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COGNITIVE STOPPING RULES FOR TERMINATING INFORMATION SEARCH IN ONLINE TASKS[1]

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Abstract

Online search has become a significant activity in the daily lives of individuals throughout much of the world. The almost instantaneous availability of billions of web pages has caused a revolution in the way people seek information. Despite the increasing importance of online search behavior in decision making and problem solving, very little is known about why people ***stop*** *searching for information online. In this paper, we review the literature concerning online search and cognitive stopping rules, and then describe specific types of information search tasks. Based on this theoretical development, we generated hypotheses and conducted an experiment with 115 participants each performing three search tasks on the web. Our findings show that people utilize a number of stopping rules to terminate search, and that the stopping rule used depends on the type of task performed. Implications for online information search theory and practice are discussed.*

Keywords: Information search, cognitive stopping rules, online search behavior, decision making, task types and dimensions

Introduction

Search behavior is a ubiquitous activity on the world wide web. The web is a vast repository of information and knowledge, and consumers around the world have begun to utilize it as their primary information search vehicle. In 2005, the web had nearly 900 million individual users,[2] and search engines such as Google and Yahoo had more than 50 million unique visitors per month.[3] In January 2005, 84 percent of web users reported using search engines, and 56 percent used a search engine at least once a day (Fallows 2005). Further, although no figures are available, the amount of time users

[1]Carol Saunders was the accepting senior editor for this paper. Moez Limayem was the associate editor. Roberto Evaristo, Souren Paul, and Theresa M. Shaft served as reviewers.

[2]"Usage and Population Statistics," from Internet World Stats, http://www.internetworldstats.com/stats.htm, accessed in 2005.

[3]"Web Design and SEO News," from 101 Web Builders, http://www.101webbuilders.com/, accessed in 2005.

spend searching for information on sites such as retailers, online news agencies, etc., is undoubtedly huge, since search engines typically are used only to direct people to destination sites. However, despite the amount of time spent performing online search, very little is known about why people stop their search behavior. Prior research has demonstrated that people use heuristics, or stopping rules, to terminate information search in a variety of tasks (e.g., Browne and Pitts 2004; Busemeyer and Rapoport 1988; Connolly and Thorn 1987; Nickles et al. 1995; Pitz et al. 1969; Saad and Russo 1996). In the present research, we provide a theoretical foundation for cognitive stopping rule use in online search tasks. We then develop a theoretical distinction between several types of online search tasks and investigate stopping rule use in such tasks.

Understanding why people stop information search is important to both theory and practice in a wide variety of domains. Nearly all problem solving and decision making behavior relies on information search (Simon 1981). Information search has a direct impact on the number and quality of alternatives considered and on the alternative ultimately selected (Bazerman 2006). In the context of search on the world wide web, the issue of stopping is even more critical since in many cases a person could conceivably search forever. Thus, understanding the mechanisms people use to stop online search is of particular importance.

From a practical perspective, understanding stopping behavior in web-based information search has important implications for the design of websites. For example, an understanding of consumer stopping behavior can help website designers develop features that will cause people to stop on their sites and that will provide people with greater benefits and higher user satisfaction. This can lead to increased advantages for both website owners and consumers.

The rest of the paper is organized as follows. We first present theoretical background concerning online search and the use of stopping rules and then describe different types of online search tasks. We then present our hypotheses, discuss the research methodology used in this study, and present the results of an experiment. We conclude with a discussion of our findings, limitations of the study, and directions for future research.

Background

Online Search Behavior

A significant amount of research has been conducted concerning online search over the past few years (for overviews and frameworks, see Hodkinson and Kiel 2003; Kulviwat et al. 2004; Lueg et al. 2003; see also Marchionini 1995).[4] From an economic perspective, researchers have compared the costs and benefits of online and offline search environments (e.g., Klein and Ford 2003). Costs of online searching have also been examined both from an economic standpoint and a psychological standpoint (e.g., Hodkinson and Kiel 2003; Sohn et al. 2002). In the marketing literature, researchers have examined consumer online information search about brands (e.g., Ward and Ostrom 2003; Wu and Rangaswamy 2003), prices (e.g., Jiang 2002), and products (e.g., Rowley 2000). Researchers in decision making have investigated expert–novice differences in online information search (e.g., Cothey 2002; Jaillet 2003; Yuan 1997), decision aids in online search (e.g., Häubl and Trifts 2000), including the use of shopbots and intermediaries (e.g., Ellis et al. 2002; Montgomery et al. 2004; Rowley 2000), and online information foraging (e.g., Liu et al. 2004; Pitkow et al. 2002; see also Pirolli and Card 1999). Additionally, researchers have examined search factors such as breadth and depth (Johnson et al. 2004; Tauscher and Greenberg 1997), frequency and duration, (Bhatnagar and Ghose 2004), and intensity (see Hodkinson and Kiel 2003) of online search behavior.

However, despite the extensive literature in online information search from a variety of perspectives, research concerning why people stop their information search has been noticeably absent. Little research to date has investigated online searchers' stopping rules. However, it is critical to investigate stopping rules in the context of online search because online search differs from other types of search such as interviewing people or talking with friends, reading newspapers, magazines, or books, driving from store to store, etc. (Kulviwat et al. 2004; Rowley 2000). Both the speed and reach of searching online are different. Speed is much faster, and reach is almost infinite (for practical purposes it is infinite, since there are billions of web pages and people's time is finite and limited). Thus, stopping rules in online search are likely to be different than search in other contexts. We turn now to the literature on stopping behavior in information search.

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[4]Online search behavior has been characterized as either *browsing* or *directed search* (Rowley 2000; see also Breitenbach and Van Doren 1998). Browsing behavior occurs when people have no particular goal in mind or only a vague notion; directed search occurs when people know at least generally what they are looking for and have a task in mind that can direct their search (Berthon et al. 1999; Vandenbosch and Huff 1997). In the present research, we are interested only in directed search behavior.

Stopping Rules in Information Search

Information search is a process in which a person seeks data or knowledge about a problem, situation, or artifact. The process is characterized by divergent thinking, in which a person opens his or her mind to new possibilities and perspectives (Couger 1996). The search process is terminated at some point because the person judges that he has enough information to move to the next stage in the problem-solving or decision-making process. To make this judgment of sufficiency, the person invokes a heuristic, or *stopping rule* (Browne and Pitts 2004; Nickles et al. 1995).

The economic assumption concerning stopping behavior beginning with Stigler (1961) has been that people continue to search for information until the marginal value of additional information equals the marginal cost of acquiring that information (see also Klein and Ford 2003). Subsequent normative rules proposed for stopping have relied on this notion, and, in addition to the economic value of information and the expected value of additional information, have included the expected loss from stopping (see, e.g., Busemeyer and Rapoport 1988; Kogut 1990; Spetzler and Stael von Holstein 1975). However, research has found that these normative stopping rules are difficult for people to apply (Busemeyer and Rapoport 1988; Rapoport 1966), and attention has therefore been directed toward understanding and describing the stopping rules people actually use (e.g., Connolly and Thorn 1987; Pitz et al. 1969; Saad and Russo 1996). These studies have focused on the heuristic means by which people stop some aspect of the decision-making or problem-solving process.

The stopping rules people apply can be either cognitive or motivational in origin. Cognitive stopping rules result from the ways in which people process information and their mental models of tasks or environments (Nickles et al. 1995). Motivational rules result from preferences, desires, or internal or external incentives, such as deadlines, costs, or preferences for closure. In the present research, we investigate only cognitive stopping rules in information search.

Researchers have recently made a distinction between cognitive stopping rules used during different stages of decision making (Browne and Pitts 2004).[5] In the early stages, which are dominated by information search and the design of alternatives, stopping rules are used to terminate the information acquisition process and to assess the sufficiency of the information gathered. The purpose of this stage is to be certain that a sufficient knowledge foundation necessary to develop alternatives has been attained. In the latter stages of decision making, which are dominated by choice, stopping rules are used by the decision maker to stop his evaluation of alternatives and to make a choice (Simon 1981). A considerable body of research has investigated stopping rules in choice tasks (e.g., Aschenbrenner et al. 1984; Beach and Strom 1989; Busemeyer and Rapoport 1988; Gigerenzer et al. 1999; Svenson 1992). However, there have been far fewer investigations of stopping rules in information search, in which the sufficiency of information gathered is of primary concern.

Cognitive stopping rules investigating sufficiency of information were first suggested by Nickles et al. (1995). These authors proposed four rules that decision makers might use to gauge sufficiency and terminate search behavior. The stopping rules were termed the mental list rule, the magnitude threshold rule, the difference threshold rule, and the representational stability rule. The use of these stopping rules was later documented for systems analysts in an information requirements determination setting (Browne and Pitts 2004). Additionally, a fifth rule, termed the single criterion rule, was suggested in exploratory data (Browne and Pitts 2004) and subsequently verified through empirical investigation (Browne et al. 2005). Descriptions of these five rules appear in Table 1.

The five rules shown in Table 1 are cognitive stopping rules (as opposed to motivational rules) because their application is driven by decision makers' information processing. All involve reasoning and/or judgment by the participants (Nickles et al. 1995). For example, the mental list rule involves the development of a mental model containing a list of items and subsequent judgments as to whether information found matches an item on the mental list. The other rules also concern cognitive representations of various types, as described in Table 1.

Our concern in this research is with the application of cognitive stopping rules in particular types of online search tasks. We therefore turn next to defining task elements in information search.

[5]It is worth noting that although we use the term *stages* in describing the decision-making process, we expect that stopping rules for information search will be used regardless of whether a decision-making process is linear, semi-linear, or iterative, or has another structure (see Cohen et al. 1972; Mintzberg et al. 1976; Saunders and Jones 1990). In the present research we assume that there is a principal information gathering effort that the decision maker utilizes before beginning to converge on a choice. Stopping behavior thus reflects a global assessment of information sufficiency. However, other decision-making models, such as those of Mintzberg et al. and those underlying methodologies such as prototyping, reflect a more iterative, piecemeal information gathering process. In such cases, we expect that stopping rules will still be used for information gathering, both locally (at each iteration) and for the overall effort.

Table 1. Cognitive Stopping Rules (adapted from Browne et al. 2005)

Rule	Description	Example
Mental List	Person has a mental list of items that must be satisfied before he will stop collecting information.	In searching for information concerning the purchase of a home, a person continues until he satisfies all the elements on his mental list (e.g., number of bedrooms, size of yard, and quality of school district).
Representational Stability	Person searches for information until his mental model, or representation, stops shifting and stabilizes. The focus is on the stability of the representation.	To diagnose a patient's illness, a physician asks the patient to describe his symptoms. When the physician reasons that his mental model of the patient's condition is no longer changing, he stops asking the patient further questions.
Difference Threshold	Person sets an *a priori* difference level to gauge when he is not learning anything new. When he stops learning new information, he stops his information search.	In gathering requirements for a new information system, a systems analyst interviews users until he determines that he is no longer learning new information. At that point, he terminates the requirements elicitation process.
Magnitude Threshold	Person has a cumulative amount of information that he needs before he will stop searching. The focus is on having "enough" information.	When perusing a newspaper article, a reader may skim the article until he has enough information to develop an idea of what it is about.
Single Criterion	Person decides to search for information related to a single criterion and stops when he has enough information about that criterion.	To choose a university to attend, a high school student searches only for information concerning the quality of the universities' overseas programs.

Task Elements in Information Search

To develop a framework for investigating stopping rules in web-based search, we began with the identification of important task elements. Past research on stopping rules has largely neglected task elements and has focused instead on documenting the existence of stopping rules in particular contexts. To develop a description of task elements in the present research, we followed the task characteristics approach as described by Fleishman and Quaintance (1984), Hackman (1969), and Wood (1986), in which we assumed that certain task elements elicit particular types of behaviors from participants. Two elements emphasized as important in numerous prior problem-solving and decision-making studies are the degree of task structure and the cognitive strategy the decision maker uses to represent the task (e.g., Davies 2003; Greeno 1976; Morera and Budescu 1998; Porter 2004; Simon 1973, 1981; Srivastava and Raghubir 2002). We hypothesized that these two task elements would be useful in helping understand stopping rule use in web-based search.

Task structure refers to the degree to which the necessary inputs, operations on those inputs, and outputs are known and recognizable to the decision maker (Byström and Järvelin 1995; March and Simon 1958; Simon 1973, 1981; Vakkari 1999; see also Rowley 2000). With well-structured tasks, decision makers understand the nature of the problem and the steps necessary to solve it. Thus, task structure reflects the state of the problem environment as perceived by the decision maker (Campbell 1988). Following much previous research, we have defined the task's structure as either well-structured or poorly structured (e.g., Greeno 1976; Reitman 1964; Simon 1973, 1981; Sinnott 1989).

The second element of importance is the strategy the decision maker adopts to represent the task. Again following previous research, we have specified the nature of the decision maker's representation as either decompositional or holistic (Morera and Budescu 1998; Simon 1981; Smith 1998; Srivastava and Raghubir 2002). In tasks for which a decomposition strategy is used, the information available is at least in part discrete; various task elements, criteria, or attributes can be separately identified, and the resulting mental representation is one in which the constituent elements can be individually recognized. In holistic tasks, the information available may or may not be discrete, but the mental representation is organic and integrative; the person represents the task as a whole and acts based on his "sense" or "image" or "gist" of the situation rather than on individual elements.

Whether a person utilizes a decomposition strategy or a holistic strategy is thought to depend on several factors, two of which are task complexity and experience with a task. In the context of online search, task complexity is primarily a function of the decision maker's information processing requirements. In general, the higher the information processing requirements for an individual, the more complex the task (Byström and Järvelin 1995; Vakkari 1999). When information processing requirements are high, decision makers may experience information overload (Reeves 1996). Information overload can cause an inability of people to focus their analysis (Grise and Gallupe 1999), particularly in an online environment (Nadkarni and Gupta 2004; Rowley 2000). Information overload also causes decision makers to filter out much of the available information (Miranda and Saunders 2003; Schultze and Vandenbosch 1998), which diminishes the likelihood of a decomposition strategy. Thus, complexity inhibits the ability to decompose tasks. As noted by Simon, "in the face of complexity an in-principle reductionist may be at the same time a pragmatic holist" (1981, p. 195).

To operationalize complexity, we utilized the typology of complex tasks proposed by Campbell (1988). Campbell's typology reflects a task's information processing requirements, including the number of information cues available to and the distinct acts that must be executed by the decision maker (see also Wood's [1986] *component complexity*). Campbell asserted that complexity is a function of the presence of (1) multiple paths to a desired end state, (2) multiple desired end states, (3) conflicting interdependence among paths, and (4) uncertainty between potential paths and potential end states. We used the typology to control the level of complexity in our experiment tasks, which are described in the methodology section below.

A second factor important for representation strategy is experience with a task. In online environments, research has shown that users with task experience have more efficient and analytical search strategies (Fenichel 1981; Kim 2001; see also Kulviwat et al. 2004). Experience allows a person to identify particular elements of a task and to be more selective in his or her search behavior (Ellis and Haugan 1997; Kuhlthau 1993; Simon 1981). The identification of discrete elements and increasing selectivity suggests that people with experience will utilize decompositional search strategies (Shanteau 1992; Simon 1981). People without experience may not know which factors are important and are therefore less likely to approach the problem by searching for discrete elements.

Thus, tasks with lower complexity in which the decision maker has experience will tend to be approached using a decomposition strategy[6]. Tasks with higher complexity in which the decision maker has less experience will tend to be approached using a holistic strategy.

In the present research, we used two combinations of the structure and strategy dimensions to create task types to investigate online search. Those combinations were well-structured/decomposition strategy tasks and poorly structured/holistic strategy tasks. We now build our hypotheses concerning stopping rule use in these types of tasks.

Hypotheses

When a task is well structured to participants and is decomposable, we hypothesize that people will use the mental list and single criterion rules (Browne et al. 2005). Both rules lend themselves naturally to decomposition, since they involve delineating one or more elements of a larger whole. Use of the mental list rule causes the decision maker to focus on a set of relevant items or factors (Nickles et al. 1995), while use of the single criterion rule causes a focus on one critical factor.

When the task is poorly structured and does not lend itself to a decomposition strategy, we anticipate use of the magnitude threshold and representational stability rules. When using the magnitude threshold rule, a person stops when he judges that he has "enough" information. Therefore, when sensing whether an information search is adequate, a judgment that a sufficient volume of information has been acquired acts as the stopping mechanism. Thus, volume, not specific elements, is the key to this rule. The representational stability rule causes a person to stop searching when his internal representation of a situation stabilizes. The person monitors his mental model of the situation and stops when he judges that additional information is not causing his mental model to change. Thus, people using this rule also do not rely on specific items or elements to stop their search.

[6]True "experts" in a domain often use holistic strategies for lower complexity tasks using pattern recognition processes (see Simon 1987). However, unlike the classic pattern recognition contexts of chess masters and air traffic controllers, the types of tasks utilized in the present research, such as shopping for consumer items, are arguably ones for which true expertise is not easy (or perhaps even possible) to develop (the experiences with the contexts are too infrequent and too varied, and feedback concerning pattern accuracy is too ambiguous, to allow strong patterns to be recognized). In any case, although our participants had experience in the lower complexity tasks, there is no reason to believe that any of them were experts. Thus, for the contexts in this study, tasks of lower complexity for which participants had experience should elicit decompositional strategies.

Based on this reasoning, we generated the following hypotheses (stated in the alternative form):

H1: More participants will use the mental list and single criterion stopping rules than the magnitude threshold, representational stability, and difference threshold stopping rules for well-structured, decomposable tasks.

H2: More participants will use the magnitude threshold and representational stability stopping rules than the mental list, single criterion, and difference threshold stopping rules for poorly structured, holistic tasks.

Methodology

Experimental Tasks

We sought tasks for this experiment that would reflect the theory discussed above and provide strong tests of potential differences in stopping rule use. We developed three tasks containing specific search characteristics.

To test our first hypothesis, we utilized two tasks. One task asked participants to search for a 32-inch television at BestBuy.com. This task was well structured, since the inputs, operations, and outputs of the problem should have been recognized and easily understood by participants (i.e., people understand shopping for consumer items, which includes providing input criteria [such as price or brand], evaluating those criteria based on information found, and utilizing the evaluations to continue or terminate search behavior). We also designed the task to elicit a decomposition strategy from participants. All participants in the demographic group of our sample had experience shopping for consumer items. In terms of complexity, gathering information about a television is a basic decision task with various alternatives to be evaluated according to a set of decomposable criteria such as price and product features (even if people were not initially aware of the features, such as resolution or viewing angle, we expected them to approach the task by considering various criteria). This task thus contained low complexity according to Campbell's typology (1988, p. 46). Based on the theory presented, we expected that people would utilize the single criterion rule or mental list rule for stopping search in this task. People should be able to identify a single criterion that is important to them or to create a mental list of items and search for information until that criterion or the list of items is fulfilled.

A second task asked participants to search for a job with Amazon.com. This task is also well structured because participants should clearly understand the nature of the problem and what is required of them. Further, participants should also have experience with this type of task, since people in the United States hold an average of 4.4 jobs between the ages of 18 and 22 and 3.3 jobs between the ages of 23 and 27.[7] This task is of medium complexity using Campbell's typology, since there are multiple paths to a desired outcome (being offered a job by Amazon) and there is some uncertainty concerning the likelihood of being offered a job depending on the position for which one applies. However, as in the product search task, this task also contains decomposable elements such as location, salary, job responsibilities, etc. Thus, because of the task's well-structuredness, participants' experience, and only medium complexity, we anticipated the use of the mental list rule and single criterion rule in this task as well. If the hypothesis is supported in both tasks, it will increase the generalizability of the findings.

To test the second hypothesis, we chose a search problem that was poorly structured and, due to its complexity and participants' lack of experience with such tasks, not easily decomposable. This task asked participants to search online for the map of a battlefield, in particular, the Battle of Fallen Timbers (a battle between troops of General Anthony Wayne and early American tribes that occurred near Toledo, Ohio, in 1794). The Battle of Fallen Timbers was chosen because of its relatively small battle area and because advance research showed that maps of the battlefield were both relatively scarce online (in contrast to, say, Gettysburg) and somewhat varied. Participants were also told that they would need to draw the battlefield from memory after performing their search. Because there is no developed cognitive template (for most people) and no clear definition of what constitutes a "battlefield" *a priori*, this task was not well structured. There is also no reason to believe that participants would have had experience with such a task. In terms of complexity, this task is a "fuzzy" task (high complexity, high information processing requirements) in Campbell's typology: there are multiple potential paths to a correct answer, there are multiple potentially "correct" answers (in the sense that any of a number of sketches could be judged as accurate), and there is uncertainty regarding which information will lead to a correct answer. Thus, we anticipated that participants would represent this task holistically. Therefore, due to the lack of structure and the holistic representation, we expected that participants would use either the representational stability rule or magnitude threshold rule for this task.

[7]"National Longitudinal Survey of Youth," Bureau of Labor Statistics, http://www.bls.gov/opub/ted/1998/Oct/wk2/art01.htm.

Participants and Procedure

A total of 115 undergraduate and M.B.A. students from a large research university participated in the study in a laboratory setting. Subjects were 69 percent male and 31 percent female, and reported a mean of 7.1 years using the world wide web. Members of this age group (18 to 34) are the heaviest users of the web,[8] and thus this population is ideal for investigating online search behavior. Students received a significant amount of course credit (10 percent of the course grade) as motivation to participate. In addition, the instructions made clear that the proctor would check participants' answers before assigning the course credit. Participants were given experiment booklets containing instructions, the three online search tasks, and, following each task, two purposefully redundant questions about stopping behavior:

1. Why did you stop searching for information when you did?

2. How did you decide to stop searching for information?

Participants read the instructions, performed all three search tasks individually online, and answered the questions in the booklets. The order of the tasks was randomized across participants. No time limits were placed on performance of the tasks.

Coding

The written answers to the questions about stopping were used to determine stopping rule usage. Two research assistants unfamiliar with the purposes of the study and blind to its hypotheses coded the subjects' answers into one of the five specified stopping rule categories or an "other" category using descriptions of the categories. The coders agreed on 326 of the 345 participant responses, for an interrater agreement of .945. We calculated Cohen's kappa to assess the proportion of agreement not attributable to chance. Cohen's kappa was .926, which is considered "almost perfect" agreement (Landis and Koch 1977). A third coder coded the responses on which the first two coders disagreed, and agreed with one of the original coders on 15 of the 19 disagreements. The agreed-upon codes were used in the subsequent analyses, and the four responses upon which there was no agreement were put into the "other" category.

[8]"Markets Take Note: The Elusive 18-34 Year-Old is Habitually Online," comScore Media Metrix, http://www.internetadsales.com/modules/news/, 2004.

Results

We first checked to see whether any differences existed in stopping rule use across the two groups of subjects (undergraduates and MBA students). There were no differences in any of the tasks (all $p > .78$) and the data were thus combined for analysis. Additionally, no differences in stopping rules used were expected due to the ordering of tasks, since there was no apparent way for subjects to "learn" about cognitive stopping rules they applied in previous tasks. To test for order effects, we organized subjects' responses for each task according to whether they performed that task first, second, or third. We then used the Friedman test for related samples for each task to test whether subjects' coded responses differed depending on when they performed the task, and found no differences due to order (all $p > .19$).

The results of the data coding appear in Table 2. The table shows the number of participants who were coded as having used one of the rules to stop his or her information search for each task.[9] As can be seen, there were large absolute differences between stopping rule usage across the three tasks. Table 3 shows example statements coded into stopping rule categories.

To test the hypotheses, we utilized the binomial test of significance (Conover 1999). For each null hypothesis, we assumed that use of the five stopping rules would be equally likely (i.e., there is a .2 probability of occurrence for each rule). Thus, for the tests in this section, our hypotheses took the form H_0: $p \leq .4$ versus H_1: $p > .4$, since we were testing whether two of the rules were used more often than the other three. To test H1, we compared the number of people who used either the mental list rule or single criterion rule versus the number of people who used the other three rules for the product search task. The test revealed a significant difference (exact binomial (one-tailed) $p < .0001$). We performed the same comparison for the job search task. The difference was also significant for this task ($p < .0001$). In both tasks, more people used the mental list and single criterion stopping rules than the other rules. These results support H1.

[9]The "other" category contained several types of responses, including responses on which the two coders and the tie-breaking coder could not agree (i.e., the three coders all coded a particular response differently), responses that had no content (e.g., several participants stated they stopped searching for a map because they "found a map"), and responses on which the coders believed that a participant was using a stopping mechanism not reflected in the five stated stopping rules. Because the "other" category included responses that were unclear, and because those responses were highly heterogeneous, we excluded the category from the analyses that follow. Our hypotheses concerned only the five stopping rules identified in past literature.

Table 2. Stopping Rule Use Results by Task

	Map Search	Product Search	Job Search
Mental List	14	63	63
Representational Stability	23	10	3
Difference Threshold	8	0	1
Magnitude Threshold	56	15	8
Single Criterion	3	18	14
Other	11	9	26

Table 3. Stopping Rule Coding Examples

Stopping Rule	Example Code
Mental List	"I knew I wanted something bigger than 27 inches but less than $350. I contemplated which TV would fit my criteria better. I stopped searching because I clicked on several TVs and this one offered the features I wanted at the lowest price."
Representational Stability	"I felt that I had gathered an accurate portrayal of the battlefield."
Difference Threshold	"I kept finding the same information in every search."
Magnitude Threshold	"I found a good historical replication of the area of Fallen Timbers and the battle that took place there. I thought I had enough information to draw a reasonable-looking map."
Single Criterion	"I have a Sharp TV at home and it has lasted me over 5 years. This means I view it as a quality product and I did not need to search any more."

To test H2, we conducted a binomial test comparing the number of people who used either the magnitude threshold or representational stability rule versus the number of people who used the other three rules in the map search task. The difference in the use of the rules was again highly significant ($p < .0001$), with more people using the hypothesized stopping rules than the other three rules. These results support H2.

Thus, both of our hypotheses were supported. More participants used the mental list and single criterion stopping rules than the other stopping rules for well-structured, decomposable tasks. More participants used the magnitude threshold and representational stability stopping rules than the other stopping rules for the poorly structured, holistic task.

To gain further insight into stopping rule use, we performed planned comparisons to test differences between individual stopping rules used within each task (following the hypotheses stated above). The results of these tests provide a richer understanding of the specific stopping rules used within each task in addition to the composite results of our hypotheses. We again employed the binomial test (the hypotheses were H_0: $p \leq .5$ versus H_1: $p > .5$ for each test). Because we used multiple tests for each task, the possibility of drawing false conclusions from the tests was of concern. To control the overall error rate, we used the false discovery rate (Benjamini and Hochberg 1995; Genovese and Wasserman 2002), a method that can be used regardless of the underlying distribution of data and that controls type I errors while simultaneously allowing type II errors to be reduced (a characteristic not shared by family-wise error rate methods such as Bonferroni) (Verhoeven et al. 2005). In the false discovery rate procedure, the p-values for the hypothesis tests are ordered from lowest to highest. The decision as to whether to reject each null hypothesis then proceeds according to the following rule (Benjamini and Hochberg 1995):

- If $p_{(k)} \leq \alpha$, reject all null hypotheses and stop, else continue;
- If $p_{(k-1)} \leq (k-1)\alpha/k$, reject $H_{(2)}\ldots H_{(k)}$ and stop, else continue;
- Etc.

Table 4. Product Search Task Binomial Tests

Test	Exact Binomial One-Tailed p-Value	FDR Threshold	Significance
ML > DT	0		Yes
SC > DT	0		Yes
ML > MT	< .0001		Yes
ML > RS	< .0001	.033	Yes
SC > RS	.092	.042	No
SC > MT	.364	.05	No

Key: ML = Mental List; DT = Difference Threshold; RS = Representational Stability; MT = Magnitude Threshold; SC = Single Criterion
FDR = False Discovery Rate
Significance tests assume α = .05.

Table 5. Job Search Task Binomial Tests

Test	Exact Binomial One-Tailed p-Value	FDR Threshold	Significance
ML > DT	< .0001		Yes
ML > RS	< .0001		Yes
ML > MT	< .0001		Yes
SC > DT	.0005		Yes
SC > RS	.006	.042	Yes
SC > MT	.143	.05	No

Key: ML = Mental List; DT = Difference Threshold; RS = Representational Stability; MT = Magnitude Threshold; SC = Single Criterion
FDR = False Discovery Rate
Significance tests assume α = .05.

The test thus specifies that the researcher begin with the highest p-value and compare it to the value calculated from the rule above. When and if a p-value is reached that is lower than the calculated value, that null hypothesis and all other hypotheses with lower p-values are rejected (Verhoeven et al. 2005).

For the product search task, the results of our analyses appear in Table 4. Each row of the table shows the comparison being tested, the exact p-value from the binomial test, and the false discovery rate threshold calculated using the rule above (to the point at which hypotheses were rejected). As Table 4 shows, the mental list rule was used by significantly more people than the difference threshold, magnitude threshold, and representational stability rules, providing strong evidence for the use of this stopping rule in this type of task. There was less support for the use of the single criterion rule, providing weaker indication for this rule in the product search task.

For the job search task, Table 5 shows that the mental list rule was used more than the other three rules. Additionally, the single criterion rule was used more than the difference threshold and representational stability rules. The results for these two tasks provide additional understanding of the differences shown above in the tests of H1.

The tests for the map search task appear in Table 6. The magnitude threshold rule was used significantly more than the single criterion, mental list, and difference threshold rules. The representational stability rule was used significantly more than the single criterion and difference threshold rules. Together, these results provide additional understanding of H2. Further interpretations of all these findings are provided in the discussion section.

Table 6. Map Search Task Binomial Tests

Test	Exact Binomial One-Tailed p-Value	FDR Threshold	Significance
MT > SC	< .0001		Yes
RS > SC	< .0001		Yes
MT > ML	< .0001		Yes
MT > DT	< .0001		Yes
RS > DT	.005	.042	Yes
RS > ML	.094	.05	No

Key: ML = Mental List; DT = Difference Threshold; RS = Representational Stability; MT = Magnitude Threshold; SC = Single Criterion
FDR = False Discovery Rate
Significance tests assume $\alpha = .05$.

Discussion

Implications

Information search is a fundamental activity in problem solving and decision making. The present study hypothesized different use of cognitive stopping rules based on theoretical differences between types of online search tasks. Our findings add to the growing theory and empirical knowledge base concerning stopping rule use in information search. The implications of our findings are important for both theory and practice.

Our tests of stopping rules using different levels of task structuredness and different types of mental representations has improved our theoretical understanding of stopping rule use in online search behavior. With tasks that are well structured and that lend themselves to decomposition (are of low or medium complexity and for which people have at least some experience), use of the mental list rule is dominant and the single criterion rule is also used to a great extent. For tasks that are poorly structured and that lend themselves to holistic representation strategies (are of high complexity and for which people have little or no experience), the magnitude threshold and representational stability rules are most common. The dimensions of task structure and nature of the person's representation (as determined by complexity and experience) thus appear to be important influences on the stopping rules used by people to gauge the sufficiency of information gathered during online search.

Our results appear to be highly generalizable in online search, as the tasks we used are common search task types. For example, the poorly structured/holistic representation type of task is a very common search task on the world wide web. In such cases, the searcher knows generally what he is looking for (and thus the task is directed search rather than simply browsing), but the complexity of the search and his lack of experience prevent him from decomposing the task into discrete items of information. Instead, the decision maker seeks to achieve a sense, or the gist, of the situation. This requires that he find enough information to develop an adequate representation. In our experiment, we used the map search task to represent this type of task and, as hypothesized, the magnitude threshold and representational stability stopping rules were used most often by participants. Many other web search tasks are similar. These may include searches in which people must understand or interpret complex, visual information such as models, figures, graphs, pictures, and many forms of artistic expression (e.g., paintings or sculpture). Similar search behavior can also be anticipated for initial searches in basic research of all kinds (e.g., academic, medical, legal, general interest), in which people attempt to understand complex, amorphous phenomena such as new ideas, methods, or lines of argument, or different cultures, norms, or ways of communicating. In such cases, people generally attempt to gain a sense of the topic (Kuhlthau 1993), and the lack of structure, the complexity, and the person's lack of experience lead to a holistic approach to the problem. Thus, in such situations people can be expected to use the magnitude threshold rule ("I have enough information") or the representational stability rule ("My mental model of this situation is no longer changing") to stop information search.

The product search and job search tasks (well structured and decomposable) in our study also represent a vast category of search tasks. We found strong support for the use of the mental list stopping rule and moderate support for the use of the single criterion rule during the product search and job search tasks. In addition to product and job searches, many other types of search fit into this category of well-structured tasks in which people's experience with such tasks and the lack of complexity allow them to decompose the information they find into discrete elements. For example, many entertainment searches are also representative of this type of task. A person may search for a possible concert to attend (which may be evaluated by date, cost, location, etc.) or a possible restaurant to patronize. Searching for a new car to purchase, or a summer camp to attend, or stocks in which to invest also fit within this nearly limitless category of search.

From a practical standpoint, our findings are relevant for improving website design. One important goal of most websites is that they are sticky, in the sense that once a person lands on a website, he or she "sticks" there (Davenport 2000). Stopping rules are one reason a person might stick to a website. Research has shown that people often visit relatively few websites during online search. For example, Johnson et al. (2004) found that most people visit only a few websites in a category each month (e.g., 1.2 bookseller sites and 1.8 travel sites). Given these findings, it is critical to online companies that when a person samples a site or checks information there, he sticks to that site (Bhatnagar and Ghose 2004). Otherwise, he may be unlikely to return.[10]

Website designers often have many degrees of freedom in how they structure web pages and what features they include to increase stickiness. The findings in the present study suggest that websites should be designed differently depending on the type of search strategy that users will employ. If website designers can take advantage of the stopping rule strategies people use in information search, website stickiness may be enhanced. In situations in which websites are providing content that is complex and likely to be unfamiliar to users, web designers can take two possible strategies: they can either attempt to build structure and reduce complexity to help users decompose the task, or they can provide information that will contribute to holistic representations. To operationalize the first strategy, designers can provide explanations of the types of products available on the site and what users need to do to successfully navigate the site, provide strong help facilities such as a full index, and highlight important features of the site, how to find relevant information, how to complete a purchase, etc. For example, real estate companies figured out some years ago that when they provide housing information online, they need to include a significant amount of information to help potential buyers decompose this complex search process, such as information about mortgages, insurance, school districts, furniture, and many other relevant items (Browne et al. 2004). For the second strategy, in cases with complex products or services that do not easily lend themselves to decomposition, designers could decide to utilize the fact that people are likely to form holistic representations of situations by creating "atmospheres" or "experiences" on websites (such as an atmosphere for a "dream" vacation or a BMW convertible).

On the other hand, with a well-structured problem for which users have experience, web designers should focus on providing answers to items on people's mental lists or addressing single criteria on which people tend to focus. For example, important criteria or specifications can be prominently labeled or linked on a website, and frequently asked questions may be used to answer items on people's mental lists.

Another practical implication of the current research concerns the design of search engines (including general search engines such as Google and Yahoo and those at specific retailing, entertainment, and other destination sites). Our results suggest that different representations should be made available for different types of searches, utilizing both querying mechanisms and reporting facilities. For example, querying mechanisms can be designed that allow people to list or check features of items, as is currently facilitated when searching for new homes on real estate sites or searching for vacations on travel sites. Current reporting mechanisms on search engines can be enhanced by, for example, replying to queries with lists of items (corresponding to people's known mental lists) and highlighting particular criteria (known to be most important to many people). This would aid in the use of the mental list and single criterion rules in decomposable tasks. For other queries, responses could include information such as pictures or diagrams (in addition to or instead of lists of items) to facilitate the development of holistic representations. For example, when someone is searching for a time-share condominium to purchase, pictures of the building and surrounding area are crucial factors. When someone is searching for a piece of clothing to purchase, he or she is unlikely to be satisfied with only a list of the item's features and dimensions.

Limitations

The present research has several limitations that are worth noting. First, we studied only two types of search tasks using

[10]Of course, from a consumer's standpoint, stopping rules can cause a person to stick to a website prematurely, before appropriate information has been gathered. Thus, being conscious of and understanding one's own stopping rules is an important issue that might be investigated in future research.

two combinations (well-structured/decomposable and poorly-structured/holistic) of the dimensions important for determining stopping rule use. One of the other possible combinations, a poorly structured/decomposable task, has been studied in another context. Specifically, in a study of experienced systems analysts gathering requirements for a new information system, Browne and Pitts (2004) found the predominant use of the difference threshold rule. In such a situation, the lack of structure apparently discourages people from relying on a mental list. However, systems analysts used their experience to decompose the task and were able to detect when they were not learning anything new, which is possible with discrete requirements statements such as "the system will need to keep track of customer orders." The difference threshold rule, therefore, acts as a reasonable stopping criterion in such tasks. However, although this task type has been studied in a requirements determination context, the stopping rules may differ in an online search task (since, as noted earlier, online search is different from an interview search due to its speed and access to extensive information stores). Therefore, it is important to investigate stopping rules in this type of task in online search. Further, stopping rules in a well-structured/holistic task have not been studied in the present research or elsewhere. Thus, this task type is also worth investigating in an online search context.

Additionally, we investigated only the task characteristics of structuredness and representation strategy. These characteristics were chosen for their theoretical importance and use in much past research. However, there may be other task characteristics that are important as well. For example, we theorized that task experience is one factor influencing the representational strategy people use in an information search. It is possible, however, that task experience has a direct effect on stopping rule use. Many other task characteristics may also impact stopping rules.

Third, we measured task structure and representation strategy as two discrete categories each. However, both are actually continua. Tasks can be well structured, poorly structured, or something in between (see Byström and Järvelin 1995). Representation strategies people use can be decompositional, holistic, or some hybrid of the two ranging along a continuum. Thus, there could be differences in stopping rules used if these two variables were measured using a range of categories.

Fourth, as noted above, the "other" category in our coding scheme contained both responses that reflected some content (e.g., possible cognitive stopping behavior not captured by the five stated rules) and responses that reflected no content. The fact that we did not ask the coders to distinguish between these types of statements is a limitation of the study.

Finally, we did not include experiment controls other than those stated earlier. For example, we did not perform a manipulation check to be sure that participants understood the tasks. Thus, this is also a limitation of the current study.

Future Research

An important line of future research that would complement the studies performed thus far is to correlate data about *how* people search for information with stopping rules used. People may search for information in a variety of ways—top-down or bottom-up, breadth-first or depth-first, by trial and error, or arbitrarily (Johnson et al. 2004; Smith 1998). For people who use a particular search strategy in a task, does this correlate with the stopping rules they use? Further, can the direction of causality be determined? That is, does the search strategy determine the stopping rule used, or does the stopping rule the person intends (consciously or subconsciously) to use determine his or her search strategy? These are important questions that could add useful insights to information search theory and practice.

A second area for future research concerns the possibility of identifying additional cognitive stopping rules. Although the list of rules utilized in the present study is believed to capture the vast majority of stopping behavior, as evidenced by the coding of responses, the list is not exhaustive. Other cognitive stopping mechanisms undoubtedly exist. Exploratory studies with different stimuli might reveal the use of additional cognitive stopping rules.

A third future research area concerns motivational reasons for stopping search, including time, cost, and importance of the search. For example, the time-sensitivity of a task may play an important role in the stopping rule a person uses for a task. In situations in which a decision needs to be made immediately, in contrast to situations in which there is plenty of time, the stopping rule used may be quite different. If a person needs to meet a deadline for a project, his reason for stopping may hinge consciously or subconsciously on the motivational factor of time rather than on cognitive factors. As another example, booking a vacation for next week versus booking a vacation for 6 months from now may cause people to use different stopping rules. Another task characteristic is the importance of the search. If a person is searching for something that has an important outcome, his strong incentive for the search may subconsciously influence his stopping point. For example, searching for information to try to discover whether someone has a serious disease may cause the use of different stopping rules than searching for information to purchase a television. Similarly, searching for information concerning a potential purchase of a $20,000 item is likely different than searching for information concerning a $10 item. Further, the importance of the decision may cause people to seek information from different sources (see Saunders and Jones 1990), which may cause different stopping rules to be utilized. Finally, lack of importance and/or time may induce a person to "give up" on a search without finding enough (or any) information. Thus, additional affective factors such as frustration and impatience may also influence stopping behavior. Therefore, investigations of time-sensitivity, importance of the search, and other motivational factors provide fruitful opportunities for future research.

Future research could also investigate stopping rule use when the timing and sequence of information acquired varies (Saunders and Jones 1990). For example, as noted above, when a decision is important people may spend a considerable amount of time searching for information online. In such situations, relevant information may ebb and flow through the lifecycle of the search. At times the searcher may discover a rich vein of information that can be mined extensively; at other times, the searcher may proceed for relatively long stretches of time and find nothing relevant. In such cases, what stopping rules does a person apply? Do people stop prematurely, at local minima? How do they gauge sufficiency of information in such situations? The sequence of information acquisition can have an important impact on such searching. If relatively important information is encountered early in the search process, the decision maker may terminate the search too soon, missing potentially critical information. Can processes to structure searches and/or information more effectively be designed for websites or search engines to eliminate the likelihood of premature stopping? Such structuring seems like a more realistic possibility online than in the non-digital world. These questions provide useful ideas for further research.

Another area for future research concerns the prescriptive implications of stopping rule use in online search. Does the use of particular stopping rules result in better information from the information search phase of decision making? In their study of stopping rules in information requirements determination, Browne and Pitts (2004) found that analysts using the mental list and difference threshold stopping rules gathered a greater quantity of information than analysts using the magnitude threshold rule, and that analysts using the difference threshold rule gathered better quality information than those using the magnitude threshold rule. Similar studies could be conducted in the online search environment to discover whether the use of certain stopping rules results in better information gathered for the subsequent choice phase of decision making.

A final area of interest concerns the impact of cognitive load on stopping behavior. In the present research, we hypothesized that complex tasks in which users did not have much experience (the map search task) would lead to the use of certain stopping rules. However, we did not test cognitive load directly, nor did we explore its limits. It is possible that different stopping rules may be used when people encounter information overload in a task due to high complexity, lack of experience, time constraints, etc. Tasks that test the limits of cognition (e.g., working memory capacity) may require a different set of dimensions for determining stopping rule use. For example, information overload may lead to the use of the single criterion stopping rule not due to experience in knowing what is important, but rather as a satisficing strategy to cope with too much information in a short period of time. In such a case, the simplicity or complexity of applying the stopping rule may be a key dimension rather than (or in addition to) the representational strategy employed. As another example, research has shown that time pressure can change the nature of information search in some contexts from analytical to recognition-based (e.g., Klein and Calderwood 1991), which is also a simplification due to cognitive load. The use of simple heuristics has been found in numerous situations involving choice (e.g., Gigerenzer et al. 1999), and it seems likely that similar satisficing strategies may be used in information search tasks involving high cognitive (or, for that matter, motivational) load. Stopping rules utilized in information search under conditions of information overload and other boundary conditions of cognition and motivation represent a fertile area for future research.

Information search is now at the center of consumer behavior on the world wide web. Understanding why people stop searching is thus critical to comprehending online behavior. The present research provides another step in building this understanding.

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