Facilitating Dataset Search of Non-Expert Users through Heuristic and Systematic Information Processing

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Abstract

Data has become increasingly critical in professional roles and workplaces where it has not been used previously. Dataset search engines, however, do not offer a good user experience, which makes searching for datasets complex and confusing. This research aims at exploring technological affordances that potentially facilitate dataset search, especially for non-expert users. The Heuristic-Systematic Model of information processing is used as a theoretical basis for proposing that technological affordances, in particular. a relevance cue and content preview, would activate heuristic and systematic information processing, respectively, therefore enabling more effective searches. 89 participants recruited via Amazon Mechanical Turk participated in an experimental survey study in which they were presented with a dataset search prototype and asked questions about their user experience. The results suggest that both affordances positively impact user experience, with a significantly greater effect on non-expert users. The insights offered by this study imply the importance of understanding the specific needs of non-expert users as well as the potential of the visual cues and content previews to enable the public to harvest the power of data in the interactive search environment.

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Introduction

In a world that is increasingly digital, millions of datasets have been uploaded to the web. Governments, companies, universities, commercial entities, and more are sharing data that spans the breadth and depth of research (Noy et al., 2019). The onset of big data and technology like machine learning has expanded the scale of data analysis to regularly exceed what can be plotted by hand (Rule et al., 2018). This explosion of data use and size has prompted both the sharing of data online and an increasingly critical role of data in every domain and professional role (Koesten et al., 2017).

Because data and data analysis are essential in professional roles and the workplace, it is important to consider the accessibility of dataset search for non-expert users. Consider a journalist tasked with covering a topic they do not have academic or professional experience in (Koesten et al., 2017). To write a reputable article, the journalist needs to incorporate factual data despite being a non-expert in the subject. The search experience of a non-expert, who may not know what subject specific terminology to use, may be different from that of an expert with experience in researching the topic. As stated by scientists Rule, Tabard, and Holland, "making data and analyses understandable and public is crucial to advancing open science and enabling reproducibility (2018, p. 1)." When considering dataset search, it is imperative to ensure that lack of expertise is not a barrier to accessing information.

Regardless of user expertise, the current state of dataset search makes the acquisition of datasets tedious and confusing. In the context of search, datasets can be understood as data that is explicitly organized in a structure such as a relational database, spreadsheet, or web table (Koesten et al., 2017). The ideas and tools from web search are not directly applied to datasets

(Rieh et al., 2016), as search is designed for documents instead of structured data (Cafarella et al., 2011). For example, unlike documents, structured data is embedded in textual web pages and must be extracted in order to be used (Cafarella et al., 2011). Additionally, there is not a centralized data design that extends beyond individual databases (Cafarella et al., 2011). This means that users searching for datasets are faced with a complex, multi-step process that varies from site to site.

Ultimately, dataset search tools often do not offer a good user experience, which leaves expert and non-expert users alike at a disadvantage when searching for data (Koesten et al., 2017). Despite the necessity of making datasets easily available online, little is known about how people search for data (Koesten et al., 2017). In order to understand how to improve the user experience of dataset search and enhance data accessibility, it is pertinent to understand how users interact with and process the information they encounter when searching for data. This study seeks to learn more about what non-expert users need in an ideal dataset search engine by investigating dataset search through the lens of information processing, with the goal of introducing technological affordances to facilitate dataset search for non-expert users.

Background

In the search process, users try to locate content that will satisfy their query. To do so, they must navigate the tools provided by the search engine as well as the information presented in various search results. Thus, search engines need to present information in a way that facilitates the discovery of desired content. Non-expert users may not have the experience necessary to easily navigate the varying individual data designs present in existing databases. To avoid overwhelming or confusing its users, the structure of a search engine needs to allow them to easily hone in on and select the information that is pertinent to them.

For non-experts, dataset search engines need to activate a user's stored knowledge about search in order to allow them to quickly accomplish their data search goals. This stored knowledge can be understood as a heuristic, which is a learned judgement that requires limited cognitive effort to be produced (Chaiken, 1980). In the context of search, an example of a learned heuristic may be that clicking a search button allows the user to view search results. Heuristics allow a user to judge the validity or usefulness of content based on surface level cues, without the need to closely analyze detailed information (Chaiken, 1980). Thus, heuristic processing that directs a user's attention to the dataset most in line with the search query would allow a non-expert user to circumvent an analysis of dataset content that they may not have the background knowledge or expertise to do. Based on the potential of heuristics to improve non-expert search experience, the Heuristic-Systematic Model of information processing, or HSM, is one way to approach the design of a dataset search interface that allows for better user experience than existing models.

The HSM posits two models of processing by which judgements are made: heuristic processing and systematic processing. As already discussed, heuristics have the potential to facilitate non-expert users searching for data. For heuristic processing to occur, heuristics must be previously stored in memory, retrieved from memory, and relevant to whatever task is at hand (Chen et al., 1999). This means that the context and cues of the task must be salient enough to activate a stored heuristic (Koh & Sundar, 2010). When considering dataset search, any technological affordances intended to make search easier for non-expert users must be attention grabbing and able to activate a heuristic that the user has already associated with searching for information in other contexts and environments.

As noted by Fu and Sim, users overwhelmed by information are drawn towards indicators of content quality (2011). In the context of online news, interface cues have been found to have significant positive effects on users' perception of news content (Go et al., 2014). Similarly, work with Wikipedia found that peripheral cues increased users' credibility judgement towards article content (Lim, 2012). For each of these studies, the cue successfully oriented user attention, resulting in a more positive outcome towards what the cue was orienting them towards. In the context of a dataset search engine, a salient cue on the interface that points towards the result most relevant to a user's search query may improve the user experience of the site and thus facilitate dataset search. The positive impact of attention orienting cues on user perception found in previous studies leads to H1 of the study:

H1: The presence of relevance cues is likely to enhance users' perception of interface usability and usefulness of a dataset search engine.

The second component of the HSM is systematic processing, which requires significantly more cognitive energy than heuristic processing (Chaiken, 1990). Whereas heuristic processing is automatic, systematic processing requires active scrutiny of the judgement task at hand. Systematic processing consists of in-depth analysis of information, particularly focused on the information's semantic content (Chen, 1999). People will engage in systematic processing if they think that heuristic cues are not enough to create judgemental confidence (Koh & Sundar, 2010).

As noted by Koesten et al., finding a useful dataset requires examining its content in order to understand what information it contains, as well as how complete, accurate, and up-to-date this content is (2017). However, accessing, reviewing, and evaluating the content of a dataset requires cognitive effort, not to mention the expertise in understanding the statistical information contained in a dataset. This kind of systematic processing poses challenges especially to non-expert users, who may become overwhelmed simply by getting the datasets downloaded. Therefore, interface features that afford a quick and easy preview of the dataset content might facilitate such need and assist non-expert dataset search. The efficacy of content preview in facilitating a user's decision to select content has been explored with online video clips (Yoon & Kim, 2019). This study found that a thumbnail and title resulted in a positive effect on video selection. It is possible that this effect can also be found in the context of dataset search content previews, which leads to H2 of the study:

H2: The presence of dataset content previews is likely to enhance users' perception of interface usability and usefulness of a dataset search engine.

The motivation and experience of expert versus non-expert users may play a key role in the level of information processing they achieve. Heuristic processing is typically expected to be used before systematic processing, as it requires less cognitive effort than systematic processing and is thus quicker and less taxing (Chen et al., 1999). The least effortful outcome, however, is not always the most desirable. The sufficiency principle consists of a continuum of judgement confidence with two critical points: a perceiver's actual confidence level, and the level of confidence they want to be at. The larger the gap is between the two points, the more likely systematic processing is to override heuristic processing; if a user wants to know more than they already do, they will put more effort into understanding the content (Chen et al., 1999). However, the desire to increase judgement confidence may not be enough to engage beyond heuristic processing. When searching for datasets, a non-expert may be too overwhelmed by subject matter they are not experienced with to be able to effectively use systematic processing. In order to understand what technological affordances best facilitate search, it is possible that individual differences in expertise will moderate the impact of the independent variables, which leads to H1a and H2a of the study:

H1a: The impact of relevance cues will be moderated by individual difference variables.

H2a: The impact of content preview will be moderated by individual difference variables.

Because the two independent variables, relevance cue and content preview, have been hypothesized through the lens of the HSM, it is possible that combination of the two features will have an effect on the level of processing that occurs. This leads to the final hypothesis of the study:

H3: Relevance cue and content preview interact in their effects on users' perception of interface usability and usefulness of a dataset search engine.

The goal of creating technological affordances that orient a user's attention towards the result that satisfies their search query is to create a dataset search interface with a better user experience than the ones that currently exist. If a user is able to easily find what they need, they will likely perceive the interface to be more usable and useful than an interface that is complicated to navigate. Thus, this study looks to see if the identified independent variables improve user search experience by better facilitating search.

Methods

Participants

An experimental study was conducted with N = 89 participants recruited from Amazon Mechanical Turk, aged between 25-34 on average, 36% female. 76% of the participants had an educational background of an associate's degree or higher. Finance and insurance, manufacturing, and construction were the most frequently reported occupations held by participants.

Design

Participants were divided into four different conditions using a 2(content preview: present, absent) x 2(relevance cue: present, absent) between subject design, with moderators of motivation and expertise in dataset search and the topic presented in the website prototypes. For these conditions, "present" indicates that the feature, a relevance cue or dataset content preview, was part of the prototype; "absent" indicates that the prototype did not contain this feature. These variables, along with the number of participants in each condition, are presented in the table below. Dependent variables included perceived usefulness, ease of use, usability, and technology adoption intention, which are a measurement of how useful and usable the participant finds the prototype to be. Recognition and recall were also used to measure level of information processing.

Table 1

Experiment Design of Independent Variables

	Content Preview	
Relevance Cue	**Present**	**Absent**
Present	Relevance Cue + Content Preview N = 20	Relevance Cue + NO Content Preview N = 23
Absent	NO Relevance Cue + Content Preview N = 23	NO Relevance Cue + NO Content Preview N = 28

Materials

Website prototypes. Four different prototypes, made with Adobe XD, were used in the study. Each prototype had two main screens: a home screen and a screen showing the same search four results. On the home screen was the title “data.search” and a search bar that was prefilled with the query “Alaska crime rate 2019.” When the participant clicked the search button, they were shown the subsequent screen with search results. A back button allowed the participant to go back to the home screen if they wished to do so. Though fictitious, the content in the results was modelled off of other existing dataset search sites and data, to ensure that obviously incorrect or inconsistent information would not sway the participant’s perception of the site.

For the prototypes with a dataset content preview, each search result had a link beside it stating “preview dataset.” When clicked, this link produced a table with rows and columns filled with numerical data, as well as headings such as “crime type” and “year.” A participant could close the preview via a link stating “close preview” and continue the process for each subsequent search result’s preview.

For the prototypes with a relevance cue, participants had the option to click on a link above the search results stating “show relevance.” When this link was clicked, rectangles appeared beside each search result. These rectangles were partially filled with color to represent relevance; the most relevant option was filled the most, the next relevant option was filled slightly less, and so forth. Most search engines already order results by relevance. Results were ordered by date, with the most recent result appearing first on the list. Visuals of the prototypes are found in Appendix A.

Survey. A survey made with Qualtrics was used to provide participants with a link to the data.search prototype and to measure their responses to the site. To measure if heuristic processing occurred, participants were provided with four different home screens of data.search. Participants who were more engaged in heuristic processing would recognize the interface better than those who were not, and thus should select the proper image. One image was the true home screen, while the other three were manipulated to differ with a combination of different colors, search bar placement, website title, or website catchphrase. For example, the true home screen showed text stating "a search engine for datasets," whereas an alternative option read "searching for datasets." These four models are shown in Appendix B; the correct option is b.

To measure if systematic processing occurred, participants were asked to identify Alaska's 2019 crime rate from a multiple choice list of answers that included 8, 85, 885, and 8,000. Participants who were more engaged in systematic processing will have paid more attention to the content, and thus would have been able to recall this information better than those who were not. The answer, 885, was present in the description of a search result for all prototypes, as well as in the dataset for the prototypes that featured a content preview. This preview is shown in the third image of Appendix A. The ability to properly recall information indicates that participants engaged with the information and thus systematic processing occurred. Additionally, participants were also asked to write out the information they saw on data.search (i.e. content, features) which served as a check to see if they explored the interface.

To measure perceived usefulness, ease of use, usability, and technology adoption intention, pre-existing scales sourced from Venkatesh, Lund, Tulles and Stetson, and usability.gov were modified to suit dataset search. Similarly, motivation and expertise in the topic of dataset search and crime rates were measured based on modified questions from Lee and Kim and Lee et al., respectively. Among demographic questions was a technology fluency scale sourced from Rosen et al., an internet search intensity scale from Edison and Geissler, and questions about age, gender identity, ethnicity/race, education level, and industry of work sourced from Hughes et al. to gain a better grasp on participant background and experience. Motivation for crime rate and dataset search, expertise in crime rate and dataset search, technology fluency, and internet search intensity were used as moderating variables that identified participant level of expertise. A list of survey scales modified for the study is found in Appendix C.

Procedure

Participants were directed to the Qualtrics survey via MTurk. Once reading the informed consent form and agreeing to participate in the study, they were informed that they would be exploring the functionality of the preview of a website designed for datasets. They were given a brief definition of a dataset before reading the following prompt:

> *You are asked to write a report on crime rate trends in the United States. Specifically, you are informed that Alaska had the highest crime rate in the U.S. in the year of 2019. Now, you are instructed to find relevant data to add to your report. You need to find what the 2019 Alaska crime rate is.*

After reading the prompt, participants clicked on a link that opened the data.search prototype in a new tab. Once they explored data.search, they returned to the survey and the remaining questions. At the end of the survey, they were debriefed and thanked for their time.

Results

In order to test the hypotheses that predicted the main effects and interaction effects of the two independent variables (i.e. relevance cue and content preview) on the dependent variables (i.e. perceived usefulness, ease of use, usability, technology adoption intention), as well as the moderation effects of the individual difference variables (i.e. topic motivation, topic expertise, data motivation, data expertise, internet search intensity, technology fluency), a number of three-way ANOVAs were conducted; T-tests were used to determine the impact of the independent variables on heuristic processing (i.e. recognition) and systematic processing (i.e. recall). Prior to testing the hypotheses, scale reliability of all the measurements were assessed using Cronbach's alpha (Santos). As shown in Table 2, all of the scales have reached a Cronbach's Alpha that is greater than 0.70, indicating high levels of scale reliability such that summer scores were used in the consequent tests.

Table 2

Table containing variable type (moderating or dependent), variable name, and Cronback's Alpha value.

Variable Type	Variable Name	Cronbach's Alpha
DV	Ease of Use	0.897
	Perceived Usability	0.93
	Technology Adoption Intention	0.884
	Usability	0.722
Moderator	Data Expertise	0.883
	Data Motivation	0.896
	Internet Search Intensity	0.861
	Technology Fluency	0.912
	Topic Expertise	0.928
	Topic Motivation	0.89

Relevance Cue

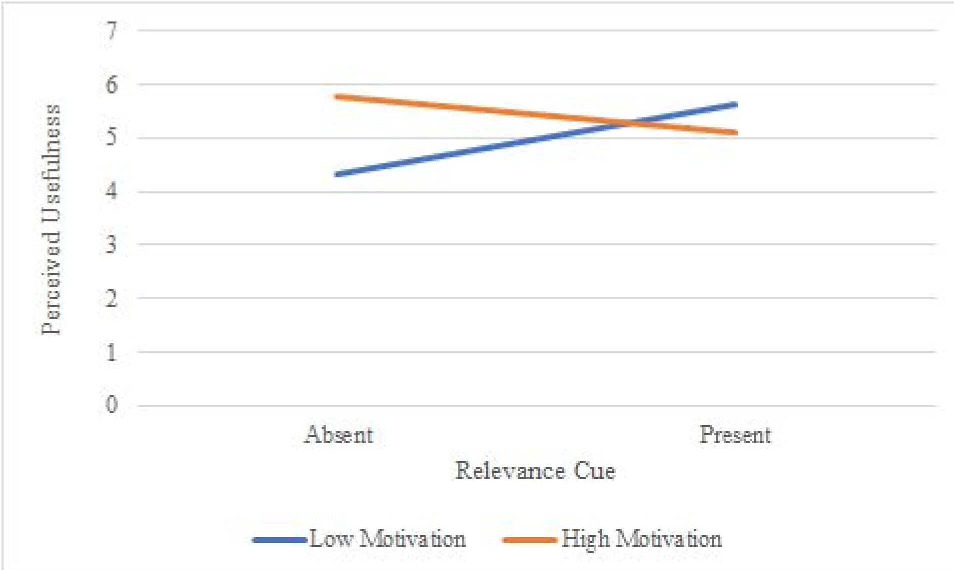
H1 and H1a hypothesized that the relevance cue would positively influence the outcome variables, e.g. perceived usefulness, ease of use, usability, and technology adoption, and such an effect would be moderated by individual difference variables such as expertise, motivation, technology use, previous search behaviors. Three-way ANOVAs were conducted to examine whether the hypotheses were supported. The results revealed that no statistically significant main effect of relevance cue was found. However, the tests showed several interaction effects between the relevance cue and some of the individual difference variables, which are discussed below.

Interaction Effects

Data Motivation. There was a statistically significant interaction effect of the relevance cue and data motivation on perceived usefulness, $F(1, 89) = 4.206$, $p < 0.05$. As shown in Figure 1, for users with low data motivation, relevance cues had greater perceived usefulness than no relevance cues. However, for those with high data motivation, relevance cues resulted in slightly lower perceived usefulness than no relevance cues.

Figure 1

Interaction Effect of Data Motivation and Relevance Cue on Perceived Usefulness



Internet Search Intensity. A statistically significant interaction effect was found between the relevance cue and internet search intensity influencing participants' perceived usefulness, $F(1, 89) = 5.416$, $p < 0.022$, shown in figure 2; and ease of use, $F(1, 89) = 4.098$, $p < 0.05$, shown in figure 3. The interaction effect of the relevance cue and internet search intensity on technology adoption intention is approaching significance, $F(1, 89) = 3.906$, $p = 0.052$, shown in figure 4. For users with low internet search intensity, relevance cues had greater perceived usefulness, ease of use, and technology adoption intention than no relevance cues. However, for those with high internet search intensity, relevance cues resulted in slightly lower perceived usefulness, ease of use, and technology adoption intention than no relevance cues.

Figure 2

Interaction Effect of Internet Search Intensity and Relevance Cue on Perceived Usefulness

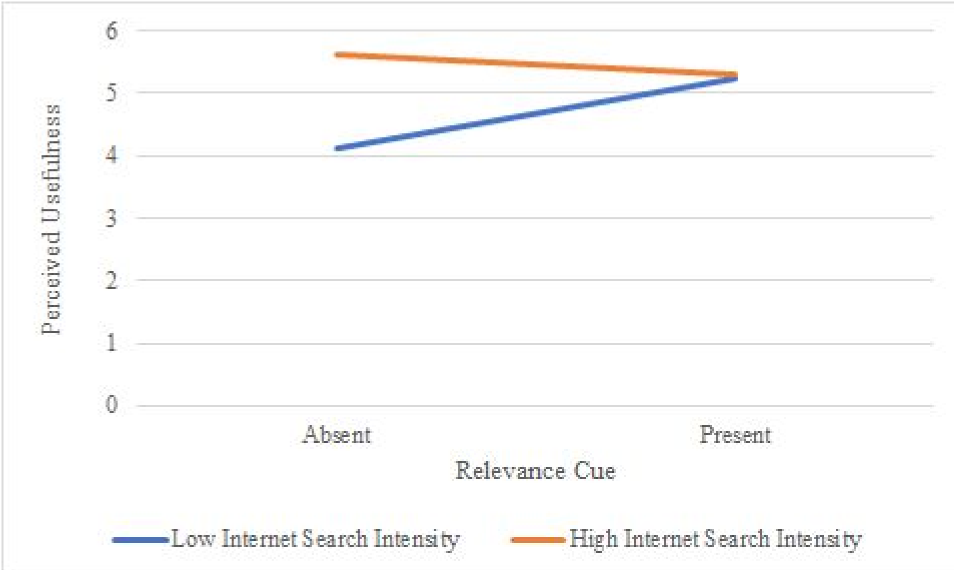


Figure 3

Interaction Effect of Internet Search Intensity and Relevance Cue on Ease of Use

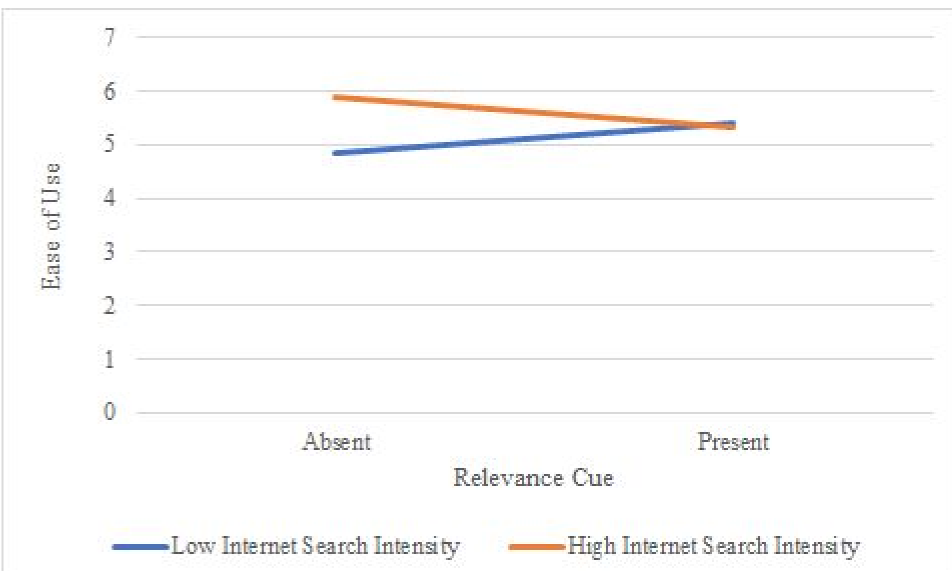
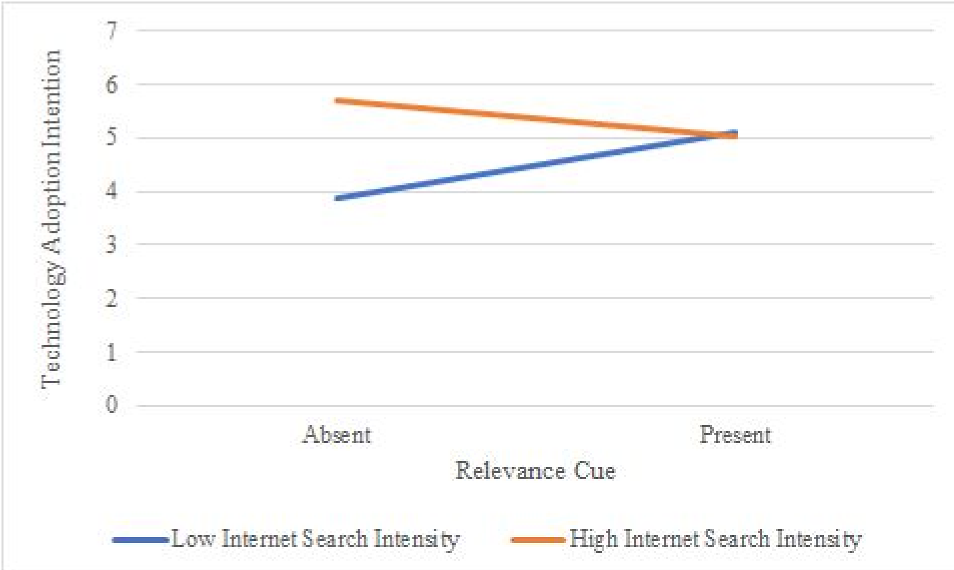


Figure 4

Interaction Effect of Internet Search Intensity and Relevance Cue on Technology Adoption Intention



Content Preview

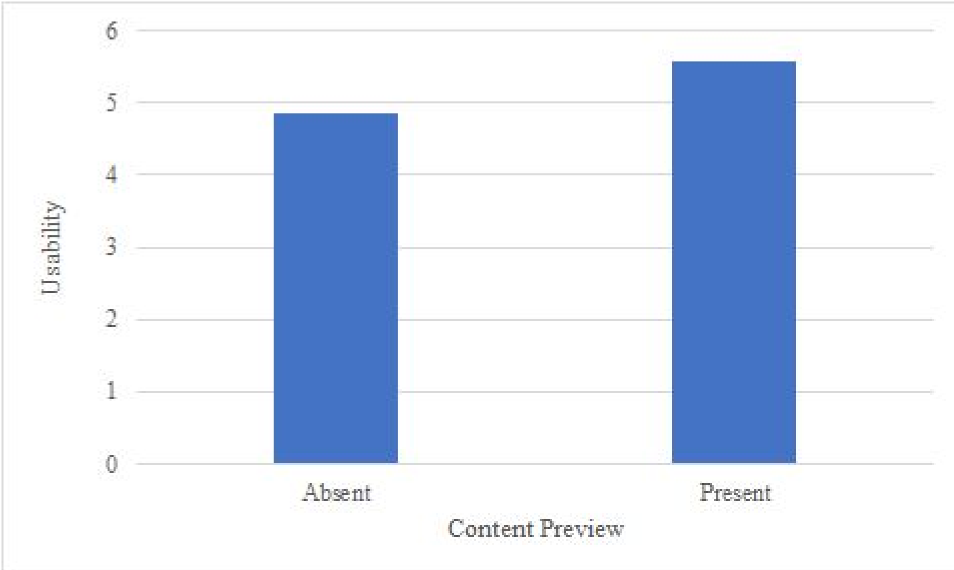
H2 and H2a hypothesized that content preview would positively influence the outcome variables, e.g. perceived usefulness, ease of use, usability, and technology adoption intention, and such an effect would be moderated by individual difference variables such as expertise, motivation, technology use, and previous search behaviors.

Main Effect

The three-way ANOVA revealed a statistically significant main effect of content preview on usability when controlling for participants' internet search intensity, $F(1, 89) = 4.412$, $p < 0.05$, shown in figure 5. Participants in the content preview present condition ($M = 5.568$, $SD = 1.359$) rated the interface with a higher level of usability than those in the content preview absent condition ($M = 4.941$, $SD = 1.594$).

Figure 5

Main Effect of Content Preview on Perceived Usefulness



Similarly, the main effect of content preview on usability was also found when controlling for individual differences such as data expertise, $F(1, 89) = 4.359$, $p < 0.05$; Topic Expertise, $F(1, 89) = 5.228$, $p < 0.05$; and Topic Motivation, $F(1, 89) = 4.279$, $p < 0.05$.

Interaction Effects

Data Expertise. There was an interaction effect approaching significance of content preview and data expertise on usability, $F(1, 89) = 3.825$, $p = 0.054$, shown in figure 6. For users with low data expertise, content preview had a slightly lower usability than no content preview. However, for those with high data expertise, content preview resulted in greater usability.

Figure 6

Interaction Effect of Content Preview and Data Expertise on Usability

Topic Expertise. There was a statistically significant interaction effect of content preview and topic expertise on technology adoption intention, $F(1, 89) = 4.294$, $p < 0.05$, shown in figure 7. There was an interaction effect approaching significance in a similar pattern of content preview and topic expertise on perceived usefulness $F(1, 89) = 3.76$, $p = 0.056$, shown in figure 8, and usability, $F(1, 89) = 3.66$, $p = 0.059$, shown in figure 9. For users with low topic expertise, content preview had greater technology adoption intention, perceived usefulness, and usability than no content preview. However, for users with high topic expertise, content preview resulted in slightly lower technology adoption intention, perceived usefulness, and usability.

Figure 7

Interaction Effect of Content Preview and Topic Expertise on Technology Adoption Intention

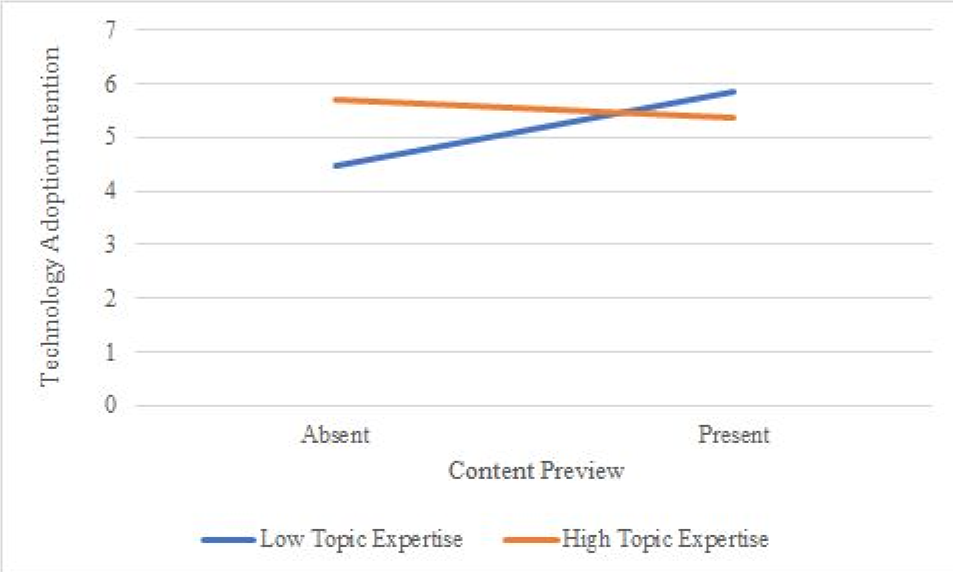


Figure 8

Interaction Effect of Content Preview and Topic Expertise on Perceived Usefulness

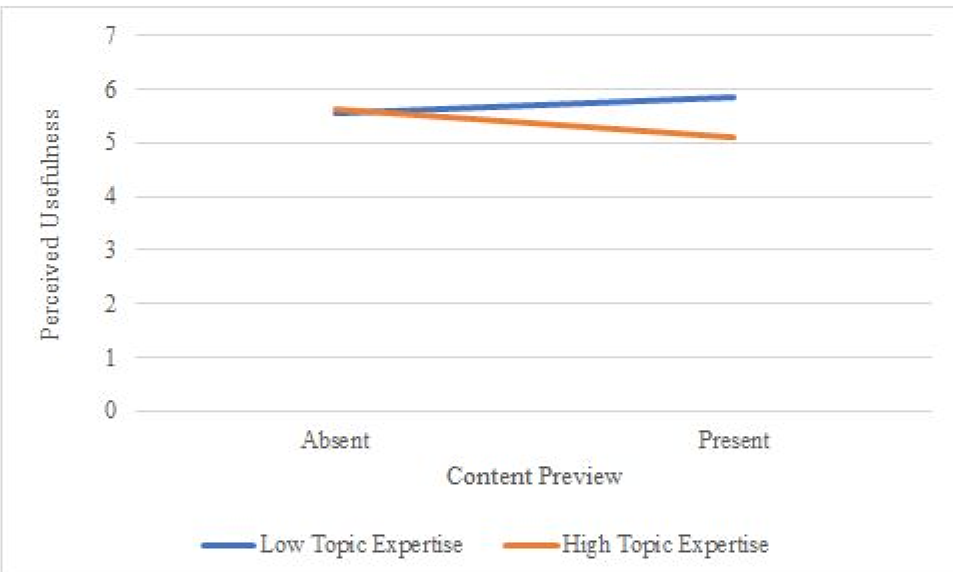
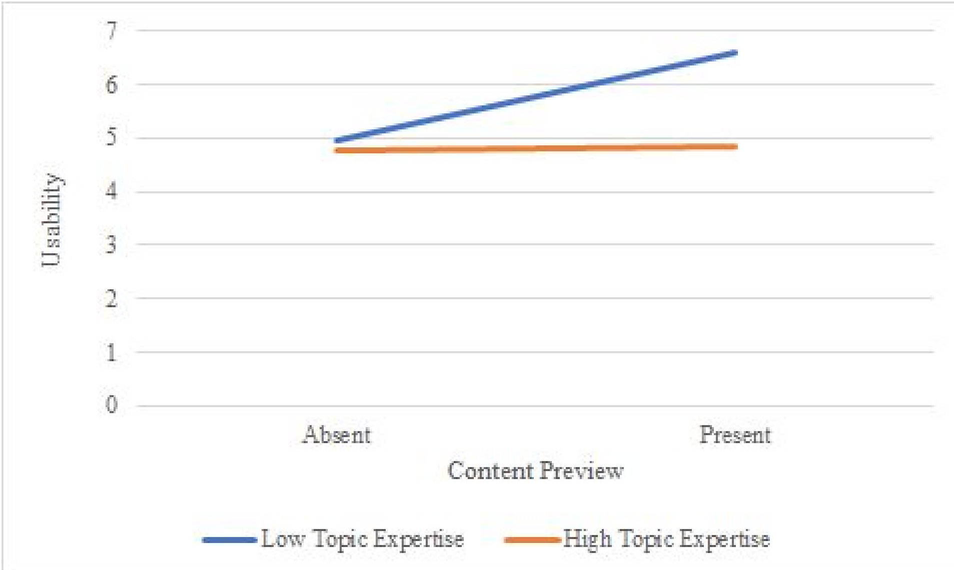


Figure 9

Interaction Effect of Content Preview and Topic Expertise on Usability



Topic Motivation. There was an interaction effect approaching significance of content preview and topic motivation on perceived usefulness, $F(1, 89) = 3.487$, $p = 0.065$, shown in figure 10; and ease of use, $F(1, 89) = 2.958$, $p = 0.089$, shown in figure 11. For users with low topic motivation, content preview had greater perceived usefulness and ease of use than no content preview. However, for those with high topic motivation, content preview resulted in slightly lower perceived usefulness and ease of use.

Figure 10

Interaction Effect of Content Preview and Topic Motivation on Perceived Usefulness

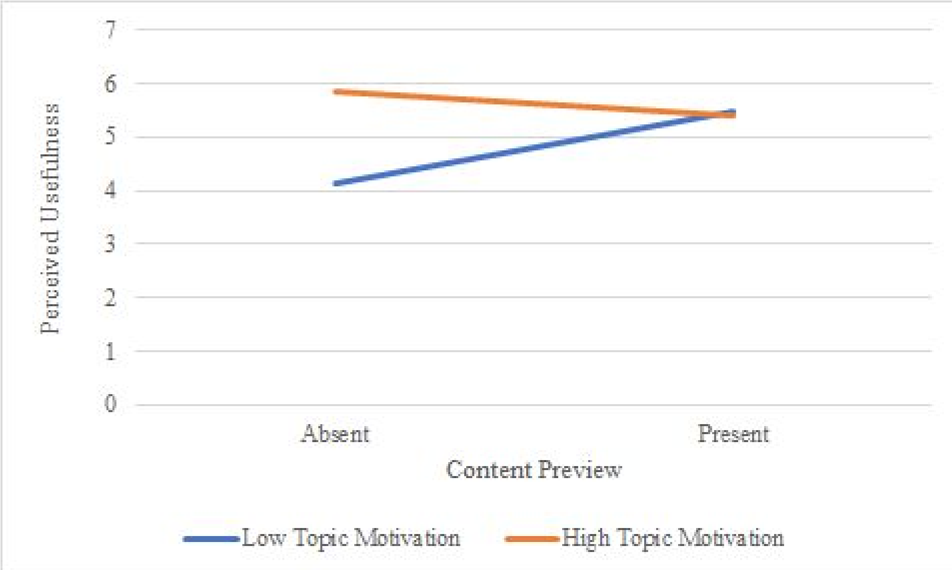
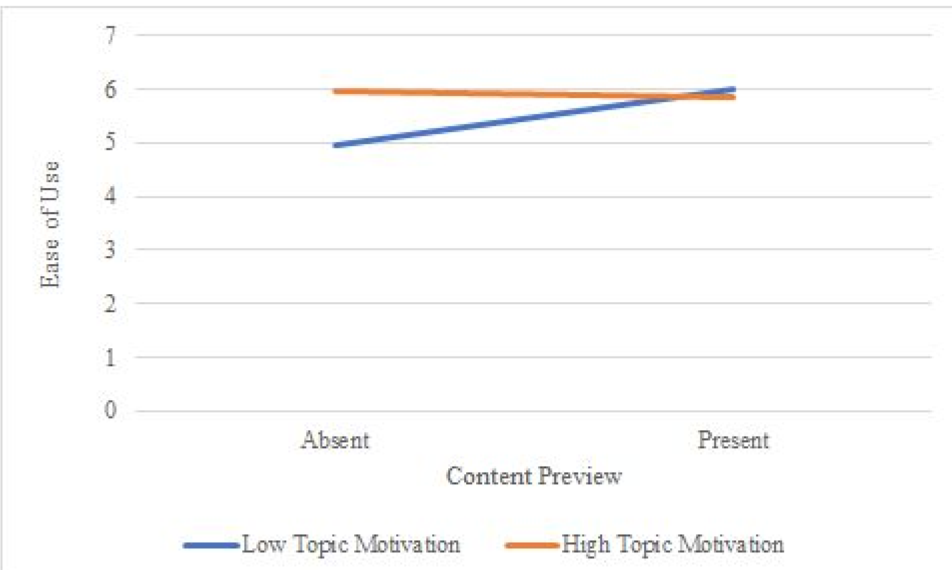


Figure 11

Interaction Effect on Content Preview and Topic Motivation on Ease of Use

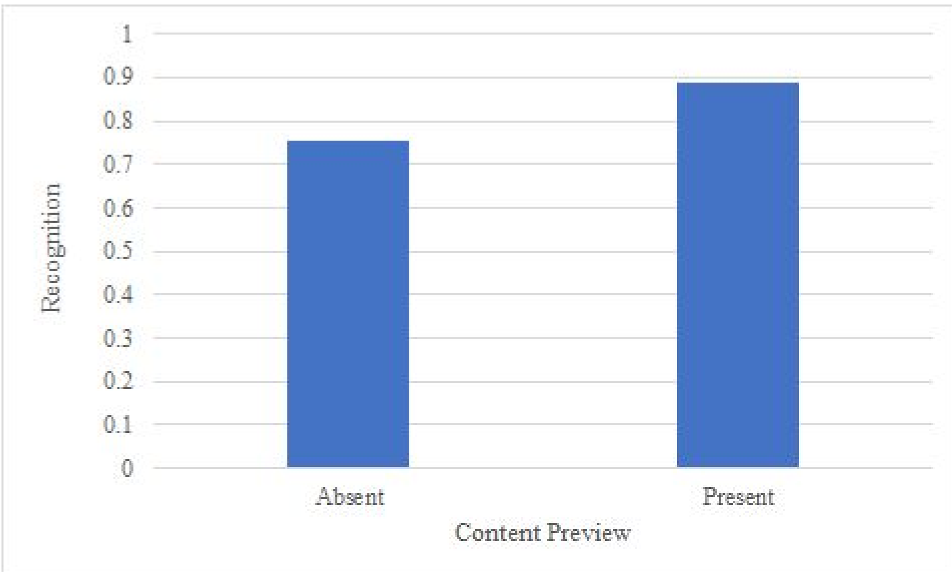


Heuristic and Systematic Processing

Of the variables used to measure heuristic and systematic processing, neither reached significance. The effect of content preview $t(87) = -1.612$, $p = 0.056$ on recognition was approaching significance, as recognition was higher with content preview (*M* = 0.8864, *SD* = 0.32104) than without content preview (*M* = 0.7556, *SD* = 0.43461).

Figure 11

Main Effect of Content Preview on Recognition



Interaction of Relevance Cue and Content Preview

H3 hypothesized that relevance cue and content preview would interact in their effects on users' perceptions of interface perceived usefulness, ease of use, and usability, as well as their technology adoption intention. No statistically significant interaction between the two variables was found. A list of the variables that approached or reached significance with ANOVA analysis can be found in table 3 below.

Table 3

*Table containing independent variables, moderators, and dependent variables that approached or reached significance with ANOVA analysis. Includes source of significance (IV indicates a main effect, Moderator*IV indicates an interaction), degrees of freedom, F, and p values.*

IV	Moderator	DV	Source	df	F	p
Relevance Cue	Data Motivation	Perceived Usefulness	Moderator * IV	1, 89	4.206	0.044
	Internet Search Intensity	Perceived Usefulness	Moderator * IV	1, 89	5.416	0.022
		Ease of Use	Moderator * IV	1, 89	4.098	0.046
		Technology Adoption Intention	Moderator * IV	1, 89	*3.906*	*0.052*
Content Preview	Data Expertise	Usability	IV	1, 89	4.359	0.036
			Moderator * IV	1, 89	*3.825*	*0.054*
	Internet Search Intensity	Usability	IV	1, 89	4.412	0.039
	Technology Fluency	Usability	IV	1, 89	*3.803*	*0.055*
	Topic Expertise	Perceived Usefulness	Moderator * IV	1,89	*3.76*	*0.056*
		Usability	IV	1, 89	5.228	0.025
			Moderator * IV	1, 89	*3.66*	*0.059*
		Technology Adoption Intention	Moderator * IV	1, 89	4.294	0.041
	Topic Motivation	Perceived Usefulness	Moderator * IV	1, 89	*3.487*	*0.065*
		Ease of Use	Moderator * IV	1, 89	*2.958*	*0.089*
		Usability	IV	1, 89	4.279	0.042

Discussion

The present study offers valuable insight into means to facilitate dataset search, as well as the impact of user expertise on search experience. Both independent variables, the relevance cue and dataset content preview, produced statistically significant results that indicate their efficacy in orienting the user's attention towards results useful for their search query. While the relevance cue showed no direct effect on users' perceptions of the interface, it did interact with moderating variables such that non-expert users consistently experienced a benefit from the cue's presence. The content preview showed a significant effect on perceived usability, in which users perceived an interface with content preview to be more usable than an interface without. Similar to the relevance cue, content preview interacted with moderators such that its presence improved the experience of non-experts to a greater extent.

Relevance Cue as a Visual Reinforcement

The relevance cue was investigated as a means to guide a user's attention to the results most pertinent to their query by activating heuristic processing. Such an effect of the relevance cue is limited to expert users possibly due to its lack of novelty. Previous research has shown that online users are strongly guided by relevancy ranking (Unkel and Haas). Relevancy ranking, however, is typically represented by search result order, in which the most relevant result is the first to appear in the list of search results (Glick et al.). The relevance cue in this study was visualized in the form of a rectangular icon, while search results were listed by recency. The visualization of the relevance cue as a secondary reinforcement when gauging relevance benefited those with low expertise, who reported higher perceived usability, ease of use, and technology adoption intention when using an interface with a relevance cue in comparison to one without, whereas users with high expertise reported the opposite. Experts accustomed to dataset search may view a second relevance reinforcement as repetitive and unnecessary, thus resulting in their lower rates of perceived usability, ease of use, and technology adoption intention when presented with a relevance cue.

Content Preview as an Easy Access to Data Information

The dataset content preview was investigated as a means to assist a user in understanding the content of a dataset by activating systematic processing. The results support this hypothesis, as usability of the interface was ranked significantly higher when it had a content preview than when it did not. While the significant main effect of content preview indicated that its presence enhanced perceived usability despite individual idiosyncrasies, similar to the relevance cue, its interactions with the moderators show that non-expert users received greater benefits from the content preview, as they rated interfaces containing the preview with higher perceived usefulness, ease of use, usability, and technology adoption intention than those without. The effect of content preview was limited among experts, potentially due to the fact that experts, frequent searchers, in particular, may have already established techniques to determine what results best satisfy their search query, so the content preview might not have been as effective to further facilitate their search.

There is one exception to this trend: users with high data expertise rated the content preview interface with higher usability, whereas those with low data expertise did not report a benefit. A plausible explanation is that the ability to view datasets prompted users to evaluate the quality of data, a cognitive task that could be overwhelming to those with low data expertise who lacked the background knowledge or capabilities, thus depleting the positive impact of content preview.

Ultimately, the content preview reduced the complexity of the dataset search process by providing an easy way to access and evaluate dataset content and determine if it satisfies their query.

Facilitating Non-Expert Dataset Search

It is unclear if the heuristic systematic model of information processing is the ideal model to explain the results produced by this study, as the measures of recall and recognition were not robust. However, the lack of statistical evidence does not mean that the effects of the relevance cue and content preview were not mediated through the mechanism of the HSM, as heuristic and systematic processing was only measured with single-item measurements.

Based on the significant interactions found between both independent variables and the moderators, it is clear that level of expertise has a significant impact on search experience. Through this study, we've learned that technological affordances designed to facilitate search are useful, as non-experts reported a better search experience based on cues designed to orient their attention towards results that most satisfy their search query. These findings encourage more studies investigating the search habits of non-expert users, as well as the importance of modifying dataset search engine designs to better suit users. When developing search engines for dataset, guidelines should include features that are specifically designed to attract and guide a user's attention, like the relevance cue and content preview explored here.

Limitations and Future Directions

Future research can employ a more thorough HSM measurement, or adopt alternative ways of measuring HSM processing to investigate if HSM can serve as the theoretical explanation of the observed effects.

Overall, The results of this study are especially encouraging when considering the lack of interactivity this prototype interface offered. The interface only presented four search results and a user could not enter new search queries to expand their search. Though the interface offered a few screens and clickable options, it was ultimately limited in functionality and relatively static. Furthermore, participants were assigned a task that was potentially uninteresting or unimportant to them. The positive user experience associated with the relevance cue and content preview in a limited environment has the potential to be far more rewarding in the context of a user performing a search important to them in a more functional interface.

Conclusion

The results produced by this experimental study suggest that dataset search engines should be developed with user expertise in mind in order to better facilitate non-expert search. Non-expert users consistently experienced a positive effect from technological affordances designed to orient their attention towards relevant results, as visualizing a relevance cue was especially helpful for this population. The positive user experience resulting from the independent variables is especially encouraging when considering the relatively static interface used in this study; in a truly interactive environment, the results found in this study are likely to be expanded.

Ultimately, as data becomes critical to many disciplines, it is essential to consider the non-experts in need of datasets who previously did not use data and hence lack the skills and training useful for implementing dataset search. Open science promises potential accessibility of data to researchers and the public, but if non-experts are unable to properly navigate the search process to access these datasets, the data published online is not useful or usable. In its current state, the general public is faced with the barrier of a complex dataset search process that inhibits them from fully harvesting the power of online datasets. The findings of this study are a step towards simplifying the dataset search process and thus removing a barrier between datasets and those who seek them.

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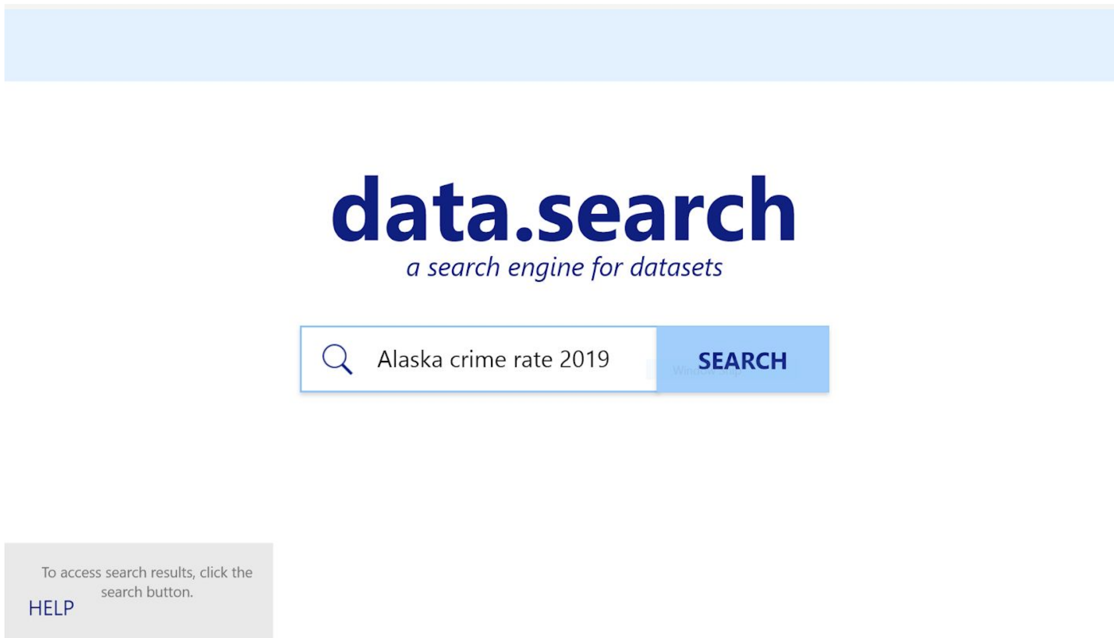
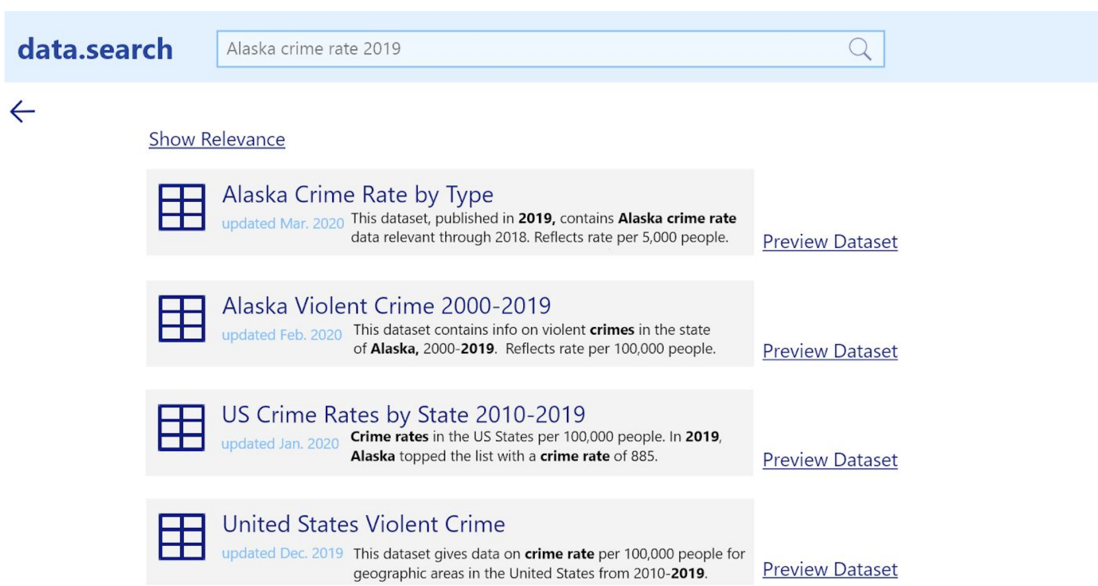
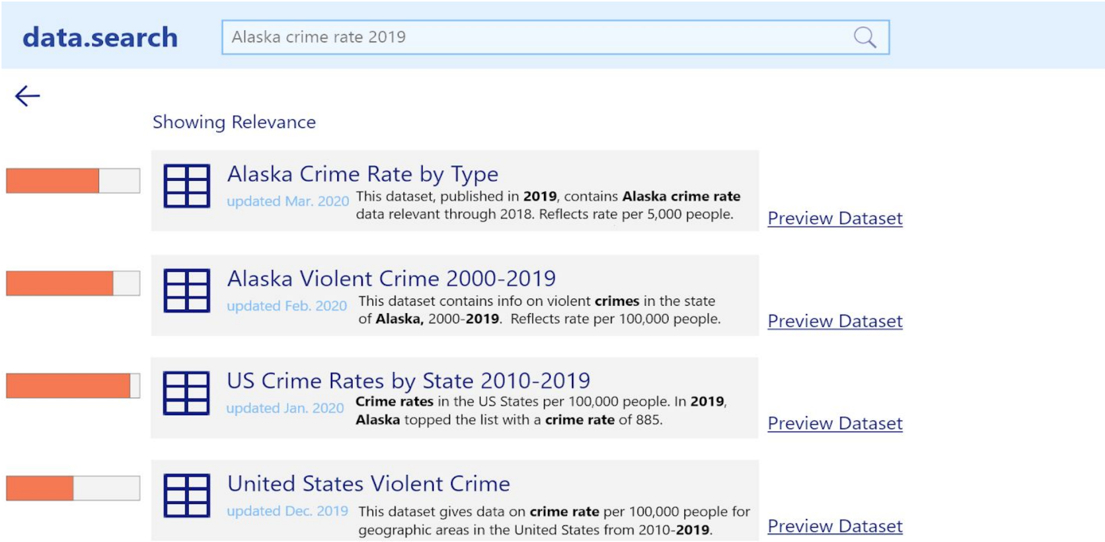
Appendix A: Prototypes

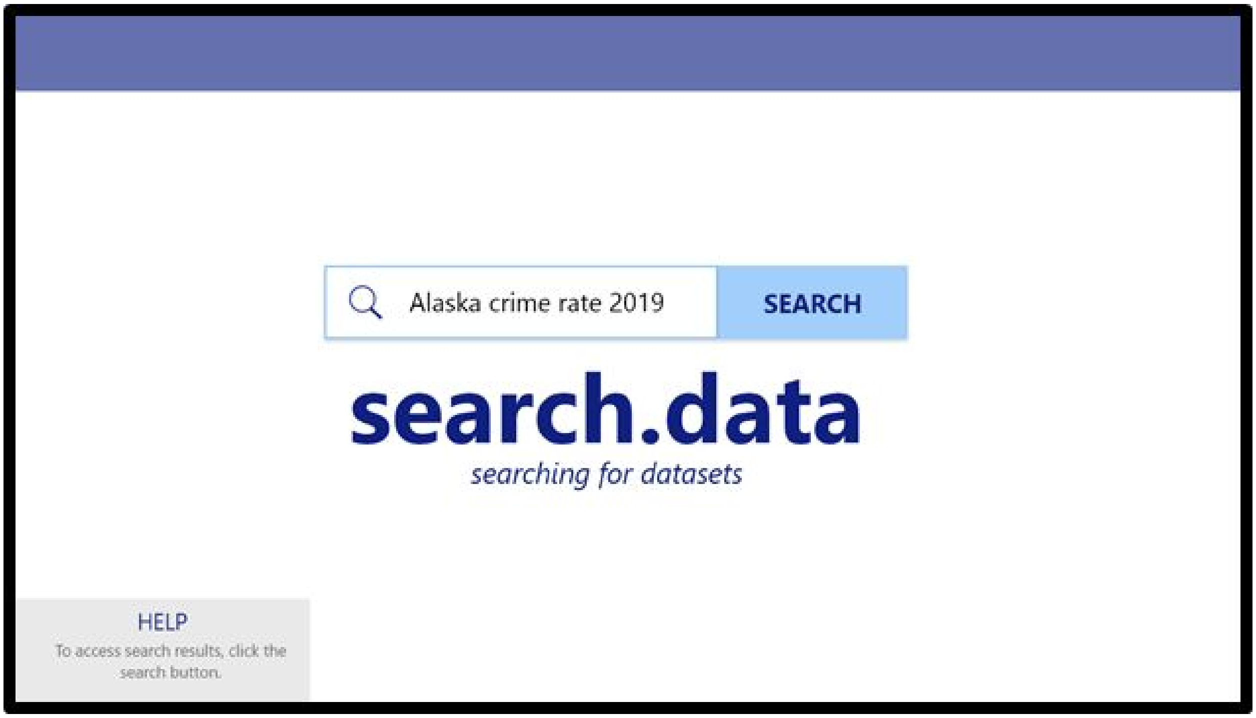




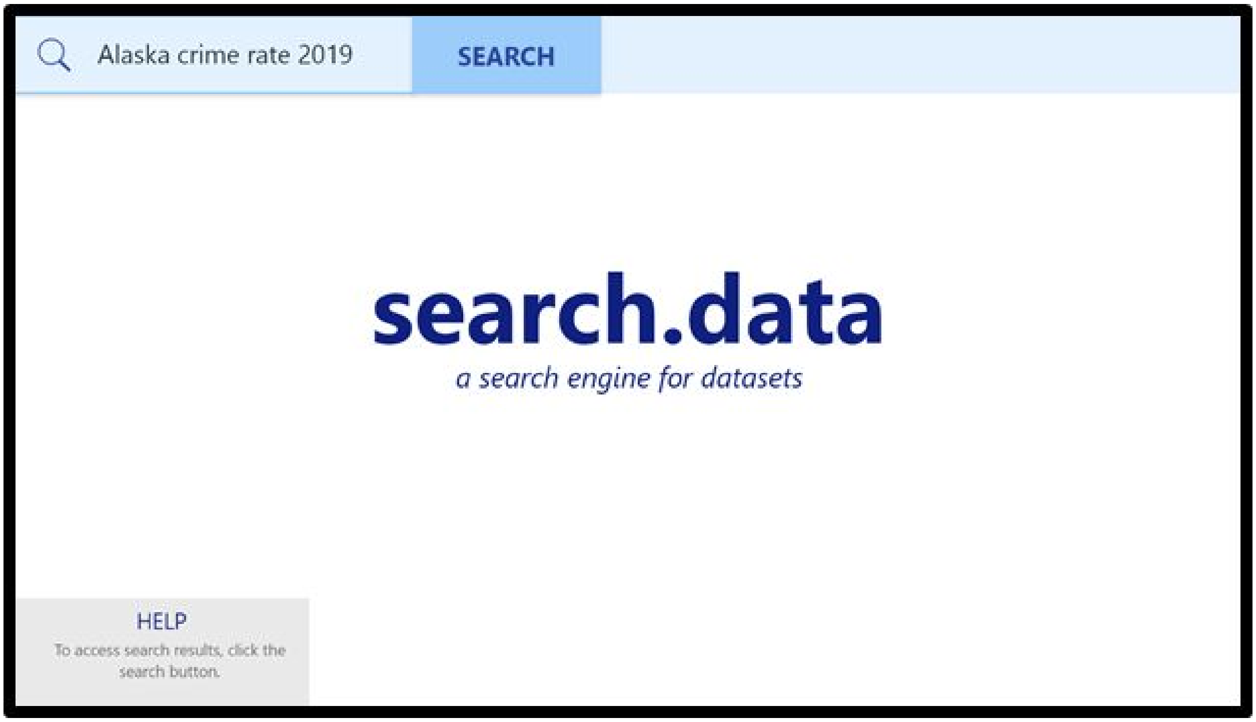

data.search
Alaska crime rate 2019
Showing Relevance
Alaska Crime Rate by Type
updated Mar. 2020
This dataset, published in 2019, contains Alaska crime rate data relevant through 2018. Reflects rate per 5,000 people.
Preview Dataset
Alaska Violent Crime 2000-2019
updated Feb. 2020
This dataset contains info on violent crimes in the state of Alaska, 2000-2019. Reflects rate per 100,000 people.
Preview Dataset
US Crime Rates by State 2010-2019
updated Jan. 2020
Crime rates in the US States per 100,000 people. In 2019, Alaska topped the list with a crime rate of 885.
Preview Dataset
United States Violent Crime
updated Dec. 2019
This dataset gives data on crime rate per 100,000 people for geographic areas in the United States from 2010-2019.
Preview Dataset


data.search
Alaska crime rate 2019
Show Relevance
Alaska Crime Rate by Type
updated Mar. 2020
This dataset, published in 2019, contains Alaska crime rate data relevant through 2018. Reflects rate per 5,000 people.
Alaska Violent Crime 2000-2019
updated Feb. 2020
This dataset contains info on violent crimes in the state of Alaska, 2000-2019. Reflects rate per 100,000 people.
US Crime Rates by State 2010-2019
updated Jan. 2020
Crime rates in the US States per 100,000 people. In 2019, Alaska topped the list with a crime rate of 885.
United States Violent Crime
updated Dec. 2019
This dataset gives data on crime rate per 100,000 people for geographic areas in the United States from 2010-2019.
Close Preview
State
Year Alaska New Mexico Tennessee Arkansas
2019 885 857 624 544
2018 867 839 606 526
2017 870 842 609 529
2016 853 825 592 510
2015 869 841 608 528

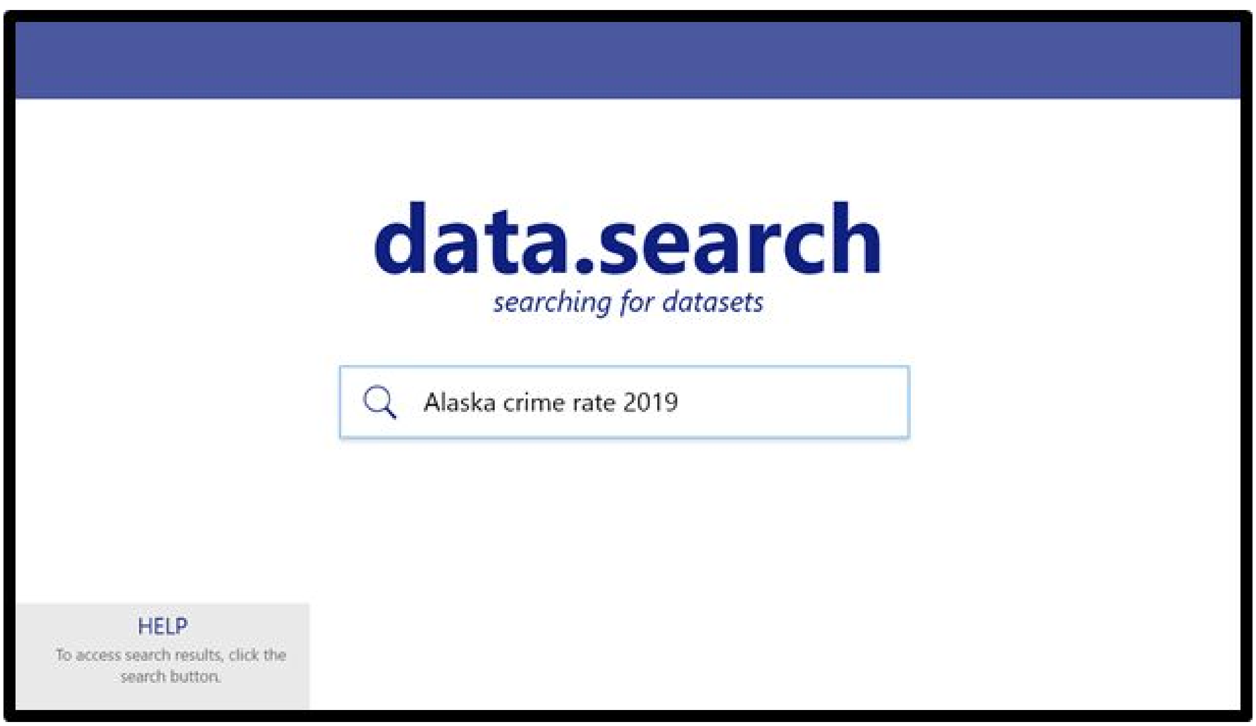
Appendix B: Heuristic Check

a) 

b) 


Alaska crime rate 2019
SEARCH
search.data
a search engine for datasets
HELP
To access search results, click the search button.

c)


data.search
searching for datasets
Alaska crime rate 2019
HELP
To access search results, click the search button.

d)

Appendix C: Modified Survey Scales

1. Perceived Usefulness
    a. This website would improve my performance when searching for datasets.
    b. This website would make me more effective when searching for datasets.
    c. This website is useful for searching datasets.
2. Ease of Use
    a. The way to interact with this website was clear and understandable.
    b. It did not take a lot of effort to interact with this website.
    c. I found this website easy to use.
3. Usability
    a. I found this website to be unnecessarily complex.
    b. I needed to learn a lot of things before I could use this website.
    c. I felt very confident using this website.
4. Technology Adoption Intention
    a. I would be likely to use this website for dataset search in the future.
    b. I would recommend this website to others for dataset search.
    c. I would like to visit other websites similar to this one for dataset search.
5. Motivation - Datasets
    a. Searching for datasets is interesting to me.
    b. Searching for datasets is important to me.
    c. Searching for datasets is relevant to me.
6. Expertise - Datasets
    a. I know why data is needed and how data can be produced.
    b. I am familiar with terms and ideas related to statistics.
    c. I am confident in my abilities to search and find useful data.
    d. I am confident in my abilities to review and assess data.
    e. I am confident in my abilities to interpret and understand data.
7. Motivation - Topic
    a. Learning about crime rates is interesting to me.
    b. Learning about crime rates is important to me.
    c. Learning about crime rates is relevant to me.
8. Expertise - Topic
    a. I am very familiar with the subject of crime rates.
    b. I am very knowledgeable about the subject of crime rates.
    c. I follow the subject of crime rates very closely.