]	**[0.33, 1.77]**	[-0.06, 1.75]	[-0.32, 1.50]	[-0.19, 1.17]
Literature	**Mode**	-0.85	-0.05	-0.39	0.28	-0.13	-0.18	-0.68
	HDI	[-2.09, 0.10]	[-1.84, 2.21]	[-1.53, 0.99]	[-0.81, 1.22]	[-1.32, 1.17]	[-1.50, 1.13]	[-1.71, 0.37]
Music	**Mode**	0.40	0.61	1.39	-0.95	-1.72	-1.57	-0.24
	HDI	[-1.14, 1.99]	[-1.95, 6.27]	[-0.78, 7.16]	[-2.96, 0.84]	[-7.72, 0.47]	[-7.29, 0.73]	[-2.04, 1.18]
Perform arts	**Mode**	-0.01	0.42	-0.85	0.27	0.62	0.79	-0.11
	HDI	[-2.42, 2.39]	[-2.85, 5.72]	[-3.66, 1.53]	[-2.11, 2.74]	[-1.86, 3.31]	[-1.62, 3.61]	[-2.36, 2.47]
Science & engineering	**Mode**	0.36	-0.13	-0.06	-0.23	0.73	0.22	0.43
	HDI	[-0.47, 1.15]	[-1.63, 1.65]	[-1.13, 1.06]	[-1.07, 0.61]	[-0.20, 1.83]	[-0.74, 1.36]	[-0.37, 1.26]
Everyday/other	**Mode**	-0.29	0.15	**-1.06***	-0.94	-0.36	-0.26	0.17
	HDI	[-1.26, 0.57]	[-1.47, 2.43]	**[-2.24, -0.05]**	[-2.09, 0.08]	[-1.70, 0.73]	[-1.38, 1.02]	[-0.72, 1.08]

Note: * indicates that the null value (zero) is rejected.

Table 2: Creative process stages across different domains of creative tasks. Each column shows results for one Bayesian logistic regression model with the eight domains as predictor variables. The predicted outcome is a binary variable that indicates whether the stage was included in the task or not. Cells marked in bold show domains that had an effect in that model. The mode values show the log odds increase/decrease. $\hat{R}$ of all the models were less than 1.1 for all the parameters.

		Intercept	Find goals	Look up	Explore	Create ideas	Combine ideas	Select ideas	Execute	σ
Model 1: search	**Mode**	0.33	-0.97	**2.03***	0.58	0.68	-0.52	-0.18	0.33	**1.01***
	HDI	[-1.52, 2.24]	[-2.01, 0.09]	**[0.95, 3.30]**	[-0.52, 1.71]	[-0.41, 1.75]	[-1.58, 0.54]	[-1.32, 1.00]	[-0.71, 1.45]	**[0.04, 3.49]**
Model 2: Videos	**Mode**	**-1.30***	0.19	1.06	-0.07	0.14	0.02	-0.43	**0.82***	**0.33***
	HDI	**[-2.61, -0.06]**	[-0.50, 0.88]	[-0.02, 2.08]	[-0.89, 0.73]	[-0.59, 0.88]	[-0.67, 0.78]	[-1.23, 0.41]	**[0.09, 1.57]**	**[0.01, 1.63]**
Model 3: Images	**Mode**	**-1.54***	0.45	**-1.27***	**1.66***	**0.93***	0.36	-0.48	-0.01	**0.84***
	HDI	**[-3.39, -0.11]**	[-0.27, 1.26]	**[-2.50, -0.24]**	**[0.63, 2.70]**	**[0.12, 1.73]**	[-0.44, 1.18]	[-1.40, 0.39]	[-0.84, 0.85]	**[0.19, 2.59]**
Model 4: Social sites	**Mode**	**-2.72***	0.04	0.11	0.37	**0.98***	0.57	0.13	0.36	**0.69***
	HDI	**[-4.56, -1.09]**	[-0.86, 0.90]	[-1.23, 1.63]	[-0.77, 1.51]	**[0.07, 1.98]**	[-0.30, 1.53]	[-0.80, 1.09]	[-0.56, 1.33]	**[0.08, 1.8]**

Note: * indicated the null value (zero) is rejected

Table 3: Use of tools to support the creative process. Each row shows results for one Bayesian regression model with the seven creative stages as predictor variables. The predicted outcome is a binary variable that indicates whether the tool was used in the task or not. Cells marked in bold show stages that had an effect in that model. The mode values show the log odds increase/decrease. $\hat{R}$ of all the models were less than 1.1 for all the parameters.

The results of the random effects logistic regression models are shown in Table 3. In Table 3, each **row** shows results for one of the models. According to the results, there is evidence that (1) when participants were doing tasks that included the need to *look-up* relevant information, the log odds of using search engines increased 2.03 in Model 1, whereas the log odds of using images dropped 1.27 in Model 3; (2) when participants tried to *explore* potentially relevant information, the log odds of using images increased 1.66 in Model 3; (3) when participants attempted to create ideas, the log odds of using images and of using social sites increased 0.93 in Model 3 and 0.98 in Model 4, respectively; and (4) when participants attempted to put ideas into practice (*execute*), the log odds of using videos increased 0.82 in Model 2.

These results show that participants used different resources and tools to support different stages of their creative processes and provide practical data about what types of information may be most useful to users during different creative stages. While it is not surprising that users would make use of different tools for different stages, our results show *which* specific tools were the most relevant to specific stages. These findings suggest opportunities for search systems to predict a users' stage and use this information to help show specific types of content (for example, to use queries and interaction history to determine domains and possible stages).

5.2.3 Users' satisfaction of tools to support stages. To investigate participants' satisfaction with using each tool for different stages (Q.6), we developed seven Bayesian random effects ordered probit regression models, one for each stage (e.g., find goals, look-up, etc.). Ordered probit regression is recommended when the outcome is ordinal values, especially when the values are not normally distributed [34]. In each model, the predicted variable is an ordinal variable that indicates the satisfaction score of the tool. The predictors of each model are dummy variables corresponding to the tool that was evaluated. In addition to including the random effects associated with domains, we also included random effects in each

		Model 1: Find goals	Model 2: Look up	Model 3: Explore	Model 4: Create ideas	Model 5: Combine ideas	Model 6: Select ideas	Model 7: Execute
Intercept	Mode	6.53	6.21	6.26	6.05	6.04	6.15	6.34
	HDI	[6.07, 7.04]	[5.87, 6.56]	[5.86, 6.72]	[5.4, 6.74]	[5.57, 6.50]	[5.44, 6.82]	[5.62, 7.1]
Search	Mode	0.27	**0.50***	0.15	0.20	0.00	0.17	-0.04
	HDI	[-0.18, 0.77]	**[0.16, 0.79]**	[-0.22, 0.52]	[-0.39, 0.81]	[-0.47, 0.43]	[-0.56, 0.79]	[-0.55, 0.53]
Videos	Mode	0.36	0.32	**0.46***	0.61	0.08	0.29	0.46
	HDI	[-0.31, 0.96]	[-0.05, 0.72]	**[0.03, 0.97]**	[0.00, 1.47]	[-0.43, 0.64]	[-0.47, 1.10]	[-0.07, 1.01]
Images	Mode	0.38	0.08	0.06	0.47	**0.54***	-0.48	0.18
	HDI	[-0.21, 0.96]	[-0.39, 0.54]	[-0.35, 0.49]	[-0.22, 1.09]	**[0.04, 1.11]**	[-1.29, 0.22]	[-0.43, 0.89]
Social sites	Mode	**-0.94***	**-0.84***	**-0.75***	**-1.35***	-0.65	-0.03	-0.69
	HDI	**[-1.74, -0.27]**	**[-1.42, -0.30]**	**[-1.23, -0.17]**	**[-2.34, -0.37]**	[-1.33, 0.03]	[-1.20, 1.31]	[-1.44, 0.10]
σ_υ	Mode	**1.01***	**0.91***	**1.31***	**1.38***	**0.64***	**0.95***	**1.73***
	HDI	**[0.23, 1.55]**	**[0.54, 1.3]**	**[0.88, 1.77]**	**[0.88, 2.01]**	**[0.01, 1.09]**	**[0.07, 1.50]**	**[1.22, 2.34]**
σ_ω	Mode	0.06	0.05	0.05	**0.09***	0.07	0.11	0.11
	HDI	[0, 0.73]	[0, 0.48]	[0, 0.61]	**[0.01, 1]**	[0, 0.72]	[0, 1.03]	[0, 1.24]

Note: * indicated the null value (zero) is rejected

Table 4: Satisfaction with using each tool in different creative process stages. Each column shows results for one Bayesian ordered probit regression model with the four resources/tools as predictor variables. The predicted outcome is an ordinal variable that indicates satisfaction score of the tool. Cells marked in bold show recourses/tools that had an effect in that model. The mode values show the latent variable, μ increase/decrease (see Equations 3 in Appendix C). $\hat{R}$ of all the models were less than 1.1 for all the parameters.

model to control the impacts of repeated measurements (different tools could be evaluated by the same participant multiple times).

The results of the ordered probit regression models are shown in Table 4. Each **column** shows results for one of the models. The results of the table show that *across different domains and different participants* there is evidence that participants were likely to feel more satisfied with (1) using search engines when they attempted to look up information (Model 2), (2) using videos to explore potentially relevant information (Model 3), and (3) using images to help combine their ideas (Model 5). Based on the results of Model 1, 2, 3, and 4, we also found that people were likely to feel less satisfied with using social sites across several creative process stages (finding goals, look-up, explore, and create ideas). The findings in Table 4 also suggest that there were random effects that resulted from the repeated measurements by participants (σ_υ). This is not surprising, and indicates expected individual biases in using ratings. Table 4 also shows that the random effects associated with the domains of the creative tasks (σ_ω) were very weak, indicating little overall effects of domains on satisfaction with the tools.

6 DISCUSSION

In this paper, we used well-established psychology-based creativity research to ground definitions of creativity, creative processes, and creative tasks in the context of information search. Our findings provide insights about (1) how people use search engines and information resources to support their everyday creativity tasks, (2) the ways that creative process stages that are involved in their tasks, and (3) how they use different information resources to support different creative stages. In this section, we summarize our findings and discuss implications for future research.

With respect to **RQ1** (What types of tasks?), we found that participants looked for information to support a wide range of creative tasks (see Table 1), suggesting many opportunities (and challenges) for search systems to support everyday creativity. Considering **RQ2** (What computing platforms and information tools were used?), we found that in 42% of the tasks (n=74), combinations of devices were used, illustrating the importance of cross-session and cross-device search task resumption [62] in order to support creative tasks. Search engines were frequently used in all the task domains and images played a frequent role in arts & crafts and visual arts tasks. Videos were also commonly used, especially in arts & crafts, science, and literature/writing.

RQ3 addressed the creative process stages involved in our participants' creative tasks. For this question, our results show several interesting findings. First, we found that all of the creative stages we investigated were commonly involved in our participants' tasks. The look-up and explore stages were involved in 86% and 75% of tasks respectively, and even the least common stage (select ideas) was reported in 33% of the tasks. Second, we found that most of our participants' tasks involved *multiple* creative stages – 73% involved at least three different stages.[3] Consistent with prior work on task-based search [30], these results indicate that system awareness of the searcher's ongoing task and task-stage is important for search systems to provide stage-appropriate information.

RQ4 considered the relationships between task domain, creative process stages, and information resources/tools. Our Bayesian logistic regression models found that the look-up stage was less likely to be included in arts & crafts tasks, the explore stage was less likely in everyday/other tasks, and that the creating ideas stage was more likely in visual arts and arts & crafts tasks. Second, we examined whether different stages involved the use of different information resources/tools. Our regression models found that when doing tasks that involved the look-up stage, participants were more likely to use search engines and less likely to use images; that the explore stage increased the use of images, and that the creating ideas stage increased the likelihood of using images and social sites. Finally, we examined participants' satisfaction using different tools to support different stages. Our results showed that participants were likely

[3]**Number of stages included in a task (number of unique tasks)**: one-stage (18), two-stages (29), three-stages (34), four (29), five (21), six (17), and seven-stages (25).

to be more satisfied with using search engines to look-up information, using videos to explore potentially relevant information, and using images to help combine ideas. Participants were less satisfied with using social sites across several stages (finding goals, look-up, explore, create ideas). These results illustrate the importance of understanding users' current tasks and task stages, and point to *specific opportunities* for task-aware search systems to assist users with task- and stage-appropriate information in creative tasks.

Creative tasks: In the most of the tasks we analyzed, searching for information was not the ultimate goal, but was part of a process to achieve the creative goals of the task. Several of the creative stages we investigated are components of other types of information seeking tasks (e.g., look-up). However, several stages are more characteristic of creative tasks (e.g., create ideas, combine ideas). In this sense, creative tasks may be viewed as different from "regular" problem solving tasks. For example, Mumford et al. has concluded that creative tasks may differ from standard problem-solving tasks in that they require both convergent and divergent thinking, more cognitive effort, and may involve combining/reorganzing existing knowledge [42]. Based on these perspectives, we see opportunities for future IR research to address users' needs in different creative stages (e.g., see work on "create" tasks by Kelly et al. [31]).

7 IMPLICATIONS

Below we discuss implications of our work in terms of developing search systems to support creative tasks and future research.

(1) Systems should support cross-device search. In our survey, 47% of the creative tasks were performed across different platforms, suggesting the importance of support for continuing searches across devices. One possible way to support cross-platform creative tasks is to facilitate rich history-keeping and re-finding. Although many search engines currently support cross-platform history features, there are still challenges about how best to support users. For instance, most existing browsers display search history in chronological order, which may make it difficult for users to uncover and make sense of relationships between the information encountered, different creative stages, and keep track of different creative tasks that may be worked on in parallel. Future work should explore approaches to support making use of search history and saved content across different platforms, stages, and projects.

(2) Images and videos play important roles. Our results show that images and videos were an important resource for many creative searches and that they were frequently used in conjunction with search engines. In addition, our results show that the use of resources/tools differs across creative process stages (Table 3). This suggests that creativity can be supported through a better understanding of how to mix and rank different types of vertical content on a search result page based on users' task domain and creative process stage. For instance, in our study, participants were more likely to use videos in the execute stage (figure out how to put my ideas into practice to achieve my goal). One possible reason is that for many people, it is easier to learn procedural knowledge from videos than from textual materials. This is consistent with prior work that has shown that participants searched for videos to learn procedural knowledge about craft techniques and skills [59]. Furthermore, research from learning science has suggested that some types of knowledge are easier to learn with certain media formats than others (e.g., introducing complex topics is easier to learn with videos) [5, 41]. Future research should explore how search engines can better support users to learn different types of knowledge (e.g., declarative vs. procedural knowledge) by optimizing multimedia search results. Our results suggest that users search for information that is not only relevant, but also easy to learn and apply.

(3) There are specific opportunities for task- and stage-aware support. Our results show that for particular creative stages, participants were more likely to use certain tools (e.g., there was increased use of images for the creating ideas stage). In addition, participants had a higher probability of feeling satisfied using certain tools for particular creative stages (e.g., using images to help combine ideas). These findings illustrate opportunities for systems to support users' in particular types of creative tasks and stages.

Interestingly, Table 4 (Model 3) shows that no specific tool was preferred for the "explore" stage. Shneiderman suggested that faceted search interfaces, dynamic queries, and rich mechanisms for organizing search results are possible approaches to supporting users in exploration stages [52]. In addition to supporting the "look up" and "explore" stages, tools could be designed to integrate with search processes to support ideation. For example, Kerne et al. [32] created a novel tool that enables users to collect multimedia content (such as text, images, and videos) as they search.

As our findings suggest, creative tasks are often longitudinal, multi-stage, and multi-session tasks. Search system support for these tasks may benefit not only from traditional methods for session identification, but also from *stage identification* to understand and classify the users' current creative stage. Moreover, information needs may change as users move from one task stage to another. Future work is needed to better understand the relationships of users' information needs across different creative stages.

8 CONCLUSION

In this study, we explored the role that information search plays in supporting everyday creativity. We observed that people engage in information seeking to support an array of creative tasks across different domains and that they often use multiple devices and information resources/tools to support these activities. Our participants' tasks involved multiple creative stages that involved different, more divergent needs (e.g., create ideas) than other types of directed, convergent searching (e.g., find information). We found that search engines and other information resources/tools (e.g., images, videos, social media) are strategically used by people to support their creative processes, but there are opportunities to provide better support. Our findings provide insights into the relationships between creative task domains, creative stages, and information tools to support these activities. These results highlight particular challenges and opportunities for task- and stage-aware search systems to support users working on creative tasks and provide a foundation for future research to investigate ways to design search engines to better support users' creative processes.

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A KEYWORDS OF MTURK HIT GROUPS

Keywords used in the posting of Amazon Mechanical Turk (MTurk) HIT groups:

- **Group 1**: crafts, architectural design, culinary arts;
- **Group 2**: humor, theater, film;
- **Group 3**: invention, entrepreneurial ventures, product design;
- **Group 4**: visual arts, interaction design, visual design, graphic design;
- **Group 5**: writing, presentation, report writing, creative writing.

B SURVEY QUESTIONS

Q.1. For this set of questions, please think about a time recently when you went online to look for useful resources or information to help you create something. For example: designing something, coming up with a solution to a problem, brainstorming for a project, creating a new recipe, working on a writing project, remodeling your house, and so on.

Q.2. Still focusing on the task you just described, please tell us about your creative process in the task. For example, you can tell us how you started this task, what sites or resources did you use, your strategies to find information or resources, and so on.

Q.3. Which of the following did you use to look for information in this task? Choose all that apply:

- Desktop or PC,
- Smartphone,
- Tablet,
- Smart TV (Apple TV, Roku, Play TV, etc.),
- Google Home or Alexa,
- other (please specify)

Q.4. Which of the following tools did you use as part of your search? Choose all that apply:

- Search engines (Google, Bing, Yahoo, etc.)
- Videos (Youtube, Vimeo, ect.)
- Images (Pinterest, Instagram, Tumblr, Flickr, etc.)
- Social sites (Facebook, Twitter, Reddit, Google+, etc.)
- Other (please specify)

Q.5. For which of the reasons below did you use *<option selected in Q.4>* in the task (Choose all that apply):

- **Figure goals**: figure out my goal (what I want to create/design or which problem I want to address/solve)
- **Look up**: look up information relevant to my goal
- **Explore**: explore (gather a broad of range of potentially related information) about my goal
- **Create ideas**: create a large variety of ideas that may achieve my goal
- **Combine ideas**: combine some ideas that I have already had
- **Select ideas**: select the best ideas from all the new ideas that I have created
- **Execute**: figure out how to put my ideas into practice to achieve my goal
- Not applicable

Q.6. How satisfied were you with using *<option selected in Q.4>* to: *<option selected in Q.5>*

C BAYESIAN ANALYSIS

In the Bayesian models, we adopted Gelman et al.'s suggestions by setting Cauchy distributions as the default weakly informative priors for **intercept** (β_0) and **coefficients** (β_j) [21]. The half-Cauchy distribution is used as the default prior for **scale parameters** (σ) [20]. Normal distribution is used as the priors for **random effects** (ω and υ).

High-density interval (HDI) is recommended to be used for the credible interval in Bayesian analysis [34, p.89]. 95% HDI includes all the most credible values (ones with highest probability density) of the parameter. It should be noted that HDI is different by definition from the CI, which is a limit that provides no distributional information about the parameter values [34].

C.1 Logistic Regression Model

$$\begin{aligned} \mu_i &= logistic\,(\beta_0 + \sum_j \beta_j x_{ij}) \\ y_i &\sim Bernoulli\,(\mu_i) \\ \beta_0 \sim Cauchy\,(0, 10);\ & \beta_j \sim Cauchy\,(0, 2.5) \end{aligned} \tag{1}$$

The sum-to-zero constraint ($\sum_j \beta_j = 0$) is added in the model.

C.2 Rand. Effects Logistic Regression

$$\begin{aligned} \mu_i &= logistic\,(\beta_0 + \omega_{[domain[i]]} + \sum_j \beta_j x_{ij}) \\ y_i &\sim Bernoulli\,(\mu_i) \\ \omega &\sim Normal\,(0, \sigma_\omega);\ \sigma_\omega \sim Cauchy^+\,(0, 5) \\ \beta_0 &\sim Cauchy\,(0, 10);\ \beta_j \sim Cauchy\,(0, 2.5) \end{aligned} \tag{2}$$

ω is the random effects in the model. The $domain[i]$ refers to the domain of the task that participant i conducted ($domain[i]$ = 1,...,8).

C.3 Rand. Effects Ordered Probit Regression

$$\begin{aligned} \mu_i &= \beta_0 + \upsilon_{[user.id[i]]} + \omega_{[domain[i]]} + \sum_j \beta_j x_{ij} \\ p(y_i = k \mid \mu_i, \boldsymbol{\theta}) &= \phi(\theta_k - \mu_i) - \phi(\theta_{k-1} - \mu_i) \\ \upsilon &\sim Normal\,(0, \sigma_\upsilon);\ \omega \sim Normal\,(0, \sigma_\omega) \\ \sigma_\upsilon, \sigma_\omega &\sim Cauchy^+\,(0, 5) \\ \beta_0 &\sim Cauchy\,(0, 10);\ \beta_j \sim Cauchy\,(0, 2.5) \\ \theta_k &\sim Normal(k + 0.5, 0.25) \end{aligned} \tag{3}$$

In the model, it is assumed that there is a latent variable (μ_i) influencing participant's responses to an ordinal variable, y_i, through some "threshold concepts" that are modeled by a series of threshold values ($\theta_1, \theta_2, ..., \theta_{K-1}$, where K equates the number of ordered options in the ordinal variable). In the model, υ and ω are the random effects. ϕ refers to the cumulative distribution function. $Normal(k + 0.5, 0.25)$ is used as the prior for each threshold values ($k = 2, .., K - 2$) [34]. To make the model determined, the two extreme thresholds are fixed to meaningful values on the outcome scale [34]: $\theta_1 \equiv 1 + 0.5$ and $\theta_{K-1} \equiv K - 0.5$. The sum-to-zero constraint ($\sum_j \beta_j = 0$) is added to the model.