The Effects of Adding Search Functionality to Interactive Visualizations on the Web

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ABSTRACT
The widespread use of text-based search in user interfaces has led designers in visualization to occasionally add search functionality to their creations. Yet it remains unclear how search may impact a person's behavior. Given the unstructured context of the web, users may not have explicit information-seeking goals and designers cannot make assumptions about user attention. To bridge this gap, we observed the impact of integrating search with five visualizations across 830 online participants. In an unguided task, we find that (1) the presence of text-based search influences people's information-seeking goals, (2) search can alter the data that people explore and how they engage with it, and (3) the effects of search are amplified in visualizations where people are familiar with the underlying dataset. These results suggest that text-search in web visualizations drives users towards more diverse information seeking goals, and may be valuable in a range of existing visualization designs.

ACM Classification Keywords
H.5.m. Information Interfaces and Presentation (e.g. HCI): Miscellaneous

Author Keywords
Interaction; Visualization; Search; Evaluation.

INTRODUCTION
Text-based search is widely used on the web in order to enable users to meet a variety of goals. Whether it is to browse between webpages, locate a keyword of interest on a particular page, or facilitate quick actions that shortcut tedious manual navigation on mobile devices, search has largely become an interface expectation and necessity. Thus, it comes as no surprise that data visualization designers have begun to add search to the visualizations they create for the web.

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To demonstrate search within the context of data visualization, consider the *Women in Films* visualization in Figure 1 that explores gender diversity in high grossing films. A text-based search box at the bottom left allows users to enter either a writer or a film name. After three characters, any film whose writer or name matches the substring is highlighted, while others fade out. This functionality empowers users to rapidly search for specific films without resorting to an exhaustive, guess-and-check strategy.

Despite these clear benefits, it remains unclear how the mere *presence* of text-based search impacts how website visitors explore data. When people explore a visualization, they may have explicit information-seeking goals (*e.g.* looking for a particular point of data), implicit information-seeking goals (*e.g.* opting to meander through a dataset until a goal is formed), or they may arrive at a website with no data-centric goals at all. From a design perspective, content creators may need to weigh several questions when considering to add search functionality to their visualizations:

- If search is built into a visualization, do people notice and use it?
- How does search impact a user's experience of the visualization? Does it change their goals or interaction patterns?

Given the resources of time and effort that it takes to create a compelling data visualization, designers cannot simply assume people will use search, or that search will benefit exploration. From a research perspective, it is unclear whether making relatively small additions to a visualization, like adding text-based search, results in a significant difference in how the user will engage with data. Motivated by the intuition of adding search to visualizations and the unanswered questions of its benefits and trade-offs, we isolate and quantitatively study its effect on users' goals and behavior in the context of open-ended web exploration.

Defining and Bounding Search
"Search" has many definitions in human-computer interaction and data visualization. For the scope of this paper, we refer to search as **text-based search functionality integrated with interactive visualizations**. To clarify, below are a set of juxtapositions with altering definitions and scopes of "search".

Figure 1. Search mechanisms in interactive data visualizations have been used sporadically throughout research and in practice. Little is known, however, about how search impacts how people interact with visualizations. We contribute an analysis of search mechanisms in visualization. Our experiment results indicate that most users will use search when available, and that search leads to positive increases in measures related to engagement. (The example on the left is from an interactive visualization *Women in Films* on the web [21].)

Search as a task vs. search as a functionality. A search task in HCI can refer to a user task, such as seeking information in a system. Search functionality, then, is defined broadly as the features the system provides to support users to complete their tasks. This might mean, for example, menu bars and button layouts in addition to text-based search.

Faceted search vs. text-based search. Faceted search includes user-interface functionalities for accessing information organized according to a faceted classification system, which can allow users to retrieve certain parts of information by applying multiple filters. Text-based search, in contrast, generally refers to functionality which accepts text input and displays results matching the input.

Contributions

In this paper, we contribute a study on the effects of text-based search in interactive data visualizations. In an experiment with five stimuli and 830 crowdsourced participants, we quantify how search can shape user behavior and goals with visualizations on the web- even when they are not explicitly given a task to complete.

The results of these experiments suggest that (1) people generally use search when it is present, (2) the presence of search encourages people to actively look for individual data items, (3) search encourages users to spend more time examining detail in the data, and (4) search nudges users towards more diverse exploration patterns. Finally, we find that these effects are modulated when search accompanies a dataset in which people have no familiarity.

Taken together, these results lend insight to the practical effect of text-based search on web visualizations with everyday people. With actionable information about the role of search, visualization designers can make informed choices about how to best support exploration and engagement in the data visualizations they create. In addition, findings relating behavior differences to interaction design in visualization may provide initial evidence towards the development of future theoretical interaction frameworks, which provides a baseline for investigating the underlying mechanisms of those differences.

BACKGROUND

The widespread use of search in general computing systems has led to taxonomies and in-depth studies on the design space of search within the HCI community. While a full review of this space is beyond the focus of this work, we find that recent work from Wilson *et al.* is particularly relevant [49, 50, 51]. In *Search User Interfaces* [49], Wilson described a design space of search user interfaces (SUIs), including issues such as faceted search and auto-complete. These results directly inform the dimensions we consider of the design space of search in visualization. Additionally, the metrics from Wilson *et al.*'s evaluation of search interfaces, such as how search can lead to engagement with individual pieces of information, inform the metrics we use in our experiment [51].

Most research on search in visualization has focused on visualizing the results of search queries rather than search as an interaction mechanism. Nevertheless, there is some overlap in this thread of prior work and the goals of this study. To that end, we turn to SUIs in visualization.

Search User Interfaces and Visualization

Visualization has been used extensively to support users' search processes. With the growth of SUIs, structured 2D

Source	Year	Title	Search Scope	Trigger	Autocomplete	Transition	Encoding Change
Paper	2002	SpaceTree [39]	tree node name	on click	(unclear)	highlight	color
Web	2003	WordCount/QueryCount [25]	words or queries	on enter	no	filter out other data	position
Web	2004	Zipdecode [22]	zip codes	while typing	no	highlight and zoom in	color
Paper	2006	NameVoyager [47]	baby names	while typing	no	filter out other data	position
Paper	2006	TimeTree [26]	person or position names	on click	no	highlight	color
Paper	2007	NewsLab [23]	news content	(unclear)	(unclear)	(unclear)	(unclear)
Paper	2007	VisLink [11]	words	(unclear)	(unclear)	highlight	color
Paper	2009	ResultMaps [10]	metadata	on click	(unclear)	highlight	color
Paper	2010	VizCept [9]	node names	on click	(unclear)	highlight	color
Paper	2010	GeneaQuilts [4]	any entry or attribute	(unclear)	(unclear)	highlight	color
Paper	2013	GPLOM [29]	car properties	while typing	yes	highlight	color
Paper	2014	Footprints [30]	document text content	on enter	(unclear)	reposition	position
Paper	2014	Overview [6]	document text content	on click	(unclear)	highlight	color
Paper	2015	VAiRoma [8]	location or article names	on click	(unclear)	highlight	addition
Web	2015	Clustergram [20]	gene names	on click	yes	highlight and zoom in	color and size
Paper	2016	ResViz [18]	staff names	(unclear)	(unclear)	(unclear)	(unclear)
Web	2016	Who Marries Whom [38]	job names	on enter	yes	highlight	opacity and size
Web	2016	Women in Films [21]	film names	while typing	no	fadeout other data	opacity
Web	2016	NBA 3-Point Record [1]	player names	on enter	yes	fadeout other data	opacity

Table 1. Text-based search has appeared in multiple visualizations throughout research and the web. The above are a sample. We categorize each across several dimensions, including the scope of the search, how the encoding changes, and others. Notably, some prior research systems do not contain sufficient detail to determine how text-based search is used in the visualization.

visualizations were introduced to display search results to support or substitute standard results lists [49]. Several forms of visualizations have been explored in these systems. *Treemaps* were used to show search results in ResultMaps [10], an interface to a digital library. *Faceted search* was used in the systems including Dotfire [41], Envision [35], and List and Matrix Browser [32], grouping specific facets of metadata using both the horizontal and vertical axes. *Timelines* were used in Perspective Wall [34] and Continuum [2] to display the search results in the form of time series. More recently, more complex visualizations have been created to support search systems. In PivotPaths [16], after typing search keywords, the user can explore the search results of faceted information resources displayed in an interactive visualization.

What is common between "search mechanisms for visualization" and "visualizing search results" is that they both have visualization and search components. This raises considerations for the present work, such as the impact of search on the visual display. These works also differ from the present focus in several ways. First, many prior systems do not support textual search, rather relying on graphical methods to construct queries [41, 2]. Second, many systems use search as the starting point for analysis, meaning that subsequent searches change the dataset display in the visualization [16, 32, 34, 35]. Of these systems, ResultMaps most closely resembles the use of search as an interaction mechanism. In ResultMaps, an initial visualization of the data is given as a treemap, and search is used as a means to highlight sub-sections of the treemap.

Query-Based Interfaces

Query-based interfaces are part of a long thread of research in data visualization. Queries are core components of well-known systems such as Polaris [43] and HomeFinder [48]. Evaluating query interfaces consisting of sliders, Ahlberg *et al.* found that queries enabled people to quickly hone in on data of interest. Keim and Kriegel emphasize the notion of using boolean logic to join queries and ask more complex questions of data [31]. Text-based search could potentially be used as a mechanism for more complex queries, using schemes such as the ones described here.

Natural Language Interfaces

Setlur *et al.*'s Eviza system [40], a *natural language interface* for visual analysis, is closely related to the focus of this paper. Eviza uses a text-based search bar (or voice) to allow users to ask questions of the data. In a user study, Setlur *et al.* found that users produced queries aligning with several visualization tasks: navigation, calculation, comparison, and more. Our goal is complementary- acknowledging that search mechanisms have been included in prior systems and visualizations on the web, and that they will become more powerful thanks to work similar to Setlur *et al.*- how do these mechanisms shape users' experience and understanding of a visualization?

Design of Search in Visualization

Even after narrowing our focus to text-based search on the web, there are a variety of potential design choices- some of which are unique to data visualization. As opposed to the typical results page of a search engine, designers must bear in mind the perceptual interactions between visual encodings in a visualization, such as integral and separable features [45]. Motivated in part by these challenges, as well as the search design space articulated by Wilson in *Search User Interface* [49], we use the following characteristics to describe how visualizations in the past have defined search:

- *search scope:* Do searches access just the primary labels (often names) of the data or do they access the full dataset, including metadata?
- *trigger:* How should search be triggered? Search can be triggered, for example, by clicking a "search" button, pressing an "enter" key, or updating continually as the user types.
- *autocomplete:* As the user types, does the search box suggest queries based on the dataset?
- *transition:* How will the user be notified that the results have been updated? In most search interfaces, only the search results are shown, and the others are hidden from the

user. While this may be desirable in some cases for data visualization, it's also possible to increase the saliency of selected data elements, decrease the saliency of remaining data, or lend focus to search results through automated zooming.
- *encoding change:* What visual encoding changes will accomplish the aforementioned increases and/or decreases in saliency (*e.g.* color, opacity, width, size)?

The results of categorizing several prior research systems and visualizations on the web are shown in Table 1. Besides these examples, text-based search has also been supported in some visualization development tools, such as Prefuse [27] and Tableau Software [42], where visualization designers can choose from different design options related to search. Researchers have also expressed intuitions on the potential benefits of search. For example, in NameVoyager [47], where users can search baby names by prefix, the authors mention: *"A user might not think that searching the data set by prefix would be interesting, but seeing the striking patterns for single letters like O or K could encourage further exploration."* In a study on the social impact of NameVoyager [28] by Heer *et al.*, search functionality was also specifically mentioned: *"Many participants searched for their own occupations and those of friends and family."*

These works including the search examples and the social impact studies motivate the need to isolate and quantitatively study the broader effect of search, and inform our experiment design.

EXPLORING THE IMPACT OF SEARCH

Our study on the effect of text-based search on visualizations aims to investigate open-ended user exploration on the web, where users may not have explicit analytical goals. We aim to examine (1) how users' exploration strategy is influenced by the **presence of search**, and (2) how users' exploration behavior is influenced by the **use of search**.

We used a **between subjects design** in which each participant was randomly assigned to either the **no search** or **search present** condition. In the *search present* condition, a search box was always present in the visualization, enabling text-based search. Functionally, users had to click the text-box and type queries to activate the search-based highlighting. In order to maintain ecology validity in the study, *i.e.* recognizing that users may pursue open-ended exploration rather than specific data-seeking tasks, we did not force a user to use search when it was present. In the resulting analyses, therefore, we focus in part on the group of participants who **used search**.

By drawing on analytic approaches from several recent studies examining user behavior and performance with interactive visualizations on the web [19, 5, 44, 15, 24], we frame our research questions as follows:

- **self-reported exploration strategy:** does the presence of text-based search impact peoples' reported exploration strategies? When search is present, what proportion of users make use of it? Does dataset familiarity matter?
- **exploration behavior:** does the use of text-based search impact measures of behavior, such as total exploration time, the location of data investigated, or the proportion of time spent viewing detailed information about chart elements?

Procedure and Tasks

Participants were recruited through Amazon's Mechanical Turk (AMT) to participate in a maximum of one of the five visualization stimuli. Each participant was randomly assigned to either the *no search* or *search present* condition. Based on completion times in pilot experiments, each participant was paid $2.00 in order to exceed US Minimum Wage. All participants viewed an IRB-approved consent form.

Our procedure consisted of four phases: *Training*, *Exploration*, *Insight/Strategy*, and *Demographics*.

Training: we provided participants with an instruction page that briefly described their task and the interaction mechanisms in the visualization. For example, for the 255*Charts* experiment participants were told:

> *In the next page, you will explore an interactive visualization. Your task is to analyze data on the economy from a popular news website. On the following pages, you will be asked to briefly describe the findings you identified, and answer questions on your understanding of the visualization.*

Participants were shown an animation of the interactive features available. In the *search present* condition, an extra sentence explained that the text box could be used to search for specific charts. No other indication of search functionality was provided.

Exploration: The *Exploration* phase began with a paragraph that introduces participants to the visualization and their task. Participants were instructed that they may interact with the visualization without any time limit. When participants indicated they were finished exploring the visualization, they advanced to the next phase.

Insight/Strategy: Participants were asked about findings they made in the visualization and the strategies they used during exploration. Specifically, participants were asked *During exploration, did you actively search for items that you thought might be in the visualization?* They were then asked to list any such data items they specifically sought out during their exploration.

This protocol included additional steps to help ensure reliability in participants' self-reported answers. First, an example case was provided tailored to the visualization stimuli to help understand the question, *e.g.*, in 255*Charts*, the example was "someone who works in computing may be interested in the 'Computer systems design and programming' industry". Second, we included options for uncertainty in the single-choice response, *i.e.*, the participants chose among yes, no, and not sure. Third, we provided participants with a list of items they interacted with as a memory trigger. Specifically, participants who indicated they had actively sought specific data items, were asked to select which data items they sought, choosing from a dynamically generated list of the items they interacted with for more than 500ms. We refer to these engagements

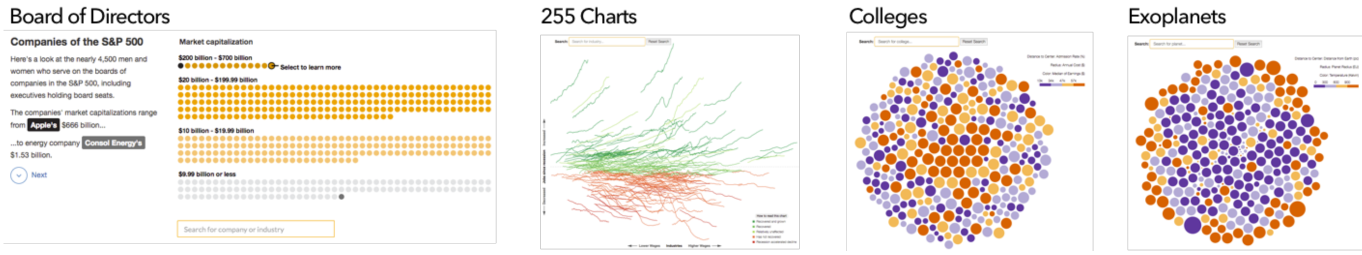

Figure 2. Experimental stimuli used to evaluate the effects of text-based search on visualization use and exploration. Each stimuli has been augmented to include search. From left to right: "Inside America's Boardrooms" from the Wall Street Journal- a multi-section visualization exploring company leaders. "How the Recession Reshaped the Economy, in 255 Charts" from The New York Times- showing how industries recovered or fell after the recent US recession. The final two visualizations are used to test specific hypotheses about the value of visualization, *e.g.*, whether the general familiarity of the dataset impacts the likelihood of users making use of search. (Not shown) An identical version of the third chart was also tested, with anonymized college names.

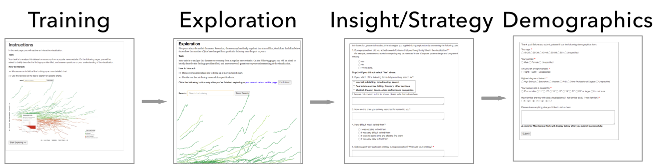

Figure 3. In our experiments with five visualizations, participants completed a training phase before heading to the exploration section. When they were finished exploring the interactive (no time limit), they moved to the next section where they describe their insights and strategies of exploration. In the final section, they provided demographic information.

with data items as "visits"; the 500ms threshold mitigates accidental visits from stray mouse movement.

Demographics: Participants provided basic demographic information.

Experiment Stimuli

Each of the following visualizations were equipped with two conditions: *no search* and *search present*

VIS 1: 255 Charts (The New York Times)

The first visualization we augmented with text-based search is from The New York Times, titled "How the Recession Shaped the Economy, in 255 Charts" [3] (see Figure 2). We refer to this as 255*Charts* through the remainder of this paper.

Representation and Data: 255*Charts* includes 255 line charts distributed across the viewport in a scatterplot-like fashion. Each line in 255*Charts* represents how a particular industry of the US Economy – Home Health Care Services or Air Transportation, for instance – grew or declined from 2004 to 2014. Mousing-over an industry's chart reveals a detailed line-chart view showing specific values, years, and industry information.

Search Design: For participants in our *search present* condition, the search box appeared at the top-left, allowing users to search "Industry Names" with auto-complete available. Search is triggered by an update of each character, allowing partial searches (*e.g.* "comp" for "computer sales" or "computer engineering").

VIS 2: Board of Directors (The Wall Street Journal)

We augmented an interactive visualization from The Wall Street Journal titled, "Inside America's Boardrooms" [33]. This scrolling visualization includes multiple stages with the same basic view (a grid of dots, see Figure 2, far left). We refer to this as *BoardofDirectors* through the remainder of this paper.

Representation and Data: The *BoardofDirectors* visualization includes companies from the S&P 500. The companies are represented by colored dots, and grouped into views, where they are sorted according to the market capital, the percentage of directors who are women, and other related fields. The user can navigate through the views in a storytelling form by clicking the "Next" button on the lower left, or jump to a certain view by clicking buttons at the top of the visualization. Mousing-over a company brings up a detailed view, including the company's name, the industry it belongs to, and a list of other data attributes.

Search Design: Search was added on the bottom-right of the visualization, supporting queries on "Company Names" and "Industry Names" with auto-complete enabled. Search was triggered as each character was typed, and partial queries were possible. To display the search results, the selected data was highlighted by dark gray outlines, while unselected charts decreased slightly in opacity. The search box remained visible across all views.

VIS 3-5: Familiar and Unfamiliar Bubble Charts

One factor worth considering in text-based search is that its effectiveness may be limited by whether a person *knows what to search for*. In other words, does the familiarity of the dataset impact search behavior? It is with this in mind that we designed three additional visualizations of similar form (bubble charts), but with varying familiarity (Figure 2).

Representation and Data: The data sources and mapping for the datasets are as follows:

- *Colleges*: we selected 300 colleges from the College Scoreboard dataset [36]. Each college was represented by a circle, of which the radius, color, distance to center mapped to the college's annual cost, median earning of the students, and admission rate.
- *AnonColleges*: we used exactly the same data source and mapping as *Colleges*, except we anonymized the names of colleges. College names were anonymized via a script that combined fictitious town names and a typical col-

lege/university prefix or suffix (*i.e.*, *X* university, university of *X*, *X* community college, etc.)

- *Exoplanets*: We selected 300 data points from the extrasolar planets dataset, to control for data size relative to the college datasets. Each planet was represented by a circle, of which the radius, color, distance to center mapped to the planet's radius, temperature and distance to the solar system.

In each bubble chart, circles represented data elements that contain three data attributes, represented by color, size, and distance to the center of the chart. We selected 300 data points from each of the three datasets, to control for data size. Mousing-over a circle brings up a detailed view, showing text values for the underlying data element.

Search Design: Search appeared on the top-left of the bubble chart, with auto-complete enabled. Searches and highlighting were triggered on character press. To display search results, the selected data items maintained opacity, while unselected items were deemphasized through a slight decrease of opacity.

Measures

We include both quantitative and qualitative measures derived across the phases of the experiment.

In the *Strategy* phase, quantitative measures include:

- *intent*: the proportion of participants who indicated that they intentionally sought specific data items in the visualization.
- *active search count* the number of data items participants selected as items they intentionally sought in the visualization (as opposed to incidental findings).

Self-reported quantitative measures were collected via steps described in Section 3.1 Procedure and Tasks. Through free-response questions, we also collect participant comments on their strategies and experience of the experiment.

In the *Exploration* phase, we collect which data elements each participant visited (*i.e.* interacted with for longer than 500ms), as well as any search queries. Quantitative measures include:

- *exploration time*: the total time a participant spent on the *Exploration* phase.
- *average visit time during exploration*: the average time a participant spent viewing the details of a data item during exploration.
- *average visit time during search*: the average time a participant spent viewing the details of a data item while an active search query was highlighting items in the visualization (*search present* condition only).
- *average visit time outside search*: the average time a participant spent viewing the details of a data item while outside of a search query (*search present* condition only).

Pilots, Analyses, and Experiment Planning

We conducted several pilot studies to help establish our measures and procedure. In response to concerns about the limitations of null hypothesis significance testing [14, 46], we model our analyses on HCI research that seeks to move beyond these limitations (*e.g.* Dragicevic [17]), primarily focusing on confidence intervals and effect sizes. Following Cumming [14], we compute 95% confidence intervals using the bootstrap method, and effect sizes using Cohen's d- which is the difference in means of the conditions divided by the pooled standard deviation. While we include significance tests and related statistics, it is with the intention of supplementing these analyses.

	no search	search present	used search	total
255Charts	57	102	(72, 70.6%)	*159*
BoardofDirectors	47	151	(49, 32.5%)	*198*
Colleges	68	93	(75, 80.6%)	*161*
AnonColleges	53	103	(68, 66.7%)	*156*
Exoplanets	61	95	(65, 68.4%)	*156*

Table 2. We evaluate the impact of text-based search using a between-subjects design across multiple visualizations. The table shows participant numbers for each experiment, determined by running effect size and power analyses on pilot studies. More participants were added to the *search present* condition based on proportions of use derived from pilot studies.

The results of our pilots showed some measures from the *Exploration* phase were non-normally distributed, according to a Shapiro-Wilk test. These measures, such as $exploration-time$, were right-skewed with long tails. Because common transforms (*i.e.* log, square-root) did not lead to changes in the Shapiro-Wilk result, we use the non-parametric Mann-Whitney test to compare these conditions.

To ensure our experiments included enough participants to reliably detect meaningful differences between the conditions, we conducted effect size and statistical power analyses. Specifically, we used pilot studies to estimate the variance in our quantitative measures, and combined these with the observed means to approximate how many participants were needed. Additionally, from pilot studies we estimate the percentage of users who are likely to use search, adding more participants to the *search present* condition to ensure roughly equal numbers of participants in the "used search" and "no search" groups (see Table 2 for specific proportions and outcomes).

RESULTS

In total, we recruited 830 participants through Amazon's Mechanical Turk for the study. For each visualization, participants were assigned into one of the two conditions, *search present* and *no search*.

Proportion of People who Use Search When Present

Exploration behavior: when search is present, what proportion of users make use of it?

In general, a majority of people used text-based search when present in a visualization. The proportion of participants that used search were similar in the most of the visualizations (70.6% for *255Charts*, 80.6% for *Colleges*, 66.7% for *AnonColleges* and 68.4% for *Exoplanets*). However, the proportion was lower for *BoardofDirectors* (32.5%). We visit possible reasons for this outlier and design implications that follow this finding in the discussion.

Search's Effect on Information Seeking Goals

Self-reported exploration strategy: does the presence of text-search impact peoples' reported exploration strategies?

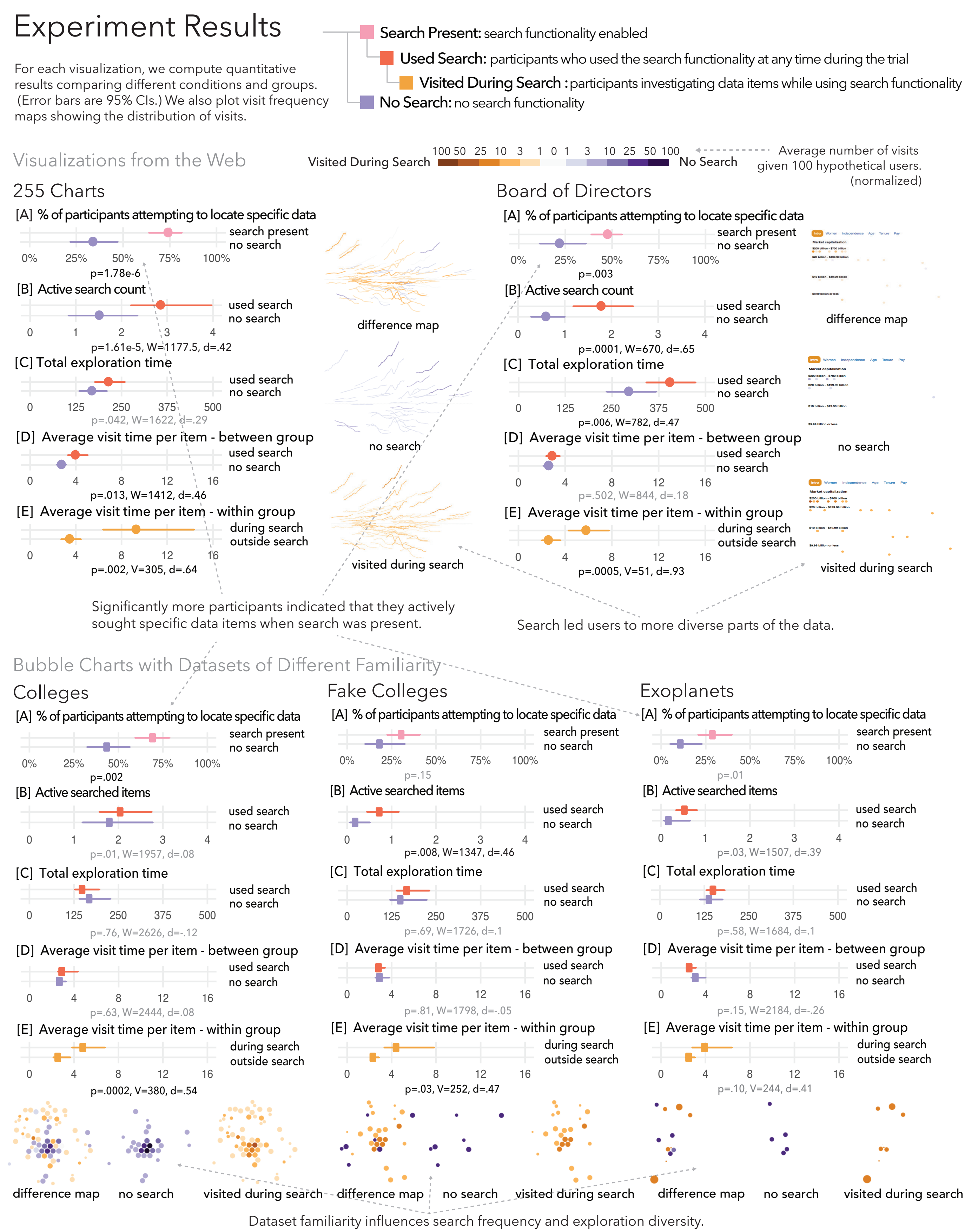

Figure 4. Experimental results comparing original visualizations with versions that integrate search. The results suggest that adding search enables a subset of users to identify specific data of interest in visualizations, and that in many cases this leads to more time spent with individual data items, an indicator of greater engagement with data. Maps showing items visited during search (orange) versus items visited when users did not have search (purple) suggest that search leads users to different parts of the data.

For all except one condition, *AnonColleges*, significantly more participants indicated that they actively sought specific data items when search was present (significance determined by a two-proportion z-test, see also the top chart in each column of Figure 4).

Of note is that *AnonColleges* and *Colleges* are identical in visual form and data attributes, except for the plaintext college-name field. Specifically, in *Colleges*, the proportion difference was 25.7% (95% CI [9.5%, 42.1%]), with 69.9% affirmative in the *search present* condition and 44.1% in the *no search* conditon. *AnonColleges*, on the other hand, showed a difference of 12.2% (95% CI [-3.0%, 27.4%]), with 31.1% affirmative in the *search present* condition and 18.9% in the *no search* conditon. We consider differences in these findings related to exploration strategies and their implications further in the discussion.

Search's Effect on Information Seeking Patterns

Exploration behavior: does the use of text-based search impact measures of behavior, such as the location of investigated data?

If a participant indicated that they intentionally sought specific data items in the visualization, they were shown a list of every item they interacted with (defined as viewing for more than 500ms, to account for accidental interaction). Given these sets, we generate maps that show patterns of where participants visited. Specifically, we normalize the number of visits to each data item, and add a diverging gradient that indicates how often data items were selected by participants who used search versus those who did not use search.

Figure 4 shows three of these normalized maps for each visualization, including proportions for participants who used search, those who did not, and a diverging map showing the difference. Notably, across all conditions, with the possible exception of *Exoplanets*, participants select a **more diverse** set of data items. For example, in the *BoardofDirectors* visualization, participants who did not use search generally indicated their intent for items in the upper left of the view. In contrast, participants who used search indicate a wider range of values, spanning more of the range of the data.

Search's Effect on Exploration Time

Exploration behavior: does the use of text-based search impact measures of behavior, such as the total time spent on exploration?

We measure exploration time, *i.e.* the total time spent interacting with the visualization, at three levels of granularity. First, we collect the overall time, meaning the time from which the participant begins exploring, to the time they click to indicate they are finished and ready for the next section. Second, we collect the amount of time a person spends looking at the details of a data item. Finally, for participants who use search, we distinguish between "visit" times when a search is active (*i.e.* data items are highlighted) and inactive. In the latter case, the user is examining item detail without the aid of search.

At the overall exploration time level, significant differences are only found for the "in the wild" visualizations. For example, in *BoardofDirectors* we found that the average participant who used the search functionality spent more time (M = 117 seconds 95% CI [93.1, 147.5]) than those in *no search* condition (M = 76.9 seconds 95% CI [55.5, 109.8]). Following Cumming's methodology for interpreting confidence intervals [14]. Given the upper and lower limits of the confidence intervals, the average participant in the group spends at least the same time on exploration, and up to 92 seconds more.

We note that longer exploration time, while reported in prior studies (*e.g.* Boy *et al.* [5]), may indicate greater engagement of participants, it could also indicate difficulty in using aspects of the visualization, like search. For this reason, it is necessary to further differentiate aspects of time, such as time spent examining individual data items.

Time Examining Individual Data Elements

Exploration behavior: does the use of text-based search impact measures of behavior, such as the proportion of time spent viewing detailed information about chart elements?

At the second level of time-granularity, we analyze the average time participants spent viewing the details of each data element, which we term a "visit". This difference was significant only in *255Charts*, where the average participant who *used search* spent more time visiting a data item (M = 3.9 seconds 95% CI [3.2, 4.9]) than those in the *no search* condition (M = 2.7 seconds 95% CI [2.3, 3.1]). Given the upper and lower limits of the confidence intervals, the average participant who used the search functionality spends at least same time visiting a data item, and up to 2.6 more seconds (d = 0.46 [0.17, 0.7]). We revisit this finding in the discussion, as *255Charts* is also different from all other visualizations in that a "visit" brings up a secondary chart.

At the third level of granularity, we compare visits within the search condition, specifically visits that occur while search is active, against those that occur when search features are not in use. As shown in the bottom confidence interval charts in each column of Figure 4, participants spent significantly more time with data items when search was active, for all conditions except *Exoplanets* ($p = .10$).

These results suggest that, in most cases, data items that are visited during search are examined for longer. This effect is particularly strongest in the news visualizations, where visits during search are higher than all population-level visit times (see Figure 4). For example in *255Charts*, the average participant spent more time visiting a data item found by using text-based search (M = 9.2 seconds 95% CI [6.5, 13.8]) than through browsing (M = 3.4 seconds 95% CI [2.7, 4.3]). Given the upper and lower limits of the confidence intervals, the average participant in the group spends at least 2.2 more seconds visiting a data item found through text-based search, and up to 11.1 more (d = 0.64 [0.34, 0.87]). In *BoardofDirectors*, we found that the average participant spent more time visiting a data item found by using text-based search (M = 5.7 seconds 95% CI [4.3, 7.8]) than through browsing (M = 2.5 seconds 95% CI [2, 3.4]). Given the upper and lower limits of the confidence intervals, the average participant in the group spends at least 0.9 more seconds visiting a data item found through text-based search, and up to 5.8 more (d = 0.93 [0.43, 1.41]).

DISCUSSION

As shown in Figure 4, the results of these experiments suggest that the *mere presence* of text-based search in visualization can impact users' self-reported exploration strategy, the data they explore, and how long they explore specific items of data. Results from the controlled variation of dataset familiarity suggest that the effects of text-based search change depending on the topic of a visualization. We turn our attention to possible causes for these findings, notable uses of search by participants, and the implications these findings carry for the design of visualizations.

Search Encourages Personalized Information-Seeking

Our results indicate that most people use text-based search when it appears alongside a visualization. Furthermore, people who utilized search were more likely to indicate that they actively sought specific data items in the visualizations. While these results may not be surprising in their own right, our observations suggest that the data people looked for while using search was often deeply personal. As one participant who searched for 'Duke' stated:

> *Duke University is very expensive at $61,000 a year... when I was a kid I wanted to go to Duke.*

Similarly, a participant that used a partial query 'Tech', provided the finding:

> *Tech colleges promise the most consistent ROI... [I'm] interested in science. Also, my brother applied to these schools*

Quotes like those above suggest that simple interaction mechanisms such as text-search have the capability of changing user's relationship with the visualization. While it is possible that these participants could have arrived at their insights without the use of search, doing so may have been more haphazard or time-consuming given the initial interaction schemes and visual forms.

From a design perspective, it may be important to emphasize that some people did *not* use search, even when it was present. Use of search ranged from a high of 81%, *Colleges*, to a low of 33% *BoardofDirectors*. This low value is an outlier, but remains an interesting case worthy of further investigation. One possibility for the low use of search is that people simply didn't notice it. Due to constraints in the form of the visualization, search appeared in the bottom-right (Other positions were possible, but it was unknown apriori that position may have an effect).

Another possibility is that the interaction scheme of *BoardofDirectors* is what practitioners and researchers sometimes refer to as "scrollytelling", where the main narrative of the visualization is controlled by user scrolling or clicking to advance the "slides". Effects like these raise questions of whether there is an upper limit on the number of available interactions that a given person will make use of during exploration.

Search Encourages Diverse Engagement with Data

When participants used search queries, they engaged with individual data items for significantly longer than when search queries were inactive. A likely explanation for this trend is that search queries serve as an implicit indicator of interest. However, it's worth noting that this deeper engagement was facilitated by the presence of search.

However, the strength of the effect differed across conditions. In 255*Charts*, for example, data items that were visited during searches outpaced non-search visits (according to 95% CIs) by at least 2.2 seconds, and up to 11.1 on average. One possible reason for these differences corresponds to the depth of detail available to users on-demand. A unique feature of 255*Charts* is that, on mouseover, a secondary line chart appears, showing additional data for the given industry (see Figure 4). In contrast, the details shown in the bubble charts consist of a few simple data items: college cost, planet temperature, etc. The effect was similar in *BoardofDirectors*, where multiple data elements about companies were shown on mouseover.

The results show a longer exploration time found in the *BoardofDirectors* visualization. Unlike the other visualizations, *BoardofDirectors* has multiple tabs, which may have led users to compare highlighted search results in different views by switching between tabs.

A possible consideration for design, then, is that the value of search increases alongside the amount and quality of data revealed in detail views in an interactive visualisation. Future research might investigate the role of detail quantity and quality of exploration patterns, as well.

Text-based Search in Visualization Task Taxonomies

Beyond measures of behavior, the value of search mechanisms in visualization may be more clearly articulated through existing task taxonomies. One that is particularly relevant is Brehmer and Munzner's typology of abstract visualization tasks [7]. In their taxonomy, *search* is used as a general term referring to multiple user goals, including lookup, browse, locate, and explore. We contextualize each of these within the *Colleges* condition of our visualization:

- *lookup* (location known, target known): the user knows exactly which college they are looking for and exactly where it is in the visualization
- *browse* (location known, target unknown): the user has characteristics of a college that they are interested in (ex: high tuition) guiding them to a region of the visualization, but does not have any specific college in mind.
- *locate* (location unknown, target known): the user is looking for information about a specific college, but does not know where in the visualization that college might be represented.
- *explore* (location unknown, target unknown): the user is not looking for any particular college or characteristic.

While the visualizations we tested largely support *browse* and *explore*, they fall short in *locate* goals without search. Because of the density of the data, labels are supported through interaction mechanisms rather than natively appearing on the page. As a result, finding a specific college, industry, planet, or company can be challenging.

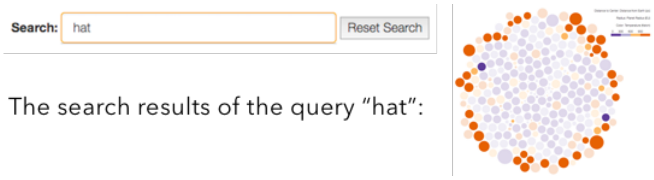

Figure 5. Some participants used text-based search to explore the data in creative ways. In one case, a participant noticed that some planets had common substringsin their names. They arrived at the query "hat", and produced a finding about common data features among "hat" planets. ("HAT" happens to be the organization that discovered these planets.)

Search Enables Creative Exploration of Unfamiliar Data

The flexible nature of linking text-based queries to visual encodings (such as highlighting) in visualizations enables some users to investigate data in surprising ways. For example, in the *Exoplanets* condition, one participant used partial queries to investigate relationships in the naming schemes of the planets. As shown in Figure 5, the participant appears to have arrived at a query of 'hat' - a naming prefix of the exoplanets discovered by the Hungarian Automated Telescope (HAT) network. Analysis of interaction logs shows that this participant began exploration by mousing over planets at random, until noticing that some had this common prefix. In the free-response section, the participant described their strategy:

> *I compared different properties of the different groups of planets with similar names to those with different names*

Queries like this demonstrate a possible ancillary benefit of text-based search: partial queries across data fields allow people to segment unfamiliar data in novel ways, even if the data is unfamiliar to them.

Keyboard-based Features for Accessibility

In addition to exploration behaviors and strategies, our experimentation with text-based search raised questions of accessibility in visualization. Visualizations can be difficult to interact with for people with motor deficiencies, *i.e.* people who cannot use a mouse to generate precise movements, as interactive elements may be only a few pixels wide. However, the W3 Standards organization lists extensive accessibility principles for web designers [12]. Text-based search mechanisms in visualization, applied at the appropriate scope, increase accessibility by supporting keyboard based interaction, which is a key recommendation of W3. While accessibility has not been addressed broadly in the visualization community, the results of this study, along with other findings that multi-modal interaction mechanisms are generally beneficial [37, 13], add a perspective to this ongoing thread.

LIMITATIONS

Our study of text-based search in visualizations was within a limited scope in three aspects: (1) data characteristics, (2) visualization types and (3) user background. First, all the visualizations used in our study consist of 200-500 data items. Each data item has at least one key (*e.g.*, industry name in 255*Charts*), which is used for text-based search. Second, the visual representation of the visualizations was single view including all data items, with details revealed by mouseover. More complex representations such as coordinated multiple views were not used in this first study. Third, participants of our study were closer to a general population with diverse backgrounds, not domain experts. In addition, there are alternative mechanisms supporting text-based search, such as drop-down boxes and sliders, which may yield different behavioral results and raise new design trade-offs. The generalization of our results beyond these constraints is open to investigation.

The effect of search on comprehension is a likely a delicate dance in which design, data, target audience, and encoding interact to nudge its effect on the user. While we investigated the impact of search in different visualizations, we do not know the effect of varying choices in the visualization design space as it relates to search. Future research can build upon these experiments to investigate increasingly diverse combinations of search and interaction mechanisms to generate clearer design guidelines (for example, when is search *not* useful or harmful?)[1].

Finally, the measures we have for understanding the overall impact of any interaction mechanism still leave a lot to be desired. In this study, we used a combination of behavior, open-response, and survey questions to try and understand the overall impact of search in visualization. However, in a realistic environment in which goals are not prescribed to the user, they do not always translate cleanly to clear success/failure outcomes - is the person who found their home institution in the *Colleges* condition but visited nothing else less successful than the person who broadly explores the entire visualization? More research is needed to understand exactly when a visualization succeeds or fails in the open web environment. Future work in this area will likely require close collaboration with practitioners who create visualizations for the masses.

CONCLUSION

Across the web, designers build thousands of data-dense visualizations for the public to explore and comprehend. Surprisingly, only a very small subset of these visualizations are accompanied by text-based search mechanisms. While text-based search has often been used in conjunction with large datasets for analysts, our results suggest that its inclusion in everyday visualizations, even those with relatively small amounts of data, may encourage engagement and support user information seeking goals that are difficult with other forms of interaction. Through experiments with five visualizations, we find that in most visualizations, a majority of users will use text-based search features if present, and that search can shape people's experience and behavior with visualizations. Results of the experiments also indicate the average participant who used text-based search engaged with individual data items for longer, and explored different parts of the data. The results of these experiments have practical implications for design, and more broadly serve as a case study in how interactive data visualizations can be augmented to support diverse information seeking goals.

[1] **To facilitate future work, all experiment materials, participant data, and analyses scripts are available online:** https://wpivis.github.io/search-in-vis.

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