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Consumers' Cognitive Lock-in on Websites: Evidence from a Neurophysiological Study

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The objective of this research was to investigate neurophysiological mechanisms underlying the development of cognitive lock-in. Cognitive lock-in describes a situation in which a consumer has learned how to use a website, based on repeated interactions with it, with the consequence that more experience reduces the probability to switch to a competitor's website. A major reason for the reduced switching probability is that interaction with an unfamiliar website typically implies high levels of cognitive load. Researchers conducted an experiment measuring cognitive load while consumers performed online purchasing tasks. Results show that participants visiting the same website multiple times have different cognitive load patterns than participants visiting different websites. The former group rapidly moved from controlled processing to automatic processing, which is metabolically less costly, leading to cognitive lock-in. Theoretical contributions and managerial implications are discussed.

KEYWORDS automatic processing, brain, cognitive load, consumer neuroscience, controlled processing, electroencephalography (EEG), lock-in

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INTRODUCTION

Prior online shopping research suggests that consumers visit a very limited number of websites when shopping for products and services (Johnson et al. 2004). Moreover, evidence indicates that the more often a consumer visits a website (thereby increasing total interaction time), the more he or she is inclined to make a purchase on this site (Johnson, Bellman, and Lohse 2003). The same authors, reflecting on their findings, suggested that a cognitive lock-in phenomenon could be at play. As consumers invest cognitive resources to learn how to use a website, this process creates a shift in the cost-benefit analysis of switching from a current website to a competing website. Thus, the more consumers become experienced with a website, the less they are inclined to switch to a competitor.

Biologically, this result can be explained by the functioning of the human brain. Prior research in psychology, behavioral economics, neuroeconomics, and cognitive neuroscience (e.g., Camerer et al. 2005; Satpute and Lieberman 2006) suggested that a dual-process model underlies human problem solving and decision-making, consisting of controlled processing (conscious, serial, effortful, and slow) and automatic processing (unconscious, parallel, effortless, and fast). As people acquire skills through practice (thus moving from controlled to automatic processing), activations in specific brain regions change (Hill and Schneider 2006). Most changes occur in the frontal lobe (involved in task control and working memory) and the parietal lobe (involved in attention). Thus, evidence from brain research indicates that when processing moves from controlled (e.g., new task) to automatic (e.g., routine task), parietal and frontal cortical brain activity decreases (Schneider and Chein 2003). Based on a human-computer interaction task, one study has shown that practice leads to significant increases in performance and to a simultaneous decrease in brain metabolism (Haier et al. 1992). Thus, learning how to use a computer program through repeated interactions leads to a physiologically more efficient use of brain resources. This automaticity, in turn, makes users feel that their interaction with a system is cognitively less demanding relative to other alternatives (Murray and Häubl 2007).

The cognitive lock-in phenomenon has been identified in prior research on electronic interfaces in numerous studies (Murray and Häubl 2003, 2007; Zauberman 2003; Johnson et al. 2004; Steckel et al. 2005; Shih 2012). Murray and Häubl (2007) suggested a theory of cognitive lock-in that focuses on skill-based habits of use. However, no research has yet investigated actual consumers' cognitive activity during website visits leading to cognitive lock-in. Prior research investigating cognitive lock-in has only used performance-based and self-reported measures to assess consumers' cognitive resource usage. While these measurements have advanced the researchers' understanding of the cognitive lock-in phenomenon, they suggest that investigating cognitive activity with neurophysiological measures will provide a valuable complementary view. The major fact underlying this argument is that human physiology, cognition, and behavior are interrelated phenomena. Consequently, having an exclusive focus on one of these components necessarily results in an incomplete understanding of a phenomenon (Cacioppo et al. 2000).

The main objective of this article is to investigate lock-in development in order to better understand how consumers form their online retailer preferences. To this end, the researchers used electroencephalography (EEG) to study if cognitive resources used by consumers vary across multiple visits to websites. A better understanding of lock-in phenomenon has implications for both theory and practice. For instance, by observing when cognitive lock-in occurs across a series of website visits, a firm could design marketing activities aimed at making it attractive to new visitors to revisit their website at least a given number of times to increase lock-in probability. In general, given the importance of the consumer patronage decision in academia and business, a better understanding of cognitive lock-in is of outstanding importance to online marketing.

In the remainder of this article, the authors first review research on cognitive lock-in and cognitive load. They then propose their hypotheses. Next, they present the experimental study, followed by the results and a discussion of their implications for marketing theory and practice, and outline the limitations of the present study. Finally, they suggest avenues for future research.

THEORETICAL BACKGROUND

Consumers' Cognitive Lock-in

Shapiro and Varian (1998) suggested that there are several types of lock-in effects, ranging from contractual agreements to loyalty programs. The specific type of lock-in investigated in the current research is the "brand-specific training" (Shapiro and Varian 1998, 117), in which consumers invest cognitive resources in learning to use a new system (e.g., a website), which consequently creates switching costs. Cognitive lock-in is defined as "a specific type of loyalty that occurs when a cost-benefit analysis suggests to the buyer that the cost of switching away from an incumbent product outweighs the benefit of using an alternative product" (Murray and Häubl 2007, 78).

In order to learn to use a specific retail website, consumers must invest cognitive resources. As they use a specific website multiple times, they become more skillful in using this site. Consequently, their future visit duration is likely to decrease when performing a specific task, such as making a purchase (Johnson et al. 2003). As with most skill acquisition patterns, learning how to use a website follows the power law of practice (Johnson et al. 2003). Consumers improve their ability to perform a task over time but at a decreasing rate (Newell and Rosenbloom 1981). Thus, the slope of a typical learning curve is steep in the beginning of a human computer interaction process, while it flattens in later stages of experience, a fact that has also been proven in the human-computer interaction domain (e.g., Haier et al. 1992).

Cognitive lock-in is a predictor of several important outcome variables, such as website perceived value, satisfaction, shopping experience, revisit intentions, and intended and actual purchases (Newell and Rosenbloom 1981; Johnson et al. 2003; Zauberman 2003; Murray and Häubl 2007). For instance, Johnson and colleagues (2003) showed that website learning rate increases visitors' probability of purchase, suggesting that website ease-of-use is a major factor influencing cognitive lock-in and consequently online purchase. Murray and Häubl (2007) also indicated that interface ease-of-use plays an important role in consumers' lock-in; they suggested that ease-of-use mediates the relationship between consumer experiences and the formation of consumer preferences. Thus, by performing the same task on the same website, consumers become skillful at it and perceive the website as easier to use, which leads to cognitive lock-in. However, Murray and Häubl (2007) also showed that cognitive lock-in is context-specific. For instance, cognitively locked-in consumers are inclined to revisit the same website to perform a given task (e.g., apparel shopping) but will not necessarily use the same website for a different task (e.g., book shopping).

Murray and Häubl (2003) argued that when consumers learn to use a new interface, they acquire both transferable and non-transferable skills. Transferable skills provide consumers with skills that can be used on other competing websites (e.g., steps involved in an online purchase), whereas non-transferable skills are idiosyncratic to a specific website (e.g., website's unique layout). Non-transferable skills are at the basis of cognitive lock-in. Hence, most retailers must balance demands on both types of skills to provide a good customer experience (i.e., transferable skills) but to also try to differentiate their website experience (i.e., non-transferable skills) to create consumer cognitive lock-in. Research indicates that when competing interfaces are very similar, consumers are more likely to switch to a competitor, whereas when competing interfaces are fairly different, consumers tend to stay with their current interface (Murray and Häubl 2003).

Cognitive Load

Cognitive load theory (Sweller 1988) provides an explanation for consumers' website cognitive lock-in. This theory describes how cognitive resources are used during learning and problem solving. More specifically, it focuses on working memory constraints. Cognitive load theory suggests that automation is at the basis of efficient learning because it decreases the demand on working memory (Sweller, Van Merrienboer, and Paas 1998). All information can be processed consciously or automatically (Schneider and Shiffrin 1977); however, automation requires practice. By largely bypassing the working memory, information that is automatically processed is cognitively less demanding (Sweller 1988). Consequently, familiar tasks are performed easily, whereas unfamiliar tasks (that have not been automated but can principally be completed) are perceived as more demanding and effortful, and also take more time to be performed. Based on cognitive load theory, the researchers suggest that consumers' cognitive lock-in is attained when consumers automatically process information. This, in turn, leads to increased task performance, which can be measured based on decreased website visit duration (i.e., time to complete a specific task such as an online purchase).

Cognitive load refers to "any demands on working memory storage and processing of information" (Schnotz and Kürschner 2007, 471). In order to measure this construct, three major types of metrics can be used, namely based on (1) performance, (2) subjective rating, and (3) physiology (Wierwille and Eggemeier 1993). First, performance-based measurement techniques use objective performance indices such as completion time and number of errors. Second, subjective rating represents self-reported measurement instruments. Self-reported measures of cognitive load are often biased due to the difficulty of individuals to discern between task demand and invested effort (Veltman and Gaillard 1996). Prior research on consumers' cognitive lock-in has used both types of measurement techniques (Johnson et al. 2003; Murray and Häubl 2003, 2007; Shih 2012). More recently, however, several physiological measures have been found to correlate with cognitive load (Klimesch 1999; Oken, Salinsky, and Elsas 2006). This makes possible a more accurate measurement of the phenomenon. First, in contrast to performance-based metrics, physiological measurement of cognitive load is more direct (it is not to be assumed that increased load leads to decreased performance or increased error rate). Second, in contrast to self-reported measures, physiological measurement is not distorted by biases that result from human perception, preferences, or cognitive limitations (e.g., limited short-term memory may bias self-reports when participants are required to give retrospective accounts of their cognitive load perceptions). Human-computer interaction research indicates that (1) heart rate (HR) increases with mental effort (e.g., Roscoe 1992), (2) heart rate variability (HRV) decreases as memory load increases (e.g., Jorna 1993), and (3) electrodermal response (EDR) increases with increasing cognitive demand (Boucsein 1992). In addition, EEG indices of cognitive load have also been developed to assess the information processing capability of an individual (Freeman et al. 1999; Berka et al. 2007).

HYPOTHESES

As a consequence of repeated task execution, skills develop and behaviors typically become automated (Murray and Häubl 2007; Wood and Neal

2009). Thus, consumers revisiting the same website for the same purpose multiple times are hypothesized to move from controlled processing to automatic processing. This shift is characterized by a lower cognitive load. However, cognitive load of consumers visiting different websites for the same purpose is hypothesized to stay in a more controlled processing mode because only a limited number of skills are transferable across websites (e.g., steps involved in an online purchase). Thus, consumers revisiting a website and consumers visiting new websites are expected to follow different learning patterns, which are reflected by their actual cognitive loads. Based on Johnson and colleagues (2003), who suggested that the website ease of use during the first website visit is central to cognitive lock-in and purchase probability, the current researchers contrast consumers' first website visit cognitive load with their subsequent visits' cognitive load.

H1: Relative to their first visit's cognitive load, consumers performing the same task on the same website and those performing the same task on different websites have different cognitive load patterns (i.e., first visit cognitive load vs. subsequent visits' cognitive load).

Furthermore, Murray and Häubl (2007, 81) showed that after only two trials of an interface, more than 60% of their study participants elected to stay with the incumbent interface, suggesting that the move from controlled to automatic processing could be observed very quickly when it comes to websites. This leads to the second hypothesis.

H2: Consumers performing the same task on the same website move from controlled (i.e., more cognitive load) to automatic processing after only a few visits (i.e., less cognitive load after two to three visits).

If consumers identify contextual cues that can be associated with learned skills, those cues will trigger automatic processing. However, if the context does not provide meaningful cues, consumers must invest more cognitive resources to make sense of the context, resulting in increased use of controlled processing. Building on evidence from neuroscience (Hill and Schneider 2006), the current researchers argue that as a website becomes more familiar, consumers can more quickly recognize meaningful contextual cues (e.g., a familiar website layout), which triggers automatic processing. However, an unfamiliar website should lead to controlled processing. Therefore, they propose that cognitive loads at the beginning of a website visit are different between controlled and automatic processing. This leads to the third hypothesis.

H3: As a website visit unfolds, controlled processing and automatic processing show different cognitive loads.

METHODOLOGY

Sample and Procedure

A laboratory experiment was performed to test the hypotheses. During the experiment, subjects were asked to perform multiple online music shopping trips. A prepaid credit card was provided to participants to complete online purchases up to the actual download of the music. While the task was performed, subjects' brain activity was measured using EEG. The researchers obtained the institution's ethics committee approval.

A pretest with five subjects was performed to test the experimental apparatus and task duration. For the main study, fourteen novice participants (i.e., no online purchases in the investigated product category) were recruited from the institution's student panel (no subject from the pretest participated in the main study). A between-subjects design was used for the experiment. The participants were randomly assigned to either the "Same website" condition (i.e., multiple visits to a single website, $n_{\text{Same}} = 6$) or to the "Different websites" condition (i.e., single visits to multiple websites, $n_{\text{Different}} = 8$). When compared to traditional behavioral research, sample sizes tend to be relatively small in neuroscience studies (Lieberman, Berkman, and Wager 2009). Sample sizes of recent neurophysiological studies investigating computer interfaces range from $n = 6$ (Dimoka and Davis 2008) to $n = 20$ (Léger, Vom Brocke, and Riedl 2014).

Twelve music websites were selected for the experiment. The following criteria were used to select these websites: (1) They must give the possibility to purchase and download single music tracks, and (2) the sites must differ from each other in terms of ease-of-use. To ensure this diversity, an expert was asked to complete a purchase on each website and afterward evaluate ease-of-use using an adapted version of the scale developed by Bressolles and Nantel (2008). Results indicate that the selected websites had varying ease-of-use scores (i.e., from 5/21 to 20/21; three scale items × seven-point scale). The website selected for the "Same website" condition had an ease-of-use score of 16, which was within the confidence interval of the mean ease-of-use score (mean = 14.4; SD = 4.14). Selected websites varied from large music retailers (e.g., HMVdigital.ca) to small and new music retailers (e.g., fairsharemusic.com).

Neurophysiological Measurement

EEG is the fluctuation of voltage potential generated by postsynaptic activity of a large population of neurons in the brain. EEG data were acquired using the B-Alert® X10 device from Advance Brain Monitoring (ABM 2010). This device provides the recording of high quality EEG data via a wireless connection. The data were acquired with nine electrodes (F3, F4, F_Z, C3, C4, Cz, P3, P4, and POz, according to the international 10–20 placement system [Jasper 1958]). The sampling rate of EEG data was set at 256 hertz with a bandpass from 0.5 to 65 hertz (at 3bB attenuation). The acquisition software uses artifact decontamination algorithms for eye blinks, muscle movement, and electrical interference (Berka et al. 2004). It calculates an EEG cognitive load index developed by Berka and colleagues (2007). At every segment (epoch) of one second, the measurement instrument estimates the probability that the subject was in each of the following four cognitive states: (1) sleep onset, (2) distraction, (3) low engagement, and (4) high engagement. These four cognitive states were developed using a four-class quadratic discriminant functional analysis and absolute and relative power spectra from 1 to 40 hertz of frontal (Fz), central (Cz), and parietal (POz) EEG channels (refer to Berka et al. 2007 and Johnson et al. 2011 for additional details on the index development).

Following Freeman et al. (1999) and Pope, Bogart, and Bartolome (1995), a cognitive load (CW) odds was calculated using the average probability estimated for the first 15 seconds of interaction with each website using equation 1 below. This relatively short duration of visiting time was used because the current research investigates automatic and controlled processing, which depend upon the initial assessment of contextual cues. A greater CW odds indicates more controlled processing.

$$\text{Equation 1: Cognitive load odds} = (\text{Probability of high engagement} + \text{Probability of low engagement}) / (\text{Probability of distraction} + \text{Probability of sleep onset})$$

Experimental Protocol

Upon participant consent, the EEG headset was placed on the head. To insure reliable recordings, impedance tests were performed according to the manufacturer guidelines (ABM 2010). A 15-minute baseline developed by the manufacturer was then performed to adjust the software, thereby taking individual differences of the classification model into consideration (Berka et al. 2004). Once the baseline period was completed, participants were asked to start the actual experimental task (music purchases).

Participants in the "Same website" condition were asked to purchase a song they like every time they visited their assigned website, while those in the "Different websites" condition were asked to purchase a song they like on each website they were assigned to. Participants must pause 2–3 minutes between visits to insure that they would be back to a relaxed state before starting the next shopping trip. To avoid fatigue effects, the experimental sessions were limited to 1 hour or ten purchases, whichever came first. No time limitations were given to participants for each purchase, and they were not aware of the length of the experiment. Participants were then debriefed and compensated with a $20 Amazon gift card.

RESULTS

Figure 1 shows that compared to their first website visit, participants spent generally less time on the subsequently visited websites. The trend observed for participants visiting different websites suggests that their acquired skills were not always easily transferable between the various websites ("Different websites"), compared to consumers always revisiting the same website ("Same website"). The results indicate that participants who always interacted with the same website acquired skills during their first visit and then used these skills in the following visits, which is in agreement with prior cognitive lock-in research (Johnson et al. 2003; Murray and Häubl 2007).

In order to test H1, which states that there is a difference between the experimental groups in their cognitive load when compared to their first website visit, a linear mixed multivariate regression on cognitive load difference between the first visit and other visits (log(CW) −mean_at_first_visit) with a random Gaussian intercept to account for intra-subject variability was performed. In order to test multiple patterns, three models were fitted: (1) one assuming that for each group the effect of the number of visits is constant between visits #2–#10; (2) one assuming that for each group the effects of the number of visits is linear between visits #2–#10; and (3) one assuming that for each group, the effects of the number of visits is quadratic between visits #2–#10. Using the Bayesian Information Criterion (BIC) selection model criterion, the model assuming a linear effect clearly provided the best fit (BIC = 8,883.53; 8,869.22; 8,873.42 for Models 1, 2, and 3, respectively). As depicted in figure 2, both groups showed different linear cognitive load patterns.

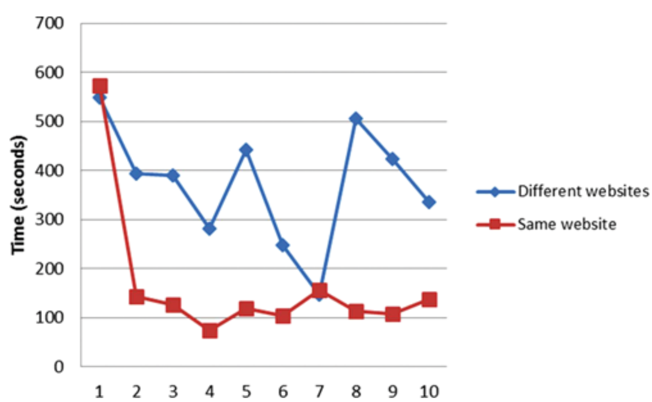

FIGURE 1 Mean time per website visit.

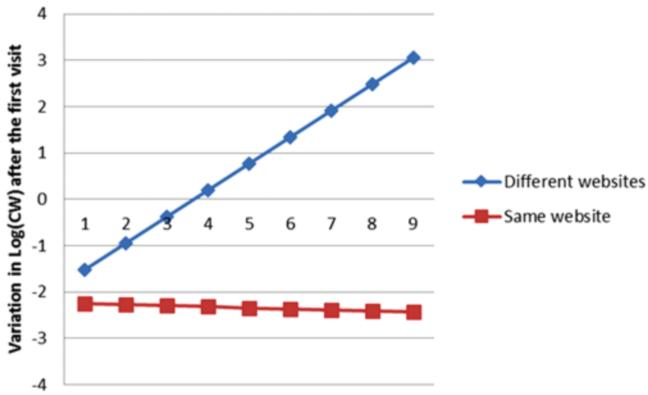

FIGURE 2 Estimated variation from initial cognitive load (CW) across website visits.

As reported in table 1, for participants in the "Same website" condition, the log(CW) decreased by more than two units after the first visit, and then the slope is not significantly different from 0 when their cognitive load is compared between visits #2–#10 ($B = -.023$, and $p = .781$). This result suggests that following their initial visit to the website, they always dedicated a similar amount of cognitive resources to their subsequent visits. In contrast, the slope for participants in the "Different websites" condition was positive and significantly different than the slope of participants in the "Same website" condition ($B = .596$, and $p = .000$). These findings provide strong support for H1.

H2 states that consumers performing the same task on the same website would rapidly move from controlled to automatic processing, thereby also rapidly reducing their cognitive load. To test this hypothesis, only data from participants in the "Same website" condition were used. A multivariate regression model on cognitive load log(CW) was performed, where fixed subject effects were added to account for intra-subject variability. In order to locate at which visit there was a change from controlled to automatic processing, researchers searched the earliest visit satisfying the following two conditions, namely (1) the CW for this visit was significantly smaller than the first one, and (2) no significant difference existed between this visit and all the remaining ones combined. The first visit satisfying this condition was the second one. Table 2 and figure 3 present the results. The cognitive load of

TABLE 1 The Effect of the Frequency and the Number of Website Visits on Cognitive Load

Solutions for fixed effects

Effect	Estimate	Standard error	*t* Value	Pr > |t|
Intercept	−2.2096	1.4072	−1.57	0.1423
#Visits	−0.02251	0.08109	−0.28	0.7814
Different_sites	−0.4694	1.8972	−0.25	0.8046
#Visits*Different sites	0.5959	0.1523	3.91	<.0001

TABLE 2 The Effect of the Number of Website Visits on Cognitive Load

Analysis of maximum likelihood parameter estimates

Parameter	Estimate	Standard error	Wald chi-square	Pr > ChiSq
Intercept	8.8031	0.4869	326.82	<.0001
Visit #1	2.4205	0.6467	14.01	0.0002
Visit #2	1.0776	0.6639	2.63	0.1045
Visits #3–#10	Ref.			

participants revisiting the same website stabilized between the second and the third visit, suggesting the presence of an early cognitive lock-in.

Moreover, based on the BIC, this model was more appropriate than a model using an individual effect for each visit (BIC = 5,458.79 with an effect for each visit, and BIC = 5,450.96 for a model assuming a common effect for visits #3–#10). This means that researchers did not lose any significant information by assuming that the log(CW) between the third and tenth visit were identical. Table 2 suggests that cognitive load was smaller for the second visit than for the first visit ($B = 1.078 - 2.421 = -1.3434$). Starting from the third visit, the CW was significantly smaller than the first visit ($B = -2.421$; $p = .000$). Results indicate that when participants interacted with a website for the first two visits, their cognitive load was higher, and it decreased and stabilized thereafter. These results strongly support H2.

H3 states that as the website visits unfold, controlled processing and automatic processing show different cognitive loads. To test this hypothesis, again only data from participants in the "Same website" condition were used. A multivariate regression model on cognitive load log(CW), where fixed subject effects were added to account for intra-subject variability, was performed.

As shown in table 3 and figure 4, the first two visits showed a decreasing cognitive load pattern as the website visits unfold, and the opposite trend was observed for visits #3–#10, where cognitive load started low and

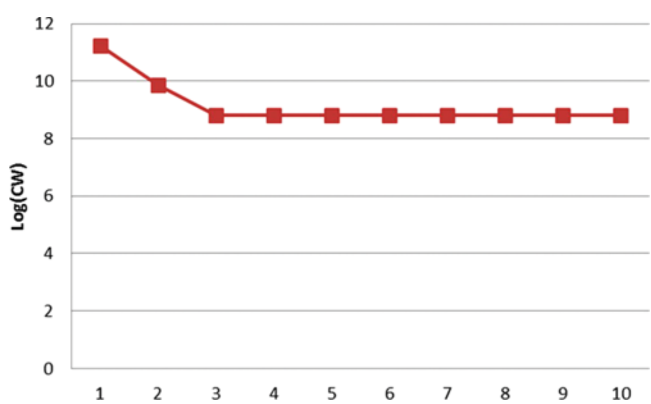

FIGURE 3 Estimated cognitive load (CW) for repeated visits (for a given participant).

TABLE 3 Cognitive Load Patterns during Repeated Visits

Analysis of maximum likelihood parameter estimates

Parameter	Estimate	Standard error	Wald chi-square	Pr > ChiSq
Intercept	7.4061	0.6237	141.00	<.0001
Visit #1	4.9024	1.3632	12.93	0.0003
Visit #2	2.9865	1.4038	4.53	0.0334
Visits #3–#10	Ref.			
Slope of visits #3–#10	0.1764	0.0498	12.53	0.0004
Slope of visit #1 vs. Ref.	−0.3083	0.1488	4.30	0.0382
Slope of visit #2 vs. Ref.	−0.2373	0.1524	2.42	0.1195

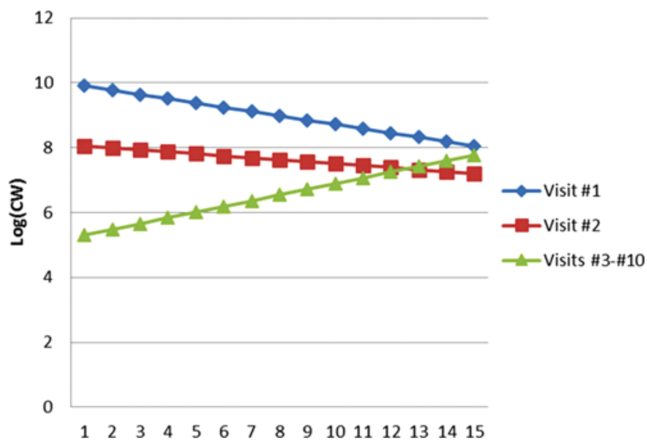

FIGURE 4 Estimated cognitive load (CW) for the first 15 seconds of a visit (for a given participant).

increased as the visits unfolded. The intercept at the first and second visit were both significantly higher than the intercept for the subsequent visits ($B = 4.902$; $p = .000$ for the first visit, and $B = 2.987$; $p = .033$ for the second visit). In addition, the negative slope estimated for the first visit was significantly different than the one estimated starting from the third visit ($B = -.309$; $p = .040$).[1] Thus, in support of H3, as participants moved from controlled (visits #1 and #2) to automatic processing (visits #3–#10), their cognitive loads differed significantly.

DISCUSSION

Overall, the results of this study suggest that consumers' information processing is strongly influenced by the number of visits to a given website. First, researchers found that consumers using the same website to perform a specific task do acquire skills that reduce their cognitive load, whereas consumers using different websites to perform the same task seem to acquire little or no transferable skills (H1). Second, focusing on consumers revisiting a website to perform a specific task, researchers found that they rapidly acquire these skills, moving from controlled to automatic processing between their second and third website visits (H2). Third, the results indicate that cognitive load associated with controlled and automatic information processing varies in opposite directions as the website visit unfolds (H3).

Considering these results, the present study makes several contributions to theory. First, drawing upon cognitive load theory, this study proposed and empirically validated an underlying cognitive mechanism explaining consumers' lock-in (Johnson et al. 2003; Murray and Häubl 2007; Shih 2012). Second, using an objective cognitive load measure, results derived from neurophysiological (EEG) data confirm that consumers rapidly move from controlled to automatic processing when it comes to website learning. Specifically, consumers' cognitive load patterns are significantly influenced by website familiarity. Finally, this research contributes to the nascent research area of consumer neuroscience by shedding light on neurophysiological mechanisms underlying consumer behavior (Lee, Broderick, and Chamberlain 2007; Hubert and Kenning 2008; Ariely and Berns 2010).

In addition to these theoretical contributions, the results also have implications for website managers. The present study highlights the strategic importance of website design decisions. For instance, a highly differentiated website will be more difficult to learn for consumers because they will not be able to easily apply their learned skills from other websites. However, if they eventually learn the required skills to use a highly differentiated website, they will move to automatic processing, and a cognitive lock-in is the consequence, and thus it becomes less likely that consumers switch to another site. On the contrary, a website that is similar to competition will be easy to learn but will not contribute to the firm's market differentiation and will not promote cognitive lock-in. Moreover, the results highlight the importance of website revisits. Thus, managers must design marketing activities that will make consumers return to their websites at least three times (see figure 4). Based on the purchase scenario used in the present experiment, researchers found that information processing becomes automatic with the third visit on a website, implying relatively low degrees of cognitive load. As an example, sales promotions making consumers to revisit a website (e.g., 20% discount on the first three transactions) or subscription-based sales promotions such as Amazon's Prime would contribute to revisit frequency.

This study has limitations which must be considered. First, as with most neuroscientific research (Lieberman et al. 2009), the sample size is relatively small. Thus, additional studies replicating and extending the results using different and larger samples must be performed to provide additional evidence for the findings. Despite this limitation, however, researchers want to highlight that statistically significant results based on a small sample size indicate large effect sizes. Thus, they consider their findings as solid, yet they must be characterized as explorative. Second, the two experimental conditions were designed for theory testing purposes. In practice, it is possible that many consumers' website patronage decisions are not well reflected by these two experimental conditions. For instance, consumers may alternate between two or more competing websites when shopping for a given product (Park and Fader 2004). Moreover, it is possible that the product category affects the results. Here, researchers investigated online music purchases. However, in order to test the validity of the results, future studies could replicate the study using other product categories, thereby potentially revealing possible moderation effects of product type (e.g., hedonic vs. utilitarian).

Altogether, researchers consider the present study as a contribution that helps to explain why consumers have preferences for different websites and also why some websites are more successful than others. Humans have a tendency to keep their cognitive load low, as signified by the principle of least effort (Zipf 1949), because this is metabolically more advantageous (to save energy). Thus, bringing consumers' information processing mode in the brain from controlled to automatic is important. It will be rewarding to see what insight future consumer research will reveal on this topic.

NOTE

1. However, note that when researchers combined all the repeated visits (visits #2–#10), the slope for the first visit was still negative, but the difference with the slope for the repeated visits then had a p value slightly above the nominal level of 5% ($B = -.284$; $p = .056$).

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