6-30-2021

Efficiency and Exposure: Reconciling the Effects of Website Browsing Behaviors for Non-transactional Outcomes

Brian Dunn

Utah State University, brian.dunn@usu.edu

Narayan Ramasubbu

University of Pittsburgh, narayanr@pitt.edu

Matthew L. Jensen

University of Oklahoma, mjensen@ou.edu

Dennis F. Galletta

University of Pittsburgh, galletta@pitt.edu

Paul Benjamin Lowry

Virginia Polytechnic Institute and State University, paul.lowry.phd@vt.edu

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Dunn, B., Ramasubbu, N., Jensen, M. L., Galletta, D. F., & Lowry, P. B. (2021). Efficiency and Exposure: Reconciling the Effects of Website Browsing Behaviors for Non-transactional Outcomes. *AIS Transactions on Human-Computer Interaction*, 13(2), 206-242. <https://doi.org/10.17705/1thci.00148>
DOI: 10.17705/1thci.00148

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Brian Kimball Dunn

Huntsman School of Business, Utah State University, brian.dunn@usu.edu

Narayan Ramasubbu

Katz Graduate School of Business, University of Pittsburgh, narayanr@pitt.edu

Matthew L. Jensen

Price College of Business, University of Oklahoma, mjensen@ou.edu

Dennis F. Galletta

Katz Graduate School of Business, University of Pittsburgh, galletta@pitt.edu

Paul Benjamin Lowry

Pamplin College of Business, Virginia Polytechnic Institute and State University, paul.lowry.phd@vt.edu

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Brian Kimball Dunn

Huntsman School of Business, Utah State University
brian.dunn@usu.edu

Narayan Ramasubbu

Katz Graduate School of Business, University of
Pittsburgh

Matthew L. Jensen

Price College of Business, University of Oklahoma

Dennis F. Galletta

Katz Graduate School of Business, University of
Pittsburgh

Paul Benjamin Lowry

Pamplin College of Business, Virginia Polytechnic
Institute and State University

Abstract:

Organizations invest heavily in developing and maintaining websites to meet various transactional (e.g., online purchases) and non-transactional (e.g., influencing brand attitude and disseminating product information organizational goals). In considering non-transactional outcomes—specifically brand attitude formation and information dissemination—one finds that two literature streams emerge, although they present different recommendations. First, cognitive attitude formation research recommends designing interfaces to promote an efficient experience that takes less time and requires less movement among webpages. On the other hand, the mere exposure literature recommends that longer durations and more exposure to related ideas should improve non-transactional outcomes. To understand the relationship between these two perspectives, we tested related hypotheses in a within-subjects observational experiment with a follow-up survey 10 days later. Building on theory regarding task characteristics, we also included goal-directedness as a hypothesized moderating variable. We found that more time spent on a website was associated with greater brand attitude improvement and product knowledge retention, but that more webpage views was associated with reduced product knowledge. In addition, the task type influenced the relationships between webpages viewed and brand attitude and between time spent and product knowledge retention.

Keywords: Mere Exposure, Cognitive Attitude Formation, Website Design, Interface Design, Brand Attitude, Information Recall.

Shuk Ying Ho was the accepting senior editor for this paper.

1 Introduction

A 2016 Gartner study suggests that firms spend more money on their website than any other discrete marketing-related activity: on average, they allocate nine percent of their total marketing budgets to creating, maintaining, and analyzing websites (Panetta, 2016; Pemberton, 2016). The U.S. Government's HealthCare.gov website, which researchers have estimated to have involved 60 consulting companies and to cost US\$2.1 billion, illustrates the extreme cost sometimes involved in building and managing these websites (Wayne, 2014). Even after a website's initial launch, website owners continue to invest additional resources into their websites to keep content current, maintain their infrastructures, optimize performance based on quantitative analyses, and adapt to changes in available technology, design trends, and user-browsing habits. Moreover, website owners spend tens of billions of dollars annually on online marketing and advertising activities to attract visitors to their websites (Lunden, 2013).

Given these large expenditures, organizations' websites need to achieve their objectives, such as to influence brand attitudes, disseminate information, and facilitate transactions. Prior research has shown that the way individuals behave on a website may vary dramatically depending on their characteristics and how they perceive website elements (Benlian, 2015; Cyr, Head, Larios, & Pan, 2009; Lee, Hodges, & Watchravesringkan, 2015; Nadkarni & Gupta, 2007; Wells, Valacich, & Hess, 2011). These elements—design choices that a website's owner makes—influence the way users interact with a website and, thus, potentially increasing the website's ability to achieve its owner's aims by steering users toward preferred on-site behavior (Ho & Bodoff, 2014). Consequently, before making design choices about website elements, website owners need to determine which measurable browsing behaviors their website should encourage.

Some website objectives have clear preferred user behavior. For instance, for an ecommerce website whose owners want immediate sales, completing a transaction constitutes the preferred user behavior. Accordingly, a considerable body of information systems (IS) research has examined user-related antecedents that predict purchasing behavior (e.g., Cyr, 2013; Everard & Galletta, 2005; Gefen, 2002; Lowry, Vance, Moody, & Beckman, 2008; McKnight, Choudhury, & Kacmar, 2002). However, researchers have not as widely researched browsing behavior-related antecedents of non-transactional website objectives, such as branding and information dissemination. In this study, we consider two such non-transactional objectives—brand attitude and product knowledge retention—and the browsing behavior that website owners should encourage from users to achieve these objectives. In considering this context, we consider two relevant literature streams: 1) the cognitive attitude formation literature (e.g., Payne, Bettman, & Johnson, 1993; Todd & Benbasat, 1991) and 2) mere exposure theory (Zajonc, 1968, 2001). These two literatures address this context from different perspectives and, thus, yield different recommendations. In our study, we focus on reconciling these perspectives.

According to the cognitive attitude formation literature, users form attitudes about information search based on the need to conserve limited cognitive resources (e.g., Payne et al., 1993; Simon, 1955) and prefer tools (e.g., websites) that require lower expenditures. Online behavior research considers users "cognitive misers" (e.g., Liu & Goodhue, 2012; Wells et al., 2011) and suggests that users will prefer a website and perceive its owner more positively when they have an efficient experience that requires minimal time and webpage views to complete the task for which they visited the website (Hong & Thong, 2013; Moody & Galletta, 2015). Research has even shown this preference for efficiency to prompt physiological responses (Fehrenbacher & Djamasbi, 2017).

The mere exposure literature, on the other hand, describes a preference development process that bypasses cognitive choice in attitude formation (Janiszewski, 1993; Zajonc, 2001). Studies that have examined the mere exposure effect have found that individuals ascribe more positive affect to stimuli that they are exposed to more frequently, for longer durations, or both (Janiszewski, 1993; Zajonc, 2001). In the online context, this literature suggests that users will perceive a website and its owner more positively and better recall information learned there when they are exposed to more of its content through viewing more webpages and spending more time on the website.

Interestingly, when considered in light of the surrogate measurements that researchers have often used to measure effort and exposure—time spent on a task and number of webpages used—one could see these two perspectives as being at odds with each other. Studies based on cognitive attitude formation call for efficient experiences that take less time and require less information processing, while mere exposure theory calls for longer-duration experiences with more exposure to stimuli. This apparent discrepancy could leave website owners with a dilemma in deciding how to best design a website to achieve objectives such as improving brand attitude and product knowledge retention. In this study, we evaluate these two

perspectives and examine how they contribute to users' brand attitudes and knowledge retention. In doing so, we shed light on whether website owners should encourage more efficient user behavior in terms of time and webpages viewed (using the cognitive attitude formation lens) or rather should prefer to encourage behavior that results in greater exposure in terms of time and webpages viewed (using the mere exposure lens). Furthermore, we propose that the preferred approach may differ depending on the task that users complete and that users' a priori familiarity with a website's sponsor will affect our dependent variables as well.

To investigate, we conducted a within-subjects laboratory experiment in which participants interacted with three existing brand-oriented websites. We gathered data regarding user brand attitudes and product knowledge retention about 10 days following the laboratory sessions. We included two task types (high goal-directedness vs. low goal-directedness) and incorporated this manipulation as a moderating variable. We also evaluated results across three different consumer-oriented automobile manufacturer websites, which corresponded with three different levels of brand familiarity.

Our empirical results confirmed the quandary that website owners face in balancing efficiency and exposure. We found that greater time exposure was associated with improved brand attitude and product knowledge recall. However, we found that more webpage views were associated with diminished product knowledge recall. Moreover, we also found that the task's goal directedness was a significant moderating variable in predicting both dependent variables, which suggests that circumstances related to specific use cases influence whether efficiency or exposure is more salient. These results offer designers and website owners important guidance on how to manage their websites to elevate brand attitudes and increase the extent to which users retain product knowledge.

2 Theory and Hypotheses

Scholars have spent considerable effort studying how interaction with websites can facilitate transactional behavior. In particular, numerous researchers have considered how website designs and interactions affect a user's intent to purchase in an ecommerce context (e.g., Benbasat, 2006; Campbell & Wells, 2013; Coyle & Thorson, 2001; Everard & Galletta, 2005; Gefen, 2002; Gefen, Karahanna, & Straub, 2003; Jiang & Benbasat, 2007a, 2007b; Lorenzo-Romero, Constantinides, & Alarcón-del Amo, 2013; Lowry et al., 2008). This research has yielded important insights for website owners in achieving an important website objective. However, websites can also produce other highly desirable, non-transactional objectives through user interaction, such as increasing a user's attitude toward the website's brand (i.e., brand attitude) and informing users about a company's qualities and products (i.e., product knowledge).

We define brand attitude as how an individual internally evaluates a brand (Mitchell & Olson, 1981; Xu, Thong, & Venkatesh, 2014b), which results in a relatively enduring belief (Lutz, 1975). Product knowledge refers to how an individual recognizes and understands a brand's products (Jiang & Benbasat, 2007a). In this study, we specifically use the term product knowledge to refer to retention of details regarding a brand's products after performing an information search task on the brand's website. More positive brand attitudes result in higher initial trust in consumer ecommerce websites (Lowry et al., 2008), increased intentions to purchase (Goodrich, Schiller, & Galletta, 2015; Lee, Lee, & Yang, 2017), and better financial performance and stock returns (Aaker & Jacobson, 2001). Research has also linked greater product knowledge to an increased likelihood to purchase (Lin & Chen, 2006) and "consistently ranks among the most important influences regarding consumer purchase behavior" (Wang & Hazen, 2016, p. 462). Additional likely consequences from elevated brand attitude and product knowledge include improvements in word-of-mouth recommendations, more positive product reviews, and an increase in more helpful community engagement (Zhang, Hu, & Guo, 2017).

To understand which online behaviors website owners should encourage to promote these outcomes, we consider the cognitive attitude formation literature and mere exposure theory. The cognitive attitude formation literature (e.g., Payne et al., 1993; Todd & Benbasat, 1991) suggests that technology systems yield better outcomes for their owners when they encourage an efficient experience; mere exposure theory (e.g., Janiszewski, 1993; Zajonc, 2001), on the other hand, suggests that greater exposure to stimuli will be more effective when one considers non-transactional outcomes.

If we consider how past researchers have measured "efficiency" and "exposure", the cognitive attitude formation and mere exposure perspectives offer conflicting practical guidance to website owners concerning the browsing behaviors they should promote. Studies that have explored efficiency's importance in non-transactional outcomes have used task-completion time (i.e., how long an individual interacts with a website

to complete a task for) as a primary way to measure efficiency whereby the less time required to complete a task, the more efficient the task-completion experience (e.g., Galletta, Henry, McCoy, & Polak, 2006; Payne et al., 1993). This measure represents a rate: time required divided by number of tasks. Where a user completes only one task, then the task-completion time simply constitutes the amount of time spent exposed to the website. Researchers have also used this same time measurement to describe exposure with more time equating to greater exposure (Bornstein, 1989). Thus, researchers have used time to measure both efficiency and exposure—more time means less efficiency in completing a task but more exposure.

Researchers have also used counts of viewed stimulus materials to represent both efficiency and exposure. For example, Todd and Benbasat (1992a) considered additional information units as a source of additional effort that would reduce efficiency in an apartment-finding task. Similarly, Galletta et al. (2006) considered the number of different webpages that users viewed as a form of effort that created inefficiency in the online shopping context. Similarly, researchers have extensively used counts of stimulus experiences to describe exposure. In a seminal case, Zajonc (1968) counted exposure to unfamiliar men and unfamiliar Chinese written characters. Similarly, Ballard, Hennigan, and McClure (2017) counted how many times individuals drank a beverage across multiple days. In both cases, higher counts equated to greater exposure. Thus, based on these past usages, fewer webpage views and less time required (per task completed) can reflect efficiency in a website experience, while *more* webpage views and *greater* time required can reflect exposure in the same experience.

Next, we present the conflicting arguments for efficiency producing better non-transactional results (Section 2.1) and for exposure producing better non-transactional results (Section 2.2).

2.1 The Case for Efficiency

Individuals are motivated to form accurate and effective attitudes and preferences (Petty & Cacioppo, 1986). Researchers typically view this attitude formation as a cognitive task in which individuals expend cognitive resources to determine attitudes and preferences based on perceived effectiveness of performance. However, because individuals have limited cognitive resources (Simon, 1978), they satisfice in the attitude-forming process by accepting and adopting “good enough” attitudes and preferences rather than persevering to find optimal ones (Karimi, Papamichail, & Holland, 2015; Liu & Goodhue, 2012; Simon, 1955; Wells et al., 2011). Thus, in determining these attitudes and preferences, individuals will likely favor efficiency over absolute accuracy (Payne et al., 1993).

Research in the IS literature has considered IS efficiency as important since the discipline’s early days, with early work evaluating systems using time efficiency and effort efficiency as dependent variables (e.g., Card, Moran, & Newell, 1980; Gaylin, 1986; Gerlach & Kuo, 1991; Gray, John, & Atwood, 1992; Roberts, 1980; Roberts & Moran, 1983). In several studies in the problem-solving context, Todd and Benbasat (1991, 1992b, 1992a, 1994) repeatedly found that, when choosing between better performance and less cognitive effort, users preferred less cognitive effort and, thus, a more effort-efficient experience.

More recently, much IS research has arisen that indicates efficiency’s value in the specific context of website interactions in information-oriented tasks. Galletta et al. (2006) developed and tested a website-navigation cost model that calculates the cost of completing a task on a given website by combining users’ a priori familiarity with the website’s taxonomic structure, the number of webpages they need to navigate through to obtain the information they seek, and the amount of time they need to complete the task. According to the model, task-completion costs increase when users need to expend greater cognitive resources (e.g., when they have low a priori familiarity or when they must navigate through more webpages). The study found that greater cost corresponded with negative user perceptions in terms of attitude toward the website and intent to return and with users’ performance in completing the task. Similarly, in studying the effects of recommendation agents in the online context, researchers have found manipulations that result in lower cognitive loads to result in better product knowledge retention and to have a positive impact on product acceptance (Tam & Ho, 2006). Researchers have also found time efficiency, a key component of usability (Nielsen, 2012), to increase satisfaction and loyalty (Casaló, Flavián, & Guinalíu, 2008) and perceived task success (Palmer, 2002).

Additionally, this line of enquiry has formed the basis of much of the usability literature that one can find in the practitioner community. This literature advocates for website designs that promote a time-efficient experience through clear sign-posting, consistent navigation, and minimal non-instrumental distraction (e.g., Krug, 2005; Nielsen, 2000). It cites Simon’s (1955) work and echoes sentiments that Piroli and Card (1999)

expressed, which Pirolli (2007) sums up in asserting that users engaged in information-search tasks “will prefer technologies that tend to maximize the value (or utility) of knowledge gained per unit cost of interaction” (p. 14). Localized to the online context, the cognitive attitude formation literature contends that users will prefer websites that provide them with satisfactory information while requiring the least amount of effort. Thus, using the aforementioned time and webpage measures to quantify efficiency, we propose the following hypothesis to empirically test the case for efficiency in the brand attitude context:

- H1:** The greater the a) amount of time users spend and b) number of webpages they view on a given website in completing a task, the less positive their brand attitude.

Relatedly, a less-efficient experience could have a negative effect on how well users retain product knowledge. As we note above, a website visit that requires more effort to complete the same task incurs a higher cost in terms of cognitive resources expended as a user must perform more actions and consider more content along the path to complete the task (Galletta et al., 2006). Thus, we can consider this greater cost to complete the task as an increase in the user’s cognitive load. From this perspective, the additional cognitive effort that the brain needs to expend to parse navigational information in searching for the content it needs to complete the task depletes resources that it might otherwise had paid to acquiring and retaining content-based knowledge. Indeed, much research has shown that limiting cognitive load has positive effects on learning and knowledge retention (e.g., Chandler & Sweller, 1996; Hessler & Henderson, 2013; Raman et al., 2010; Van Merriënboer, Schuurman, De Croock, & Paas, 2002). Inversely, then, we would expect that a less-efficient task-completion experience that causes a greater cognitive load should inhibit individuals from retaining knowledge and hypothesize:

- H2:** The greater the a) amount of time users spend and b) number of webpages they view on a given website in completing a task, the less product knowledge they retain.

2.2 The Case for Exposure

The mere exposure lens offers a different perspective from the cognitive attitude formation lens. Mere exposure refers to the phenomenon whereby repeated exposure to a given stimulus, absent concurrent adverse events, produces a positive affect toward that stimulus (Bornstein, 1989; Inoue, Yagi, & Sato, 2018; Lowry et al., 2008; Zajonc, 1968, 2001). In other words, greater exposure to the same positive or neutral stimulus promotes a preference for that stimulus. Zajonc (1968, 2001) contends that merely being exposed to a stimulus is a sufficient condition to predict preference given that the stimulus presentation does not coincide with individuals perceiving any negative event. Researchers have demonstrated this effect in many contexts and used it extensively in communications, marketing, and psychology research (e.g., Abernethy, 1991; Janiszewski, 1993; Monahan, Murphy, & Zajonc, 2000; Shapiro, MacInnis, & Heckler, 1997; Shapiro & Nielsen, 2013).

Despite its potential usefulness for IS research, mere exposure appears in few IS studies. Researchers have used the concept to explain potential adopters’ preference for innovations that they have seen more frequently (Moore & Benbasat, 1991) and their preference for brands they have seen in a social media context (Xie & Lee, 2015). Other IS researchers have referred to mere exposure to explain how brand images strengthen brand attitudes in certain online contexts (Lowry et al., 2008), how users develop attachments in Web-based communities (Ren et al., 2012), and how product exposure affects product recommending (Parsons & Ralph, 2014).

Much research that has tested the mere exposure effect includes experiments in which participants experienced stimuli that appeared multiple times at varying frequencies and for varying durations. Subsequently, participants provided responses regarding preference and/or knowledge retention (Bornstein, 1989). For instance, in his seminal paper on the subject, Zajonc (1968) reported on experiments that demonstrated the mere exposure effect in predicting preference for nonsense words, Chinese written characters unfamiliar to the participants, and photographs that depicted unfamiliar men. In each case, more exposures to the stimuli resulted in greater positive affect in each case. Other researchers have expanded on these findings and discovered that not only exposure frequency but also exposure duration relates to both learning and positive affect (Stang, 1975) and that mere exposure can positively affect how well individuals can recall presented stimuli (Sawyer, 1973).

Researchers have explained the mere exposure effect as resulting from an inherent, basic fear of the unfamiliar (Zajonc, 2001). Research that has used galvanic skin response testing and shown that unfamiliar stimuli provoke agitation in subjects supports this perspective (Zajonc, 1968). Other research has demonstrated that the effect does not require cognitive processing (Fang, Singh, & Ahluwalia, 2007;

Janiszewski, 1993). In studying brand names and product packaging, Janiszewski (1993) found that the mere exposure effect was significant even when the consumer could not recall the initial exposure to the stimulus. Consequently, incidental, unintentional, and even unrecognized exposure to a stimulus can result in the mere exposure effect. Janiszewski argued that this effect occurs through the pre-attentive processing mechanism whereby an individual's subconscious notices stimuli but the individual's brain filters them out before the individual becomes consciously aware. Thus, small exposures can begin to have a positive effect even when an individual does not cognitively process brand information when exposed to it.

In summary, when considering non-transactional website outcomes, the mere exposure perspective suggests that the more an individual is exposed to stimuli (in terms of both webpage views and exposure time), the more familiar the individual will become with the stimulus and the stronger the positive effect. Thus, in contrast to H1, to test the case for mere exposure, we propose the following alternative hypothesis related to brand attitude:

AltH1: The greater the a) amount of time users spend and b) number of webpages they view on a given website in completing a task, the more positive their brand attitude.

Additionally, a number of studies into the mere exposure effect have measured the effect in terms of knowledge retention. For instance, research has shown that greater exposure (in terms of duration and/or frequency) leads to improved recall of Welsh alphabet characters (Bornstein & D'agostino, 1992), geometric shapes (Mandler, Nakamura, & Van Zandt, 1987), in-game advertisements in video games (Martí-Parreño, Bermejo-Berros, & Aldás-Manzano, 2017), and website advertisements (McCoy, Everard, Galletta, & Moody, 2017). Interestingly, Mandler et al. observed that the recognition of the stimuli is not statistically related to subjects remembering having viewed the stimuli as part of the experimental task (1987), again corroborating the idea that mere exposure occurs at the pre-processing cognitive level. Thus, in contrast to H2, we propose the following alternative hypothesis:

AltH2: The greater the a) amount of time that users spend and b) number of webpages they view on a given website in completing a task, the more product knowledge they retain.

2.3 Efficiency vs. Exposure and Online Task Type

Designing for efficiency or exposure becomes further nuanced when one considers users' intent when arriving at a website. Not all users visit a website to perform the same task, and some users may intend to accomplish multiple tasks depending on why they visited the website (Lowry, Gaskin, & Moody, 2015). For example, a user might visit Amazon's website one day to find how much a specific book costs (a narrow task) and then visit it the next day to determine which vacuum cleaner under US\$200 best suits the user's household needs (a broad, open-ended task). The characteristics of the task that a user wants to perform can affect the user's browsing behavior, which includes the effort the user needs to make to complete the task with a given tool (Punj & Stewart, 1983; Shugan, 1980).

Researchers have typified information-search tasks in an online environment according to their goal directedness (Browne, Pitts, & Wetherbe, 2007; e.g., Deng & Poole, 2010; Hoffman & Novak, 1996; Nadkarni & Gupta, 2007). Goal directedness refers to the degree to which a task requires one to achieve a clear, predetermined objective (Hoffman & Novak, 1996; Nadkarni & Gupta, 2007). For example, purchasing a specific camera model online would constitute a high goal-directedness task, while researching the merits of various camera models based on their features would reflect low goal-directedness (Hoffman & Novak, 1996).

Numerous studies have identified goal directedness's importance in information-search tasks (e.g., Deng & Poole, 2010; Finneran & Zhang, 2003; Jiang & Benbasat, 2007a; Nadkarni & Gupta, 2007; Novak, Hoffman, & Duhachek, 2003; Speier & Morris, 2003; Wells, Fuerst, & Palmer, 2005; Xu, Benbasat, & Cenfetelli, 2014a). Two studies (Deng & Poole, 2010; Nadkarni & Gupta, 2007) have found that more goal-oriented users behave differently than less goal-oriented individuals and that the former prefer websites with less complexity and greater structure when completing a goal-directed task. Accordingly, Deng and Poole (2010) concluded that goal-oriented users "place great emphasis on the efficiency of achieving their task/goal with a minimal expenditure of energy or effort" (p. 716) because, according to the authors, expending additional energy is associated with anxiety, which rises when a goal becomes more difficult to achieve. On the other hand, when a user pursues a less goal-directed task (e.g., a hedonic task), then arousal itself may be the user's goal.

We expect to see a similar effect in our study wherein individuals who complete low goal-directedness tasks will view more effort (as measured based on time spent and webpages viewed) more positively compared to individuals who complete high goal-directedness tasks. Thus, we hypothesize:

- H3:** The a) amount of time that users spend and b) number of webpages that they view on a given website are more positively associated with their brand attitude when they conduct low goal-directedness tasks than when they conduct high goal-directedness tasks.

Other research has considered tasks based on their specificity (i.e., greater goal directedness) and found a significant interaction between an assigned task's specificity and the relevance of content that a website presents to users in predicting information recall in an information search context, which implies an increase in performance when a website provides information more efficiently (Tam & Ho, 2006). More goal-directed tasks depend on cognitive processing, whereas individuals perform less goal-directed more intuitively (Wells et al., 2005). Thus, the additional cognitive processing that users need to perform to complete more goal-directed tasks takes up cognitive resources that they might use for other purposes, such as retaining information. Thus, we expect that, in a lower goal-directedness situation that frees up more cognitive resources, spending more time and viewing more webpages will be associated more positively with product knowledge retention than in the more cognitive-intense higher goal-directedness condition.

- H4:** The a) amount of time that users spend and b) number of webpages they view on a given website are more positively associated with product knowledge retention when they conduct low goal-directedness tasks than when they conduct high goal-directedness tasks.

2.4 Familiarity

Lastly, we verify the relationship between a priori familiarity with a brand and our dependent variables brand attitude and product knowledge when individuals perform an online information search task. As we note above, many studies have identified a link between familiarity and preference (e.g., Axelrod, 1968; Ballard et al., 2017; Johar, Mookerjee, & Sarkar, 2014; Zajonc, 1968; Zajonc & Markus, 1982). Therefore, we propose that, even when this familiarity exists a priori, greater familiarity with a brand prior to an experience with the brand's website will be associated with a more positive brand attitude.

- H5:** Higher a priori brand familiarity is positively associated with a user's brand attitude.

3 Methodology

To test our hypotheses, we performed a laboratory experiment following a two (task type: high vs. low goal-directedness) by three (website: high-familiarity website vs. moderate-familiarity website vs. low-familiarity website) mixed-model factorial design. Task type served as a between-subjects variable and website served as a within-subjects variable. We randomly assigned participants to a task type condition and they interacted with the three websites. We gathered data from three sources: 1) a pre-task survey, 2) recordings of participants' interactions with the three websites during a laboratory session, and 3) a post-task survey that we administered about 10 days after the laboratory session.

3.1 Research Participants

We recruited participants from an undergraduate psychology participant pool at a major university in the United States (US). The participants received academic credit for their participation. In total, 216 participants started the study; however, we excluded data from 14 participants because they did not complete the study, failed attention checks, or did not follow instructions. As a result, our final sample comprised data from 202 participants. Among the participants in our final dataset, 56.7 percent were female, 97.5 percent had lived in the United States for 10 years or more, and the mean age was 19.1 years old ($SD = 3.1$ years).

3.2 Experiment Procedures

After the participants arrived in a computer laboratory, we briefed them about the experiment and obtained their informed consent. The participants completed the pre-task survey before we randomly assigned them to a task type condition. We based these task type conditions on manipulations for more goal-directed and less goal-directed conditions similar to manipulations that previous studies have used (Deng & Poole, 2010; Nadkarni & Gupta, 2007). We then directed participants to interact with three randomly ordered websites and instructed them to answer questions about the information found on each website (note that we

instructed participants to interact with all three websites). The questions about the websites varied by condition as we describe below. Laboratory sessions included 30 to 50 participants in each session. Approximately 10 days ($M = 10.14$; $SD = 2.22$) after each participant's lab session, we emailed a link to the post-task survey that we instructed them to complete. We initially included the time lag between pre-task and post-task surveys in all analyses but found it to be insignificant in all tests. Therefore, we excluded this lag from our analyses.

During the experiment session, we asked the participants to interact with the three real-world websites to accomplish their tasks. We tracked their actions to understand the relationships between those actions and subsequent attitudes. The three websites had a similar structure (i.e., products in product families) and content (each product had multiple webpages of information related to it). In determining the appropriate stimulus websites, we needed to select a product category relevant to the experiment participants. As such, we selected car manufacturer websites as our stimuli as cars constitute a high-involvement product and participants would likely know about them well (Johnson & Russo, 1981). In doing so, we followed other established researchers who have used this product category as a context to study brand attitudes (e.g., Moorthy, Ratchford, & Talukdar, 1997; Punj & Staelin, 1983; Ratchford & Srinivasan, 1993).

We included three websites for a robustness check to ensure we could generalize our results over both familiar and unfamiliar websites and to test the effects that brand familiarity had on our dependent variables. Thus, we identified Toyota's U.S. website, Mitsubishi Motors' U.S. website, and Seat Motors' (a Spanish car manufacturer that sells its vehicles in the United Kingdom (UK)) U.K. website as appropriate website stimuli (see Appendix A for sample screenshots). We selected these websites partly based on website popularity values that we found on Alexa.com at the time we conducted the experiment. According to Alexa, Toyota's U.S. website constituted the most frequently visited Japanese automaker website in the US, whereas Mitsubishi's constituted the least visited Japanese automaker. Similar findings emerged from a pilot study ($n = 38$) that we conducted. In the pilot study, we polled participants about several brands on a scale from one to seven. They rated Toyota as among the most familiar ($M = 5.89$, $SD = 1.58$), Mitsubishi as considerably less familiar, ($M = 3.81$, $SD = 2.01$) and Seat as barely familiar at all ($M = 1.33$, $SD = 0.83$). Although Seat has never marketed cars in the US, we told the participants to assume that Seat planned to sell cars in the U.S. market in the next six months. To account for participants' varying familiarity with these brands and the potential influence that familiarity might have had on our results (Baker, Hutchinson, Moore, & Nedungadi, 1986; Campbell & Keller, 2003; Kent & Allen, 1994; Laroche, Kim, & Zhou, 1996), we tested the effects of brand familiarity as a main effect.

3.3 Experimental Measures

3.3.1 Explanatory Variables

We also manipulated the experimental task by randomly assigning participants to either the high goal-directedness task ($n = 100$) or the low goal-directedness task ($n = 102$). Both tasks exposed participants to several car models and numerous branded webpages from each manufacturer. Regardless of task condition, we instructed all participants to interact with all three websites. The tasks differed based on how specific the information was that users needed to collect (Tam & Ho, 2006). In the high goal-directedness task, we instructed the participants to use the three stimulus websites (and only those websites) to answer nine discrete, factual questions about the brand and specific car models (three for each website) with 10 multiple-choice options per question and an additional "can't find/don't know" option. See Table A2 in Appendix A for the questions we used in the goal-directed condition. We asked the participants who we assigned to the low goal-directedness task to use the three websites to find four car models in total that they liked and explain why those models appealed to them.

The participants also completed a scale for brand familiarity using seven items that we derived from the existing literature (Alba & Hutchinson, 1987; Campbell & Keller, 2003; Collins, 2007; Kent & Allen, 1994; Lowry et al., 2008; Stewart, 1992). We captured the time that participants spent (in seconds) and how many webpages they viewed on each website using Windows Problem Steps Recorder (PSR) logs. To achieve variation in time spent and webpages viewed, we allowed participants to spend as much time as they wished to perform the task. In doing so, we also allowed natural website browsing behaviors and their consequences to emerge. We instructed the participants to turn on PSR to capture their actions in the XML-formatted log file (see Figure A2 in Appendix A). Thus, participants generated a unique recording of their interactions with each website that we could match with their pre-task and post-task survey responses. We

parsed the XML files using a custom Perl script and summarized them to determine the values for the time they spent and how many webpages they viewed on each website.

3.3.2 Response Variables

In a post-task survey, we collected data for two response variables: brand attitude and an objective measure of product knowledge retention. We collected this data approximately 10 days after participants completed the experimental task. We used established instruments to measure brand attitude (Gardner, 1985; Liu & Shrum, 2002; Machleit & Wilson, 1988). We measured product knowledge by asking the participants to name up to five car models that the three brands in the stimuli manufactured. We display the individual items and measurement properties for all scales that we used in the experiment in Appendix B.

3.3.3 Control Variables

In the pre-task survey, we gathered participant demographics and control variables (see Appendix B). Although we selected a high-involvement product for the experiment (Johnson & Russo, 1981), we also measured product involvement because it affects information search (Schmidt & Spreng, 1996) and brand attitudes (Petty, Cacioppo, & Schumann, 1983). We also measured participants' product involvement using an established scale (Zaichkowsky, 1994) to capture the degree to which participants engaged with cars. Finally, we included dummy variables to control for the websites that the participants viewed (i.e., Toyota and Seat). Since the participants viewed *actual* websites (i.e., they did not view websites in a controlled environment), including the websites as variables helped to account for potential differences between websites that could have affected brand attitude and product knowledge (e.g., number of available car models). We used a mean substitution procedure for participants who neglected to complete each control variable item.

4 Analysis Results

Table 1 presents the descriptive statistics of the variables that we used in the analysis.

Table 1. Descriptive Statistics of Model Variables

Variable	Unit	Brand	High goal-directed	Low goal-directed
			Mean (SD)	Mean (SD)
Webpages	Number of webpages viewed	Toyota	17.81 (7.83)	14.49 (14.00)
		Mitsubishi	23.23 (12.79)	12.13 (10.52)
		Seat	27.26 (11.40)	17.68 (12.99)
		All Brands	22.77 (11.51)	14.76 (12.75)
Time	Seconds	Toyota	101.94 (41.46)	114.72 (85.33)
		Mitsubishi	160.25 (62.11)	91.63 (72.64)
		Seat	180.51 (68.12)	108.87 (78.61)
		All Brands	147.57 (67.05)	105.07 (79.38)
Brand attitude	Likert-type scale (1-7)	Toyota	4.77 (1.19)	5.17 (0.87)
		Mitsubishi	4.61 (0.99)	4.50 (1.06)
		Seat	3.85 (1.23)	3.95 (1.14)
		All Brands	4.41 (1.21)	4.54 (1.14)
Product knowledge	Car models recalled (0-5)	Toyota	2.55 (1.54)	2.69 (1.68)
		Mitsubishi	0.70 (0.95)	0.72 (0.79)
		Seat	0.11 (0.45)	0.18 (0.45)
		All Brands	1.12 (1.49)	1.19 (1.54)
Brand familiarity	Likert-type scale (1-7)	Toyota	3.82 (1.17)	4.05 (1.27)
		Mitsubishi	2.88 (1.19)	2.77 (0.96)
		Seat	1.6 (0.75)	1.47 (0.65)
		All Brands	2.77 (1.39)	2.76 (1.45)
Product involvement	Likert-type scale (1-7)	Total	5.52 (0.86)	5.53 (0.85)

4.1 Model Specification

To understand the effect that the explanatory variables had on the response variables, we conducted analyses using two generalized estimating equations (GEEs). The first GEE examined the effect that the explanatory variables had on brand attitude and the second GEE on product knowledge retention. We used GEEs because they allow interactions between categorical (e.g., task type) and continuous (e.g., webpages and time) variables. In addition, GEEs can model correlated observations from the same participant (Myers, Montgomery, Vining, & Robinson, 2012). The participants in our data collection interacted with and recorded their attitudes about brands associated with the three websites. Therefore, their actions and attitudes were not independent observations. Supplemental analysis suggested that an exchangeable correlation structure was the most appropriate for brand attitudes and an AR(1) correlation structure was the most appropriate for product knowledge (see Appendix C, Table C1). We used the GENLIN procedure from SPSS (v. 24) to create the GEEs.

Equations 1 and 2 represent our theoretical models and specify the terms of each GEE. These models control for the potential effects of the website and account for expected main and interactive effects.

$$\begin{aligned} \text{Brand Attitude}_{\text{Brand}} = & \beta_0 + \beta_1 (\text{Toyota Website}) + \beta_2 (\text{seat website}) + \beta_3 (\text{Product Involvement}) \\ & + \beta_4 (\text{Brand Familiarity})_{\text{Brand}} + \beta_5 (\text{Years U.S. Residency}) + \beta_6 (\text{participant sex}) + \beta_7 (\text{Participant} \\ & \text{Age}) + \beta_8 (\text{Task Type}) + \beta_9 (\text{Webpages}) + \beta_{10} (\text{Time}) + \beta_{11} (\text{Task Type} \times \text{Webpages}) + \beta_{12} \\ & (\text{Task Type} \times \text{Time}) + \varepsilon \end{aligned} \quad (1)$$

$$\begin{aligned} \text{Product Knowledge}_{\text{Brand}} = & \beta_0 + \beta_1 (\text{Toyota Website}) + \beta_2 (\text{Seat Website}) + \beta_3 (\text{Product} \\ & \text{Involvement}) + \beta_4 (\text{Brand Familiarity})_{\text{Brand}} + \beta_5 (\text{Years U.S. Residency}) + \beta_6 (\text{Participant Sex}) + \\ & \beta_7 (\text{Participant Age}) + \beta_8 (\text{Task Type}) + \beta_9 (\text{Webpages}) + \beta_{10} (\text{Time}) + \beta_{11} (\text{Task Type} \times \\ & \text{Webpages}) + \beta_{12} (\text{Task Type} \times \text{Time}) + \varepsilon \end{aligned} \quad (2)$$

To examine the fit of the models, we employed an iterative technique that Hosmer and Lemeshow (2000) recommended and previous researchers have used (e.g., Meservy, Jensen, & Fadel, 2013; Zmud, Shaft, Zheng, & Croes, 2010). We first created models that included only the control variables and then added the hypothesized main and interactive effects. We compared the fit of these models using the corrected Quasi-likelihood under the independence model criterion (QICC; Pan, 2001), which penalizes unnecessary model complexity and indicates better fit with a lower value. As Tables C2 and C3 in Appendix C illustrate, the hypothesized models for both brand attitude and product knowledge retention produced the best fit. Table 2 presents the results for the hypothesized models for brand attitude and product knowledge retention as Equations 1 and 2 specify.

The effects of time spent on brand attitude and product knowledge retention were both positive and significant. These findings concur with the case for exposure and support Alth1a and Alth2a. However, the number of webpages that participants viewed had a significant and negative effect on product knowledge, which concurs with the case for efficiency and supports H2b. Therefore, we interpreted and plotted each interaction.

First, Figure 1 plots the significant interaction between task type and webpages for brand attitude across the three car manufacturer brands. Consistent with H3b, the relationship between number of webpages participants viewed and brand attitude was positive for the low goal-directed treatment but negative for the high goal-directed treatment. In addition, the effect that the interaction between task type and time had on product knowledge retention approached significance ($p = .067$). We plot this interaction in Figure 2, which shows a positive relationship between time and product knowledge retention for low goal-directed tasks. However, for high goal-directed tasks, we see a slightly negative relationship between time and product knowledge retention. These findings concur with our arguments for H4a, although we require additional empirical evidence to support this hypothesis.

Brand familiarity demonstrated significant effects on brand attitudes and product recall. These results support H5. However, we did not find support for H1b, Alt H1b, H3a, and H4b. Notably, three control variables played prominent roles in the model: 1) years of U.S. residency decreased brand attitudes, 2) gender affected knowledge retention in that male participants had greater knowledge retention for automobile-related content, and 3) the individual websites influenced brand attitude and product knowledge retention. As the results in Table 2 illustrate, participants expressed less positive brand attitude and lower product knowledge retention about Mitsubishi and Seat cars than Toyota. Table 3 summarizes our results from testing our hypotheses.

Table 2. GEE Results of Models for Brand Attitude and Product Knowledge Retention

Parameter	Brand attitude				Product knowledge			
	Coeff. (SE)	Wald χ^2	Df	Sig.	Coeff. (SE)	Wald χ^2	Df	Sig.
Intercept	4.212 (0.3241)	168.870	1	<0.001	-0.863 (0.4472)	3.727	1	0.054
Website (Toyota)	0.200 (0.0841)	5.668	1	0.017	1.445 (0.1154)	156.799	1	<0.001
Website (Seat)	-0.425 (0.1049)	16.368	1	<0.001	-0.034 (0.0737)	0.219	1	0.640
Product involvement	0.121 (0.0727)	2.765	1	0.096	0.111 (0.0621)	3.186	1	0.074
Brand familiarity	0.231 (0.0431)	28.683	1	<0.001	0.378 (0.0451)	70.525	1	<0.001
Years U.S. residency	-0.188 (0.0638)	8.631	1	0.003	0.085 (0.0541)	2.499	1	0.114
Participant sex	0.205 (0.1062)	3.737	1	0.053	-0.468 (0.0978)	22.956	1	<0.001
Participant age	-0.018 (0.0091)	3.785	1	0.052	-0.023 (0.0212)	1.153	1	0.283
Task type	0.041 (0.2309)	0.032	1	0.859	0.236 (0.2098)	1.265	1	0.261
Webpages	0.008 (0.0066)	1.560	1	0.212	-0.015 (0.0065)	5.695	1	0.017
Time	0.003 (0.0011)	9.711	1	0.002	0.003 (0.0012)	4.750	1	0.029
Task type × webpages	-0.023 (0.0110)	4.492	1	0.034	0.005 (0.0084)	0.312	1	0.577
Task type × time	0.001 (0.0018)	0.327	1	0.567	-0.003 (0.0015)	3.344	1	0.067

Figure 1. Task Type × Webpages Interaction on Brand Attitude for Toyota, Mitsubishi, and Seat Brands

Figure 2. Task Type × Time Interaction on Product Knowledge Retention for Toyota, Mitsubishi and Seat Brands

Table 3. Summary of the Results from the Hypothesis Testing Case for Efficiency

Hypothesis	Expected effects	Result
Case for efficiency		
H1a	The greater the amount of time users spend on a given website in completing a task, the less positive their brand attitude.	Not supported
H1b	The greater the number of webpages users view on a given website in completing a task, the less positive their brand attitude.	Not supported
H2a	The greater the amount of time users spend on a given website in completing a task, the less product knowledge they retain.	Not supported
H2b	The greater the number of webpages users view on a given website in completing a task, the less product knowledge they retain.	Supported
Case for exposure		
AltH1a	The greater the amount of time users spend on a given website in completing a task, the more positive their brand attitude.	Supported
AltH1b	The greater the number of webpages users view on a given website in completing a task, the more positive their brand attitude.	Not supported
AltH2a	The greater the amount of time users spend on a given website in completing a task, the more product knowledge they retain.	Supported
AltH2b	The greater the number of webpages users view on a given website in completing a task, the more product knowledge they retain.	Not supported
Interactions with task type		
H3a	The amount of time that users spend on a given website is more positively associated with their brand attitude when they conduct low goal-directedness tasks than when they conduct high goal-directedness tasks.	Not supported
H3b	The number of webpages that users view on a given website is more positively associated with their brand attitude when they conduct low goal-directedness tasks than when they conduct high goal-directedness tasks.	Supported
H4a	The amount of time that users spend on a given website is more positively associated with user product knowledge retention when they conduct low goal-directedness tasks than when they conduct high goal-directedness tasks.	Marginally supported
H4b	The number of webpages that users view on a given website is more positively associated with user product knowledge retention when they conduct low goal-directedness tasks than when they conduct high goal-directedness tasks.	Not supported
Familiarity		
H5	Higher a priori brand familiarity is positively associated with a user's brand attitude.	Supported

5 Discussion

In this study, we examine questions about what browsing behaviors a website should encourage to improve two non-transactional objectives: brand attitude and product knowledge retention. Two relevant theoretical lenses offer potentially conflicting practical recommendations: the cognitive attitude formation perspective suggests that users will view a website more favorably and retain more knowledge when they find the website efficient to navigate, while the mere exposure perspective suggests that these outcomes will occur when a user is exposed to brand-related stimuli more frequently and for longer durations. From a pragmatic standpoint, these lenses create a conundrum for website owners: should they encourage website interactions that favor efficiency or those that encourage lingering? With this observational study, we shed light on this design conflict by considering efficiency and exposure based on the time that individuals spend and the number of webpages they view on a given website and examining the question in both high and low goal-directedness contexts. Consistent with the expectations in past research, we found that more individuals view familiar brands more positively after a Web-based user interaction.

5.1 Contributions to Research and Practice

This research makes several contributions to research and practice. First, we found general support for the notion that both efficiency and exposure constitute influential factors in how users perceive brands and brand-related information when completing information-search tasks. Although we observed more significant effects for exposure, we also observed significant effects for efficiency, which suggests conflict in terms of when each one becomes salient. These conflicting findings illustrate the complex potential tradeoffs that website designers face as they consider how to design websites to achieve their objectives. To untangle these conflicting findings, we address the findings associated with time and webpage views separately.

Second, we found that time had a uniformly positive relationship with brand attitude and a positive relationship with product knowledge retention for low-goal directedness tasks. This result paints a relatively stable picture of time's effect: for non-transactional outcomes, more time exposed to stimuli is associated with better outcomes for website owners. This finding suggests that navigational efficiency may not represent the most important consideration when designing websites. However, we note that this finding concurs with recent research that has indicated that non-utilitarian factors (e.g., aesthetics) better predict attitudes toward websites (Jiang, Wang, Tan, & Yu, 2016). That said, we found an important boundary condition on time's effect: the anticipated improvements associated with increasing time reversed when users performed high goal-directedness tasks.

Based on our empirical results and past studies on the mere exposure effect, we suggest two possible reasons that may explain the disparity between our outcome and some earlier findings that favored efficiency. First, we focus on the question primarily from website owners' perspective and on non-transactional dependent variables related to their brands, and, second, given the 10-day lag between when we conducted the experiment and collected data for the dependent variables, our results avoid priming effects and may rely less on cognitive appraisal and more on the latent, pre-attentive processing that researchers have found to be instrumental to the mere exposure effect's success. Crucially, these two explanations relate to each other.

In the first case, prior studies have typically considered websites and other such digital content systems from the perspective of transactional outcomes, such as intent to purchase (e.g., Benbasat, 2006; Campbell & Wells, 2013; Galletta et al., 2006; Lowry et al., 2008; McKnight & Choudhury, 2006) and intent to return (e.g., Coyle & Thorson, 2001; Galletta et al., 2006; Goel, Johnson, Junglas, & Ives, 2011; McCoy, Everard, Polak, & Galletta, 2008). Often, these findings have been built on cognition-based premises. For instance, researchers have used information foraging theory (Pirulli & Card, 1999) in developing the expectation that users make rational, cost-based browsing decisions (Galletta et al., 2006; Moody & Galletta, 2015). They have also used cognitive decisions to explain the effect that trust (McKnight et al., 2002) and presentation formats (Jiang & Benbasat, 2007a) have on users' ecommerce behaviors. Indeed, the question posed to users regarding whether they intend to perform an action requires users to engage in a cognitive evaluation process using criteria (e.g., cost of action, expected outcome) to arrive at a justifiable conclusion. In contrast, research shows that outcome variables such as brand attitude and product knowledge retention come about less so due to cognitive processing and more so due to emotion and latent memory (Lowry et al., 2008, 2012).

Furthermore, as prior studies have shown (e.g., Fang et al., 2007; Janiszewski, 1993; Zajonc, 1968), mere exposure is effective and predictive regardless of whether individuals cognitively process information. In our study, we collected the non-transactional dependent variables about 10 days after participants completed our experiment. Given this time lag, the participants were more apt to provide emotion-based and latent responses rather responses that resulted from immediate cognitive processing (e.g., priming) following an experience. Thus, the time lag may have revealed more enduring emotional and latent memory outcomes than traditional, immediate experimental priming would have. For website owners, this outcome indicates that they need to consider and measure non-transactional outcomes across a longer period of time rather than as the immediate effect of an online experience.

Next, although mere exposure appears to be the more important factor when one measures it based on duration, we found that the number of webpages participants viewed had a contradictory effect on brand attitude and product knowledge retention. The number of webpages participants viewed related to a negative main effect on product knowledge recall and was involved in an interaction effect that reduced brand attitudes. These findings show that stimulus exposure frequency had a more nuanced effect on our dependent variables than exposure duration. For low goal-directedness tasks, we found that brand attitude

improved when the time that participants spent on a given webpage increased (duration) but the number of webpages they viewed *decreased*. We also found a similar result for product knowledge recall. Taken together, these findings suggest that, depending on a user's intentions when entering a website, website owners should encourage different on-website browsing behaviors and provide users with low goal-directedness intent an experience that maximizes the interaction's duration while minimizing the number of webpages they navigate.

The finding that users' navigation among more webpages corresponded with lower product knowledge retention echoes earlier findings in the cognitive attitude formation literature. According to cognitive attitude formation, greater cognitive effort expended during a task comes at the cost of decreased information recall (Tam & Ho, 2006), while lesser effort corresponds with a more positive attitude (Galletta et al., 2006).

Our results also confirm the finding from past literature (e.g., Axelrod, 1968; Ballard et al., 2017; Johar et al., 2014; Zajonc, 1968; Zajonc & Markus, 1982) that familiarity yields better brand attitudes. This finding corresponds with the idea that, psychologically, users prefer things (e.g., brands) that they know better and, therefore, view them as "safer" than things they know less well.

Finally, we note that a website design approach that benefits a website's owner does not necessarily match with users' best interests. From the cognitive attitude formation perspective (e.g., Payne et al., 1993; Todd & Benbasat, 1991), systems that allow users to complete tasks with a minimal time and effort improve users' welfare. Considerable research has confirmed that, from users' perspective, time and effort represent costs that they try to avoid paying (e.g., Galletta et al., 2006; McCoy et al., 2008; Moody & Galletta, 2015). However, our findings show that, from a website owner's perspective and in terms of users' attitude toward the website owner's brand and degree to which they retain product knowledge, the website owner benefits more when at least part of this cost (i.e., time) increases. Limits likely exist for the length of time that users will tolerate as they navigate websites that increase their exposure. However, our findings suggest some benefit for website owners in creating a positive but longer website experience. As Pirolli (2007) asserts, users prefer technologies that maximize the value of the knowledge they gain per unit of cost. However, website owners may have other preferences.

5.2 Limitations and Future Research Directions

Despite our promising findings, our research has limitations that suggest useful future research opportunities. First, we considered a specific context: college students interacting with car manufacturer websites. We controlled for website and manipulated familiarity and the task to better generalize our findings. Nonetheless, laboratory experiments may have limited generalizability. We selected car-related websites primarily due to previous findings that show consumers have high product involvement with automobiles (e.g., Punj & Staelin, 1983) and involvement's usefulness in eliciting phenomenological behavior (e.g., Gu, Park, & Konana, 2012; Phelps & Thorson, 1991). However, future research should consider the likelihood that products and subject matters that elicit low user involvement may produce different results.

Moreover, because we used car manufacturer websites as our stimulus websites, each website contained a similar latent and hierarchical structure with a car brand at the top followed by vehicle categories, vehicle models, and vehicle trims. Indeed, due to this similar structure, we could control for website structure. However, due to product type or subject matter, other websites could require substantially different structures that could produce different outcomes. We controlled for website in all analyses to address possible related confounds. However, further investigation into website structure would shed important light on these matters. For instance, researchers could vary product or content type and website structure (e.g., testing website layout designs' depth and breadth).

Second, the participants could freely interact with the websites in the way they preferred. This experimental approach followed similar website research that has allowed more natural (Galletta et al., 2006; Moody & Galletta, 2015) and, thus, arguably more ecologically valid interactions (Brewer & Crano, 2000). However, depending on users' actions and the navigational decisions they made in completing the tasks we assigned, they could have been exposed to different sets of branding material. Therefore, all relationships we observed in this study are associative and we need additional research to demonstrate causality. We note, however, that each manufacturer website uniformly portrayed its brand's products in a positive manner. Furthermore, we attempted to capture relevant differences by modeling the effects of number of webpages viewed and time spent along with control variables for each website. By randomizing participants, we also helped to control for these effects. Therefore, the potential for confounding effects resulting from individual,

idiosyncratic browsing behavior was likely small. That said, researchers should conduct future work in which they specifically manipulate time and number of webpages viewed.

We also acknowledge that the time limitation that we used as a parameter in collecting data may have affected user behavior. We used this time limitation to help encourage participants to have a time-similar experience across the two different task types. However, it may have affected user behavior in unexpected ways. Future research may benefit from running a similar study without time limits.

Next, time spent and webpages viewed may not have had a linear effect on brand attitude and product knowledge retention. Indeed, while earlier research has shown a linear relationship for time on positive affect (Stang, 1975), other research has found an inverted U-shaped relationship (Hamid, 1973). We expect that diminishing effects on brand attitude and product knowledge retention will likely emerge as time spent increases to high levels. We do not know the point at which these diminishing returns begin, although such information has significant practical value and, therefore, requires more research.

Finally, the 10 days we waited for before collecting data for our dependent variables constitutes one of the most important factors in our study. With this lag, we could gather responses that resulted less from priming and more from latent emotion and knowledge. Further delving into this lag effect could provide important additional insight into the interplay among efficiency, exposure, and non-transactional outcomes. For instance, varying the length of time between when researchers conduct an experimental task and collect data for dependent variables could enable them to better understand any time-based transitions from primarily cognitive to primarily emotional evaluations. Perhaps more interestingly, a longitudinal study in which researchers meted out the exposures over days or weeks and required users to complete multiple tasks could facilitate a more nuanced investigation into the tradeoffs between efficiency and exposure.

6 Conclusion

Companies that seek to improve non-transactional outcomes for their websites face difficult challenges when designing websites to promote the browsing behaviors that yield those outcomes. In our study, we considered the seemingly contradicting views that emerge when one considers both the cognitive attitude formation literature, which suggests that website owners should encourage efficient experiences, and the mere exposure perspective, which suggests that they should expose users to more content for long periods. Our findings provide evidence that the specific circumstances of a user's visit dictate the more salient recommendation. Indeed, while we found that time spent on a website generally had a positive and significant main effect in predicting improved brand attitude and increased product knowledge retention, we also found that the task's nature moderated these effects

These findings contribute significantly to explaining the relationship between users' behavior in a digital content environment and how they perceive that environment's sponsor. We used non-transactional outcomes as our dependent variables, which researchers have not studied as thoroughly as transactional outcomes, such as intent to purchase. We also show the different circumstances where the cases for efficiency and exposure become specifically salient. Finally, by using a 10-day lag between when we conducted our experiment and collected data for our dependent variables, our study suggests the differing roles that emotional response and cognitive response play in building attitudes toward website sponsors and how one or the other may be more relevant depending on the task that users perform.

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Appendix A: Methodology Support

Stimulus Materials

We show sample screenshots from the three websites that we used in the experiment in Figure A1.

Figure A1. Experimental Stimulus Websites (Top: Toyota.com, Middle: MitsubishiUSA.com, Bottom: Seat.co.uk)

Pilot Study

In deciding which websites to use, we conducted a pilot study to identify brands (and accompanying websites) with high, medium, and low familiarity scores. We used the first five items in the familiarity scale that we show in Table B1 to gauge familiarity. Table A1 presents the results for all the brands that we tested during the pilot. We selected Toyota because the familiarity did not differ between Honda and Toyota and the color scheme on Toyota's website resembled the color scheme on the Mitsubishi and Seat websites.

Table A1. Descriptive Statistics Pilot Study of Brand Familiarity

Brand	N	Rank	Mean familiarity (SD)
Honda	38	1	5.42 (1.42)
Toyota	38	2	5.31 (1.58)
Subaru	38	3	4.00 (1.91)
Mitsubishi	38	4	3.81 (2.01)
Infiniti	38	5	3.69 (2.18)
Seat	38	6	2.33 (0.83)

Task Type

The goal-oriented task used in the experiment included nine discrete, factual questions that we instructed participants to answer. We list these questions in Table A2.

Table A2. Goal-oriented Task Questions

Brand	Abbreviation	Question
Toyota	Qprice	What is the "starting price" (i.e., list price exclusive of options or upgrades) of the Toyota Tundra Double Cab?
Toyota	Qsize	In liters, what is the size (displacement) of the engine available with the Toyota Camry Hybrid LE?
Toyota	Qdealer	What does Toyota recommend as the closest Toyota car dealership for someone living in zip code 92691?
Mitsubishi	Qwarrant	What is the maximum number of years covered under warranty on the Mitsubishi i-MiEV's main drive lithium ion battery?
Mitsubishi	Qseats	How many people does Mitsubishi suggest its Lancer Sportback can seat?
Mitsubishi	Qmirror	What price does Mitsubishi list for the chrome side mirror covers accessory available for the Outlander Sport?
Seat	Qcolors	How many color options are available on the Seat Ibiza SC FR?
Seat	Qmpg	What is the official estimated gas mileage (mpg) range in "urban" driving for the Seat Altea XL?
Seat	Qcity	In which city did Seat open its first manufacturing plant in 1953?

Finally, when participants recorded their activities using the Windows Problem Steps Recorder (PSR), they created an XML file that described their recorded activities. We show an XML file example in Figure A2. Using a custom-made Perl script, we parsed the XML files into tab-delimited files (see Figure A3), which we then summarized to create values for time and webpages viewed for each website.

Product Knowledge Retention Scoring

We collected dependent variable data for brand attitude and product knowledge retention about 10 days after participants completed the experiment. We sent these post-task surveys out in batches, which resulted in a time lag from between six and 15.5 days with a median of 10.3 and a mean of 10.1 days depending on when participants completed it. We measured participant scores for brand attitude using an instrument that we developed from other established instruments (Gardner, 1985; Liu & Shrum, 2002; Machleit & Wilson, 1988).

On the other hand, we scored product knowledge retention based on a survey question that asked participants to list as many car models as they could from the three manufacturers up to five models total (although, at the time we conducted the experiment, Mitsubishi's website presented only four valid models). Therefore, we included control variables for website to account for the disparity in available car models. Participants then typed the models' names into blanks provided. We scored each participant based on the number of correct models they named. To count as a correct answer, users had to name a car's consumer model (not trim levels) that the manufacturer's website presented at the time we conducted the experiment.

Of course, participants varied in how they spelt the models, which meant we had to make judgments about whether to classify a submission as correct or not. For each brand, we accepted the following misspellings:

Toyota: Camary, Cambry, camery, Camrey, camri, carmey (for Camry); Carola, Carolla, Corolla, corella, corola, Corollsa, Corrolla, Corrola (for Corolla); fordrunner, forerunner, Four Runner (for 4Runner); Prias, Prius, Prys, Pryus (for Prius); rad4, Rav, Rav5 (for RAV4); Sequoya (for Sequoia); Siena (for Sienna); tachoma, Takoma, Tocomo (for Tacoma); Tuundra (for Tundra); Venzas (for Venza)

Mitsubishi: galante, Gallant, Galuant, Glant (for Galant); i-Meid, miev (for i-MIEV); laner (for Lancer)

Seat: Altera, Aletra, Alta (for Altea); Abiza, Ibiaz (for Ibiza); Exio (for Exeo); Leo (for Leon).

On the other hand, the following were *not* accepted, either due to the entry being the name of a trim (e.g., "SC FR", a trim offered for multiple Seat models), the name of a no-longer-current model that was not on the website (e.g., "Celica"), the name of a model made by a manufacturer that was not part of the experiment (e.g., "Challenger"), or that was otherwise not an accurately identified, valid model (e.g., "Sky Rocket"). The following, then, were not accepted:

Toyota: avis, Bolt, camera, celica (not current), Challenger, chevy, Civic, Crew Max (trim level), CRV, douge, echo (not current), Eclipse, elantra, evo, Explorer, Fit, homery, hundai, Hybrid, Ion, lancer, odyssey, outback, outlander, pacifica, ranger, RX7, RX8, RX9, Salora, Scion, Siantra, Sierra, Single Cab (trim level), Sivci, Solara (not current), Solanco, Sonata, Supra (not current), Tahoe, Takoya, Titan, tocumpsa, Ultima, Versa

Mitsubishi: 3000 (not current), CRX, Dart, Diamante (not current), Eclipse (not current), eclispse, elantra, Endevor (not current), Equipse, firebird, Forrester, G, Highlander, Hybrid, Kizashi, Mazda, mieus, Montera, Montero (not current), rav 4, RX, rx-3, Sasuki, Skyline, Sport, Spyder (not current), Suzuki, Tribeca, Tudnra

Seat: Acura, Alanta, Aleza SC, Alta, Avalon, Camry, clio, Evo, Explorer, Extre, fc lx, Fiat, Ford focus, Honda accord, infiniti G35, Highlander, Inca, isca, lancer, MDX, mini, No Vat, rouge, S, SC FR (trim level), scion tc, SE 76, Sky Rocket, XL FR (trim level)

When participants entered the same model name multiple times, we scored it as one correct answer. For example, one participant entered "Camry 1998" and "Camry 2008", which we scored as one correct response for Camry. When respondents entered both a model and trim, we counted it as a correct answer for the model (e.g., we scored the response "Outlander Sport" as a correct response since "Outlander" was a valid model). Finally, the car manufacturers marked some trim levels as if they were models. In particular, Mitsubishi often marketed its Lancer Evolution (or "Evo") as its own model with the word Lancer omitted from the name, which presented a problem in scoring that we resolved by counting either "Evolution" or "Lancer" but not both (we also accepted the nickname "Evo" in place of "Evolution").

```

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<head>
<meta http-equiv="Content-Type" content="text/html; charset=utf-8" />
<link rel="stylesheet" type="text/css" href="main.css"></link>
<title>Recorded Problem Steps</title>
</head>
<body>
<!-- This is the recorded XML problem data that was used in generating this page. -->
<xml id="recordedata">
<?xml version="1.0" encoding="UTF-8"?>
<Report>
  <System MajorVersion="6" MinorVersion="1" ServicePackMajor="1" ServicePackMinor="0" BuildNumber="7601" Sku="4" Platform="1" />
  <UserActionData>
    <RecordSession SessionCount="1" StartTime="12:29:49 PM" StopTime="12:50:14 PM" ActionCount="382" MissedActionCount="0">
      <EachAction ActionNumber="1" Time="12:30:02 PM" Pid="3180" ProgramId="0000f519feec486de87ed73cb92d3cac802400000000" File>
        <Description>User left click on "Mozilla Firefox (list item)" in "Program Manager"</Description>
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        <CursorCoordsXY>41,751</CursorCoordsXY>
        <ScreenCoordsXYWH>0,0,2560,1024</ScreenCoordsXYWH>
        <UIStack>
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          <Level Name="FolderView" RoleId="9" Role="window" Class="SysListView32" Coordinates="0,0,2560,1024" />
          <Level RoleId="9" Role="window" Class="SHELLDLL_DefView" Coordinates="0,0,2560,1024" />
          <Level Name="Program Manager" RoleId="9" Role="window" Class="Progman" Coordinates="0,0,2560,1024" />
        </UIStack>
      </EachAction>
      <EachAction ActionNumber="2" Time="12:30:07 PM" Pid="3180" ProgramId="0000f519feec486de87ed73cb92d3cac802400000000" File>
        <Description>User left click on "Internet Explorer (list item)" in "Program Manager"</Description>
        <Action>Mouse Left Click</Action>
        <CursorCoordsXY>43,642</CursorCoordsXY>
        <ScreenCoordsXYWH>0,0,2560,1024</ScreenCoordsXYWH>
        <UIStack>
          <Level Name="Internet Explorer" RoleId="34" Role="list item" Coordinates="593,0,74,85" />
          <Level Name="Desktop" RoleId="33" Role="list" Coordinates="0,0,2560,1024" />
          <Level Name="FolderView" RoleId="9" Role="window" Class="SysListView32" Coordinates="0,0,2560,1024" />
          <Level RoleId="9" Role="window" Class="SHELLDLL_DefView" Coordinates="0,0,2560,1024" />
          <Level Name="Program Manager" RoleId="9" Role="window" Class="Progman" Coordinates="0,0,2560,1024" />
        </UIStack>
      </EachAction>
    </RecordSession>
  </UserActionData>
</Report>

```

Figure A2. Sample XML File Created by the PSR

208	12:27:00 PM	44820	Mouse Left Click	User left click on "X (editable text)" in "New Cars - Used Cars for Sale - SEAT SEAT.co.uk - Win
209	12:27:02 PM	44822	Mouse Left Click	User left click on "IBIZA SC (link)" in "New Cars - Used Cars for Sale - SEAT SEAT.co.uk - Win
210	12:27:11 PM	44831	Mouse Left Click	User left click on "Survey Qualtrics Survey Software Current Progress 51% (page tab)" in "Ne
211	12:27:14 PM	44834	Mouse Left Click	User left click on "New SEAT Ibiza SC 2012 - Sport Coupé - Ibiza Sport Coupé SEAT.co.uk (page
212	12:27:15 PM	44835	Mouse Wheel Down	User mouse wheel down on "BROCHURE REQUEST (editable text)" in "New SEAT Ibiza SC 2012 - Sport C
213	12:27:17 PM	44837	Mouse Wheel Up	User mouse wheel up on "New SEAT Ibiza SC 2012 - Sport Coupé - Ibiza Sport Coupé SEAT.co.uk (pane
214	12:27:20 PM	44840	Mouse Wheel Down	User mouse wheel down on "New SEAT Ibiza SC 2012 - Sport Coupé - Ibiza Sport Coupé SEAT.co.uk
215	12:27:23 PM	44843	Mouse Wheel Up	User mouse wheel up on "New SEAT Ibiza SC 2012 - Sport Coupé - Ibiza Sport Coupé SEAT.co.uk (pane
216	12:27:31 PM	44851	Mouse Left Click	User left click on "VERSIONS (editable text)" in "New SEAT Ibiza SC 2012 - Sport Coupé - Ibiza S
217	12:27:35 PM	44855	Mouse Left Click	User left click on "New SEAT Ibiza SC 2012 - Sport Coupé Versions SEAT.co.uk (pane)" in "New S
218	12:27:36 PM	44856	Mouse Left Click	User left click on "FR (editable text)" in "New SEAT Ibiza SC 2012 - Sport Coupé Versions SEAT
219	12:27:37 PM	44857	Mouse Wheel Down	User mouse wheel down on "SEAT Ibiza - SC FR SEAT.co.uk (pane)" in "SEAT Ibiza - SC FR SEAT
220	12:27:40 PM	44860	Mouse Wheel Up	User mouse wheel up on "FR Interior Dash (graphic)" in "SEAT Ibiza - SC FR SEAT.co.uk - Windows In
221	12:27:46 PM	44866	Mouse Left Double Click	User left double click on "You'll love the SEAT Ibiza FR. It's designed to be driven - with great looks
222	12:27:46 PM	44866	Mouse Left Click	User left click on "You'll love the SEAT Ibiza FR. It's designed to be driven - with great looks
223	12:27:47 PM	44867	Mouse Left Click	User left click on "SEAT Ibiza - SC FR SEAT.co.uk (pane)" in "SEAT Ibiza - SC FR SEAT.co.uk
224	12:27:50 PM	44870	Mouse Wheel Down	User mouse wheel down on "SEAT Ibiza - SC FR SEAT.co.uk (pane)" in "SEAT Ibiza - SC FR SEAT
225	12:27:50 PM	44870	Mouse Wheel Up	User mouse wheel up on "The sleek design of the SEAT Ibiza FR includes headlights with optional LED
226	12:27:51 PM	44871	Mouse Wheel Down	User mouse wheel down on "SEAT Ibiza - SC FR SEAT.co.uk (pane)" in "SEAT Ibiza - SC FR SEAT
227	12:27:55 PM	44875	Mouse Left Click	User left click on "Next (link)" in "SEAT Ibiza - SC FR SEAT.co.uk - Windows Internet Explorer
228	12:27:56 PM	44876	Mouse Left Click	User left click on "Next (link)" in "SEAT Ibiza - SC FR SEAT.co.uk - Windows Internet Explorer
229	12:27:57 PM	44877	Mouse Left Click	User left click on "Next (link)" in "SEAT Ibiza - SC FR SEAT.co.uk - Windows Internet Explorer
230	12:27:58 PM	44878	Mouse Wheel Up	User mouse wheel up on "SEAT Ibiza - SC FR SEAT.co.uk (pane)" in "SEAT Ibiza - SC FR SEAT.co.uk
231	12:27:58 PM	44878	Mouse Wheel Down	User mouse wheel down on "Diesel Engines (editable text)" in "SEAT Ibiza - SC FR SEAT.co.uk -
232	12:28:02 PM	44882	Mouse Left Click	User left click on "Car Configurator CTA (graphic)" in "SEAT Ibiza - SC FR SEAT.co.uk - Window
233	12:28:08 PM	44888	Mouse Wheel Down	User mouse wheel down in "SEAT Car Configurator - Windows Internet Explorer"
234	12:28:12 PM	44892	Mouse Left Click	User left click on "Continue to Engine (link)" in "SEAT Car Configurator - Windows Internet Expl
235	12:28:15 PM	44895	Mouse Left Click	User left click on "Continue to Design (link)" in "SEAT Car Configurator - Windows Internet Expl
236	12:28:34 PM	44914	Mouse Left Click	User left click on "Survey Qualtrics Survey Software Current Progress 51% (page tab)" in "SE
237	12:28:35 PM	44915	Mouse Left Click	User left click on "9 (radio button)" in "Survey Qualtrics Survey Software Current Progress
238	12:28:36 PM	44916	Mouse Wheel Down	User mouse wheel down on "Survey Qualtrics Survey Software Current Progress 51% (pane)" in "
239	12:28:42 PM	44922	Mouse Left Click	User left click on "Survey Qualtrics Survey Software Current Progress 51% - Windows Internet
240	12:28:43 PM	44923	Mouse Left Click	User left click on "Cars, Crossovers, Coupes, Convertibles, Sedans & Electric / Mitsubishi M
241	12:28:44 PM	44924	Mouse Left Click	User left click on "SEAT Ibiza - SC FR SEAT.co.uk (page tab)" in "Cars, Crossovers, Coupes, Ca
242	12:28:45 PM	44925	Mouse Left Click	User left click on "SEAT Car Configurator (page tab)" in "SEAT Ibiza - SC FR SEAT.co.uk - Wind
243	12:28:47 PM	44927	Mouse Left Click	User left click on "Close Tab (Ctrl+W) (push button)" in "SEAT Car Configurator - Windows Inter
244	12:28:48 PM	44928	Mouse Left Click	User left click on "SEAT Ibiza - SC FR SEAT.co.uk (page tab)" in "Cars, Crossovers, Coupes, Ca
245	12:28:49 PM	44929	Mouse Wheel Up	User mouse wheel up on "The Ibiza FR is bursting with technology. A latest generation electronic XDS
246	12:28:51 PM	44931	Mouse Left Click	User left click on "ALTEA XL (link)" in "SEAT Ibiza - SC FR SEAT.co.uk - Windows Internet Expl

Figure A3. Example of Tab-delimited File Parsed from the XML File that Figure A2 Shows

Appendix B: Measurement Details

Table B1. Pre- and Post-Task Survey Items

Construct (α^1)	Indicator	Item	Source
Brand attitudes (0.947)	BA1	Please indicate how you feel about (brand): From “dislike” to “like”.	Gardner (1985), Li, Daugherty, & Biocca (2002)
	BA2	From “bad” to “good”.	Gardner (1985), Li et al. (2002)
	BA3	From “unappealing” to “appealing”.	Li et al. (2002)
	BA4	From “unpleasant” to “pleasant”.	Gardner (1985), Li et al. (2002)
	BA5	From “unattractive” to “attractive”.	Li et al. (2002)
	BA6	From “boring” to “interesting”.	Gardner (1985), Li et al. (2002))
Brand familiarity (0.835)	BF1	Estimate when you last saw an advertisement for (brand) or one of its vehicles.	Kent & Allen (1994), Stewart (1992)
	BF2	I personally know a lot of people who own a car made by (brand).	Campbell & Keller (2003)
	BF3	I have read a lot of articles about (brand) and/or the cars they make.	Campbell & Keller (2003)
	BF4	I have significant personal experience with cars made by (brand).	Campbell & Keller (2003)
	BF5	I know a lot about (brand) and the cars they make.	Alba & Hutchinson (1987), Lowry et al. (2008)
	BF6	I could talk about (brand) for a long time.	Lowry et al. (2008)
	BF7	I understand (brand) well enough to evaluate it.	Lowry et al. (2008)
Product involvement (0.875)	PI1	To me, cars are... (seven-point bipolar from “important” to “unimportant”)	Zaichkowsky (1994)
	PI2	To me, cars are... (seven-point bipolar from “boring” to “interesting”)	Zaichkowsky (1994)
	PI3	To me, cars are... (seven-point bipolar from “relevant” to “irrelevant”)	Zaichkowsky (1994)
	PI4	To me, cars are... (seven-point bipolar from “exciting” to “unexciting”)	Zaichkowsky (1994)
	PI5	To me, cars are... (seven-point bipolar from “mean nothing” to “mean a lot”)	Zaichkowsky (1994)
	PI6	To me, cars are... (seven-point bipolar from “appealing” to “unappealing”)	Zaichkowsky (1994)
	PI7	To me, cars are... (seven-point bipolar from “fascinating” to “mundane”)	Zaichkowsky (1994)
	PI8	To me, cars are... (seven-point bipolar from “worthless” to “valuable”)	Zaichkowsky (1994)
	PI9	To me, cars are... (seven-point bipolar from “involving” to “uninvolving”)	Zaichkowsky (1994)
	PI10	To me, cars are... (seven-point bipolar from “not needed” to “needed”)	Zaichkowsky (1994)

We computed alphas for each brand's website and then averaged them together for an overall alpha. The lowest alpha for any brand was brand familiarity for the Mitsubishi website ($\alpha = .810$)

Table B2. Factor Analysis by Brand

Indicator	Toyota			Mitsubishi			Seat		
	Brand att.	Prod. inv.	Brand fam.	Brand att.	Prod. inv.	Brand fam.	Brand att.	Prod. inv.	Brand fam.
BA1	0.906	-0.029	0.035	0.923	0.000	0.075	0.909	0.005	-0.023
BA2	0.816	0.105	0.085	0.861	0.081	0.039	0.903	0.005	-0.052
BA3	0.914	0.058	0.119	0.907	0.032	0.141	0.923	0.035	-0.006
BA4	0.900	0.062	0.117	0.908	0.082	0.109	0.897	0.070	-0.031
BA5	0.923	-0.015	0.035	0.852	0.057	0.158	0.910	-0.029	0.045
BA6	0.851	0.043	0.036	0.820	0.167	0.185	0.876	0.115	0.027
PI_IMP	0.018	0.744	-0.076	0.120	0.715	-0.127	0.016	0.684	-0.021
PI_MEAN	0.034	0.716	0.146	0.018	0.723	0.095	0.122	0.717	0.125
PI_EXC	-0.014	0.715	0.364	-0.025	0.768	0.237	-0.045	0.798	0.040
PI_APP	0.026	0.703	0.274	0.150	0.720	0.223	-0.035	0.766	-0.060
PI_REL	0.101	0.686	0.037	0.109	0.688	-0.093	0.097	0.665	-0.098
PI_INT	0.010	0.674	0.292	0.099	0.694	0.268	-0.045	0.798	0.040
PI_INV	0.107	0.671	0.108	0.159	0.681	0.036	0.084	0.693	-0.045
PI_VAL	-0.013	0.646	0.022	-0.048	0.632	0.067	-0.018	0.620	-0.055
PI_NEED	0.003	0.639	-0.093	-0.012	0.603	-0.078	0.070	0.565	0.042
PI_FAS	-0.046	0.608	0.338	-0.005	0.660	0.216	-0.125	0.696	0.011
BF1	0.165	0.299	0.421	0.257	0.052	0.310	0.038	-0.211	0.629
BF2	0.332	0.024	0.455	0.197	0.028	0.508	0.082	-0.162	0.669
BF3	0.046	0.163	0.780	0.048	0.143	0.792	-0.067	0.136	0.776
BF4	0.225	-0.108	0.626	0.115	-0.077	0.637	-0.014	-0.028	0.772
BF5	0.050	0.157	0.773	0.087	0.125	0.814	-0.030	0.080	0.842
BF6	0.033	0.170	0.804	0.067	0.136	0.770	-0.028	0.159	0.735
BF7	-0.007	0.193	0.797	0.018	0.127	0.811	-0.026	-0.013	.781

Table B3. Correlation Matrix (All Websites)

Variable	Time	Product involvement	Brand familiarity	Product knowledge
Webpages	0.744***	-0.036	-0.184***	-0.151***
Time		-0.040	-0.168***	-0.104**
Product involvement			0.160***	0.206***
Brand familiarity				0.481***

*** p < 0.001, ** p < 0.01, * p < 0.05

Appendix C: Supplemental Analysis

To determine the most appropriate correlation structure to account for repeated observations from participants, we used Pan's (2001) quasi-likelihood under independence model criterion (QIC). A lower QIC value indicates a better fit between the data and correlation structure. Using the QIC, we evaluated four potential structures for use in the main analysis: exchangeable, AR(1), m-dependent, and unstructured. We display the results in Table C1. We judged different correlation structures to be appropriate for the two models. Therefore, we selected the best performing correlation structures for each dependent variable. We used the exchangeable correlation structure for brand attitudes and the AR(1) correlation structure for product knowledge.

Table C1. Comparison of Correlation Structures

Model dependent variable	Correlation structure	QIC
Brand attitudes	Exchangeable	664.302
	AR(1)	664.395
	M-dependent	664.342
	Unstructured	664.339
Product knowledge	Exchangeable	580.640
	AR(1)	580.596
	M-dependent	583.582
	Unstructured	584.384

We show comparisons to determine the best fit for the models in Tables C2 and C3. These comparisons demonstrate that the hypothesized models that Equations 1 and 2 specify provided the best fit.

Table C2. Brand Attitude GEE Results for Controls Only and Hypothesized Models

	Controls Only				Hypothesized			
	Coeff. (Std. Err.)	Wald χ^2	Df	Sig.	Coeff. (Std. Err.)	Wald χ^2	Df	Sig.
Intercept	4.496 (0.4652)	93.404	1	<0.001	4.212 (0.3241)	168.870	1	<0.001
Website (Toyota)	0.177 (0.0868)	4.149	1	0.042	0.200 (0.0841)	5.668	1	0.017
Website (Seat)	-0.374 (0.1116)	11.236	1	0.001	-0.425 (0.1049)	16.368	1	<0.001
Product involvement	0.119 (0.0718)	2.763	1	0.096	0.121 (0.0727)	2.765	1	0.096
Brand familiarity	0.220 (0.0453)	23.528	1	<0.001	0.231 (0.0431)	28.683	1	<0.001
Years U.S. residency	-0.175 (0.0861)	4.137	1	0.042	-0.188 (0.0638)	8.631	1	0.003
Participant sex	0.263 (0.1057)	6.166	1	0.013	0.205 (0.1062)	3.737	1	0.053
Participant age	-0.015 (0.0076)	3.948	1	0.047	-0.018 (0.0091)	3.785	1	0.052
Task type					0.041 (0.2309)	0.032	1	0.859
Webpages					0.008 (0.0066)	1.560	1	0.212
Time					0.003 (0.0011)	9.711	1	0.002
Task type $\times$ webpages					-0.023 (0.0110)	4.492	1	0.034

Table C2. Brand Attitude GEE Results for Controls Only and Hypothesized Models

Task type × time					0.001 (0.0018)	0.327	1	0.567
Corrected quasi-likelihood under independence model criterion	692.344				662.160			

Table C3. Product Knowledge GEE Results for Controls Only and Hypothesized Models

Model factors	Controls Only				Hypothesized			
	Coeff. (Std. Err.)	Wald χ^2	Df	Sig.	Coeff. (Std. Err.)	Wald χ^2	Df	Sig.
Intercept	-1.173 (0.4898)	5.741	1	0.017	-0.863 (0.4472)	3.727	1	0.054
Website (Toyota)	1.489 (0.1138)	170.957	1	<0.001	1.445 (0.1154)	156.799	1	<0.001
Website (Seat)	-0.075 (0.0734)	1.04	1	0.308	-0.034 (0.0737)	0.219	1	0.64
Product involvement	0.106 (0.0631)	2.809	1	0.094	0.111 (0.0621)	3.186	1	0.074
Brand familiarity	0.38 (0.0454)	70.002	1	<0.001	0.378 (0.0451)	70.525	1	<0.001
Years U.S. residency	0.121 (0.0567)	4.557	1	0.033	0.085 (0.0541)	2.499	1	0.114
Participant sex	-0.472 (0.0988)	22.84	1	<0.001	-0.468 (0.0978)	22.956	1	<0.001
Participant age	-0.016 (0.0234)	0.446	1	0.504	-0.023 (0.0212)	1.153	1	0.283
Task type					0.236 (0.2098)	1.265	1	0.261
Webpages					-0.015 (0.0065)	5.695	1	0.017
Time					0.003 (0.0012)	4.750	1	0.029
Task type × webpages					0.005 (0.0084)	0.312	1	0.577
Task type × time					-0.003 (0.0015)	3.344	1	0.067
Corrected quasi-likelihood under independence model criterion	575.978				574.574			

Table C4. Alternative GEE Models for Brand Attitude

Model factors	Coeff. (Std. Err.)	Coeff. (Std. Err.)	Coeff. (Std. Err.)	Coeff. (Std. Err.)	Coeff. (Std. Err.)	Coeff. (Std. Err.)
Intercept	4.496 (0.4652)***	4.189 (0.3057)***	4.336 (0.3736)***	4.431 (0.4389)***	4.352 (0.3861)***	4.212 (0.3241)***
Website (Toyota)	0.177 (0.0868)*	0.19 (0.0853)*	0.226 (0.0834)**	0.23 (0.0831)**	0.233 (0.0829)**	0.200 (0.0841)**
Website (Seat)	-0.374 (0.1116)***	-0.427 (0.1100)***	-0.427 (0.1076)***	-0.416 (0.1052)***	-0.426 (0.1049)***	-0.425 (0.1049)***
Product involvement	0.119 (0.0718)	0.123 (0.0728)	0.13 (0.0741)	0.131 (0.0741)	0.128 (0.0723)	0.121 (0.0727)
Brand familiarity	0.220 (0.0453)***	0.224 (0.0446)***	0.225 (0.0431)***	0.224 (0.043)***	0.225 (0.0429)***	0.231 (0.0431)***
Years U.S. residency	-0.175 (0.0861)*	-0.177 (0.0611)**	-0.226 (0.0745)**	-0.234 (0.0838)**	-0.197 (0.0756)**	-0.188 (0.0638)**
Participant sex	0.263 (0.1057)*	0.242 (0.1075)*	0.221 (0.1075)*	0.222 (0.1075)*	0.217 (0.1072)*	0.205 (0.1062)
Participant age	-0.015 (0.0076)*	-0.011 (0.0075)	-0.015 (0.0079)	-0.017 (0.0083)*	-0.019 (0.0084)*	-0.018 (0.0091)
Task type					-0.277 (0.1089)*	0.041 (0.2309)
Webpages		0.012 (0.0041)**		-0.005 (0.0058)	-0.003 (0.0058)	0.008 (0.0066)
Time			0.003 (0.0005)***	0.004 (0.0008)***	0.004 (0.0008)***	0.003 (0.0011)**
Task type × webpages						-0.023 (0.0110)*
Task type × time						0.001 (0.0018)

* p < 0.05; ** p < 0.01; *** p < 0.001

Table C5. Alternative GEE Models for Product Recall

Model factors	Coeff. (Std. Err.)	Coeff. (Std. Err.)	Coeff. (Std. Err.)	Coeff. (Std. Err.)	Coeff. (Std. Err.)	Coeff. (Std. Err.)
Intercept	-1.173 (0.4898)**	-0.999 (0.485)*	-1.166 (0.4916)**	-0.909 (0.4679)	-0.923 (0.472)	-0.863 (0.4472)
Website (Toyota)	1.489 (0.1138)***	1.483 (0.1141)***	1.487 (0.1151)***	1.498 (0.1156)***	1.499 (0.1156)***	1.445 (0.1154)***
Website (Seat)	-0.075 (0.0734)	-0.048 (0.073)	-0.073 (0.0735)	-0.044 (0.0727)	-0.045 (0.0729)	-0.034 (0.0737)
Product involvement	0.106 (0.0631)	0.104 (0.0629)	0.105 (0.0633)	0.107 (0.0626)	0.107 (0.0628)	0.111 (0.0621)
Brand familiarity	0.38 (0.0454)***	0.377 (0.0451)***	0.38 (0.0454)***	0.377 (0.0451)***	0.377 (0.0452)***	0.378 (0.0451)***
Years U.S. residency	0.121 (0.0567)*	0.121 (0.0511)**	0.123 (0.0575)*	0.099 (0.0519)	0.104 (0.053)*	0.085 (0.0541)
Participant sex	-0.472 (0.0988)***	-0.461 (0.0983)***	-0.471 (0.0993)***	-0.469 (0.098)***	-0.47 (0.098)***	-0.468 (0.0978)
Participant age	-0.016 (0.0234)	-0.018 (0.0239)	-0.016 (0.0235)	-0.020 (0.023)	-0.02 (0.023)	-0.023 (0.0212)

Table C5. Alternative GEE Models for Product Recall

Task type					-0.04 (0.1035)	0.236 (0.2098)
Webpages		-0.007 (0.003)*		-0.013 (0.0044)**	-0.013 (0.0044)**	-0.015 (0.0065)*
Time			<0.0001 (0.0006)	0.001 (0.0008)	0.001 (0.0008)	0.003 (0.0012)*
Task type × webpages						0.005 (0.0084)
Task type × time						-0.003 (0.0015)
* P <0.05; ** P <0.01; *** P <0.001						

About the Authors

Brian Kimball Dunn is an assistant professor at the Huntsman School of Business at Utah State University. He has a Bachelor of Arts degree in German from Brigham Young University and a Masters of Business Administration degree from UC-Irvine. Following a 10-year career in e-commerce and online marketing, he received his PhD in information systems from the University of Pittsburgh. His research interests include the effects of human-computer interaction on brand-related outcomes and user behavior within digital content platforms. His work has been published at *Journal of Management Information Systems*, *Information Systems Research*, *European Journal of Information Systems*, *AIS Transactions on HCI*, and *Decision Support Systems* and he serves as a workshop co-chair for AIS HCI special interest group (SIG-HCI).

Narayan Ramasubbu is an associate professor at the Katz Graduate School of Business at the University of Pittsburgh. He received his Bachelor of Engineering from Bharathiar University, India, and PhD in business administration from the University of Michigan. His research interests include software product development and services delivery; design, implementation, use, and governance of enterprise information systems; information technology-driven innovation; and user behavior within digital platforms. He has served on the editorial review board of the *Journal of AIS* and is an associate editor at *Management Science* and *MIS Quarterly*.

Matthew L. Jensen is an associate professor of management information systems and a co-director of the Center for Applied Social Research at the University of Oklahoma. His interests include computer-aided decision making, human-computer interaction, and computer-mediated communication. He studies how people attribute credibility in mediated interactions and how people filter and evaluate information they find online. His research has been published in *Information Systems Research*, *Journal of Management Information Systems*, *MIS Quarterly*, and other journals. He has been primary investigator or coprimary investigator on externally funded research projects totaling more than US\$8 million.

Dennis F. Galletta is an AIS Fellow, a LEO lifetime achievement awardee, Ben L. Fryrear Faculty Fellow and Professor at the University of Pittsburgh, where he serves as Doctoral Director for the Business School. He has published 51 papers with 17 in *Financial Times* outlets (*JMIS*, *MISQ*, *ISR*, and *Management Science*). He has also published 55 refereed conference papers and four books. He is an editorial board member at *JMIS*, and has been on several other boards. He currently serves as an *MISQ* Senior Editor and won a "Developmental Associate Editor Award" in 2006. He won a Provost's Mentorship Award in 2016. He was program co-chair for ICIS 2005 and AMCIS 2003, chaired the first AMCIS in 1995, and co-chaired ICIS 2011. He served as AIS President, ICIS Treasurer, AIS Council Member, and Editor-in-Chief of *AISWorld*. He was founding co-Editor in Chief of *AIS Transactions on HCI* from 2008-2018, and established the concept of Special Interest Groups in AIS in 2000.

Paul Benjamin Lowry is the Suzanne Parker Thornhill Chair Professor and Eminent Scholar in Business Information Technology at the Pamplin College of Business at Virginia Tech where he is also the BIT Graduate Programs and PhD director. He is a former tenured Full Professor at both City University of Hong Kong and The University of Hong Kong. He received his PhD in MIS from the University of Arizona and an MBA from the Marriott School of Management. He has published more than 231 publications, which includes more than 140 journal papers in *MIS Quarterly*, *Information Systems Research*, *Journal of MIS*, *Journal of the AIS*, *Information Systems Journal*, *European Journal of Information Systems*, and so on. He is a former co-EIC of *THCI*. He is a department editor at *Decision Sciences Journal*. He is on the senior editorial board of *JMIS*, an SE at *JAIS* and *ISJ*, and an AE at the *EJIS*. He has also served multiple times as track co-chair at ICIS, ECIS, and PACIS. His research interests include organizational and behavioral security and privacy; online deviance, online harassment, and computer ethics; HCI, social media, and gamification; and business analytics, decision sciences, innovation, and supply chains.

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