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RESEARCH NOTE

EXAMINING THE MEDIATING ROLES OF COGNITIVE LOAD AND PERFORMANCE OUTCOMES IN USER SATISFACTION WITH A WEBSITE: A FIELD QUASI-EXPERIMENT[1]

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Navigation structure and user familiarity are critical for user satisfaction, yet the mediating mechanisms by which they affect satisfaction remain unclear, especially from a cognitive perspective. To extend understanding of the drivers of user satisfaction with a website, this study focuses on the mediating roles of cognitive load and performance outcomes (in the form of efficiency and accuracy) according to a cognitive cost–benefit framework and cognitive load theory. The hypotheses were tested with data from a field quasi-experiment among 238 participants using two websites. The results indicated that cognitive load and performance outcomes fully mediated the effect of user familiarity on user satisfaction, and that cognitive load partially mediated the impact of navigation structure. In addition, the mediating effect of cognitive load appeared stronger than that of performance outcomes. Overall, the cognitive cost–benefit framework sheds light on the underlying influence processes and mechanisms by which navigation structure and user familiarity affect user satisfaction. The findings reveal that costs might have more profound influences on user satisfaction in an information-seeking context than benefits do.

Keywords: User satisfaction, website navigation structure design, user familiarity, cognitive load, performance outcomes

Introduction

User satisfaction is crucial to a website's success. In general, user satisfaction with a website reflects people's evaluations of and affective attitudes toward the site, determined through their direct interactions and use (Muylle et al. 2004). Such satisfaction can influence users' revisit rates, trust, purchase decisions, and loyalty—and thus firm profits (Casaló et al. 2008; Cyr 2008; Lee et al. 2015).

Among the different reasons people visit websites, information seeking is a common motive and therefore represents a crucial context for examining user satisfaction (Rains and Karmikel 2009; Reuters 2012). Many people use search

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engines to locate websites to visit, then rely on each site's navigation structure to find the information they need (AGConsult 2010; McGovern 2010; Nielsen 2000).[2] According to Hoehle and Venkatesh (2016), the logical path of an information system is a vital component of user interface design that determines usability. Unlike traditional software that usually has a designated flow to follow, people have more flexibility and autonomy in choosing the paths to navigate through different pages on a website (Agarwal and Venkatesh 2002). Thus, navigation efficiency is critical for user satisfaction with a website and its success (Agarwal and Venkatesh 2002; Venkatesh and Agarwal 2006). Although the significance of a website's navigation design is well recognized, disorientation remains a serious problem that often leads to user dissatisfaction and frustration (Chen et al. 2011; Galletta et al. 2006; Schmutz et al. 2009).

Finding information on a website is also a cognitive task that involves information processing, cognitive learning, and decision making (Al-Maskari and Sanderson 2010; Gwizdka 2010). The significance of cognitive analyses for improved user interface designs is also emphasized by existing human–computer interaction (HCI) research (Agarwal and Venkatesh 2002). Accordingly, user satisfaction in an information-seeking context can be analyzed from a cognitive perspective (Bevan 2009; Casaló et al. 2008; Chen et al. 2011). In general, people's orientation or disorientation on a website stems from the site's design features, as well as user characteristics, which influence their performance and cognitive load. For example, a well-designed navigation structure enables people to find information easily by prompting, guiding, and facilitating their choice of appropriate paths to reach target information (Webster and Ahuja 2006). A website's navigation structure is the manifestation of how information is organized and presented to users, which greatly affects whether they can find target information or become disoriented on the site. In addition, user characteristics also influence how well people find information as well (Al-Maskari and Sanderson 2010; Argyriou 2012; Chevalier and Kicka 2006). Because experience gained from previous visits can lower the amount of cognitive processing people incur to find information on a site, user familiarity should reduce disorientation and trial-and-error behaviors, in that people accumulate knowledge about appropriate paths to find the information they want (Chen et al. 2011; Galletta et al. 2006; Katsanos et al. 2010). As extant HCI literature suggests, website design features and user characteristics are both significant and should be properly considered and addressed in system developments to enhance user satisfaction (e.g., Hong et al. 2004).

[2]According to McGovern (2010), more than 70% of users begin website tasks by clicking on a link on a page, rather than using search features. Similarly, AGConsult (2010) reports that many people turn to search only after they fail to navigate the links of a website to find the information they want.

Despite acknowledgments of the importance of navigation structure design and user familiarity on satisfaction (Galletta et al. 2006; Kincl and Štrach 2012), the underlying influence processes and mechanisms remain somewhat unclear (Cyr 2008; Nadkarni and Gupta 2007), especially in relation to established cognitive theories. To advance knowledge of user satisfaction with a website, it is critical to scrutinize the relationships between user satisfaction and key antecedents, through the lenses of established theories, as well as empirically examine the underlying mechanisms by which they affect satisfaction. By doing so, it becomes possible to develop appropriate guidelines and principles for improving website designs that ultimately will ensure better user experiences. In particular, we postulate that cognitive load and performance outcomes, as consequences of a website's navigation structure design and user familiarity as well as precursors of user satisfaction, can address the missing link between user satisfaction and important antecedents. In this setting, a cognitive load is the amount of cognitive processing a person incurs to find information; the performance outcomes reflect the effectiveness and efficiency with which he or she finds that information (Chevalier and Kicka 2006). Accordingly, we examine why and how performance outcomes and cognitive load, together with their antecedents, might determine user satisfaction in an information-seeking context. In particular, we ask, *how do cognitive load and performance outcomes mediate the effects of navigation structure and user familiarity on a person's satisfaction with a website?* With a field quasi-experiment, we examine these previously unaddressed mediated relationships.

Literature Review

Several research streams relevant to our study—pertaining to navigation structure design and navigability, user familiarity, performance outcomes, and cognitive load—reveal the gaps that motivate our investigation.

Navigation Structure Design and Navigability

Navigation structure is a crucial website design feature; it consists of a set of hyperlinks that connect the different pages on a website (Fang and Holsapple 2011). A website's navigation structure can be measured according to its navigability, or the degree to which a person can follow the site's hyperlink structure to find information effectively and efficiently (Fang et al. 2012). Navigability closely relates to website usability (Agarwal and Venkatesh 2002), functionality (Olsina and Rossi 2002), design quality (Lee and Kozar 2006), and services (Zeithaml et al. 2008). A website's navigation structure design, measured by its navigability, therefore, should influence user performance, satisfaction, and intention to use the site (Cyr 2008; Katsanos et al. 2010; Webster and Ahuja 2006).

Navigability also is critical to user performance and website evaluations. Cyr (2008) and Palmer (2002) report positive effects of navigation design on user satisfaction; Webster and Ahuja (2006) show experimentally that a website's navigation structure design influences users' performance. Further, finding information on a website is a cognitive task, but most research ignores the associated cognitive load and its potential for explaining the influence of a website's navigation structure on user satisfaction. We summarize representative prior research in Table A1 of Appendix A; as shown, few studies investigate how navigation structure affects satisfaction in light of both the cognitive load and the performance outcomes.

User Familiarity

People's use of a website can be influenced by their familiarity with the site, which is an essential user characteristic. People gain familiarity through repeated visits to a website and thereby acquire a better understanding of its structure and content over time. Such familiarity can influence the effectiveness with which a person traverses the site to find information, as well as the cognitive processing he or she incurs to do so (Browne et al. 2007; Chevalier and Kicka 2006). For example, Galletta et al. (2006) report that familiarity affects user performance, measured by successful task completion. User familiarity also influences people's perceptions of website complexity (Nadkarni and Gupta 2007), attitudes and behavioral intentions (Galletta et al. 2006), and loyalty (Casaló et al. 2008).

The relationships of user familiarity with cognitive load or performance outcomes (effectiveness and efficiency), however, have not been explicitly examined. The influence of familiarity on user satisfaction also remains unclear. Because user familiarity reduces the uncertainty and complexity associated with finding information on a website, it should reduce the associated cognitive processing (Johnson et al. 2003) and thus people's cognitive load. In this case, performance outcomes should improve, leading to more positive evaluations of and affective attitudes toward a site. We summarize representative research in Table A2 of Appendix A, which reveals the need to further scrutinize user familiarity and empirically test its effects, with an appropriate theoretical anchor, to elucidate how such familiarity influences a person's information-seeking performance, cognitive load, and satisfaction.

Cognitive Load and Performance Outcomes

Many salient definitions of user satisfaction emphasize a person's evaluation of and affective attitude toward a focal object or technology artifact in a specific context (e.g., Al-Maskari and Sanderson 2010; Au et al. 2008). People mostly evaluate the benefits of an object or technology artifact in relation to its associated costs (Shiau and Luo 2012; Woodruff et al. 1983). That is, both the costs and benefits of finding information on a website likely determine how navigation structure and user familiarity affect user satisfaction.

As we noted previously, cognitive load refers to total mental efforts that demand the use of working memory (Paas et al. 2003); it is a cost of a cognitive task and can affect user satisfaction (Yan et al. 2015). However, its influence on user satisfaction is seldom explicitly examined, even though people engage in cognitive processing to find information. A high level of cognitive processing could lead to cognitive overload, due to the inherently limited cognitive resources people have, with negative effects on satisfaction (Nadkarni and Gupta 2007). Performance outcomes instead represent benefits of using a website, such as finding information effectively and efficiently. All else being equal, people feel more satisfied when outcomes are favorable. As Au et al. (2008, p. 46) note, performance, "defined as the perceived outcome from IS use … is one of the primary standards of comparison by which satisfaction is assessed." In a nutshell, performance outcomes reflect user-centric, utilitarian evaluations. In an information-seeking context, such outcomes include the likelihood of finding information (accuracy), the amount of time needed to find it (time efficiency), and the effort required (effort efficiency) (Galletta et al. 2006; Nilsson and Mayer 2002; Webster and Ahuja 2006).

Cognitive load and performance outcomes might be direct antecedents of user satisfaction in cognitive task contexts. Further, important precursors of cognitive load and performance outcomes in information-seeking contexts need to be scrutinized, to reveal the underlying influence patterns according to a theoretical lens. That is, we predict that both cognitive load and performance outcomes are essential for explaining why and how navigation structure and user familiarity influence satisfaction, from a cognitive perspective.

Gaps

Our literature review thus suggests several gaps. First, previous research indicates the importance of navigation structure and user familiarity for satisfaction (Cyr 2008; Palmer 2002), but the underlying influence processes and mechanisms remain unclear, especially from a cognitive perspective. Second, holistic, theory-based analyses that emphasize both cognitive load and performance outcomes for explaining user satisfaction are lacking. Few studies examine the respective influences of cognitive load and performance outcomes, two essential precursors of user satisfaction, or consider their roles in mediating the effects of navigation structure and user familiarity on satisfaction. Therefore, we investigate the effects of navigation structure and user familiarity on satisfaction by focusing on cognitive load and performance outcomes as mediators.

Theoretical Foundation

According to Beach and Mitchell (1978), when performing a task or selecting a problem-solving strategy, people seek to maximize performance or decision outcomes (e.g., quality, accuracy) while minimizing the associated costs (e.g., cognitive processing, physical effort), which provides a basis for determining their satisfaction (Melone 1990). The cognitive cost–benefit framework is congruent with extant user satisfaction literature that emphasizes users' value assessments of an information system or technology artifact (Liao et al. 2007; Melone 1990) and reveals a probable trade-off between the benefits and costs of using a system or technology artifact (Chiou 2004). This framework suggests that people's evaluations of a technology artifact reflect their analysis of how well the underlying cognitive (task) process is supported by the artifact, thereby explicating how the costs and benefits influence satisfaction. In addition, the cognitive cost–benefit framework can explain customer satisfaction, because consumers evaluate a service or product by comparing the associated benefits and costs (Lee and Cunningham 2001). Accordingly, people likely expect a website to maximize their information-seeking performance and reduce the associated cognitive load; their satisfaction then depends on the extent to which the website meets these expectations, as suggested by expectation disconfirmation theory (Oliver 1980). If people achieve desirable performance outcomes with a light cognitive processing load, they are more likely to feel satisfied (Al-Maskari and Sanderson 2010). Thus, cognitive load and performance outcomes should affect satisfaction, even if people's performance and cognitive load expectations are not explicit.

The cognitive load and performance outcomes in turn are influenced by website navigability and user familiarity, a link that we can justify using cognitive load theory (Sweller 1988). A cognitive load might be germane, intrinsic, or extraneous (Paas et al. 2003). A germane cognitive load refers to a person's effort to process and memorize new information to build schemas. The intrinsic cognitive load depends on the natural complexity of the information to be understood and materials to be learned (Sweller 2010); an extraneous cognitive load relates to how the information is organized and presented. According to cognitive load theory, an effective navigation design improves information organization and presentation and therefore reduces the extraneous cognitive load for finding information on a website. User familiarity also should lessen the germane cognitive load, because repeated visits lower the amount of new information people need to process and learn. In addition, both effective information presentations and experience from previous visits facilitate cognitive learning, which should improve performance outcomes and reduce the cognitive load (Sweller 1988). As Webster and Ahuja (2006) explain, people cope with working memory constraints and thus benefit from information cues that facilitate their cognitive activities. The effects of a website's navigation design can be understood according to the navigational information and cues it offers. By providing appropriate, orienting information, a navigation structure serves as a decision aid to guide people's pathways toward target information, while also mitigating their associated cognitive processing. As a result, a well-designed navigation structure should reduce the cognitive load and improve performance outcomes (Hannafin 1987).

Cognitive load also relates to the effort to build and enhance mental models, or schemas. People develop their long-term memory through repeated exposures to various scenarios and associated information, which they retrieve later, as necessary. Although schema building involves a cognitive load—for example, to learn the website and its associated information—an established schema can lessen the germane cognitive load for subsequent information seeking. Both the amount of time and cognitive processing required to accomplish a task decrease with more practice (Johnson et al. 2003); accordingly, the cognitive cost of finding information on a website should decrease with user familiarity, gained from prior visits. Then users can achieve desirable task performance without exceeding their cognitive capacity and feel satisfied (Gwizdka 2010).

Overall, a website's navigation design can facilitate path selection and reduce the likelihood of trial-and-error behaviors that inevitably increase the cognitive load required to find information and thereby hinder performance outcomes (Castro et al. 2007; Chevalier and Kicka 2006). User familiarity also increases performance outcomes through repeated practice and learning. By leveraging previously acquired knowledge and understanding of a website, as stored in a mental schema, people become more capable of finding information, with increased effectiveness and efficiency. According to both cognitive load theory and cognitive cost–benefit framework, the performance improvement and cognitive load reduction that result from the navigation structure design and user familiarity should increase users' satisfaction.[3]

Hypotheses

Building on this theoretical foundation, we develop hypotheses regarding the mediating roles of cognitive load and performance outcomes. A well-designed navigation structure offers adequate page sequencing and interpage linkages, with consistent navigation cues (Palmer 2002); it orients people in their browsing by signaling, prompting, and facilitating appropriate path choices toward the information they want (Nilsson and Mayer 2002). The reduced cognitive load that results from an effective navigation structure aligns with cognitive load theory, in that the extraneous cognitive load depends on how information is organized and presented (Chevalier and Kicka 2006). According to the cognitive cost–benefit framework, people seek to mitigate their cognitive load; all else being equal, they feel more satisfied if finding information on a website requires less cognitive processing (Nadkarni and Gupta 2007; Nilsson and Mayer 2002). Previous HCI research also reveals the central role of people's cognitive load in mediating the effect of a usable system on their experience of the system, given that cognitive load relates to a website's ease of use and is affected by its navigation structure (Agarwal and Venkatesh 2002; Venkatesh and Agarwal 2006). Cognitive load thus should mediate the relationship between navigability and user satisfaction, because finding information on a website is a cognitive task. If a website's navigation structure facilitates information seeking, it can reduce the cognitive load that users incur, so they should be more satisfied. In contrast, a navigation structure cannot enhance satisfaction if it fails to minimize the cognitive load associated with finding information on the site.

> *H1: The cognitive load a person incurs to find information on a website mediates the effects of the site's navigation structure on his or her satisfaction with the site.*

Through repeated visits and use, people become increasingly effective and skillful in finding information on a website because they accumulate knowledge and build a mental schema (Gefen 2000). The HCI literature suggests that familiarity represents the prior knowledge to draw upon for using an information system and thus is closely associated with learning (Venkatesh and Agarwal 2006). Such cognitive learning helps people develop mental models of a website, which then can be retrieved to distinguish highly from less relevant information and cues for path selection (Nadkarni and Gupta 2007). According to cognitive load theory, the germane cognitive load required to learn new information decreases when people become familiar with a website. That is, increased user familiarity reduces the cognitive processing required to find information (Gefen 2000; Sweller 1988). As the cognitive cost–benefit framework reveals, people also seek to reduce their cognitive cost for tasks, so user familiarity is important for reducing cognitive processing and enhancing satisfaction.

> *H2: The cognitive load a person incurs to find information on a website mediates the effects of user familiarity with the site on his or her satisfaction with the site.*

Performance outcomes pertain to the utilities and user impacts of an information system or technology artifact in a task performance context (DeLone and McLean 2003). A favorable outcome, in an information-seeking context, is locating target information effectively and efficiently. From a HCI perspective, people prefer websites that help their developing strategies to reduce the required cognitive effort (Galletta et al. 2006). According to cognitive load theory, prominent and easy-to-comprehend navigation cues, provided by a well-designed structure, reduce the extraneous cognitive load and enable people to use their working memory effectively to find information successfully and efficiently, as measured by accuracy or time (effort) requirements (Katsanos et al. 2010). In contrast, low navigability dampens user performance (Galletta et al. 2006). Congruent with the cognitive cost–benefit framework, people form satisfaction with a website on the basis of their use of the site to accomplish their objectives: maximizing benefits and minimizing cognitive costs (Nadeem 2007). The benefits of website use in turn become clearer when the performance outcomes are better. In this vein, people likely feel more satisfied with a website if its navigation design can help them achieve better performance outcomes (Au et al. 2008; McKinney et al. 2002).

> *H3: The likelihood that a person can (a) accurately and (b) efficiently find information on a website mediates the effects of its navigation structure on his or her satisfaction with the site.*

By leveraging previously acquired knowledge about a website, stored as a schema in their long-term memory, people can find information more effectively and efficiently. Ac-

[3]The performance improvement that results from the effective use of a website could lead to cognitive lock-in and preference (Johnson et al. 2003; Murray and Häubl 2011). In general, cognitive lock-in relates to preference or loyalty; satisfaction emerges from the comparison of expectations, desires, wants, ideals, or equitable performance (Nadeem 2007), which is different from preference.

cording to cognitive load theory, the germane cognitive load decreases when a mental model has already been established, such that less new information needs to be processed and learned. Increased user familiarity should lower uncertainty and make path selection for finding information easier (Gefen 2000; Sweller 1988). This reasoning is in line with existing HCI literature: Individual differences, including experience, would affect people's interactions with a website and therefore should be taken into consideration when examining user evaluation of a website (Nadkarni and Gupta 2007). Specifically, people achieve performance gains through previous experiences with and knowledge of a computer-based system (Galletta et al. 2006). Performance outcomes constitute a critical determinant of user satisfaction, which corresponds to the benefit aspect in evaluations of a website. The importance of maximizing performance outcomes for satisfaction, as partially determined by user familiarity, is consistent with the cognitive cost–benefit framework. If such familiarity fails to improve the performance achieved or perceived by people, the impacts of user familiarity on satisfaction might be less significant or even insignificant.

> *H4: The likelihood that a person can (a) accurately and (b) efficiently find information on a website mediates the effects of his or her familiarity with the site on satisfaction with the site.*

Experimental Design and Data

We tested our hypotheses in a field quasi-experiment involving two university websites, Site A and Site B, which are highly comparable in their purpose, populations served, content, and traffic. Field quasi-experiments support the design and execution of empirical investigations in a nearly natural environment, such that they control the treatment assignments but do not create or manipulate the treatment itself (Humphreys and Weinstein 2009). We examined navigability and user familiarity with a randomized, 2 × 2 design and assessed each website's navigability (high or low) with a data-driven metric (Fang et al. 2012). In Appendix B, we describe the development of the metric, detail its calculation, and illustrate its applications to evaluate the navigability of the studied university websites. User familiarity depends on whether the participant used his or her own university's website. Prior to the experiment, participants already were or were not familiar with the website they used in the experiment. We randomly assigned each participant to one of the four experimental conditions, defined by navigability and user familiarity, and sought to maintain an approximately equal number of participants in each condition. According to the data-driven metric we used, the navigability of Site A was substantially higher than that of Site B (.62 versus .54 on average).[4] We exploited the differential familiarity levels participants had obtained before the experiment and asked each to self-report his or her familiarity with the assigned website, after completing the experimental tasks. We used these self-reports, as a verification check, to confirm the different familiarity conditions.

We developed information-seeking tasks from frequently sought page sequences (i.e., key access sequences) we discovered from the logs of both websites.[5] Overall, students from both universities shared similar information needs and interests, such as finding the operating hours of the campus medical center.[6] We verified the discovered sequences by surveying 256 participants from Site A university and 165 participants from Site B university, representative of the targeted user population.[7] We then chose 15 key access sequences, further verified by 20 students in each university. These pretest participants were excluded from the actual experiment in which each participant used the assigned website to perform 12 experimental tasks, summarized in Appendix C. To complete a task, participants had to find the particular content of a page or the pages containing the target information. The specific information or screenshots of the target pages (without the URL information) to be located for each experimental task had been included in the task instructions. All participation was voluntary; each participant received $10 for his or her effort and time.

Our experiment targeted undergraduate business students of each university and recruited participants from students enrolled in introductory information systems or operations

[4]Site A was consistently more navigable than Site B in each of the fundamental navigability dimensions that our data-driven metric considered: .78 versus .65 in power, .88 versus .78 in efficiency, and .42 versus .37 in directness.

[5]We developed 15 information-seeking tasks and used 3 tasks as warm-up exercises, with the remainder left for the experimental tasks. The warm-up exercises ensured that participants understood the instructions for completing the experimental tasks and providing responses to the question items.

[6]The two websites used different wording to describe highly similar, if not identical, resources, services, and information. For example, Site A used "contact information and hours of the student health center" for information about the campus medical center's contact details and operating hours, whereas Site B referred to "contact information and operating hours of the main campus medical center."

[7]The participants from the two universities were comparable in age, number of years studying at the current university, gender composition, and self-reported familiarity with their own university site.

management courses, as required by the respective business schools.[8] We used previously validated scales to measure the constructs, with minor wording changes made to fit our context. Accuracy indicated the likelihood that a participant could find the target information; it was operationalized by the number of tasks a participant completed accurately. We considered both time and effort dimensions of efficiency, operationalized respectively as the amount of time (in seconds) and the number of clicks a participant took to complete a task, which could be highly correlated. We used a client-side monitoring software to record the start and end time of each task, the number of clicks, and the specific pages each participant accessed. We then used the recorded (actual) browsing behaviors to calculate task performance by comparing the specific pages a participant accessed in a task and the target page(s). We asked each participant to answer five items, adopted from Hong et al. (2004) and Nadkarni and Gupta (2007), regarding the cognitive load he or she incurred when choosing paths to find information. We adapted two items from McKinney et al. (2002) to measure user satisfaction, focused on the participant's experience using the assigned website to complete the experimental tasks. As controls, we assessed computer competence and self-efficacy for finding information on the Web, using three items from Shih (2006) and five items from Compeau and Higgins (1995), respectively. All the items used seven-point Likert scales (1 = "strongly disagree" and 7 = "strongly agree"). Appendix D contains all the items used in our study.

A designated computer laboratory at each university served as the facility to conduct the experiment.[9] Participants received a packet that described each task to be completed. In the experiment, they used the assigned website to perform tasks, whether their own university's or another site, and indicated the cognitive load they incurred. After completing all the tasks, each participant completed a survey with items to measure their computer competence, self-efficacy for finding information on the Web, familiarity with the website used in the experiment, assessment of the site's navigability, and satisfaction with the site. The self-reported navigability and user familiarity assessments enabled us to confirm the different conditions in our field quasi-experiment.

[8]Although students, faculty, staff, and external visitors could use a site, students constitute a crucial user group. They substantially outnumber faculty and staff combined and often use the university's site for various information.

[9]We conducted six experimental sessions at the university represented by Site A, all administered by the same two investigators; the seven sessions carried out at the university for Site B were administered by the same investigator. All sessions used identical information and followed the same procedure, regardless of their locations or administrators.

Analyses and Results

After removing incomplete responses, we had 248 participants: 128 from the Site A university and 120 from the Site B university. We used the first six tasks for screening and outlier detection. On average, each participant took 192.56 seconds to complete the first six tasks (SD = 112.4). We considered data points exceeding the mean by 3 standard deviations or more (i.e., 529 seconds or longer) as outliers and removed 10 such participants from our data analyses.[10] In Table 1, we report the number of participants in each experimental condition and provide some descriptive statistics of the variables we studied. Overall, participants in both universities were highly comparable in their age and gender composition. We observed no significant between-group differences in computer competence, self-efficacy in finding information on the Web, weekly Internet usage, or self-reported familiarity with the website.

To verify the different experimental conditions, we performed one-tailed t-tests to compare participant-provided navigability assessments and self-reported familiarity across the conditions. According to our analysis, participants could distinguish the difference in navigability between the two sites; as a group, they considered Site A significantly more navigable than Site B (5.36 versus 4.34, t = 6.29, $p < .001$), consistent with our navigability metric. The participants assigned to use their own university's site also reported substantially higher familiarity with the site than did those assigned to use the other site (4.64 versus 1.06); the between-group difference was statistically significant (t = 26.99, $p < .001$). The verification checks confirmed the different, naturally existing experimental conditions: Site A had higher navigability than Site B, and participants were more familiar with their own university's website.

Measurement Assessment

To assess reliability, we examined each item's loading on the corresponding construct, with the criterion that items with loadings greater than .7 are reliable. The loadings of each item satisfied this threshold and were statistically significant at the .001 level. We then examined construct reliability in terms of internal consistency and composite construct reliability. Each construct had a Cronbach's alpha value greater than the common threshold of .7, and the composite reliability exceeded the common threshold of .7, which jointly suggested

[10]The evaluation results also remained intact when we excluded 1.5 standard deviations as outliers, which indicates the robustness of our results to different thresholds.

Table 1. Number of Participants and Descriptive Statistics

	High Navigability		Low Navigability	
	High Familiarity (N = 61)	**Low Familiarity (N = 60)**	**High Familiarity (N = 57)**	**Low Familiarity (N = 60)**
Cognitive load	2.70 (1.13)	3.15 (1.05)	3.64 (1.40)	4.39 (1.23)
User satisfaction	5.81 (0.94)	5.96 (0.82)	5.18 (1.27)	4.55 (1.27)
Number of clicks	40.72 (14.05)	47.85 (18.61)	69.17 (20.77)	75.47 (21.48)
Time spent in each task	357.16 (146.47)	610.85 (256.48)	672.72 (203.47)	891.91 (262.19)
Number of tasks completed accurately	11.16 (1.08)	10.47 (1.26)	9.55 (1.53)	9.18 (1.97)

Notes: Standard deviations appear in parentheses.

Table 2. Summary of Reliability and Factor Loadings

Factor	Mean (Standard Deviation)	Composite Reliability	Cronbach's Alpha	Average Variance Extracted	Item	Loading	t-Statistic
Computer competence (CC)	5.51 (.98)	.94	.90	.84	CC-01	.92	44.97
					CC-02	.93	39.08
					CC-03	.91	35.03
Cognitive load (CL)	3.40 (1.34)	.88	.79	.71	CL-01	.89	52.81
					CL-02	.78	22.89
					CL-03	.87	44.85
User satisfaction (US)	5.45 (1.18)	.97	.94	.94	US-01	.97	172.23
					US-02	.97	181.09
Self-efficacy (SE)	5.86 (.73)	.86	.80	.55	SE-1	.71	10.27
					SE-2	.72	12.31
					SE-3	.76	12.95
					SE-4	.70	7.95
					SE-5	.77	18.40

appropriate reliability. We evaluated convergent validity by examining the average variance extracted (AVE) and the variance captured by indicators. Each construct's AVE was greater than the .5 common threshold, so our instruments exhibited appropriate convergent validity. We summarize the composite reliability, Cronbach's alphas, AVE, and item loadings in Table 2.

We also assessed the cross-loadings computed from the correlation between each construct's component score and the manifest indicators of other constructs; the results were satisfactory, as indicated by within-factor loadings greater than cross-loadings by .25 at least. The square root of the AVE of each construct was substantially higher than the correlation of each construct with any other construct, thus supporting discriminant validity.

Hypothesis Testing

To test the mediating effects, we first examined the direct effects of the investigated constructs, then analyzed and compared the hypothesized mediating effects using a bias-corrected bootstrapping (Preacher and Hayes 2008).

Direct Effects

The tests of the direct effects relied on analyses of covariance (ANCOVA), multivariate analyses of covariance (MANCOVA), and regression models. Because of their potential effects on cognitive load, performance outcomes, and satisfaction, we controlled for gender, age, computer competence, and self-efficacy for finding information on the Web. The

ANCOVA results showed that navigability had significant effects on cognitive load (F = 35.49, p < .001); so did user familiarity (F = 13.29, p < .001). Because of the potential correlation of accuracy with efficiency, measured by the amount of time and number of clicks a participant took to complete a task, we conducted MANCOVA of the effects of navigability and user familiarity on performance outcomes. Navigability significantly influenced the efficiency (time: F = 70.06, p < .001; click: F = 78.38, p < .001) and accuracy (F = 36.00, p < .001) of the performance outcomes. User familiarity significantly affected the amount of time a participant required to complete a task (F = 31.69, p < .001) but not accuracy (F = 1.57, p = .21) or the number of clicks (F = .60, p =.44). We used a regression model to examine the effects of cognitive load and performance outcomes on satisfaction. Cognitive load significantly affected satisfaction (coefficient = -52, p < .001); performance outcomes had a partial effect, as suggested by the significant relationship between clicks and satisfaction (coefficient = -01, p < .05) but not between time and satisfaction. Accuracy of the performance outcomes had non-significant effects on satisfaction.

Mediation Effects

We summarize the results of mediation testing in Table 3. In the first model, navigability was the independent variable, and user familiarly, computer competence, and self-efficacy were covariates. Navigability had a significant total effect on satisfaction (coefficient = .92, Z = 5.61); the inclusion of cognitive load and performance outcomes as mediators significantly diminished the direct effect on satisfaction. Further analysis revealed that only cognitive load mediated the effects of navigability (95% confidence level, did not contain 0). In another model with user familiarity as the independent variable, we used navigability, computer competence, and self-efficacy as covariates. User familiarity had a significant total effect on satisfaction (coefficient = .18, Z = 2.33); however, its direct effect on satisfaction became insignificant when we included cognitive load and performance outcomes as mediators in the model. That is, the effects of user familiarity on satisfaction were fully mediated. Both cognitive load and the number of clicks mediated the effects of familiarity on user satisfaction. In summary, the experimental data supported H1 and H2, partially supported H4b, but did not support H3 or H4a.

In addition, we compared the strength of the mediation by cognitive load and number of clicks. In both models (with either navigability or familiarity as the independent variable), the mediating effect of cognitive load appeared significantly stronger than that of the number of clicks, as suggested by their difference (95% confidence level, did not contain 0). In our comparative results, cognitive load had a more prominent mediating role than performance outcomes, implying that people rely more on the cognitive load they have incurred to determine their satisfaction.

Discussion

This study contributes to the extant literature in several ways. First, we examined the influence processes and mechanisms through which navigation structure and user familiarity affect people's satisfaction with a website. Our emphasis is on the mediating roles of cognitive load and performance outcomes, which correspond to the costs and benefits, respectively, of finding information on the site. The results provide empirical evidence in support of the cognitive cost–benefit framework, revealing that user satisfaction with a website is determined by the costs and benefits that people incur when they seek to find information on a website. The importance of navigation structure and user familiarity for satisfaction already has been recognized, but our study shows that the effects of both navigation structure and user familiarity on user satisfaction depend on the extent to which they enhance performance outcomes and reduce the cognitive load required to find information on a website. By examining the underlying influence paths, we reveal that cognitive load has a greater direct influence on satisfaction than performance outcomes do. Furthermore, the effect of a website's navigation structure is mediated by cognitive load, not by performance outcomes; the mediating effect of cognitive load appears significantly stronger than that of performance outcomes for user familiarity. In this sense, it appears that costs have a more prominent influence than benefits do in shaping user satisfaction with a website in information-seeking contexts. Previous studies focus on increasing a website's benefits for users; our results instead suggest that reducing the cognitive costs that people incur is imperative for improving satisfaction. The design of a website's navigation structure, which closely relates to users' evaluations of the website's usability, should emphasize means to reduce cognitive load to increase user satisfaction.

Second, we explain user satisfaction with a website, using established, theoretical premises in cognition. With a cognitive cost–benefit framework, we highlight the importance of cognitive load and performance outcomes for user satisfaction in an information-seeking context. Previous research using cognitive cost–benefit frameworks usually explains problem-solving choices or behaviors holistically; the current study instead emphasizes the distinct influences of cognitive load and performance outcomes and thereby produces empirical evidence of their respective (unique) effects. In turn, we reveal the need to examine these separate influences on user satisfaction, rather than considering them holistically or in an

Table 3. Summary of the Tests of Mediating Effects

Total Effect		Direct Effect		Indirect Effects				
							95% Confidence Level	
Coefficient	Z-value	Coefficient	Z-value			Point Estimate	Lower	Upper
Navigability as the Independent Variable								
.92	5.61	.44	2.21	Total		.68	.32	1.11
				Mediator	Cognitive Load	.54	.27	.87
					Click	.13	-.10	.42
					Contrast	.41	.01	.82
Familiarity as the Independent Variable								
.18	2.33	-.11	-0.75	Total		.51	.14	.51
				Mediator	Cognitive Load	.26	.10	.47
					Click	.04	.01	.14
					Contrast	.22	.04	.43

aggregated manner. By investigating objective performance outcomes (i.e., accuracy and time/effort efficiency) and subjective user evaluations (i.e., cognitive load and user satisfaction) within a single framework, we also perform a more comprehensive analysis of website success measures, thus providing a better understanding of how users assess websites, including their probable trade-offs between the associated costs and benefits.

Third, by using cognitive load theory as a lens through which to consider how cognitive load and performance outcomes are influenced by website navigation design and user familiarity, we shed light on how and why these mediators determine user satisfaction with a website. A well-designed navigation structure reduces the extraneous cognitive load; increased user familiarity lowers the germane cognitive load. As a result, people can find information more effectively and efficiently, manifested as lower cognitive processing and better performance outcomes. In turn, the reduced cognitive burden on working memory, in combination with improved performance outcomes, increases satisfaction.

Our findings have several research implications. For example, both navigation structure design and user familiarity can increase satisfaction by enhancing performance outcomes and reducing cognitive load. Therefore, researchers should consider essential website design features and user characteristics simultaneously to examine user satisfaction with a website. Our findings reinforce the need to consider navigation structure and user familiarity in an information-seeking context; both factors reduce the cognitive burden on working memory. Fine-grained analyses and models should be developed and tested empirically. From a cognitive cost–benefit perspective, cognitive processing load offers a promising topic and means to scrutinize people's uses and evaluations of a website. Toward that end, cognitive theories can shed light on underlying influence processes and mechanisms.

In illuminating the mediating roles of cognitive load and performance outcomes, our study also provides insights into how navigation structure and user familiarity can influence satisfaction. For example, if a navigation structure cannot effectively reduce the cognitive load, or people do not perceive a reduction in cognitive processing, the effects on user satisfaction may weaken. Cognitive load appears to affect user satisfaction more than performance outcomes do, in that people seem to recognize the cognitive processing they undertake and have a good sense of the time and physical effort needed to perform a task. Previous research identifies performance as an essential antecedent of satisfaction, but the relative attention to the cognitive load over efficiency, as observed in our study, could signify a diminished role of performance in the relationship of navigation structure design or user familiarity with satisfaction.

Efficiency and accuracy also seem to have differential effects on user satisfaction, constituting two fundamental, distinct dimensions of performance outcome. Our findings suggest the probable multidimensionality of performance outcomes and thus the need to examine mediating effects across different performance outcome dimensions to gain more insights into their relationships with user satisfaction. Additional empirical testing should address the effects of website design features and user characteristics across distinct performance dimensions.

Our findings also have implications for practice. First, existing website design guidelines should be reexamined, to determine how they can ensure cognitive load reductions and performance (efficiency) improvements. Lessening the cognitive load required to find information can channel the positive effects of navigation design and user familiarity to satisfaction. A well-designed navigation structure should help people complete tasks (e.g., find information) and reduce their cognitive load and disorientation (McKinney et al. 2002; Webster and Ahuja 2006). Website designers need to consider visitors' information needs and structure interpage linkages accordingly. Second, website designers should understand how user characteristics interact with website design features. Because of their time and budget constraints, designers often implement important design features selectively; however, our findings suggest they should analyze the combined effects of different design features, together with essential user characteristics. Third, designers should adopt established guidelines and preferred practices to increase users' familiarity with a focal website, which would reduce their learning curve and make their visits less cognitively demanding (Zhang et al. 2011). The resulting user familiarity should have positive effects on cognitive load, performance outcomes, and user satisfaction.

Finally, this study could be extended in several directions. Our results come from a field quasi-experiment with voluntary participants from two universities who are representative of the population served by the studied websites. Yet we acknowledge a generalizability constraint that could be alleviated by additional tests of different websites and user groups. The information-seeking tasks in our experiment reflect actual browsing behaviors recorded in the server logs and thus actual usage patterns. Accuracy significantly differs across experimental conditions but seems relatively high.[11] Therefore, further research should target more diverse tasks and user groups, and consider websites in other domains, such as e-commerce and digital government. The relationship between performance outcomes and user satisfaction also deserves more scrutiny and empirical testing. Additional studies might investigate the role of cognitive load, preferably across different websites, tasks, user groups, and contexts. Finally, other important factors also might mediate or moderate the effects of navigation structure or user familiarity, such as gender and situational factors, which should be considered as well.

[11]Average accuracy ranges between 11.16 and 9.18 across the experimental conditions. According to our two-tailed t-test results, the mean is significantly different between the high and low navigability conditions ($t = 6.93$, $p < .001$) and between high and low user familiarity conditions ($t = 2.45$, $p < .05$). These results suggest that accuracy is not consistently high across experimental conditions.

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MIS Quarterly

RESEARCH NOTE

EXAMINING THE MEDIATING ROLES OF COGNITIVE LOAD AND PERFORMANCE OUTCOMES IN USER SATISFACTION WITH A WEBSITE: A FIELD QUASI-EXPERIMENT

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Appendix A

Representative Previous Research

Table A1. Representative Previous Research Examining Navigation Design or Navigability

	Research Question	Variables	Results
Cyr 2008 (Experiment)	How do website design features (navigation design, visual design, information design) affect users' trust and satisfaction? How do trust and satisfaction affect loyalty?	Determinant: • Navigation design • Visual design • Information design Dependent Variable: • Trust • Satisfaction • Loyalty	Navigation design affects users' satisfaction and trust toward a website; it also indirectly affects users' loyalty.
Katsanos et al. 2010 (Experiment)	How does information scent, a key attribute of navigability, influence users' behaviors while exploring a website (distribution of attention, confidence in choice of link, efficiency, effectiveness)?	Determinant: • Information scent Dependent Variable: • Distribution of attention • Confidence in choice of link • Efficiency • Effectiveness	For web pages with high navigability, the distraction users experience is low, while their confidence, effectiveness, and efficiency are high for completing information-seeking tasks.
Palmer 2002 (Survey)	Developing and validating website usability, design, and performance metrics.	Determinant: • Download delay • Navigability • Site content • Interactivity • Responsiveness Dependent Variable: • Likelihood of return • Frequency of use • Satisfaction	Website navigability is positively associated with users' perceived website success, in terms of likelihood of return, frequency of use, and satisfaction.
Webster and Ahuja 2006 (Experiment)	How do perceived disorientation, navigation, and engagement affect users' performance and future intentions to use a website?	Determinant: • Navigation systems • Perceived disorientation • Engagement Dependent Variable: • User performance • Future intention to use	Website navigability directly affects users' perceived disorientation and performance, in terms of accuracy and efficiency; it indirectly affects future intentions to use.

Table A2. Representative Previous Research Examining User Familiarity

	Research Question	Variables	Results
Casaló et al. 2008 (Survey)	How do reputation, usability, satisfaction, and familiarity affect loyalty in an electronic commerce context?	Determinants: • Usability • Reputation • Familiarity • Satisfaction Dependent Variable: • Loyalty	Navigability, as part of usability, has a direct influence on user satisfaction. Users' familiarity moderates the influence of website usability on user loyalty.
Chen et al. 2011 (Experiment)	What are the interaction effects of familiarity, breadth, and media richness on users' perceptions and evaluations of a website?	Determinant: • Familiarity • Breadth • Media Dependent Variable: • Perceived disorientation • Engagement • Future intentions to use	User familiarity with a website is negatively associated with disorientation and positively associated with engagement and intentions to use the site in the future.
Galletta et al. 2006 (Experiment)	How do delay, familiarity, and site breadth interact to influence attitudes, performance, and behavioral intentions?	Determinant: • Familiarity • Delay • Breadth Dependent Variable: • Attitude • Behavioral intention • Performance	Familiarity affects users' attitudes and performance in their search for target information. Familiarity also dampens the negative effect of website delay on attitudes and performance.
Gefen 2000 (Survey)	What effects does user familiarity have on individual trust in a website?	Determinant: • Familiarity • Disposition of trust Dependent Variable: • Trust • Willingness to inquire • Willingness to purchase	Users' familiarity with the website increases willingness to inquire about products, willingness to purchase, and the level of trust.
Nadkarni and Gupta 2007 (Experiment)	Does complexity enhance or inhibit user experiences on a website?	Determinant: • Objective website complexity • Familiarity Dependent Variable: • Perceived website complexity	User familiarity moderates the positive association between objective and perceived website complexity.

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Appendix B

Data-Driven Navigability Metric and Applications to Assess Experimental Websites

We describe the formulation of the data-driven navigability metric, adapted from Fang et al. (2012), and detail its application to evaluate the navigability of the websites in our experiment. This metric is premised in the law of surfing (Huberman et al. 1998), which states that the probability $p(k)$ of surfing k hyperlinks in a session can be expressed as

$$p(k) = \sqrt{\frac{\beta}{2\pi k^3}} \exp\left[\frac{-\beta(k-\alpha)^2}{2\alpha^2 k}\right] \qquad k - 1, 2, \ldots \qquad \text{(B1)}$$

where the average number of hyperlinks surfed in a session is α, and the scale parameter β determines the shape of the probability distribution. Let $G(l)$ be the probability of surfing *at least* l hyperlinks during a session, which is the sum of $p(k)$, where $k \geq l$, such that

$$G(l) = \sum_{\forall k \geq l} p(k) \qquad l = 1, 2, \ldots \qquad \text{(B2)}$$

The metric considers three fundamental dimensions of navigability: power, efficiency, and directness.

Power

Power reveals the probability that a visitor accurately locates target information by navigating through a website's hyperlink structure. Key access sequences, discovered from web logs, approximate visitors' information-seeking targets. A key access sequence refers to a sequence of content pages frequently accessed by users. Let U be a set of n key access sequences discovered from logs, $U = \{u_i\}$, $i = 1, 2, \ldots, n$, and $u_i = \langle p_{i,1}, p_{i,2}, \ldots, p_{i,m} \rangle$, where $p_{i,j}$ is the j^{th} visited content page in u_i, $j = 1, 2, \ldots, m$. For an information-seeking target approximated by a key access sequence u_i, *power* $R(u_i)$ can be measured as the probability of locating all content pages in u_i sequentially, from $p_{i,1}$ to $p_{i,m}$. Let p_s denote the start page in the search for u_i. If $p_s \neq p_{i,1}$, let $d(p_s, p_{i,1})$ be the distance from p_s to the first sought page $p_{i,1}$. Visitors willing to surf at least $d(p_s, p_{i,1})$ hyperlinks can locate $p_{i,1}$ from p_s. According to Equation B2, $G(l)$ is the probability of surfing at least l hyperlinks; therefore, the probability of surfing at least $d(p_s, p_{i,1})$ hyperlinks is $G(d(p_s, p_{i,1}))$. In turn, the probability of locating $p_{i,1}$ from p_s can be approximated as $G(d(p_s, p_{i,1}))$. After locating $p_{i,1}$, a visitor can continue to locate $p_{i,2}$, and the probability of locating $p_{i,j}$ from $p_{i,j-1}$ can be approximated as $G(d(p_{i,j-1}, p_{i,j}))$, where $2 \leq j \leq m$. If $p_s \neq p_{i,1}$, the power $R(u_i|p_s)$ of locating u_i becomes

$$R(u_i|p_s) = G\left(d\left(p_x, p_{i,1}\right)\right)\prod_{j=2}^{m} G\left(d\left(p_{i,j-1}, p_{i,j}\right)\right) \qquad \text{if } p_s \neq p_{i,1} \qquad \text{(B3)}$$

Likewise, if $p_s = p_{i,1}$, we obtain

$$R(u_i|p_s) = \prod_{j=2}^{m} G\left(d\left(p_{i,j-1}, p_{i,j}\right)\right) \qquad \text{if } p_s = p_{i,1} \tag{B4}$$

Let P(start of seeking for $u_i = p_s$) be the probability of seeking u_i by starting from page p_s, which can be estimated from surfing data recorded in web logs. Accordingly, $R(u_i)$ is

$$R(u_i) = \sum_{\forall p_s} p(\text{start of seeking for } u_i = p_s) R(u_i|p_s) \tag{B5}$$

Not all key access sequences are equally important. Let $w(u_i)$ be the weight of u_i in U, calculated as

$$w(u_i) = \frac{v(u_i)}{\sum_{\forall u \in U} v(u)} \tag{B6}$$

where $v(u_i)$, is the frequency rate of visiting u_i. Therefore, the *power* $R(U)$ of a website can be measured as the weighted probability of achieving each information-seeking target in U on that site,

$$R(U) = \sum_{i=1}^{n} w(u_i) R(u_i) \tag{B7}$$

Power, $R(U)$, falls inclusively between 0 and 1. The higher its value, the more powerful a website's hyperlink structure design is for helping visitors locate target information on the site.

We illustrate the calculation of power with an example. In Figure B1, a sample website consists of nine pages (A, B, …, I) and has eight hyperlinks (l_B, l_C, …, l_I), pointing to web pages B, C, …, I.

The distance matrix for the site is in Table B1. For example, the distance from page A to page E is two clicks.

Let the key access sequences U identified from web logs be $U = \{u_1, u_2\}$, where $u_1 = \langle F,H \rangle$, with $v(u_1) = .15$; P(start of seeking for $u_1 = A$) = .8; and P(start of seeking for $u_1 = F$) = .2. In addition, $u_2 = \langle B,I \rangle$, with $v(u_2) = .1$; P(start of seeking for $u_2 = A$) = .9; and P(start of seeking for $u_2 = B$) = .1. Assume that $G(1) = 1$ and $G(2) = .8$, after the application of Equation B2. Then, applying Equation B3, we have

$R(u_1|A) = G(d(A,F))G(d(F,H)) = G(2)G(1) = 0.8$ by using the distance matrix in Table B1.

We apply Equation B4 and obtain

$R(u_1|F) = G(d(F,H))G(1) = 1$

Applying equation B5, we determine

$R(u_1) = P(\text{start of seeking for } u_1 = A)R(u_1|A) + P(\text{start of seeking for } u_1 = F)R(u_1|F) = 0.84$

Similarly, we can calculate $R(u_2)$:

$R(u_2|A) = G(d(A,B)G(d(B,I)) = G(1)G(2) = 0.8;$

$R(u_2|B) = G(d(B,I) = G(2) = 0.8;$ and

$R(u_2) = P(\text{start of seeking for } u_2 = A)R(u_2|A) + P(\text{start of seeking for } u_2 = B)R(u_2|B) = 0.8$

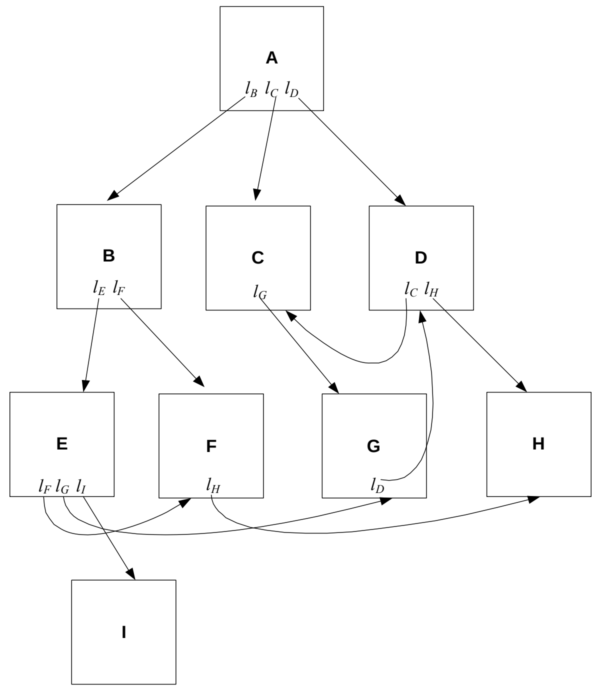

Figure B1. Sample Website

Table B1. Distance Matrix for Sample Website

	A	*B*	*C*	*D*	*E*	*F*	*G*	*H*	*I*
A	0	1	1	1	2	2	2	2	3
B	∞	0	4	3	1	1	2	2	2
C	∞	∞	0	2	∞	∞	1	3	∞
D	∞	∞	1	0	∞	∞	2	1	∞
E	∞	∞	3	2	0	1	1	2	1
F	∞	∞	∞	∞	∞	0	∞	1	∞
G	∞	∞	2	1	∞	∞	0	2	∞
H	∞	∞	∞	∞	∞	∞	∞	0	∞
I	∞	∞	∞	∞	∞	∞	∞	∞	0

Finally, with Equation B7, we calculate the power of the website in Figure B1 as

$$R(U) = w(u_1)R(u_1) + w(u_2)R(u_2) = \frac{0.15}{0.1+0.15} \times 0.84 + \frac{0.1}{0.1+0.15} \times 0.8 = 0.82$$

Efficiency

Efficiency refers to the efficiency with which a visitor locates target information. The closer a page is to the current page, the more efficient it is to locate that page. For an information-seeking target approximated by a key access sequence $u_i = \langle p_{i,1}, p_{i,2}, \ldots, p_{i,m} \rangle$, given that seeking for u_i starts from page $p_s \neq p_{i,1}$, the *efficiency* $Q(u_i|p_s)$ of achieving the information-seeking target can be measured as

$d\left(p_s, p_{i,1}\right)\sum_{j=2}^{m} d\left(p_{i,j-1}, p_{i,j}\right)$ where $d(x, y)$ denotes the distance from page x to page y. By normalizing the efficiency metric onto [0,1], we obtain

$$Q\left(u_i | p_s\right) = \frac{m\gamma - \min\left(d\left(p_s, p_{i,1}\right)\right) + \left(\sum_{j=2}^{m} d\left(p_{i,j-1}, p_{i,j}\right), m\gamma\right)}{m\left(\gamma - 1\right)} \quad \text{if } p_s \neq p_{i1} \tag{B8}$$

where m is the number of content pages in u_i; the function $\min(x, y)$ returns the smaller value between x and y; and $\gamma > 1$ is a constant. A page is most efficient to locate if it is one click away; it is least efficient if it is γ or more clicks away. Then γ can be set to an appropriate value, such that the probability of surfing γ or more clicks (i.e., $G(\gamma)$) becomes trivial. Similarly,

$$Q\left(u_i | p_s\right) = \frac{\left(m-1\right)\gamma - \min\left(d\left(p_s, p_{i,1}\right)\right) + \left(\sum_{j=2}^{m} d\left(p_{i,j-1}, p_{i,j}\right), \left(m-1\right)\gamma\right)}{\left(m-1\right)\left(\gamma - 1\right)} \quad \text{if } p_s \neq p_{i1} \tag{B9}$$

Also, $Q(u_i)$ can be derived as follows:

$$Q\left(u_i\right) = \sum_{\forall p_s} P\left(\text{start of seeking for } u_i = p_s\right) Q\left(u_i | p_s\right) \tag{B10}$$

As a result, the *efficiency* $Q(U)$ of a website is measured as the weighted efficiency of locating each information-seeking target in U on the site. That is,

$$Q\left(U\right) = \sum_{i=1}^{n} w\left(u_i\right) Q\left(u_i\right) \tag{B11}$$

and $Q(U)$ falls inclusively between 0 and 1, where 0 indicates the least efficient (i.e., average distance to the visitor-sought content pages is γ or more clicks away) and 1 is most efficient (i.e., all visitor-sought content pages are only one click away). The higher the value of $Q(U)$, the more efficient it is for a visitor to locate the target information on a website.

We illustrate this calculation, using the sample website from Figure B1 and the key access sequences. We assume that the constant γ is 5. Applying Equation B8, we find

$$Q\left(u_i | A\right) = \frac{2\gamma - \min\left(d\left(A, F\right) + d\left(F, H\right), 2\gamma\right)}{2\left(\gamma - 1\right)} = \frac{2\gamma - \left(2 + 1\right)}{2\left(\gamma - 1\right)} = 0.88 \quad \text{by using the distance in Table B1}$$

From Equation B9, 23 note

$$Q\left(u_1 | F\right) = \frac{\gamma - \min\left(d\left(F, H\right), \gamma\right)}{\gamma - 1} = 1$$

Applying Equation B10, we obtain

$$Q(u_1) = P(\text{start of seeking for } u_1 = A)Q(u_1|A) + P(\text{start of seeking for } u_1 = F)Q(u_1|F) = 0.9$$

Applying Equation B11, we determine the efficiency of the sample website in Figure B1 as

$$Q(U) = w(u_1)Q(u_1) + w(u_2) = \frac{0.15}{0.1+0.15} \times 0.9 + \frac{0.1}{0.1+0.15} \times 0.86 = 0.89$$

Directness

Directness indicates the ease with which a visitor can decide where to move from the current page to the target information. People are likely to find target information with fewer clicks if more hyperlinks point to content pages on each page. At an extreme, efficiency *Q(U)* equals 1 when each page has hyperlinks pointing to all content pages on the site; that is, all content pages are only one click away from any page, which obviously is not a good design. Placing more hyperlinks on a page makes it increasingly difficult for visitors to decide on their next move. With an information-seeking target approximated by a key access sequence $u_i = \langle p_{i,1}, p_{i,2}, \ldots, p_{i,m} \rangle$ and assuming seeking for u_i starts from $p_s \neq p_{i,1}$, directness $L(u_i | p_s)$ can be measured as $N(p_s, p_{i,1}) + \sum_{j=2}^{m} N(p_{i,j-1}, p_{i,j})$, where $N(x,y)$ denotes the average number of hyperlinks on the pages located on the shortest path from x to y, and $N(x,y)$ is ∞ if there is no path from x to y. By normalizing the directness measure onto [0,1], we obtain

$$L(u_i|p_s) = \frac{m\delta - \min\left(N(p_s, p_{i,1}) + \sum_{j=2}^{m} N(p_{i,j-1}, p_{i,j}), m\delta \right)}{m(\delta - 1)} \qquad \text{if } p_s \neq p_{i,1} \tag{B12}$$

where the function $\min(x, y)$ returns the smaller value between x and y, and δ is a constant, $\delta > 1$. Visitors have less difficultly deciding on their next move if the current page contains only one hyperlink but more difficultly if the current page contains δ or more hyperlinks. The value of δ can be user specified or set to an adequate constant, according to a generally accepted usability guideline. Similarly,

$$L(u_i|p_s) = \frac{(m-1)\delta - \min\left(N(p_s, p_{i,1}) + \sum_{j=2}^{m} N(p_{i,j-1}, p_{i,j}), (m-1)\delta \right)}{(m-1)(\delta - 1)} \qquad \text{if } p_s = p_{i,1} \tag{B13}$$

Then $L(u_i)$ is derived as

$$L(u_i) = \sum_{\forall p_s} P(\text{start of seeking for } u_i = p_s) L(u_i|p_s) \tag{B14}$$

The directness $L(U)$ of a website can be calculated as the weighted directness of achieving each information-seeking target in U on the site:

$$L(U) = \sum_{i=1}^{n} w(u_i) L(u_i) \tag{B15}$$

In addition, directness $L(U)$ falls within [0,1], with 0 indicating the most difficulty and 1 the least. The higher the value of $L(U)$, the easier it is for a visitor to decide on the next move.

To illustrate this calculation, we again use the sample website in Figure B1 and the key access sequences, and we assume the constant δ is set to 5. For the key access sequence $u_1 = \langle F,H \rangle$, the shortest path from page A to F is A(3)→B(2)→F, and the shortest path from page F to H is F(1) →H. The number of hyperlinks on a page is indicated in parentheses after the annotation letter that denotes the page. Therefore, $N(A,F) = \frac{3+2}{2} = 2.5$, and $N(F,H) = 1$. By applying Equations B12–B14, we determine

$$L(u_1|A) = \frac{2\delta - \min\left(N(A,F) + N(F,H), 2\delta\right)}{2(\delta - 1)} = 0.81;$$

$$L(u_1|F) = \frac{\delta - \min\left(N(F,H), \delta\right)}{\delta - 1} = 1;$$

$$L(u_1) = P(\text{start of seeking for } u_1 = A)L(u_1|A) + P(\text{start of seeking for } u_1 = F)L(u_1|F) = 0.85$$

For $u_2 = \langle B,I \rangle$, the shortest path from pages A to B is A(3)→B, and the shortest path from pages B to I is B(2)→E(3)→I, so $N(A,B) = 3$ and $N(B,I) = 2.5$. Applying Equations B12–B14, we obtain

$$L(u_2|A) = \frac{2\delta - \min\left(N(A,B) + N(B,I), 2\delta\right)}{2(\delta - 1)} = 0.56;$$

$$L(u_2|B) = \frac{\delta - \min\left(N(B,I), \delta\right)}{\delta - 1} = 0.63;$$

$$L(u_2) = P(\text{start of seeking for } u_2 = A)L(u_2|A) + P(\text{start of seeking for } u_2 = B)L(u_2|B) = 0.57$$

We use Equation B15 to calculate the sample website's directness as

$$L(U) = w(u_1)L(u_1) + w(u_2)L(u_2) = \frac{0.15}{0.1+0.15} \times 0.85 + \frac{0.1}{0.1+0.15} \times 0.57 = 0.74$$

Navigability

Finally, by considering power, efficiency, and directness simultaneously, we obtain a single, holistic measure of navigability. Specifically, the navigability $Nav(U)$ of a website is the harmonic mean of power $R(U)$, efficiency $Q(U)$, and directness $L(U)$:

$$Nav(U) = \frac{3R(U)Q(U)L(U)}{Q(U)L(U) + R(U)L(U) + R(U)Q(U)} \tag{B16}$$

In this equation, $Nav(U)$ is bounded within [0,1]. The greater the value of $Nav(U)$, the better is the site's navigability. We used the data-driven navigability metric $Nav(U)$ to evaluate the navigability of the two experimental websites. When mining key access sequences from web logs, we set threshold values between .05% and .175%, in increments of .025%. Table B2 reports the metric scores for each site.

According to these metric scores, the navigability of Site A is better than that of Site B, across the range of threshold values. On average, the navigability score of Site A is 14.7% higher.

Table B2. Navigability Comparison of Experimental Websites

Threshold Value	Navigability of Site A	Navigability of Site B
.05%	.62	.53
.075%	.62	.54
.1%	.62	.54
.125%	.62	.55
.15%	.63	.55
.175%	.63	.55

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Appendix C

Warm-Up Exercises and Experimental Tasks

Warm-Up Exercises

1: Find the location of the College of Business Administration and the dean's bio.
2: Find the university's president's name.
3: Find the page containing current campus news and then the page containing the information about the university (e.g., facts, history, etc.).

Experimental Tasks

1: Find the location and operating hours of the Campus Main Library.
2: Find the page containing the description of the University Athletics and then the page containing the description of the University Football team.
3: Find the location and hours of the Office of Academic Advising and then the Office of Career Services.
4: Find the page containing a list of current campus events.
5: Find the location and store hours of the Campus Bookstore.
6: Find parking permit rates and how to buy parking permits.
7: Find the contact information and operating hours of the Campus Medical Center.
8: Find the Academic Calendar and then the dates for this year's Spring break.
9: Find the current semester class schedule and then the location of a specific course offered in the semester.
10: Find the page containing Campus Directory and then the page containing Campus Map and Directions.
11: Find the page containing Campus Recreation Services and then the page containing Campus Sports Clubs.
12: Find the current semester Tuition and Rates and how to pay tuition.

Appendix D

Question Items

Computer Competence (CC; Shih 2006)
CC-1: How would you rate your general computer skills?
CC-2: How would you rate your overall competence for using Internet technology?
CC-3: How would you rate your general capability of browsing the Web?

Cognitive Load (CL; Hong et al. 2004; Nadkarni and Gupta 2007)
CL-1: I needed a lot of thinking when deciding how to navigate from a current page towards the target page/content on the experimental website.
CL-2: I often contemplated, among the hyperlinks on a current web page, which one to choose for my locating the target content.
CL-3: Generally speaking, my navigating the experimental website to locate a target page/content was cognitively demanding.

User Satisfaction (US; McKinney et al. 2002)
UST-1: Overall, I am satisfied with my using the experimental website to complete a search task.
UST-2: I am pleased with my use of the experimental website to locate target pages/content.

Self-Efficacy for Finding Information on Web (SE; Compeau and Higgins 1995)
SE-1: I can effectively navigate a website if I have seen someone else using that website before trying it myself.
SE-2: I am effective in navigating a website if I can contact someone for help if I got stuck.
SE-3: I can effectively navigate a website if someone else helps me get started.
SE-4: I can navigate a website effectively if I have just the online navigation information (available on that website) for assistance.
SE-5: I can effectively navigate a website for finding specific information if I have used similar websites before.

Verification Checks
Navigability: The experimental website provides precise structural information for guiding me to locate a target page/content effectively and efficiently (7-point Likert scale, 1 = "strongly disagree" and 7 = "strongly agree").
User familiarity: How would you rate your overall familiarity with the experimental website? (7-point Likert scale, 1 = "not good at all" and 7 = "excellent").

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