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Return on web site visit duration: Applying web analytics data

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Abstract

Much research on internet marketing and e-commerce shares a great interest in a key performance metric for e-tailer success online: the shopper's time spent on the web site, commonly known as 'web site visit duration'. Visit duration has been used as a useful proxy to measure web 'stickiness' because it enhances visitor-to-buyer conversion rate and often leads to online loyalty. The motivation of this study is the recognition of web site visit duration as an important metric to e-commerce success, and also the relative paucity of research on theoretical frameworks that explain visit duration. This study draws on the two-stage choice model literature and posits that shopper visitation to an e-commerce web site is a function of the choice decision processes. We construct a model to decompose online shoppers' decision for visit duration into two choice stages. In Stage 1, shoppers are explorative with less effortful visitation behaviour (eg using search engine to reach a site). In Stage 2, shoppers engage in more effortful and depth visitation activities (eg viewing more Web pages). We empirically test our model using observed web analytics data from 94 UK e-stores to unveil the decision process mechanism for Stage 1 and Stage 2, respectively, and also the transition between the two stages (eg bounce from the web site), which is lacking in extant literature because of its unobservable nature.

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Proxy for 'stickiness'

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Introduction

Much research on Internet marketing and e-commerce is interested in a key construct for e-tailers' success online: the shopper's time spent on the web site (also called 'visit duration'). Visit duration is measured by the amount of time a user is on a web site.¹ Although visit duration has received some criticism and involves some challenges, it nevertheless has been used as a useful proxy to measure web 'stickiness', which enhances visitor-to-buyer conversion rate, and even leads to online loyalty.

Web Site visit duration is important for several reasons. First, it positively contributes to maintaining user interest in a site, which leads to potential purchases.² These effects hold true for both short-term and long-term effects.³ Second, web site visit duration is an extremely important

Duration and banner ad placement

factor to consider when online advertising decisions need to be made. Sites with longer visitor durations are more likely to be favoured for online banner advertising investments and even lead to stronger financial performances, measured by such indicators as higher monthly stock returns.⁴

Diverging theories

However, there are divergences in theories applied to explain web site visit durations. Some research has attributed visit duration to variables such as user demographics.¹ Another study explains web site visit duration as a function of task completion.² Overall, there is relatively little research on providing an underlying mechanism for explaining web site visit durations. Therefore, the motivation of this study is to fill this literature gap.

Modelling on real web visit data

This study is organized as follows. We first review extant major Internet marketing studies that examine visit duration as their dependent variable or key construct in their research. Then we draw on the two-stage choice model literature^{5–8} to propose a plausible web site visitation decision-making model that integrates a Stage 1 choice process and a Stage 2 choice process. We present and discuss our proposed model and empirically model results by applying real web analytics data from 94 e-stores in the United Kingdom as representations of real business web sites. These results are instrumental for validating our theorized model for explaining e-store shoppers' behaviour.

Literature review and conceptual background**Depth of web site visit**

Visit duration is an important web site performance indicator⁹ and a measure for depth of web visit.¹⁰ Technically, web site visit duration is the estimated daily visit duration (mm: ss) for a target web site under investigation. Therefore, visit duration is a standard industry measure for web 'stickiness', repeat visits and enhanced firm stock returns.¹

Limitations of previous studies

Overall, there is a consensus that web site visit behaviour typically follows a sequential process¹¹ where consumers go through a sequence of web pages, detailed browsing and navigation among pages. However, divergences occur among researchers when attributing the underlying mechanism for this process. One study¹ found that web site visitor demographics can be a key driving factor. Specifically, female and older users typically visit web sites for longer, based on 50 web sites sampled. A potential limitation of the study is perhaps that there was only one retail web site represented (Amazon.com), with the remaining sites mostly featuring portal, search and entertainment sites. This drastically narrows our understanding of visit duration for e-commerce web sites, particularly business-to-consumer retail web sites.

Visitor motivations

Other schools of thought drawing from behavioural underpinnings appear to be more compelling. Sismeiro and Bucklin¹², for example, find that web site visitors' different motivations determine their web site visit duration. Some visitors simply browse the web site for purposes such as knowledge building without any purchase intentions; others perform onsite search functions for more detailed product information, typically not just on the product category, but on even more detailed product specifications.

Decision-making process in visits

Moe's study³ finds that, the more prepared the user and the more purposeful and effortful behaviour the web visitor exerts in engaging with this web site through completing a series of tasks, the more their search and engaging behaviour online exhibits sequential behaviour or activity, such that users with a task in mind are more likely to make purchase decisions on a site. It becomes critical to understand the other alternative underlying processes that lead to shoppers' visit duration on an e-tailer's web site.

Exploring information on the web by way of clicks or time spent are indicators of users' cognitive effort in processing information for assisting their decision making.¹³ In this study, the web site visit is posited as a decision-making process, where the web site per se is the object of the consumer's visitation choice. The choice to visit an e-tailer's branded web site can be decomposed into two stages (which is in line with the two-stage choice model), namely, a first stage of less effortful process, where web sites that are less interesting are eliminated, and a second stage, where shoppers engage in a more effortful viewing process (eg measured by page views per user as depth visitation behaviour) where they eventually spend quality time on the site.

Consideration and choice

Choice behaviour and choice models

In the consumer choice behaviour literature, a two-stage choice model generally serves as a base model where the consumer uses a non-compensatory screening rule to reduce the number of alternatives first (a process called Stage 1), followed by a more effortful compensatory process to arrive at a final choice decision (a process called Stage 2).⁶⁻⁸ For example, consumers often apply non-compensatory decision rules to eliminate all options that do not meet some basic standards (eg they only buy well-known brands); they then give the remaining products a chance to make up for their shortcomings and balance out. In the literature, this decision-making model is commonly referred to as 'consideration stage plus choice stage',¹⁴ or 'consider-then-choose model'.¹⁵

Assessing product and brand attributes

For instance, the purchase decision for 'Ford', 'Dodge' or 'Chevrolet' is a function of a consumer's series of assessments of car attributes, such as price, size and fuel economy.¹⁶ Gensch⁵ proposes a two-stage choice model where Stage 1 is for attribute processing to screen alternatives down to a few choices; and Stage 2 is for brand processing, where a smaller set of choices are reassessed by comparing their attributes simultaneously. A body of literature is then built upon this notion and a general consensus is reached, where a two-stage choice model captures the consumer decision process well.^{5,7}

Observed and unobserved decisions

However, for the two-stage choice model, some challenges remain. First, because of data availability, consumers' Stage 1 behaviour is typically latent, where their alternative elimination processes are unobservable. Research development, therefore, has been devoted to drawing on observed data to fill this knowledge gap. For instance, observed data could be consumer purchasing data¹⁷ and online clickstream data for online purchases.¹⁸ Other types of observed data are needed to conquer the latent process for Stage 1, the success of which

could contribute to our understanding of consumers' choice behaviour in Stage 1. Second, an often neglected area is that the transition from Stage 1 to Stage 2 is also latent, because of the fact that Stage 1 itself is unobservable, therefore rendering the boundary between Stages 1 and 2 unclear to marketing researchers — this would be a crucial limitation of the two-stage choice model, when the boundary of the stages could not even be empirically delineated, potentially undermining the theoretical value of the theory it represents.

Ratings and decision making

In this study, we posit that e-shoppers' decisions to visit an e-store follow a decision-making process where they deliberate and make further decisions to spend quality time on the site. To this end, we summarize our discussions in Figure 1. Our conceptual model puts forward that consumer brand ratings (online) have a direct impact on decision-making stages (Stage 1 and Stage 2). With readily available web analytics data, the transition from Stage 1 to Stage 2 could be addressed by using analytics data on bounce from the web site, overcoming its traditional shortcomings as constrained by its unobservable nature. In the following section, we will discuss the hypotheses development and the model more specifically as presented in Figure 1.

Linking Stages 1 and 2

Research model and hypotheses development

Figure 1 presents the specific constructs used to address our research questions. In this figure, the front half of the model (linkages between reach and bounce from site and linkage between search engine and bounce from site) explains the link between e-shoppers' Stage 1 decision-making process by way of visiting these web sites. In line with these theories, we posit that web site reach is one of the most commonly used and important web site performance metrics. It is a success indicator for accessibility and popularity, which pertains to the number of unique visits to a web site.¹⁹

Figure 1: Brand ratings and their impact on decision making

Paths to web sites

Technically, the reach of a brand's web site is calculated as the estimated percentage of global internet users who visit the target web site (eg Alexa.com). An internet-specific metric, web site reach reflects consumers' interests and trust in the utility of this product/service. Web site reach also accommodates the possibility that some consumers arrive at the target site by using search engine(s) because there are multiple ways of accessing a web site. Indeed, the use of online ratings for decision support reduces users' decision time and also increases search behaviour to acquire more detailed and thorough information.²⁰ Some users keep a short-term memory of a brand's site name or keywords and then use search engines to locate the web site address more specifically and accurately. Consistent with information systems literature and terminology used in web analytics, this paper defines the use of search engines to locate the brand's web site as the estimated percentage of visits to the target web site that came from a search engine.

Bounce rates from web sites

Web site visit behaviour is suggested to be increasingly captured by a sequential process.¹¹ One of the natural consequences for web site reach, however, is bounce from the web site. Bounce from the brand's web site is defined as the estimated percentage of visits to the target web site that consist of a single page view. The break of such a search sequence, therefore, is captured by bounce from the web site, which is an observable measurement. Theoretically, bounce from a brand's web site closely relates to consumers' web visit intention for an intended goal.

Cost versus benefit of search

In Figure 1, we use a bold circle to highlight our latent variable called 'bounce from site' since bounce serves as a natural threshold for decision-making stages, in that people who view only one page of a brand web site terminate this visit as they eliminate this web site from their consideration set. Our argument is in line with Chimera and Shneiderman,²¹ who state that the impact of web stimulus on keeping users' attention is contingent on its web saliency relative to its context. Online optimal search literature explains that consumers stop their online search once their marginal cost of searching is larger than their expected marginal benefit of searching.¹¹ The consideration set draws to an end on the web site when consumers choose to leave the web site after viewing its first webpage — this is true whether consumers are those who reach the web site naturally or those who performed a search.

Bounce and attrition

To e-marketers, consumer bounces away from the web site result in online customer attrition²² and eventually reduce their visitor-to-buyer conversion rate and retention.²³ Plaza²⁴ maintains that a lower bounce rate is a positive signal for web stickiness and higher rate of return visits. E-marketers have long recognized the benefits of leveraging search engines to boost their web site traffic. It is reasonable to postulate that web site reach either by natural reach or through search engines is proportionate to bounce rate from this web site. Research shows that consumer online search behaviour on firms' web sites is critical to their final purchase decisions.²⁵

Search and switching

However, the signs for each are different: reach signifies more likely visit to a site, and therefore less likelihood of shoppers bouncing away

from the site; use of search engine, by contrast, serves as a mental shortcut for elimination. Search engines cater for shoppers' needs in searching for short-term memorized objectives. These objects are typically non-important and the switching costs for looking away from them are low. Specifically, for Stage 1 decision making, online search is an important step for consumers to explore the brands and products they are interested in.

Search and bounce

Shoppers' search engine usage behaviour can be seen as a proxy for elimination. Therefore, elimination using a search engine is positively related to bounce from site, as both processes reduce shopper interests in further engaging with web activities. Therefore, we hypothesize that:

H1: Shoppers' reach of e-store's web site negatively relates to the bounces from this web site.

H2: Shoppers' use of search engines to locate the e-store's web site positively relates to the bounces from this web site.

Purpose and choice

Consumers who do not bounce from the web site, but choose to further engage with the site, therefore enter a Stage 2 decision-making process. The remaining hypotheses relate to the Stage 2 decision-making process on an aggregate level (see 'Stage 2 choice behaviour' in Figure 1). Shoppers who stay in this decision stage have successfully completed their Stage 1 screening process, where a large volume of brand web sites are eliminated from their consideration set using non-compensatory rules. Prior studies indicate that the more purposefully consumers can perform certain online tasks (eg search, browse or sequential nominal user tasks), the more likely they are to make purchase decisions.¹²

Traffic data

During this stage, therefore, consumers are typically involved in more effortful, compensatory decision behaviours, which is also true for online purchase decisions.¹⁸ In line with the theory of web site visit sequential process,¹¹ consumers go through a sequence of web pages, detailed browsing and navigation among pages. Such customers' web site visits are recorded as web site traffic data, which is an estimate of the brand's web site's popularity. Operationally, the site with the highest combination of visitors and page views is ranked number 1. Page view is an indicator of the success of a product web site.²⁶ Technically, it is the estimated percentage of global page views on a target web site (as provided in reports from web analytics software vendors, such as Alexa.com).

Switchers from seeking to surfing

The transition from Stage 1 entails a large number of brand web sites being reduced to a Stage 2 site choice — this requires a mechanism to stabilize consumers' online choice behaviour. Theoretically, studies from Rodgers and Cannon²⁷ and Rodgers and Thorson²⁸ suggest that, during web site visits, participants who are originally information-seekers could potentially switch to a surfing motive while in pursuit of information. We posit that 'page view per user' and 'web site traffic' are two crucial mediators between web site bounce and our dependent variable,

Clearly observing choice

‘visit duration’ (which is often used as a proxy for consumer online loyalty and retention in the literature).

Drawing on the strengths of web analytics data (a detailed discussion on data collection and validity follows in the Methods section), we found that the originally latent choice process became clearly observable and attainable to researchers. Added benefits lie in the fact that the transition from Stage 1 to Stage 2 could also be observed directly using the web site ‘bounce’ construct. Therefore, we hypothesize that:

H3: (a) Bounce from an e-store’s web site negatively relates to consumers’ page view; (b) Bounce from an e-store’s web site negatively relates to the traffic of this e-store’s web site.

H4: (a) Page views made by shoppers positively relate to shoppers’ traffic on this e-store’s web site.

Page views proportionate to duration

Visit duration is another important web site performance indicator⁹ and a measure for depth of web visit.¹⁰ Visit duration is a standard industry measure for web ‘stickiness’, repeat visits and enhanced firm stock returns.¹ Technically, visit duration is the estimated daily visit duration (mm: ss) for the target web site. This is the dependent variable for our model that is to be used as a proxy for customer retention. Danaher *et al.*¹ report that, for the top 50 web sites they sampled, the overall visit duration, that is, the decision on reach and bounce from a brand web site, ranges from a minimum of 0.5 minutes to a maximum of 84 minutes. Intuitively — and particularly from an IS perspective — it appears that page view is proportionate to visit duration and traffic built on the same web site. However, as the underlying theoretical underpinning is that we link shoppers’ cognitive decision-making process with web analytics data/variables, we believe they strengthen the research model. Web information explorations by way of clicks or time spent are indicators of users’ cognitive processing information for decision making.¹³ Therefore, we hypothesize that:

H4 (b) Page views made by e-shoppers online positively relate to the time they spend on this web site.

H5: Traffic on an e-store’s web site positively relates to the time e-shoppers spend on this web site.

Moderation effects

External links

The number of external links to an e-tailer’s web site could alleviate the diminishing effect of web traffic caused by bounce from the site.^{29,30}

When there are a large number of external links, which bring more opportunities for a site to be visited, the speed of the causation of bouncing from site on web traffic is slower. When the number of external links to an

e-tailer's web site is low, the speed of attrition of web traffic is faster. Therefore, the impact of an e-tailer's web traffic on visit duration can be moderated by its external links.^{31,32} Such links bring extra resources to enhance the positive impact of web traffic, therefore contributing to the shopper's visit duration on the e-tailer's web site. Therefore, we hypothesize that:

H6: (a) (Stage 1 Moderation): External links to e-tailer's web site positively moderate the relationship between bounce from e-tailer's site and web traffic built on this e-tailer's web site.

H6: (b) (Stage 2 Moderation): External links to e-tailer's web site positively moderate the relationship between web traffic built on this e-tailer's web site and customer's visit duration.

Lastly, we have some sample-specific control variables in the model, which will be discussed in detail in the research design and data collection section.

Research design and method

We used web analytics data for this study. Web analytics data pertains to a generic categorization that usually includes, but is not restricted to clickstream data; search analytics (eg search traffic, top queries from search traffic, search queries with impact factor and advanced uses like search engine marketing); traffic statistics (eg traffic rank, reach per centage, page views percentage, page views/user, bounce per centage, visit duration and search percentage); and audience demographics for target web site (ie age, gender, education, has children and browsing location). Many firms now offer web analytics services with some selective data freely and publicly available. Although web analytics data measures web site traffic, its unit of analysis is at micro consumer level. This makes possible aggregate data for modelling individual choice behaviour.³³

Research on internet marketing increasingly draws on a large amount of objective user-generated and system-recorded data when users/consumers interact with the target web sites. It is a powerful theory development context where a new, computer-mediated environment and large-scale (national or global) data become available to researchers. Research applications of web analytics have been found in online advertising targeting,³⁴ e-commerce, web design, internet strategy and, more generally, online consumer behaviour, for instance online search and browse behaviour,^{12,35–37} user-generated social shopping³⁸ and choice behaviour.^{18,39} Sometimes researchers collect ad hoc web analytics data for their specific research purposes (eg URL web pages, web crawling).¹¹

Web analytics data also has important methodological implications. For the focus of this study, the consumers' Stage 1 decision-making process has traditionally been latent, where their decision rules and choice process are unobservable arising from the 'data challenge'.¹⁸ Yet, with the advent of internet-based consumer data such as clickstream data, marketing

Ability to model individual choice

Internet data for research

Observable data

researchers can now explicitly model Stage 1 using observed data. This paper continues to use observed data to unveil the Stage 1 choice process using more general web analytics data beyond clickstream data.¹¹ The use of web analytics data could also unveil the unobserved decision-making process transition point from Stage 1 to Stage 2, where we argue that an aided non-compensatory process is taking place.

Brand-level data

Essentially, web analytics data are aggregated data, that is, not on an individual basis. This gives an advantage for consumer choice research, because recent literature criticizes the attribute-based consumer choice models by arguing that sometimes product attributes are simply too complex for consumers to evaluate and for researchers to observe and capture.⁴⁰ This criticism could also be valid for experience products such as movies.⁴⁰ In this study, we therefore use aggregate brand-level data to research consumers' brand choice (ie web site visits).

Data collection

The dataset for this study was composed of a list of online retailers that only have internet presences, without any physical stores at all. Internet marketing literature typically labels the latter category 'pure play e-tailer'.⁴¹ Pure-play firms only or mainly conduct their business online. We started data collection from several sources. Our sample must satisfy three conditions: first, these e-tailers must be pure play e-tailers without physical stores; second, they must have web analytic data freely available from Alexa.com; and third, they must have customer ratings scores, because we use these scores as control variables. Once the selection criterion was clear, the process of sampling was straightforward.

Bizrate and Alexa.com

We visited BizRate.com to select a sample of e-tailers. BizRate is a reliable source for consumers to compare choice alternatives and make purchase decisions.⁴² We found that customer online ratings in the 'home and gardening' products category best suited our research purpose because this category had the largest sample of retailers (1,042 e-stores at the time of data collection, that is, 3 months of web analytics data collected in January 2012) among which 139 e-stores also had web analytics data reported in Alexa.com. Other retailer categories rated by Alexa.com were much smaller — 78 out of 495 for 'computer and software'; 93 out of 815 for 'clothing and software'.

Validating the selection

For the 139 e-stores, we manually visited each of their web sites to ensure they were in a working state and then collected their web analytics data from Alexa.com. Forty-five stores were removed from our final dataset because: (1) their web sites were not functioning; (2) there were missing scores in consumer ratings; or (3) they are multi-channel firms or general merchandisers or retailers. This eventually resulted in 94 complete observations with scores for both e-stores' BizRate consumer online ratings and web traffic data from the past 3 months. Operationally, we measured each construct (see Table 2) three times with a 1-month interval (except for 'links to site' and 'rating', which were single-item constructs).

Rating and customer satisfaction

Many researchers have used BizRate data as a valid rating source and applied them on a cross-sectional basis, typically measured by a 90-day interval⁴³ or even a longer time span.⁴⁴ BizRate data has also been used as

a source of secondary customer satisfaction information in assessing their decision-making behaviour⁴⁵.

Analysis and results

Partial least squares (PLS) structural equation modelling

Increasing use of technique

We chose to run our sample in the SmartPLS 2.0 M3⁴⁶ software for this study. In management information systems research, which typically measures information data that is often restricted by sample size, non-normal data and formatively measured latent variables, there has been an increase in the use of partial least squares structural equation modelling (PLS-SEM) over time in leading journals.⁴⁷

Measurement validation

This study used reflective indicators⁴⁸ for our constructs, and therefore we evaluated reliability by means of composite scale reliability (CR) and average variance extracted (AVE).^{48,49} For all measures used in our model, their CR scores were well above the cut-off value of 0.70 (see Table 1). Similarly, constructs' AVE scores exceeded the cut-off value of 0.50, and therefore their root squares were larger than 0.70 (see bold diagonals in Table 2).

Discriminant validity

Furthermore, we observed our convergent validity by checking the standardized loadings of the measures on their respective constructs⁴⁸ and found that almost all of our measures exhibited standardized loadings exceeding 0.70.⁵⁰ The discriminant validity of the measures for our e-store sample were satisfactory.

Hypothesis testing

Employing a bootstrapping technique, the path estimates and *t*-statistics were calculated for the hypothesized relationships (see Table 3). The results illustrate that 77.8 per cent of our hypotheses are confirmed.

Search and reach affect choice differently

Hypothesis 1 and Hypothesis 2 posit the two antecedents to bounce (rate) from the e-tailer's web site, namely, the reach of customers on their web site and the use of search engine. Both relationships were supported: $\beta = -0.280$ ($p < 0.001$) and $\beta = 0.364$ ($p < 0.001$). This confirms our contention that the search behaviour and reach behaviour are different in determining their choice decision from Stage 1 to Stage 2. The use of a search engine implies a low switching cost and exploratory behaviour, which is more likely to evoke a decision to bounce away from the site.

Table 1: PLS quality criteria

	AVE	Composite reliability	Communality	Redundancy
1. Bounce	0.970	0.990	0.969	0.084
2. Bounce x Links	0.989	0.996	0.989	N.A.
3. Links to site	N.A.	N.A.	1	N.A.
4. Page views per user	0.988	0.996	0.988	0.454
5. Rating	N.A.	N.A.	1	N.A.
6. Reach	0.998	0.999	0.998	N.A.
7. Search engine	0.971	0.990	0.970	N.A.
8. Visit duration	0.991	0.997	0.990	-0.080
9. Web traffic	0.958	0.985	0.957	0.049
10. Web traffic x Links	0.980	0.993	0.980	N.A.

Table 2: Constructs' descriptive statistics and correlation matrix

	Mean	SD	Items	1	2	3	4	5	6	7	8	9	10
1. <i>Bounce</i>	38.719	10.908	3	0.985									
2. <i>Bounce x Links</i>	31787.171	35553.254	3	0.006	0.995								
3. <i>Links to site</i>	904.489	1154.462	1	-0.260	-0.658	N.A.							
4. <i>Page view per user</i>	6.327	5.313	3	-0.678	0.020	0.189	0.994						
5. <i>Rating</i>	5.894	1.000	1	-0.118	-0.012	0.001	0.212	N.A.					
6. <i>Reach</i>	0.003	0.008	3	-0.296	-0.708	0.865	0.206	0.068	0.999				
7. <i>Search engine</i>	25.976	10.491	3	0.376	-0.067	-0.059	-0.497	0.023	-0.043	0.985			
8. <i>Visit duration</i>	6.727	9.110	3	-0.593	0.154	0.028	0.865	0.168	-0.004	-0.539	0.995		
9. <i>Web traffic</i>	211407.777	163456.757	3	0.340	0.171	-0.581	-0.294	0.004	-0.449	0.162	-0.182	0.979	
10. <i>Web traffic x Links</i>	84015340.612	66134924.601	3	0.157	0.745	-0.791	-0.074	-0.059	-0.810	-0.012	0.086	0.035	0.990

Bold diagonals represent the square root of average variance extracted for multi-item scales; $N = 94$ e-stores.

Table 3: Standardised structural equation parameter estimates (*t*-values)

Hypothesis	Relationships	Loadings (<i>t</i> -values)
H1	Reach→Bounce (rate) from site	−0.280*** (4.328)
H2	Search Engine→Bounce (rate) from site	0.364*** (4.236)
H3a	Bounce (rate) from site →Page views per user	−0.674*** (12.141)
H3b	Bounce (rate) from site→Web Traffic	0.088 (0.735) [n.s.]
H4a	Page views per user→Web Traffic	−0.085 (0.964) [n.s.]
H4b	Page views per user→Visit duration	0.911*** (12.565)
H5	Web Traffic→Visit duration	0.255 † (1.849)
H6a (<i>Stage 1 Moderation</i>)	Links to site * Bounce from site→Web Traffic	−0.326* (2.419)
H6b (<i>Stage 2 Moderation</i>)	Links to site * Web traffic→Visit duration	0.393* (2.136)
<i>Control variable</i>	Consumer ratings→Visit duration	−0.003 (0.063) [n.s.]
<i>Fit measures</i>	<i>Endogenous construct</i>	
	Bounce (rate) from site: 0.22	
	Page views per user: 0.46	
	Web traffic: 0.44	
	Visit duration: 0.78	

* $p < 0.05$ (two-tailed), ** $p < 0.01$ (two-tailed), *** $p < 0.001$ (two-tailed), † $p < 0.10$ (two-tailed) (based on $t(499)$, two-tailed test).

In contrast, reach on a site indicates more determined customers for further and more effortful visitation behaviour.

Page views and 'stickiness'

For Hypothesis 3, we posit the negative causal relationships between bounce from the site and page views per user (Hypothesis 3a) and web traffic (Hypothesis 3b). For Hypothesis 3a, we found a strong negative effect ($\beta = -0.674$, $p < 0.001$), but we found a non-significant β value for Hypothesis 3b ($\beta = 0.088$, [n.s.]). Therefore, only Hypothesis 3a was supported. In Hypothesis 4, we hypothesise the positive consequences of page view per user on web traffic and visit duration. We found that there was no support for page view per user in contributing to web traffic to an e-tailer's web site, with a weak $\beta = -0.085$ ([n.s.]). However, there was strong positive support for the positive impact of page views per user on their time on the e-tailer's web site, where $\beta = 0.911$, ($p < 0.001$). The impact of web traffic on visit duration (Hypothesis 5) has only a marginal positive effect — $\beta = 0.255$, ($p < 0.10$).

Traffic and duration

Our hypothesized two-stage moderation effects of links to site in Hypothesis 3b and Hypothesis 5 received some interesting findings. For the first-stage moderation, we hypothesized in Hypothesis 6a that if e-tailers have extensive external links to this site, it moderates the relationship between bounce from the site and web traffic. Although this link was statistically supported from our empirical test, with $\beta = -0.326$ ($p < 0.05$), the main causal relationship between bounce from site and web traffic was insignificant. Therefore, this moderation should not be supported. Next, we also hypothesized in Hypothesis 6b that the links to e-tailers' sites would also moderate the causal relationship between web traffic and visit duration. This second-stage moderation was supported with $\beta = 0.393$ ($p < 0.05$). To validate this claim, we run a baseline model where the causal effect of web traffic and site visit duration is non-significant, with $\beta = -0.195$ ($p = 0.06$ [n.s.]).

Figure 2: Plotting customer e-tail web site ratings on page views and time-on-site

Figure 3: Empirical model

Rating relates to page view

Supported hypotheses

Lastly, to control for the effect arising from consumers' online rating of e-tailer's web site on visit duration, we collected additional data to test this effect. We manually collected our 94 e-stores' respective peer consumer ratings using BizRate's special section on 'Customer ratings of stores'. The rating of 94 e-stores was based on smiling faces. We then transformed them into a Likert scale from 1 to 7, with 1 being least recommended and 7 being most recommended. Consistent with intuition, site rating is positively related to page view (site visit depth and engagement) and time on site (see Figure 2 in SPSS output). From a statistical perspective our PLS modelling results show no support for the relationship between customer web site rating and their visit duration effect ($\beta = 0.003$, [n.s.]).

Overall, our endogenous constructs have high *r*-squared values supporting our research model where the construct 'bounce from site', serving as the switch from Stage 1 to Stage 2 choice model, has gained a good *r*-squared value of 0.22. The mediation effect of web traffic received an *r*-square value of 0.44 and our dependent variable, 'visit duration', was well-supported with an *r*-square value of 0.78. Therefore, we believe that the model is well-specified and supported by our empirical data (with 78 per cent of our hypotheses supported). For ease of reading, all our tested relationships are summarised in our empirical model in Figure 3.

Limitations, conclusions and future research

Two-stage decision-making process

To address the paucity of research into understanding shoppers' web site visit duration, this study draws on the two-stage decision-making process

as its theoretical base. Under this framework, we decompose shoppers' decisions to spend time on a retailer's web site into two stages. Each stage is supported by its unique web analytics data to fully operationalize our theoretical model. The first stage explains how e-shoppers arrive at the target web site. During this stage, it is used by shoppers to eliminate competing branded web sites. The latent variable, 'bounce from site', serves as a mediator for the transition between the Stage 1 and Stage 2 decision processes.

Stage 2 effort

In Stage 2, we theorize that e-shoppers engage in more effortful and deeper engagement visitation behaviour. These process were operationalised in our model using web analytics data — that is, page view per user and web traffic — and we used visit duration as the dependent variable. We further examined the potential two-stage moderation effects by external links that the e-tailing site has exchanged with, and found links to site only moderate the relationship between web traffic and web site visit duration.

Practical implications

Overall, our study has several important benefits. Consumers' choice behaviour in a retail setting is traditionally rich, but the degree of scholarly discussion is further complicated by consumers' increasing switch to online settings. In this study, we capture the benefits of web analytics data and offer a few important implications both for marketing research and practice. First, our study adds to the existing literature in several ways. Our model innovatively operationalises the transition from Stage 1 to Stage 2 for decision makers, where bounce from the target brand's web site provides such a metric (evidenced by strong and positive path loadings).

Cognitive and behavioural decision making

This change offers new insight for e-marketing to understand a new mechanism or a new theory explaining web site visit duration other than the user demographics approach found among a small number of other explanations.¹ This essentially means that the key driving forces for longer web site visits may not be fully attributed to a visitor's gender and age as Danaher *et al.*¹ proposed, but deeper reasons arising from both shoppers' cognitive and behavioural decision-making process. Our framework constitutes an internally consistent theoretical component of consumers' external information search and internal decision-making processes, both integrated into a simple and logical structural equation model.

Deepening onsite behaviour

Second, based on our study, there are a few specific measures e-commerce web site developers should pay attention to in order to increase shoppers' visit duration and to enhance business performance. For business investors, spending on search could bring immediate visitation to the site (ie Stage 1 behaviour), but not necessarily result in engagement evolving into Stage 2 behaviour for shoppers' decision making. E-tailing web site webmasters could consider more external link exchanges with other partner web sites for referrals, in order to enhance site visit duration, which can engage more depth in visitors' onsite behaviour, like page views. These are instrumental for visitor-shopper conversion rate.

Beyond self-reported behaviour

Third, methodologically, empowered by data availability using aggregate web analytics data, our study also extends our knowledge beyond findings from subjective self-reported questionnaire data, in that we can now directly observe consumers' choice behaviour in Stage 1 more

Search versus experience products

objectively. This has significantly overcome the measurement difficulty in choice models where the Stage 1 consumer consideration-set formation process has traditionally been latent and unobservable, and unobtainable to marketing researchers.

Clearly, our study is not without limitations. The e-tailers in our sample are mainly selling garden and furniture products that are 'searchable' in nature.⁵¹ These samples may be inherently less affected by consumer online rating. Many products can be categorized into search goods versus experience goods. Search goods are those attributes that could be assessed by consumers before purchase. In contrast, experience goods are those whose product characteristics are difficult to observe until consumption. Zhu and Zhang⁵² recently stated that product characteristics actually moderate the influence of online consumer reviews on consumer purchase decisions and therefore impact product sales. To this end, it is reasonable and worthwhile to examine the types of product in future studies using experience products in the web site samples that are more likely to be affected by online consumer ratings.

Ratings influence

There are also several avenues for further research. First, we used web analytics data on a market level. It would be interesting to capture a shorter time period where the publication of an online rating influences consumers' decision making and to what extent and at which stage (ie Stage 1 or Stage 2, or both). We hope our data analysis will lend more explanatory power in parameter estimation.

Post-experience rating

Second, our study only uses visit duration as the dependent variable. Other measures, such as financial performance data, would possibly lead to interesting research questions by linking online ratings, consumer online decision making and firm performance. Third, like many choice behaviour modelling papers, we only focus on a linear view of the decision-making process that is composed of two stages — it would be of great interest if future studies could examine the so-called 'feedback' effects, where consumers form their own judgements and post a new rating online after they have personally experienced decision making and completed their web site visits and potentially made a purchase. Therefore, the peer-consumer rating would change its role from a control variable to an antecedent variable in future models. This type of research would require more substantial and longitudinal data acquisition and modelling expertise.

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