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IS MY EFFORT WORTH IT? INVESTIGATING THE DUAL EFFECTS OF SEARCH COST ON SEARCH UTILITY

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Abstract

Inefficiencies associated with online information search are becoming increasingly prevalent in digital environments due to a surge in Consumer Generated Content (CGC). Despite growing scholarly interest in investigating information search behavior and practical demands to optimize users' search experience, there is a paucity of studies that investigate the impact of search features on search outcomes. We therefore draw on Information Foraging Theory (IFT) to disentangle the dual role of search cost in shaping the utility of information search. We also extend the Information Seeking Model by advancing a typology of information search tactics, each incurring distinctive search cost. Furthermore, two types of search tasks were adapted from prior research to explore how search tactics differ between goal-oriented and exploratory conditions. Our hypotheses were validated via an online experiment in which Amazon Mechanical Turk (AMT) participants were recruited and tasked to perform search tasks on custom-made online review websites. By analyzing the behavioral data generated in the experimental process, we discover that search cost reduces the expected search utility while improving the yield of search space. Moreover, certain search tactics demand more effort from exploratory searchers, which in turn undermine their search utility.

Keywords: Information Foraging Theory, Online Information Search, Search Tactics, Search Tasks, Search Cost, Search Utility.

1   INTRODUCTION

Information search is becoming increasingly demanding[1] due to a surge in Consumer Generated Content (CGC) in online environment (McAfee et al., 2012). To aid users in overcoming the hurdles in locating desired information, e-commerce and online review websites often implement custom-made search features (Teevan et al., 2004). Nonetheless, the configuration of information search features is often not optimized to accommodate users' information search behavior, leading to adverse outcome such as *information overload* (Hölscher & Strube, 2000), *sub-optimal search performance* (Öörni, 2003), and *false discoveries* (Lohr, 2012). Consequently, it is imminent to enhance our understanding of information search behavior in order to guide the design of search features that can reconcile system search capabilities and user preferences (Kuhlthau, 1999).

Despite rising academic interest in information search behavior as well as increasing practitioner demand in optimizing users' search experience, there has thus been a paucity of theory-driven studies that tackle this issue. Information search behavior is mostly studied in the literature on information seeking. Inspired by Bates' (Bates, 1979a, 1979b, 1990) seminal work that summarizes five categories of search tactics (i.e., *monitoring tactics*, *file structure tactics*, *search formulation tactics*, *term tactics*, as well as *idea tactics*), many studies have strived to code information search tactics on the basis of log files analysis (Carstens et al., 2009) and on-site observation (Hsieh-Yee, 1993). Moreover, how search tactics can be shaped by individuals' subject knowledge (e.g., Hölscher & Strube, 2000; Wildemuth, 2004; Xie & Joo, 2012) as well as tasks undertaken (e.g., Liu & Belkin, 2015; Xie & Joo, 2012) has also been examined under the premise that information seeking is driven by seekers' information needs, tasks, and knowledge (Bates, 2002; Saracevic, 1997; Vakkari, 2001; Xie & Joo, 2012). Although this stream of research offers a great deal of insights into the interaction between user and information (Järvelin & Ingwersen, 2004), the role of search feature design and theoretical grounding is largely missing in past studies.

Information Foraging Theory (IFT) holds that the time and effort expended by users in reaching a target search space can change the composition of information in the search space considerably (Pirolli & Card, 1995, 1999). Therefore, we posit that, in addition to discounting *search utility* in terms of marginal information gain per unit of time and effort, the cost associated with advancing a search process to reach a target search space (i.e., *search cost*) can potentially boost the concentration of novel and relevant information of the search space. This dual effect of *search cost* is the impetus for us to investigate the formation of *search cost* as well as to explicate the two contrasting relationships between *search cost* and *search utility*.

With the IFT as our theoretical foundation, we also draw from prior literature on *information seeking behavior* and highlight the role of *search tactics* and *search tasks* in our search framework. For instance, we extend Information Seeking Model, which delineates between *teleporting* and *browsing* search manipulation, and develop a typology of search tactics that comprises both search determination (*pre-defined* vs. *self-determined*) and search manipulation (*teleporting* vs. *browsing*) (Bates, 2002). Different search tactics, afforded by corresponding search features, incur different level of search cost. Using two information search tasks well established in prior research (i.e., *goal-oriented* and *exploratory* search tasks), we also explore how different search tasks alter searchers' evaluation of *search utility* and *search cost* (Browne et al., 2007; Nadkarni & Gupta, 2007). Empirically, we conducted an online experiment on our custom-developed online restaurant review website with real restaurant listings and reviews. By analyzing the behavioral data generated in the experimental process, we aim to answer the following research questions: First, *how does search cost exert dual effect on search utility*? Second, *how does search cost vary across different search tactics afforded by search features*? Third, *how does search task alter the formation of search cost and search utility*?

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[1] The Search Engine Unfriendliness of Web 2.0, http://searchengineland.com/the-search-engine-unfriendliness-of-web-20-12465, accessed in 2016.

2 THEORY DEVELOPMENT

2.1 Information Foraging Theory

Foraging theory posits that sentient organisms devote time and energy into finding, handling, and consuming food, resource, and information in an environment via strategic planning (Hantula, 2010). *Foraging* is determined by *currency* and *constraint* (Hantula, 2010). The former refers to the effort and time spent in foraging whereas the latter to the interaction between the foragers' capabilities and the environmental limitations (Hantula, 2010). Inspired by *foraging theory*, Pirolli and Card (1995, 1999) demonstrate that, similar to food foraging, human tends to optimize information foraging by maximizing informational return while minimizing search costs. Drawing from the marginal value theorem (Charnov, 1976), Pirolli and Card (1999) further propose the IFT on the basis of *foraging theory*. According to these researchers, the concepts of prey and patch in foraging theory can be understood respectively as information items and search space (i.e., the collection of information items) generated by utilizing search features on website (Pirolli & Card, 1999). The validity of applying foraging theory in information search context has been corroborated extensively by Pirolli and his colleagues, through their eye tracking experiments on Hyperbolic Tree Browser (Pirolli et al., 2001, 2003) and SNIF-ACT system (Fu & Pirolli, 2007; Pirolli & Fu, 2003; Pirolli et al., 2005). As a fitting theoretical lens for investigating information search (Moody & Galletta, 2015), IFT holds that the rate of information gain depends on the distance between information patches as well as the trade-off between between-patch exploration and within-patch exploitation. Likewise, we submit that the behavioral cost to traverse through search spaces as well as the trade-off between exploration and exploitation are focal determinants of *search utility*. We propose that in the context of online information search, the number of unique information items reflects users' information gain. Therefore, *search utility* (or rate of information gain) can be represented by the ratio between unique information items examined by a user and the total number of information items examined by the user. That is, the number of redundant information items that a user has to go through before encountering unique ones is a reflection of the *utility* of employing certain search features to travel across search spaces to locate valuable information items.

2.2 Marginal Value Theorem and Matching Law

Building on the foundation of the *marginal value theorem* (Charnov, 1976), *matching law* holds that any sentient organism is intrinsically motivated to distribute its behavior among alternatives in an approximate match to their relative rates of return (Herrnstein, 1961, 1970). That is, the expected value of considering alternative information is subjected to the time and energy required by additional exploration (Smith & Hantula, 2008). In this sense, *matching* is a strategy to achieve long-term optimal utility by exploring viable alternative options that can potentially grant positive marginal return (Sakai & Fukai, 2008). Users' evaluation of the return of reaching out for more options is determined by the delay induced by traveling between patches of prey (Hantula, 2010). Likewise, such delay also exists in the traversal between search spaces that are generated by using search features, which is the energy that each user devotes to using search features to switch from one search space to another (Pirolli & Card, 1999). In a sense, the number of actions and maneuvers that are required to operate a search feature resembles the cost for reaching out for additional search spaces.

Prior empirical studies on e-commerce have validated the important role temporal delay plays in determining a consumer's decision of whether to make a purchase in the current online store or to sample another online store (Ainslie et al., 1992; Green & Myerson, 2004; Hantula et al., 2008; Rachlin, 2006). DiFonzo et al. (1998) conducted an experiment on computer simulated online CD stores and found that the delay between switching from one store to another deterred consumers' decision to sample more alternative stores. Rose et al. (2005) demonstrated the adverse effect of loading time on consumers' evaluation of online stores through their experiment. Szameitat et al. (2009) invited 16 participants to play a donkey in a game with both goal-oriented (i.e., reaching a fence before the time runs out) and exploratory (i.e., collecting carrots) aspects. Since collecting carrots was associated with monetary

reward, participants were incentivized to collect as many carrots as possible. By inducing temporal delay for participants' control to take effect, Szameitat et al. (2009) confirmed that the induced delay increased participants' perceived behavioral costs and in turn deterred them from exploring for carrots even though the time limit was extended to offset the induced temporal delay. A number of other studies also examined participants' shopping behavior when multiple online stores were available with various *change over delays*, referred to as the number of mouse clicks and the length of time interval incurred in switching between different stores (DiClemente & Hantula, 2003; Hantula et al., 2008; Rajala & Hantula, 2000). The findings of these studies demonstrate that online information searchers seek to maximize their information intake over the expenditure of time and efforts (Hantula, 2010). In this study, we define *search utility* in the context of online information search as the extent to which furthering a search process yields positive marginal return. Due to human's relatively poor perception of time, the delay that discounts the marginal return of exploration is more accurately reflected by currencies such as behavioral efforts or monetary tokens (Smith & Hantula, 2003). We thus define *search cost* as the behavioral efforts expended by a user on carrying out the search in order to encapsulate the delay that diminishes the rate of information gain. More specifically, if operating a search feature demands high amount of inputs in terms of time and effort from users, the rate of gaining novel information via using this search feature will be lowered. On the contrary, using a more efficient search feature requires less behavioral efforts, thus yielding higher *search utility*. We hence hypothesize that,

Hypothesis 1: The search cost of operating search features on a website negatively influences a user's search utility.

2.3 Search Orientation

According to IFT, the trade-off between searching for alternative search spaces and exploiting the current search space also shapes the outcome of information foraging (Pirolli & Card, 1999). If users focus only on exploiting a search space, they can be exempted from the risk of reaching a search space with negative return, which occurs when *search cost* outweighs the information gain from this search space (Pirolli & Card, 1999). However, overcommitting to exploitation also comes with its downsides. First, the rate of information gain associated with exploiting a search space will keep decreasing and eventually lead to the depletion of novel information. Second, ignoring exploration also risks neglecting alternative search spaces with higher profitability, and in turn leads to sub-optimal rate of long term gain (Pirolli & Card, 1999). We posit that *search cost*, which is associated with employing a particular search feature, can influence such a trade-off. For instance, search features that require more efforts to use tend to demand more attention from users. The extended attention span compels users to devote more cognitive resources and encouraging them to change their *search orientation* from evaluating and processing information within a search space (i.e., exploitation) to exploring an alternative search space by leveraging search features. Unlike foraging in natural environment, where patches of prey remain relatively static, search spaces, which are generated by operating search features, are subjected to users' manipulation (Pirolli & Card, 1999). Consequently, it is more likely for users to obtain a more relevant and concentrated search space if they devote more effort in manipulating and refining this search space. Such a search space often comes with an improved gain function, which depicts the how information gain increases along with the time spent on examining a search space, due to the more concentrated novel and relevant information. Charnov's (1976) marginal value theorem postulates that improved gain function not only heightens the average rate of information gain but also shortens the minimum time for evaluating information in order to optimize information gain within a search space. As a result, the reduced time that is required for within-patch exploitation leads to a further skew of users' *search orientation* towards exploration. Because of the improved gain function, such a shift of search orientation tends to benefit users in the long run by improving the *search utility*. We hence hypothesize that,

Hypothesis 2: The search cost of operating search features on a website encourages a user to shift his/her search orientation from exploitation to exploration.

Hypothesis 3: The shift of a user's search orientation from exploitation to exploration positively influences his/her search utility.

2.4   Information Search Tactics

Prior research on information seeking reveals that users employ various *search tactics* when searching for information online. Bates (1979a, 1979b, 1990) defines *search tactic* as a set of actions that advance a search process and advances a typology of tactics that consists of five types: *monitoring tactics*, *file structure tactics*, *search formulation tactics*, *term tactics*, and *idea tactics*. Following her initial attempt to qualify tactics that are applied in document search on the basis of experience, conversation, and literature, Bates (1989) later proposes a more parsimonious typology of search tactics by drawing on classic information retrieval model. Specifically, Bates (1989) distinguishes between *berrypicking*, which refers to a directed search tactic that advances search through sequential modification of queries, and *browsing*, which refers to an undirected search tactic that advances search via continuous sampling and selecting among a collection of information. Bates (2002) further extends this typology by proposing the Model of Information Seeking to encompass both active and passive information seeking. This model posits that information search, an active information seeking behavior, consists of directed (i.e., *berrypicking*) and undirected search tactics (i.e., *browsing*) that differ in whether or not the search is guided by a specific goal (Bates, 2002). Many studies have empirically validated this (or similar) typology of information search tactics (e.g., *querying* vs. *browsing, teleporting vs. orienteering*) (Hölscher & Strube, 2000; Hsieh-Yee, 1998; Kuhlthau, 1993; Spink et al., 2001; Teevan et al., 2004).

Although users' maneuver in search process is adeptly captured by *directed search* and *undirected browsing* in the Information Seeking Model, how they determine their search goal has not been clarified. We posit that users' information need is not the sole determinant of their search goal. Websites can offer information scents as indicators of available information to guide users' search goal determination. In particular, Moody and Galletta (2015) conducted an experiment and found that, like smell of food, information scents could be provided by a website to better guide users' information search process. Pirolli et al. (2001, 2003) also showed that information scents improved the efficiency of information search particularly in visually dense informational environment. Pirolli and his colleagues further developed a SNIF-ACT system (Fu & Pirolli, 2007; Pirolli & Fu, 2003; Pirolli et al., 2005) on the premise that rational users rely on information scents (e.g., a hyperlink) to estimate the utility of related content. In this study, we extend the Information Seeking Model by defining *search determination* (i.e., how a search goal can be defined) as another dimension of online information search tactics in addition to *search manipulation* (i.e., how a search goal can be achieved). Table 1 details our typology of online information search tactics.

2.5   Information Search Tasks

Information search tasks can influence users' preference for information search tactics (Vakkari, 2003). Prior information seeking research has identified different types of information search tasks and investigated how they shape users' information search behavior. For instance, Bilal and Kirby (2002) looked into the log files of the search engine usage of 14 children and 9 undergraduate students and discovered that users tried to formulate their search queries more frequently when engaging in fact-based search task while browsing the result list more for self-generated search task. Hung (2005) found that users tended to adopt more complex search tactics when performing general search task as compared to specific search task. Kim and Allen (2002) included known-item search task and subject search task in their experiment and showed that, when undertaking different tasks, users employed different search tools. Shiri and Revie (2003) uncovered the search task with a more complex topic increases users' search moves. Last but not least, Xie and Joo (2012) identified work tasks and search tasks on the basis of both subjective and objective data collected from 31 respondents, and detailed the relationship between task type and respondents' preferred search tactics.
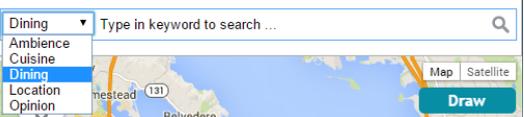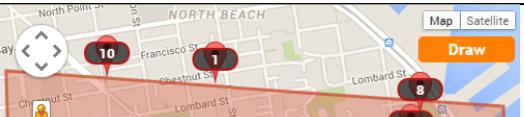
Search Determination: How a search goal is determined		
	Pre-Defined: Extent to which the search criteria are constrained by the website	Self-Determined: Extent to which the search criteria are determined by the users
Teleporting: Extent to which a search is advanced via discrete queries	**Faceted Search (FS)** Affording Pre-Defined Teleporting	**Keyword Search (KS)** Affording Self-Determined Teleporting
	A categorized filter that displays pre-defined categories of attributes and corresponding attribute values for users to determine their search criteria by selecting one or more values for each attribute.	A standard search bar that allows users to specify a category of keywords and type in one more multiple keywords to conduct search
Browsing: Extent to which a search is advanced by sifting through organized information	**Ranking Search (RS)** Affording Pre-Defined Browsing	**Interactive Search (IS)** Affording Self-Determined Browsing
	A feature that allows users to sort the list of information items according to pre-defined attributes in either ascending or descending order.	A Feature that allows the users to search for information items in two ways: (1) Moving or zooming the view port of the map to find information items within the updated view port. (2) Drawing boundaries around an area of interest via mouse cursor to find information items within this area of interest.

Search Determination: How a search goal is determined spanning; the left vertical label reads **Search Manipulation**: How a search goal can be arrived at.

Table 1.   Definition and Operationalization of Online Information Search Tactics

Nadkami and Gupta (2007) suggest that online tasks in general vary in their goal conditions. Specifically, a *goal-oriented task* specifies the goal for users to complete whereas an *experiential task* grants users the freedom of looking for anything that draws their interests (Nadkarni & Gupta, 2007). Similarly, Browne et al. (2007) distinguish between *structured search tasks*, which specify the required inputs, operations, and outputs for users, and *unstructured tasks*, which come with no well-defined objectives, when examining how users determine when to stop searching for information. Likewise, in this study, we categorize online information search tasks into *goal-oriented task*, which refers to a search task that offers a specific search goal, and *exploratory task*, which refers to a search task that gives no objective to restrict users' exploration. In line with prior information seeking literature, we postulate that certain information search tactics are more fitting for one of these two types of information search tasks. More specifically, when performing a *goal-oriented task*, users have a clear idea about the information they are looking for (Browne & Pitts, 2004). They seek to preserve the authenticity and accuracy of their objectives when expressing their goals in the form of search criteria by using search features. Therefore, compared to *pre-defined* search determination, *self-determined* search determination is more suitable for *goal-oriented task* due to the flexibility it allows for users to specify their search goals. On the contrary, users who employ *pre-defined* search determination often have to approximate their search goals by improvising the pre-defined options. This approximation likely entails prolonged heuristics, which lead to a heightened behavioral cost. On the other hand, *teleporting search manipulation* is more suitable for undertaking *goal-oriented tasks* than is *browsing search manipulation*. Goal-oriented searchers aim to arrive at their goals in a timely fashion (Bates, 2002). *Teleporting search manipulation* better satisfies this need for efficiency compared to its *browsing* counterpart, as the latter tends to compel users to exert extra efforts to go through less relevant information before reaching their goals. We hence hypothesize that,

Hypothesis 4: For goal-oriented information search task, self-determined search determination tactic heightens a user's search cost to a lesser extent comparing to pre-defined search determination tactic.

Hypothesis 5: For goal-oriented information search task, teleporting search manipulation tactic heightens a user's search cost to a lesser extent comparing to browsing search manipulation tactic.

Conversely, users who engaged in *exploratory information search task* often go with the flow and explore potentially interesting information without pre-determined goals. Therefore, it is crucial for the users to maintain an awareness of their flow of search and vicinity of search space (Teevan et al., 2004). A lack of such sense of location can lead to disorientation, loss of control, and a reduced understanding of search results (Teevan et al., 2004). *Pre-defined search determination* is more advantageous than *self-determined search determination* in terms of guiding users through the search process especially when users have no specific goals. The information scents that are generated by search features allow users to gauge the potential value of the search results (Pirolli & Card, 1999) thus helping users to establish a sense of direction. Without a specific goal, the flexibility that characterizes *self-determined search determination* can burden users and make them lost the sense of direction more easily. Consequently, disoriented users tend to waste efforts crawling through irrelevant information. On the other hand, *browsing search manipulation* tends to perform better than its *teleporting* counterpart for *exploratory* search task. Unlike *teleporting*, which often entails disjointed leap from one search space to another (Teevan et al., 2004), *browsing* makes the logical connection between adjacent information items more apparent to users therefore facilitating the continuity in the search process. The enhanced search flow not only permits the users to skip irrelevant information, but also helps them find more fruitful direction to explore (Browne & Pitts, 2004; Teevan et al., 2004). *Browsing search manipulation* ultimately mitigates the possibility for users to search in vain for potentially interesting information and reduce wasted efforts. We hence hypothesize that,

Hypothesis 6: For exploratory information search task, self-determined search determination tactics increase a user's search cost to a greater extent when compared to pre-defined search determination tactics.

Hypothesis 7: For exploratory information search task, teleporting search manipulation tactics increase a user's search cost to a greater extent when compared to browsing search manipulation tactics.

The distinction between *goal-oriented* and *exploratory* information search tasks also contributes to how users evaluate *search utility*. While *goal-oriented* tasks compel users to adopt a deductive approach to eliminate irrelevant information and pinpoint the information pertaining to their search goals, *exploratory* tasks encourage users to employ an inductive approach to consider as many potentially interesting information items as they desire. *Goal-oriented* searchers value efficiency in search process in terms of reduced time, efforts, and irrelevant information. Conversely, *exploratory* searchers are not pressured to achieve a specific objective. The freedom of willingly terminating a search process relieves searchers from the stress induced by time constraint (Moody & Galletta, 2015) and in turn reduces their sensitivity to *search cost* (DiClemente & Hantula, 2003; Hantula et al., 2008; Rajala & Hantula, 2000). As such, the detrimental effect of *search cost* on *search utility* is more pronounced in *goal-oriented* conditions as compared to in *exploratory* conditions.

As search spaces can be manipulated by utilizing search features (Pirolli & Card, 1999), by focusing more on locating a refined search space, users are more likely to obtain a more profitable search space with minimum irrelevant information. Thereby, shifting *search orientation* from exploiting a search space to exploring better alternative ones can contribute to improved *search utility* for *goal-oriented* searchers. On the contrary, it is less feasible for *exploratory* searchers to obtain an optimal search space due to a lack of specific goals. It thus is not as profitable for users to devote efforts in exploring the optimal search space. Consequently, the positive influence of *search orientation* on exploration is more pronounced in *goal-oriented* conditions as compared to in *exploratory* conditions. We hence hypothesize that,

Hypothesis 8: Compared to exploratory information search tasks, goal-oriented information search tasks strengthen the negative relationship between a user's search cost and his/her search utility.

Hypothesis 9: Compared to exploratory information search tasks, goal-oriented information search tasks strengthen the positive relationship between a user's search orientation and his/her search utility.

3 METHODOLOGY

We conducted an online experiment to validate our research framework in Figure 1. We custom-developed an online restaurant review website and implemented search features considering contemporary design and in accordance with our typology of search tactics, including Faceted Search (FS), Keyword Search (KS), Ranking Search (RS), and Interactive Search (IS) (see Table 1). To preserve the realism of our experimental setting, we populated the website with real data extracted from a popular online restaurant review website via web scrapping. Our dataset includes detailed descriptions of 1,079 restaurants in the San Francisco area along with about 268,000 reviews for these restaurants, which were written by approximately 91,000 diners. The website offers a realistic and controlled platform to track participants' search behavior, such as how they operate search features. These participants' behavioral breadcrumbs allow us to use the objective data captured in our online experiment for data analysis.

3.1   Search Task Manipulation

We developed two types of information search tasks to manipulate the impact of task type. Guided by the design of search tasks in previous studies (Browne et al., 2007; Nadkarni & Gupta, 2007; Novak et al., 2003), we implemented a goal-oriented task and an exploratory task for each participant to undertake in the experiment. The *goal-oriented* task asks each participant to search for a restaurant to have with his/her old friend. This task provides specific objective for participants to achieve, which is to locate a restaurant that fulfils a number of criteria (e.g., cuisine, location and atmosphere).

Goal-Oriented Search Task: Find a restaurant for your friend

Scenario: Sebastian was your best friend from high school, but you have not seen him for quite a while because he moved to another city right after his graduation. Last night, you received a surprise call from Sebastian who happen to be in town on business and would like to invite you to dinner this weekend. Because Sebastian has been away from San Francisco for many years, he wants you to pick a restaurant that is located midway between Sebastian's hotel and where you live. You live in the Bernal Heights neighborhood, which is located at the central area of San Francisco whereas Sebastian's hotel is situated in the Tenderloin neighborhood, which is to the north-east of your place. Also, even though Sebastian usually prefers authentic American cuisine, he finds other popular cuisines to be equally appealing so long as they are authentic. Likewise, he is easygoing and likes to follow the opinions of the majority. As your old friend, Sebastian wishes to have an enjoyable conversation with you in a casual atmosphere during your dinner. Please utilize the search features on this website to find a desirable restaurant for your dinner with Sebastian.

On the other hand, the *exploratory* task instructs each participant to freely explore the restaurants on the website according to their own preferences. This task specifies no objective for participants to arrive at and no criteria for them to fulfill when selecting restaurants.

Exploratory Search Task: Find a restaurant for yourself

There is no scenario for this task, simply take the time to explore the restaurants featured on the website by utilizing its search features. At the end this task, select the "best" restaurant for yourself to have a meal (according to your own preference for choosing restaurants).

3.2   Objective Measurements

To measure the constructs included in our research framework, we used objective indicators of participants' behavior during their search process. By leveraging on objective data gathered in the experiment, we aim to circumvent the drawbacks of employing self-report measures or secondary data. Specifically, we seek to mitigate the *common method bias* (Podsakoff et al., 2003) that often plagues subjective measures, and boost construct validity that is often lacking in secondary data studies (Vartanian, 2010). The operationalization of all constructs is summarized in Table 3

3.3   Experimental Procedure

We recruited our experimental participants from Amazon Mechanical Turk (AMT). AMT is recognized by researchers as a large and heterogeneous pool of research participants with increasing popularity and viability (Chandler et al., 2014; Paolacci & Chandler, 2014). We applied the screening criteria recommended by Chen (2012), by recruiting only workers who completed at least 10,000 HITs with 99% approval rate. Each worker was rewarded 4 US dollars for participating in our experiment.

The experimental process consisted of two stages, such that each participant undertook both *goal-oriented* and *exploratory* search tasks (with the order of the tasks being randomly determined). Prior to the start of the search tasks, each participant was directed to a questionnaire to learn more about the experiment and report demographic information. Participants then followed a link to access the experimental website. Each participant was randomly assigned to a website with one of the four search features and asked to perform one of the two search tasks. Upon completing the search task, participants were redirected back to the questionnaire to answer a set of post-task questions. At the end of the questionnaire, participants were given a completion code for starting the next stage of the experiment. We implemented a temporal separation of 6 to 24 hours between the two stages of the experiment to reduce the likelihood that the participants would recall their previous answers while preserving flexibility in participants' arrangement of time schedules for participating in this study. During the second stage of the experiment, each participant was assigned to the website version with the same search feature but was asked to complete a different search task. Participants were asked to fill out both the pre-task and post-task questionnaire just as in the first stage of the experiment.

4   DATA ANALYSIS AND RESULTS

A total of 344 participants were recruited from AMT, among which 283 participants completed the entire experimental procedure and produced valid responses. Table 4 shows the demographics of our AMT samples. SmartPLS 2.0 was employed to test both the measurement and structural properties of our research model (Chin, 1998). Partial Least Square (PLS) analysis is preferred over other analytical techniques because it simultaneously analyses the psychometric properties of the measures (i.e., the measurement model) as well as both the direction and strength of each hypothesized relationship (i.e., the structural model) (Wixom & Watson, 2001).

4.1   Measurement Model

Table 3 depicts a summary along with corresponding descriptive statics of all our objective measures. Because our constructs are all reflected by a single objective indicator, it is infeasible for us to evaluate the internal consistency as well as the convergent validity of our measures. Discriminant validity of our constructs can be ensured due to the low correlations between constructs (i.e., below 0.37).

Demographics		No. Samples	%	FS	KS	RS	IS	No. Samples	%	FS	KS	RS	IS
		Goal-Oriented Search Task [N = 196]		Search Feature Usage				Exploratory Search Task [N = 205]		Search Feature Usage			
Gender	Male	97	49.5%	211	90	131	169	103	50.2%	301	64	114	37
	Female	98	50.0%	295	90	110	190	101	49.3%	345	89	95	57
	Unwilling to disclose	1	0.5%	0	3	3	4	1	0.5%	0	0	8	0
Age	Age 19 - 29	60	30.0%	114	31	68	60	65	31.7%	148	24	74	26
	Age 30 - 49	111	56.6%	274	103	134	236	112	54.6%	364	73	116	43
	Age 50 - 64	21	10.7%	113	48	39	66	24	11.7%	24	54	25	22
	Age 65+	3	1.5%	5	1	3	1	3	1.5%	35	2	2	3
	Unwilling to disclose	1	0.5%	0	0	0	0	1	0.5%	0	0	0	0
Education	Less than college education	28	14.3%	84	54	46	65	30	14.6%	137	34	29	4
	College education or higher	168	85.7%	422	129	198	298	175	85.4%	509	119	188	90
	Unwilling to disclose	0	0.0%	0	0	0	0	0	0.0%	0	0	0	0
Income	$0 to $30,000	78	39.8%	201	68	92	140	85	41.5%	239	52	114	36
	$30,000 to $50,000	62	31.6%	162	66	72	120	67	32.7%	187	62	41	31
	$50,000 to $75,000	33	16.8%	90	36	41	59	35	17.1%	151	38	27	10
	$75,000+	20	10.2%	48	9	35	36	16	7.8%	69	1	34	17
	Unwilling to disclose	3	1.5%	5	4	4	8	2	1.0%	0	0	1	0

Table 2.   Demographics of Our AMT Samples

Construct	Definition	Operationalization	Goal-Oriented Search Task [N = 196]		Exploratory Search Task [N = 205]	
			Mean	St Dev.	Mean	St Dev.
FS Usage	The usage of Faceted Search feature	$\frac{No.\,of\,FS\,uses}{No.\,of\,total\,uses}$	0.26	0.38	0.35	0.45
KS Usage	The usage of Keyword Search feature	$\frac{No.\,of\,KS\,uses}{No.\,of\,total\,uses}$	0.13	0.29	0.12	0.28
RS Usage	The usage of Ranking Search feature	$\frac{No.\,of\,RS\,uses}{No.\,of\,total\,uses}$	0.17	0.33	0.16	0.32
IS Usage	The usage of Interactive Search feature	$\frac{No.\,of\,IS\,uses}{No.\,of\,total\,uses}$	0.20	0.33	0.08	0.24
Search Cost	Behavioral efforts expended by a user on performing a search	*No. of search actions*	91.10	73.67	87.27	76.89
Search Orientation	A user's tradeoff between exploration (conducting search) and exploitation (evaluating an information item in details) in a search process	$\frac{Time\,on\,search}{Total\,time}$	0.44	0.16	0.40	0.16
Search Utility	The extent to which a search is worthwhile in terms of discovering novel information	$\frac{No.\,of\,unique\,restaurants\,evaluated}{No.\,of\,total\,restaurants\,evaluated}$	0.75	0.22	0.77	0.22

Table 3.   Summary of Objective Measures

4.2   Structural Model

Figure 1 illustrates the structural model from our data analysis. Accordingly, *search cost* positively influences *search orientation* towards exploration (T1: $\beta = 0.367$, $p < 0.01$, T2: $\beta = 0.330$, $p < 0.01$) while negatively influencing *search utility* (T1: $\beta = -0.267$, $p < 0.01$, T2: $\beta = -0.182$, $p < 0.01$), thus corroborating Hypothesis 1 and 2. Hypothesis 3, positing a positive relationship between *search orientation* towards exploration and *search utility* (T1: $\beta = 0.220$, $p < 0.01$, T2: $\beta = 0.072$ *n.s.*), is only supported in *goal-oriented* condition.

Note: T1 indicates the path coefficients for goal-oriented search task [N = 196], whereas T2 indicates that path coefficients for exploratory search task [N = 205].
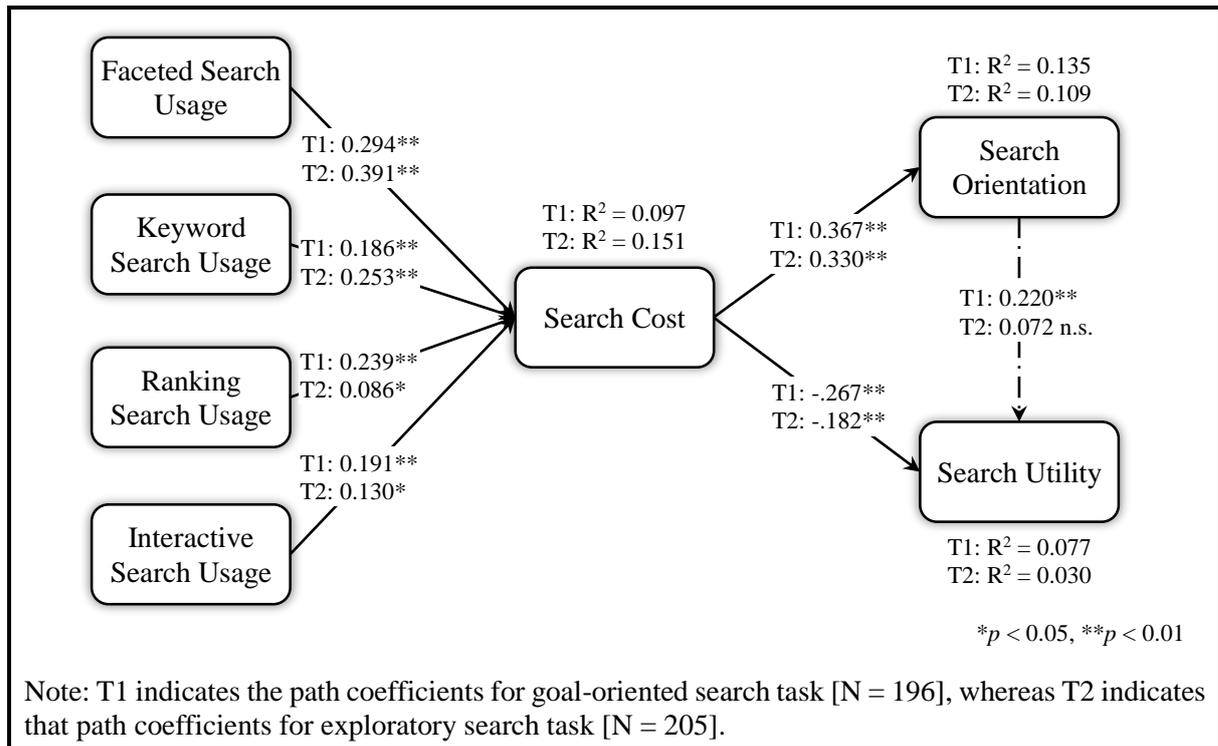
Figure 1.   Results of the Structural Model Analysis

Table 4 summarizes the testing results of our comparative hypotheses (i.e., Hypothesis 4 to 9). To test Hypothesis 4 to 6, we compare the relationships between *search feature usage* and *search cost* according to the search tactic each search feature affords. For instance, although the difference between *self-determined* and *pre-defined* search determination coincides with the Hypothesis 4 we proposed, this difference is not statistically significant. Hypothesis 5 is not supported because *pre-defined teleporting* affects *search cost* to a greater, rather than lesser, extent comparing to *pre-defined browsing*. Hypothesis 6 is partially corroborated due to the non-significant difference between *self-determined browsing* and *pre-defined browsing*, whereas Hypothesis 7 is fully supported since both comparisons between *teleporting* and *browsing* search manipulation attest to our predication and is statistically significant. On the other hand, Hypothesis 8 and 9 are validated by contrasting the path coefficients that are derived from both search tasks. The relationship between *search cost* and *search utility* is stronger in *goal-oriented* condition ($\beta = -0.267$, $p < 0.01$) than in *exploratory* condition ($\beta = -0.182$, $p < 0.01$) as we predicted. However, since the difference between path coefficients is not significant, Hypothesis 8 is not supported. Likewise, the positive influence posed by *search orientation* on *search utility* is stronger in *goal-oriented* condition ($\beta = 0.220$, $p < 0.01$) than in *exploratory* condition ($\beta = 0.072$ *n.s.*). This difference between path coefficients in statistically significant, therefore validating Hypothesis 9.

A possible explanation to the unsupported Hypothesis 4 and 5 is that, by following established guideline (Browne et al., 2007), our *goal-oriented* search task offers well-structured criteria. Although *pre-defined* search determination is not as flexible as *self-determined* search determination, it does not handicap

criteria specification when the criteria is already well-represented by the pre-defined options. Moreover, since our *goal-oriented* search task requires each participant to select a best option, *browsing* search manipulation allows users to efficiently compare viable alternatives. Hence, it does not incur excessive *search cost* compared to its *teleporting* counterpart. Moreover, the non-significant Hypothesis 8 alludes to the fact that *exploratory* searchers do not value efficiency much less than their *goal-oriented* counterparts (Hantula, 2010; Pirolli & Card, 1999).

Hypothesis	Comparison	Goal-Oriented Search Task [N = 196]		Exploratory Search Task [N = 205]		t-statistics	Supported
		β_1	SE_1	β_2	SE_2		
Hypothesis 4	SDT vs. PDT for goal-oriented task	0.186	0.049	0.294	0.036	-1.776 n.s.	Non-significant
	SDB vs. PDB for goal-oriented task	0.191	0.035	0.239	0.041	-0.890 n.s.	
Hypothesis 5	SDT vs. SDB for goal-oriented task	0.186	0.049	0.191	0.035	-0.083 n.s.	Not Supported
	PDT vs. PDB for goal-oriented task	0.294	0.036	0.239	0.041	1.008 n.s.	
Hypothesis 6	SDT vs. PDT for exploratory task	0.391	0.053	0.253	0.040	2.078*	Partially Supported
	SDB vs. PDB for exploratory task	0.130	0.037	0.086	0.038	0.830 n.s.	
Hypothesis 7	SDT vs. SDB for exploratory task	0.391	0.053	0.130	0.037	4.038**	Fully Supported
	PDT vs. PDB for exploratory task	0.253	0.040	0.086	0.038	3.027**	
Hypothesis 8	H1 for goal-oriented task vs. H1 for exploratory task	-.267	0.037	-.182	0.043	-1.498 n.s.	Non-significant
Hypothesis 9	H3 for goal-oriented task vs. H3 for exploratory task	0.220	0.043	0.072	0.041	2.491**	Fully Supported

Note: SDT refers to Self-Determined Teleporting, PDT refers to Pre-Defined Teleporting, SDB refers to Self-Determined Browsing, and PDB refers to Pre-Defined Browsing.

Table 4.   Testing Comparative Hypotheses

5   DISCUSSION

We draw on the IFT (Pirolli & Card, 1999) to investigate the role played by *search cost* in influencing the utility of online information search. We then propose a typology of information search tactics on the basis of Information Seeking Model (Bates, 2002) that consists of both *search determination* (i.e., *pre-defined* vs. *self-determined*) and *search manipulation* (i.e., *teleporting* vs. *browsing*) dimensions. We predict that different search tactics, which are afforded by specific search features, entail various degrees of *search cost*. Last but not least, consistent with prior literature, we distinguish between *goal-oriented* and *exploratory* search tasks to reveal their influence on the relationship between search tactics and search cost as well as the formation of *search utility* (Browne et al., 2007; Nadkarni & Gupta, 2007). We empirically validated our hypotheses by conducting an online experiment on our custom-made online restaurant review website with participants that are recruited from AMT. By analyzing the objective data collected from our two-stage experiment, we unveiled how different *search tactics* yield a varied degree of *search cost* and in turn shape *search utility*. Our findings suggest that *search cost* is both a boon and a bane for online information searchers. Specifically, *search cost* helps users to obtain a more relevant and profitable consideration set while discounting their evaluation for the value of search.

5.1   Implications for Research and Practice

By investigating online information search via an experimental approach, we seek to contribute to extent literature in the following ways. First, this study builds upon the premises of IFT (Pirolli & Card, 1999) and identified two opposing ways, in which *search cost* influences the utility of online information search. More particularly, according to *matching law*, the delay for traversing between search spaces induced by operating search features (i.e., *search cost*) discounts the expected return, in terms information gain, of reaching a search space (i.e., *search utility*) (Herrnstein, 1961, 1970). On the other

hand, drawing from the searchers' tradeoff between exploring alternative search spaces and exploiting the current one, we advance that *search orientation* towards exploration as the other main predictor of *search utility*. Unlike natural environment, in which patches of prey are relatively static, search spaces (i.e., collections of information) on website are subjected to users' manipulation. Therefore *search cost* compels users to shift attention towards achieving a more refined search space, and in turn heightens *search utility*. Second, realizing the possibility for websites to guide users' goal formation with information scents (Moody & Galletta, 2015), we extend Information Seeking Model (Bates, 2002) and put forward a typology of online information search tactics that encompasses both search determination (i.e., *pre-defined* vs. *self-determined*) and manipulation (i.e., *teleporting* vs. *browsing*). We believe such a typology can offer insights into the affordance of search features and bridge in between design elements and users' information search behavior. Third, we adopt both *goal-oriented* and *exploratory* information search tasks from prior literature (Browne et al., 2007; Nadkarni & Gupta, 2007) and investigate how task type shapes the nomological network of our research framework. For *goal-oriented* searchers, the efficiency of different search tactics that are performed by using search features is relatively invariant, and their *search orientation* towards exporting a more refined search space pose strong positive influence on their *search utility*. Conversely, it is more efficient for *exploratory* searchers to utilize search features that afford *pre-defined* rather than *self-determined* search determination and *browsing* instead of *teleporting* search manipulation. Moreover, in *exploratory* situation, search orientation towards exploring for an optimal search space does not make a search more worthwhile because it is unlikely to determine one without a specific goal. Last but not least, we employ a novel approach for data collection in the present study, which is to trace participants' behavioral breadcrumbs throughout the experimental process. Our approach supplies objective data for our data analysis and allows us to circumvent the drawbacks of using self-reported data or secondary data and in turn boosting the validity of our findings. This study serves as an attempt to contribute to methodological pluralism for investigating online phenomena in IS research (Dow, 2012).

This study also offers concrete guidelines for practitioners. First, this study proposes a comprehensive collection of contemporary search features for website to configure its search capability and optimize users' search experience. The configuration of search features is especially important due to the prevalence of *exploratory* situation online where users do not have a specific idea about the information they wish to obtain (Moody & Galletta, 2015). Therefore we encourage website practitioners to cater for *exploratory* searchers by affording *pre-defined* search determination via the provision of information scents and facilitating *browsing* search manipulation by allowing users to organize information according to their needs. Second, our typology of information search tactics builds the cornerstone for web designers to develop novel search features in a systematical manner. For instance, practitioners can develop novel *integrative search* features to enhance *self-determined browsing* by incorporating visualization techniques. Moreover, new *faceted search* features can be invented to facilitate *pre-defined teleporting* by offering context-aware information scents.

5.2   Limitations and Future Research Directions

This study comes with a number of limitations. First, although by employing objective data generated during our online experiment, we are able to enhance the validity of our data analysis results, the variance that can be systematically explained in our constructs is limited. This limitation is inherent in our experiment setting, which maximizes realism at the cost of control, meaning that participants' behavior can potentially be influenced by many factors, including the environment in which they participated in the experiment. Future studies can further bolster the predictive power of our search framework by conducting experiment in a controlled environment such as computer laboratory. Second, while we delving into the behavioral aspect of online information search in the present study, we acknowledge that more valuable insights can be generated by integrating behavioral data with subjective data that reflects participants' cognitive process.

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