

# The influence of information overload on the development of trust and purchase intention based on online product reviews in a mobile vs. web environment: an empirical investigation

Christopher P. Furner<sup>1</sup> · Robert A. Zinko<sup>2</sup>

Received: 23 November 2015 / Accepted: 24 August 2016 / Published online: 17 September 2016  
© Institute of Applied Informatics at University of Leipzig 2016

**Abstract** Information overload has been studied extensively by decision science researchers, particularly in the context of task-based optimization decisions. Media selection research has similarly investigated the extent to which task characteristics influence media choice and use. This paper outlines a study which compares the effectiveness of web-based online product review systems for facilitation of trust and purchase intention to those of mobile product review systems in an experiential service setting (hotel services). Findings indicate that the extensiveness of information in the review increases trust and purchase intention until that information load becomes excessive, at which point trust and purchase intention begin to decrease. The magnitude of this decline is smaller in web-environments than in mobile environments, suggesting that web-based systems are more effective in fostering focus and are less prone to navigation frustration, thus reducing information overload.

**Keywords** Mobile reviews · Mobile commerce · Word of mouth · Information overload

---

Responsible Editors: Doug Vogel, Judith Gebauer

---

✉ Christopher P. Furner  
chris.furner@gmail.com

Robert A. Zinko  
robert.zinko@newcastle.edu.au

<sup>1</sup> East Carolina University  
345 Slay Hall, Greenville, NC 27858-4353, USA

<sup>2</sup> College of Business and Law, University of Newcastle  
Sydney, NSW 2203, Australia

**JEL classification** M31

## Introduction

According to Dellarocas et al. (2010); Lee et al. (2011) and a number of other e-commerce studies, online consumer reviews serve as one of the most influential information sources for consumers who are considering making an online purchase. This is particularly true for services that are experiential in nature, where consumers are not able to “try before they buy” and are not returnable (Buhalis 2003). This makes such purchases high risk and thus forces consumers to be more reliant on the information provided by other customers. Bartikowski and Walsh (2014) found that online reviews influence both brand and product attitudes. Consumers view online consumer reviews as more trustworthy than information provided by the retailer, as it is more likely to be objective, less one-dimensional and more apt to evaluate the failure of the product to meet expectations in a wide range of usage circumstances (Cheung et al. 2009). Consequentially, a substantial degree of research regarding the characteristics of online reviews that influence purchase intention has been conducted (e.g., Dellarocas et al. 2007; Furner et al. 2012). Interestingly, researchers have found that although consumers trust the information contained in online reviews more than that provided by the seller of the product or service, this trust is not absolute. As Kugler (2014) suggested, open online review systems facilitate review manipulation by individuals who are not simply consumers of the products or services that are being reviewed. The reviewer might be the product’s

manufacturer, a retailer or even a competitor. As such, they may paint the product or service in a positive or negative light in order to encourage or discourage consumers.

Given the prevalence of ‘fake’ reviews in online review systems (Patil and Bagade 2012), trust (specifically, transaction trust) can be viewed as a proxy for the consumer’s assessment of the veracity of the review (Ludwig et al. 2013). Since online consumers rely on online product reviews to make purchase decisions and because trust is central to their assessment of those reviews, understanding trust in reviewers is paramount to electronic Word-Of-Mouth (eWOM) researchers (Furner et al. 2012; Hu et al. 2008). The development of trust in reviewers has been positively associated with purchase intention in a number of studies (e.g. Furner et al. 2012; Gefen et al. 2003). Contributing to this body of research, we outline a study which 1) investigates the influence of a previously unstudied review characteristic, information overload; and 2) compares the effect of information overload across web-based and mobile product review systems.

Review platform administrators have the ability to control the order in which reviews are presented to consumers. While early e-commerce reviews were presented in chronological order, Amazon.com began manipulating review presentation order, allowing consumers to rate the helpfulness of reviews, and displaying those reviews which were rated as more helpful first. Now, artificial intelligence and free-text parsing technology provide review platform administrators with a variety of tools for automatically prioritizing reviews. We will propose that information load has the potential to serve as one metric which might influence review effectiveness, and can be used to prioritize review presentation order.

Information overload has long been described by researchers as a phenomenon in which a decision maker becomes overwhelmed by the information which they are attempting to process in order to select a course of action (Agnew and Szykman 2005). Information overload has been tied to a number of negative decision outcomes, including lower decision quality, reduced confidence in the decision and increased time needed to make the decision (Chervany and Dickson 1974). Generally speaking, when a decision maker has very little information available, decision outcomes tend to be quite poor; but when they have an appropriate degree of information available, decision outcomes improve. Additionally, as information becomes excessive, decision outcomes tend to drop again. This yields an inverted U shape relationship between information load and decision outcomes (Jacoby et al. 1974; Park and Lee 2008). We have chosen information overload as a notable construct because it has been used extensively by marketing researchers investigating

the influence of excessive information on consumer purchase decisions (Malhorta 1984).

While mobile devices do provide for web-browsing functionality, and use of web-based product review systems can happen on a mobile device, mobile web-browsers are more constrained in terms of dexterity and the ability to foster focus than desktop or laptop (PC) based web-browsers. Since 2 decades of eWOM research has been conducted using PC based web-browsers, and since more and more computing is happening on mobile devices, differences between mobile and PC support of information processing activities would imply that the findings of PC based eWOM studies should be re-evaluated in a mobile context. For the sake of clarity, when we refer to web-based product review systems, we are referring to those using a PC, while mobile review systems refer to those read using a specific application such as the TripAdvisor app.

As more consumers turn to mobile devices to support their product evaluation activities, the influence of information overload becomes even more salient. Traditional web-based product review platforms are better at facilitating focus and easier to navigate (Furner et al. 2015a) than mobile product review platforms, which raises the possibility that frustration and information fatigue may be stronger when a user uses a mobile platform, potentially enhancing the effects of information overload.

In this study, we extend the literature on the influence of review characteristics on trust development and purchase intention by examining the effect of information overload. Further, we extend the extensive body of work related to information overload by comparing the effects of information overload between two different media – web-based online product review systems and mobile-based online product review systems. Our research questions are as follows:

RQ1: To what extent does information overload influence trust formation and purchase intention in product review systems?

RQ2: Does the influence of information overload on trust formation and purchase intention differ in web-based online product review system and mobile product review system?

To answer our research questions, we conducted a study in which scenario-based experiments were used to test the relationships between context (i.e., web-based vs. mobile) and information load and, trust and purchase intention. In the following section, relevant literature related to information overload, online word of mouth and mobile vs. web computing are reviewed.

Next, hypotheses are developed and the research model is outlined. The research methodology is then discussed. Summarizing remarks including a discussion of potential contributions and limitations conclude the paper.

## Literature review and hypothesis development

In order to investigate our research questions, we develop a model of trust and purchase intention based on literature from the disciplines of consumer behavior, specifically WOM; information processing, specifically information overload and mobile computing. The following subsections review relevant literature and describe the development of our hypotheses.

### Consumer decision making and electronic word of mouth

Malhorta (1984) reviewed research related to online consumer behavior, and modelled how consumers must decide among multiple competing products. While consumers generally possess a good understanding of their needs, they must contend with uncertainty related to how effective any give product will be in meeting their needs (You et al. 2012). From this perspective, product selection in an electronic commerce setting becomes an optimization task in the face of substantial uncertainty.

Uncertainty reduction theory (Berger 1979) contends that individuals engage in either passive (observation) or active (information seeking) strategies to reduce uncertainty. Online review systems facilitate passive uncertainty reduction, as potential consumers may 'observe' the effectiveness of a product in meeting another consumer's (the reviewer) needs without actually contacting and inquiring of the consumer. Indeed, online product reviews have been heralded as the most influential information source for online consumers (Dellarocas et al. 2007; J. Lee et al. 2011). Although these reviews may assist in uncertainty reduction, additional research has shown that not all online reviews are viewed equally. For example, the needs of the reviewer may not be consistent with the needs of the potential consumer, and assessing the needs of the reviewer may be difficult for the consumer, as feedback channels may be absent. Rhee and Yang (2015) demonstrated that different types of travellers cite different hotel attributes as being important to their purchase decision. The objectives of the reviewer may be substantially divergent from those of the potential consumer when the reviewer has a stake in the success or failure of a given product or service.

In addition, information economics researchers note that information asymmetries exist in markets for

complex goods and services (Stantchev and Tamm 2012), where suppliers are better aware of deficiencies in the ability of a product or service to meet a need, yet they may withhold that information from the consumer. While online reviews can serve as a mechanism for reducing this information asymmetry, anonymous online review systems facilitate unscrupulous manufacturers, retailers and even competitors posing as consumers. Such reviews may provide potential consumers with false information about the ability of a product to satisfy a potential need (Patil and Bagade 2012). Indeed, online reviews are one metric among many that brand managers use to assess the effectiveness of their marketing efforts and public sentiment about the products and services that they offer, and in the era of big data, they continually monitor such metrics (Vera-Baquero et al. 2015).

e-Commerce researchers widely refer to the study of online product reviews as eWOM. These systems convey reduced uncertainty about products themselves, and are distinct from online reputation systems which provide consumers a forum to evaluate retailers or individual sellers (Zhang et al. 2012). Before e-commerce, traditional Word-of-Mouth (WOM) research focused on the dynamics involved when a consumer told their acquaintances about their experiences with a product. While the influence of an individual's WOM was limited to their relatively small network of acquaintances, researchers and brand managers alike stressed the importance of developing positive WOM (e.g. Richins 1983). From the consumer's point of view, traditional WOM was an effective tool for uncertainty reduction because: 1) the potential consumer had a rich communication channel with the person conveying the WOM, as they generally spoke face to face, and the potential consumer had the ability to ask questions and assess the confluence between her/his needs and that of the person who had used the product before, 2) the potential consumer had a pre-existing relationship with the person conveying the WOM, and thus had existing attitudes about that person's trustability, reputation, expertise and competence (Hu et al. 2008 would refer to the last two as reviewer exposure), and 3) the potential consumer was not inundated with an overwhelming number of opinions related to the product or service, as s/he was constrained by the limited size of her/his own acquaintance network.

Purchase intention has been a construct of primary interest to consumer behaviour researchers since early in the development of the paradigm (Bartikowski and Walsh 2014). Indeed (Albert et al. 2014) found that purchase intention can be increased by encouraging consumers to participate in online communities. Trust has

long been considered a critical element in the development of purchase intention in a variety of e-commerce contexts (Gao and Liu 2014). Trust generally refers to one's degree of comfort acting under uncertainty about the actions that another party will take. Mayer et al. (1995), p. 712) define trust as "the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other party will perform a particular action important to the truster, irrespective of the ability to monitor or control that other party." Different types of relationships and interactions rely on different types of trust, including interpersonal affective based trust, calculative based trust and transaction trust (Serino et al. 2005). Consistent with the majority of e-commerce based studies of trust, we employ transaction trust to investigate our research question. According to Tan and Thoen (2000, p. 61) transaction trust refers to "the mental state that determines whether the truster has sufficient trust to engage in a transaction." We adopt this definition, and use the term 'trust' to refer to transaction trust.

The study of eWOM has largely focused on review and reviewer characteristics and their influence on the development of trust and purchase intention (Racherla and Friske 2012). A substantial amount of research has been directed at the effect of aggregate ratings (e.g. Park and Kim 2008; Qiu et al. 2012) and the number or reviews (e.g. Y.; Liu 2006; Yi Liu and Sutanto 2012; Park and Kim 2008) on trust formation, while individual review characteristics have received moderate attention. Common individual review characteristics which are tied to trust formation and purchase intention include argument quality, valence (Dellarocas et al. 2007) (positive or negative) and sidedness (Cheung et al. 2009) (one-sided reviews only indicate either positive or negative arguments, two-sided reviews discuss both positive and negative aspects of the product). In addition to individual review characteristics, reviewer characteristics have been shown to influence trust formation and purchase intention in eWOM. For instance Hu et al. (2008) provided evidence that several characteristics of online reviews influence product sales. Specifically, they found that reviewer reputation, reviewer exposure, product coverage (similar to argument quality) and temporal effects increase product sales when reviews are positive in valence.

With one notable exception (i.e. Park and Lee 2008), eWOM research has focused on the factors that influence consumers' decision making in a vacuum, ignoring the ancillary cognitive pressures that may be influencing the consumers' rationality while they read online reviews. In this study, we introduce one such factor, information overload.

## Information overload

Information overload has long been studied by researchers in a variety of disciplines. The underlying mechanics of the construct are simple: as decision makers are presented with too much information, their capacity to process that information is exceeded, leading to sub-optimal decision outcomes. Similar constructs include communication overload (Meier 1963), sensory overload (Lipowski 1975), cognitive overload (Vollmann 1991) and information fatigue syndrome (Wurman 2001). The inverted u-shape relationship between decision outcomes and information load has been thoroughly documented by researchers across disciplines, and seems to indicate that both information insufficiency and information overload lead to reduced decision outcomes (Eppler and Mengis 2004), while a moderate amount of information leads to better outcomes.

Information systems researchers have been using the construct since the 1960s (e.g., Ackoff 1967) for among other things, to espouse the benefits of effectively formatting and presenting data to managers. Decision processing researchers tested the impact of the construct extensively on a variety of decision outcomes by using decision making tasks and manipulating choices, the number of potential choices, irrelevant information, relevant information and contextual information (Eppler and Mengis 2004).

Consumer behavior researchers have also used the construct of information overload for decades. Specifically, Jacoby et al. (1974) provided evidence for an inverted u-shaped relationship between information load and their outcomes (performance accuracy, performance speed and 'subjective states' or feelings of satisfaction, perceptions of risk, confidence, etc.). Jacoby et al. presented a group of 192 housewives with a shopping scenario (for rice and prepared dinners) with varying degrees of information about various brands, manipulating their information load with regard to the number of brands to consider and the amount of information provided about each brand. After the manipulation, subjects were asked to rate each brand in terms of the extent to which they 'liked' the brand. Their results indicated a u-shaped relationship between information load and performance accuracy (inverted u-shape), speed, and positive subjective states (inverted u-shape).

We anticipate that consumers reading web-based online reviews will experience a similar phenomenon. Consistent with uncertainty reduction theory, consumers will attempt to access the reviewer's exposure and product coverage (Hu et al. 2008) by seeking information from the review, and in those cases where that

information is not forthcoming, consumers will develop low levels of trust (and consequentially low levels of purchase intention) based on those reviews. However, when adequate information is available in the review and consumers are able to assess the reviewer's exposure and product coverage, they will be better able to develop trusting beliefs about the reviewer, and consequentially report higher levels of purchase intention. Finally, when information is extensive, search costs will start to outweigh the benefits of uncertainty reduction, and trust formation and purchase intention will decrease, however not likely as low as when information is minimal.

H1a: There is an inverted u-shaped relationship between information load and trust formation, such that minimal information results in lower levels of trust, moderate information results in higher levels of trust, and excessive information results in moderate levels of trust in web-based product review systems.

H1b: There is an inverted u-shaped relationship between information load and purchase intention, such that minimal information results in lower levels of PI, moderate information results in higher levels of PI, and excessive information results in moderate levels of PI in web-based product review systems.

## Mobile computing

A shift toward mobile computing and away from desktop computing has been proceeding for over a decade (Lee and Benbasat 2004), as continually more individuals, and specifically more consumers are engaged using mobile devices such as smart phones rather than desktop computers to achieve their information processing objectives (Wang et al. 2006). While mobile devices are becoming more and more powerful and improvements in mobile bandwidth continue to reduce latency, a number of important differences exist between mobile and PC-based computing (Botha et al. 2009; Juliana et al. 2013). Although both web and mobile consumers are able to access the same sets of reviews, we expect the consumer's ability to seek information for the purpose of uncertainty reduction will be constrained in the mobile environment, exposing mobile users to the effects of information overload at lower levels of information load than web users. Specifically, we postulate that limits on dexterity and focus will lead to information overload in mobile review systems at lower levels of information load.

Vicente (2000) defines dexterity as the ability to accomplish tasks using one's hands, and Lee and Benbasat (2004) point out that mobile devices are far less effective at facilitating navigation, leaving users feeling like they have less control than with PC interfaces. This is because the controls on mobile devices tend to be closer together, leading developers to design more simple interfaces to minimize the instance of input errors (Browne et al. 2012). The degree of cumbersomeness of navigation and the frustration associated with navigation errors increase the search cost for consumers in a mobile environment (Furner et al. 2015a), and as such we predict that their perception of the costs and benefits of uncertainty reduction by reading extensive reviews will lead them to be more likely to abandon their active search before positive trusting intentions and purchase intentions can be formed.

Similarly, web-based interfaces are far better at fostering focus than are mobile interfaces (Furner et al. 2014). Csikszentmihalyi (1977) defines focus as the ability to center one's attention and other cognitive resources on completing a specific task within a limited stimulus field. Generally PC users are able to focus their attention on specific tasks, and 'tune out' distractions (Webster et al. 1994). This is generally not the case in mobile computing, as users are often engaged in other tasks, such as participating in meetings, talking, walking or even driving. Even if the mobile consumer is able to tune out distractions, the limited stimulus field provided by the small smartphone screen will not be as effective at facilitation focus on reviews with extensive information as a PC based system would, making information processing more difficult, and increasing the consumer's search cost for uncertainty reduction. This will lead to information overload faster (in the presence of less information) making the formation of trusting intentions and purchase intentions more difficult.

In summary, since mobile devices are less effective at fostering focus and dexterity, we argue that consumers reading product reviews on a mobile device will experience the effects of information overload in the presence of less information, and as a result will be less effective in their uncertainty reduction strategies as per uncertainty reduction theory, and will thus report lower levels of trust and purchase intention than web-based consumers.

H2a: The influence of excessive information will lead to a more substantial decrease in trust formation in a mobile online review system than in a web-based online review system.

H2b: The influence of excessive information will lead to a more substantial decrease in purchase intention in a

mobile online review system than in a web-based online review system.

Our proposed model is illustrated in Fig. 1. In the following section, we outline our methodology for testing this model.

## Methods

In order to test our hypotheses, we employed a scenario-based experiment. Such a method of testing hypotheses is particularly useful when exploring research questions where researchers need to control for variations which may occur in field studies. The scenarios used in this collection follow the protocol established by Potts (1995), in that we have incorporated characteristic elements of setting, agents and actors, as well as goals. It is the manipulation of the information load of the review which will allow us to evaluate and document variations in outcomes (Carroll 2000).

The scenario-based simulations used in this experiment required participants to interact with a mock-up of reviews of an imaginary hotel in central Paris. Some participants interacted with a mock-up of an iPhone display running the TripAdvisor app, while others interacted with a mock-up of the TripAdvisor website. The hotel industry was chosen because hospitality services are experiential in nature (Liu et al. 2013), lack the ability to ‘try before you buy’ and are not returnable (Buhalis 2003). Due to these characteristics, the purchases are regarded as ‘high risk’ by consumers, and as such should require considerable attention when purchasing (Jeong and Lambert 2001). This is consistent with current research in the area of eWOM (e.g. Sotiriadis and van Zyl 2013) in that the intangibility of the experience should enhance the uncertainty for consumers, increasing their motivation for information search and their need to rely on WOM.

## Subjects

The study included working adults, who were enrolled in a Master of Business Administration program at a large south-eastern U.S. university. MBA students were selected because they are expected to have some

experience with travel, and are reasonably analytical in their decision making processes, as evidenced by their admission into the MBA program. 264 responses were collected over two semesters, 260 of which were usable (129 subjects in the web condition, 131 in the mobile condition).

## Procedures

After the standard demographic questions, participants were instructed to act as if they had decided to take a trip to Paris, France, and were considering hotels. Subjects were divided into two experimental groups. Both groups read the same three reviews of the same hotel in Paris. One group read the reviews using the iPhone/TripAdvisor simulator, the other group read the reviews using a mock-up of TripAdvisor’s webpage. Both groups responded to the same instrument items. The only difference is the method in which the reviews were read. The iPhone simulator is high-fidelity, written using HTML5, and allows users to scroll using their computer mouse in a way that simulates the use of an iPhone.

Participants were given three reviews for the same hotel, and after reading each review, they were asked to report the level to which they not only felt that they could trust the review (using 3 items), and if they intended to purchase a room. Repeated measures are appropriate for this form of data collection both because of precedence in the field if IS (e.g. Jarvenpaa and Staples 2001) and also because it mirrors a typical use case for an individual making a hotel room purchase decision in that individuals normally read more than one review associated with each product or service.

Since argument quality and valence have been shown to influence purchase intention, all 3 reviews were the same with regard to valence and very similar in terms of argument quality. Further, all three scenarios covered the same content areas (duration and dates of stay, location in terms of both distance to tourist attractions and local availability of things to do (restaurants, cafe’s, etc.), room size, cost, quality of breakfast, and a comparable value judgment.) in differing levels of detail. The manipulation occurred regarding the extensiveness of the review (i.e. information load). The first review was extremely terse, consisting of only 39 words. As such, it could be viewed on the iPhone simulator without scrolling. The second review was considered ‘moderate’ in terms of information load, contained 311 words (e.g., Mudambi and Schuff 2010), and required two full scrolls of the iPhone simulator. The third review was extremely detailed containing 1256 words and required

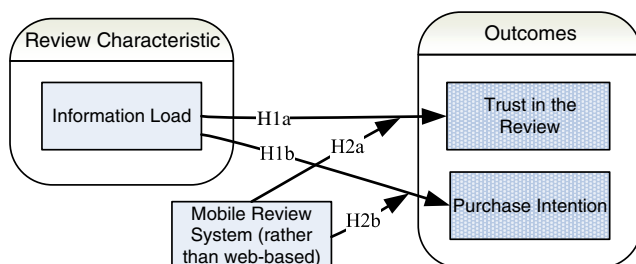


Fig. 1 Proposed model

8 and a half full scrolls of the iPhone simulator. The text of the three reviews appear in Appendix Table 6.

The trust outcome was measured with 3 items adopted from Furner et al. (2014), while purchase intention was assessed with a single question also adopted from Furner et al. (2014). These items appear in Appendix Table 7.

**Analysis and results**

260 usable responses were collected. 118 of the participants were female, 136 were male, 6 chose not to indicate their gender. The mean participant age was 30.90 with a standard deviation of 14.131, and 9 respondents chose not to indicate their age. The only multi-item variable was trust, which had a Cronbach’s  $\alpha$  of 0.848 with 3 items.

**Omnibus test**

Data were analysed using IBM SPSS Statistics version 22. As is typical with such group comparison studies (e.g., Pintrich and De Groot 1990; Realmuto et al. 1993), we initially ran an MANCOVA to evaluate the influence of our controls, age and gender on our omnibus results. We then checked for heterogeneity by inspecting the equity of covariances using Box’s M, which was not significant Box’s  $M = 19.249$  ( $F = 1.274$ ,  $df1 = 15$ ,  $df2 = 2,618,592.73$ ,  $p = .209$ ) indicating that heterogeneity is not a cause for concern (Hair 2009). Histograms were examined for indicators of outliers, and the Shapiro-Wilk statistic was examined to test for normality; no violations of these assumptions were identified (Razali and Wah 2011). To test for homogeneity of regression, we conducted multivariate tests on product terms for each manipulation (fixed factor) and control (covariate) combination, and did not identify any significant relationships, suggesting that homogeneity of regression was not a cause for concern (Wilson and Carry 1969). These results are presented in Table 1. Please note: context is the name of the dummy variable for the web vs. mobile manipulation (coded as 1 for reviews read via the simulated TripAdvisor webpage or 2 for reviews read via the TripAdvisor mobile app simulator).

**Table 1** Homogeneity of Regression Test Results

| Effect          | Wilks’ Lambda | F     | DF1 | DF2  | Sig. | Partial Eta Sq |
|-----------------|---------------|-------|-----|------|------|----------------|
| InfoLoad*Gender | 0.999         | 0.124 | 4   | 1336 | .974 | 0.001          |
| InfoLoad*Age    | 0.996         | 0.603 | 4   | 1336 | .661 | 0.002          |
| Context*Gender  | 0.996         | 1.220 | 2   | 668  | .296 | 0.004          |
| Context*Age     | 0.998         | 0.674 | 2   | 668  | .510 | 0.002          |

MANCOVA results identified significant effects of both information load and context, as well as age, however not for gender. These results are presented in Table 2.

We also examined Levene’s test of equality of error variances. We didn’t identify any problems for purchase intention ( $F = 0.793$ ,  $df1 = 5$ ,  $df2 = 702$ ,  $p = .555$ ), nor with Trust ( $F = 0.32$ ,  $df1 = 5$ ,  $df2 = 702$ ,  $p = .097$ ) (Gastwirth et al. 2009). Our tests of between subject effects for each DV suggests that both information load and context influence both DVs. These results are presented in Table 3.

**Hypothesis testing**

Following Hair (2009), we used paired t-tests to test hypotheses 1a and 1b. These results are presented in Table 4.

The results of the t-test support hypotheses 1a and 1b. H1a stated that there is an inverted u-shaped relationship between information load and trust formation, such that minimal information load results in lower levels of trust, moderate information load results in higher levels of trust, and excessive information load results in moderate levels of trust in web-based product review systems. This was the case for the both mobile (i.e., 4.97 to 5.90 to 5.64) and also web based (i.e., 4.94 to 5.88 to 4.46). Likewise, H1b stated that there is an inverted u-shaped relationship between information load and purchase intention, such that minimal information load results in lower levels of PI, moderate information load results in higher levels of PI, and excessive information load results in moderate levels of PI in web-based product review systems. A comparison of the mean responses for Trust and Purchase Intention across information load manipulations and contexts supports the inverted U-shaped relationship between information load and both outcomes, as illustrated in Fig. 2 and Fig. 3.

To test hypotheses 2a and 2b, a GLM repeated measure analysis was conducted to determine if there is a significant interaction effect between information load and the context. Results support an interaction effect between information load and both trust and purchase intention, as illustrated in Table 2). These repeated measures results are consistent with the MANCOVA results, which controlled for the influence of age and gender. These results support H2a and H2b (Table 5).

H2a stated that the influence of excessive information load will lead to a more substantial decrease in trust formation in a mobile online review system than in a web-based online review system. The results support these hypotheses showing a .26 (i.e., from 5.90 to 5.64) drop from moderate to excessive information load for mobile reviews, and a 1.42 (i.e., 5.88 to 4.46)

**Table 2** Multivariate Tests

| Effect            | Wilks' Lambda | F      | DF1 | DF2  | Sig.  | Partial Eta Sq |
|-------------------|---------------|--------|-----|------|-------|----------------|
| InfoLoad          | 0.807         | 39.440 | 4   | 1400 | <.001 | 0.101          |
| Context           | 0.961         | 14.087 | 2   | 699  | <.001 | 0.039          |
| Gender            | 0.996         | 1.288  | 2   | 699  | .277  | 0.004          |
| Age               | 0.982         | 6.582  | 2   | 699  | .001  | 0.018          |
| InfoLoad* Context | 0.925         | 13.896 | 4   | 1398 | <.001 | 0.038          |

reduction from moderate to excessive information load for web-based on-line review systems. Likewise, H2b stated that the influence of excessive information load will lead to a more substantial decrease in purchase intention in a mobile online review system than in a web-based online review system. The outcomes supported these hypotheses showing a .47 (i.e., from 5.41 to 4.94) drop from moderate to excessive information load for mobile reviews, and a 1.37 (i.e., 5.33 to 3.96) reduction from moderate to excessive information load for web-based on-line review systems.

## Discussion

Our findings suggest that there is an inverted U-shaped relationship between information load and both trust and purchase intention. Furthermore, we were able to demonstrate that the diminutive effect of excessive information is weaker when the subject is reading the review using a web-interface rather than a mobile interface. In fact, in the web context, the difference in purchase intention between low information load and excessive information load in the mobile context was not statistically significant, as the PI associated excessive information

load actually dropped slightly below that of the low information load condition.

We attribute our finding of the inverted U-shaped relationship to the effects of information overload, where the cognitive demands of processing the information begin to outweigh the potential benefit of considering more information. We ascribe our finding of a difference in the diminutive effect of information between interfaces to the ability of web interfaces to foster focus and to better enable navigation, thus reducing cognitive load as compared to mobile interfaces. In the following subsection, we discuss some of the limitations of our findings.

## Limitations

The generalizability of our findings is likely limited by the sample (Whitehead et al. 1993), which consisted of primarily working adults who were also MBA students from the United States. Although we believe that our subjects have adequate experience with online shopping and online review systems, we caution against applying these data to other cultures. Further analysis in the area of cross cultural mobile information processing could further our understanding of this topic. In addition, our survey was optional, exposing the findings to the threat of non-response bias (Whitehead et al. 1993). Since we collected no data from non-respondents, it is not possible to compare respondents to non-respondents. It was also not possible to conduct a follow up sample of non-respondents. We believe that since our instrument never asked for sensitive nor identifying information, subjects who failed to respond were unlikely to have arrived at their decision based on a strong opinion about one of the factors that we measured. As such, while a risk associated with non-response exists, we believe that it should not unduly influence our findings. We now move to a discussion of the implications of our findings, as well as areas for further investigation.

## Implications and areas for further investigation

While the influence of review length has been studied previously, our findings advance researchers' understanding of the nature of the relationship between

**Table 3** Tests of Between-Subjects Effects

| DV    | Source           | Type III Sum of Squares | df | Mean Square | F      | Sig.  | Partial Eta Sq. |
|-------|------------------|-------------------------|----|-------------|--------|-------|-----------------|
| Trust | Age              | 2.579                   | 1  | 2.579       | 2.365  | .125  | 0.003           |
|       | Gender           | 2.523                   | 1  | 2.523       | 2.298  | .130  | 0.003           |
|       | InfoLoad         | 132.750                 | 2  | 66.375      | 60.457 | <.001 | .147            |
|       | Context          | 27.864                  | 1  | 27.864      | 25.380 | <.001 | .035            |
|       | InfoLoad*Context | 60.327                  | 2  | 30.163      | 27.474 | <.001 | .073            |
| PI    | Age              | 21.983                  | 1  | 21.983      | 13.160 | <.001 | .018            |
|       | Gender           | 0.086                   | 1  | 0.086       | 0.052  | .821  | <.001           |
|       | InfoLoad         | 199.836                 | 2  | 99.918      | 59.818 | <.001 | .146            |
|       | Context          | 24.283                  | 1  | 24.283      | 14.538 | <.001 | .020            |
|       | InfoLoad*Context | 34.846                  | 2  | 17.423      | 10.431 | <.001 | .029            |



**Table 4** Paired t-test results

|                           | Information Load | Mean | N   | Std. Deviation | Std. Error Mean | <i>t</i> | <i>df</i> | Sig. (2-tailed) |
|---------------------------|------------------|------|-----|----------------|-----------------|----------|-----------|-----------------|
| Web trust                 |                  |      |     |                |                 |          |           |                 |
| Pair 1                    | Low              | 4.97 | 128 | 1.011          | .089            | -8.711   | 128       | .000            |
|                           | Med              | 5.90 | 128 | .904           | .080            |          |           |                 |
| Pair 2                    | Med              | 5.90 | 128 | .904           | .080            | 2.878    | 127       | .005            |
|                           | High             | 5.64 | 128 | 1.114          | .098            |          |           |                 |
| Pair 3                    | Low              | 4.97 | 128 | 1.011          | .089            | -5.231   | 127       | .000            |
|                           | High             | 5.64 | 128 | 1.114          | .098            |          |           |                 |
| Mobile trust              |                  |      |     |                |                 |          |           |                 |
| Pair 1                    | Low              | 4.94 | 129 | 1.066          | .094            | -8.711   | 128       | .000            |
|                           | Med              | 5.88 | 129 | .915           | .081            |          |           |                 |
| Pair 2                    | Med              | 5.88 | 129 | .915           | .081            | 16.489   | 128       | .000            |
|                           | High             | 4.46 | 129 | 1.083          | .095            |          |           |                 |
| Pair 3                    | Low              | 4.94 | 129 | 1.066          | .094            | 4.070    | 128       | .000            |
|                           | High             | 4.46 | 129 | 1.083          | .095            |          |           |                 |
| Web intention to purchase |                  |      |     |                |                 |          |           |                 |
| Pair 1                    | Low              | 4.11 | 127 | 1.279          | .114            | -8.072   | 126       | .000            |
|                           | Med              | 5.41 | 127 | 1.181          | .105            |          |           |                 |
| Pair 2                    | Med              | 5.41 | 124 | 1.148          | .103            | 4.085    | 123       | .000            |
|                           | High             | 4.94 | 124 | 1.390          | .125            |          |           |                 |
| Pair 3                    | Low              | 4.11 | 124 | 1.279          | .115            | -5.453   | 123       | .000            |
|                           | High             | 4.94 | 124 | 1.399          | .126            |          |           |                 |
| Mobile intent to purchase |                  |      |     |                |                 |          |           |                 |
| Pair 1                    | Low              | 4.12 | 129 | 1.323          | .116            | -7.545   | 128       | .000            |
|                           | Med              | 5.33 | 129 | 1.263          | .111            |          |           |                 |
| Pair 2                    | Med              | 5.33 | 129 | 1.263          | .111            | 11.135   | 128       | .000            |
|                           | High             | 3.96 | 129 | 1.360          | .120            |          |           |                 |
| Pair 3                    | Low              | 4.12 | 129 | 1.323          | .116            | 1.024    | 128       | .308            |
|                           | High             | 3.96 | 129 | 1.360          | .120            |          |           |                 |

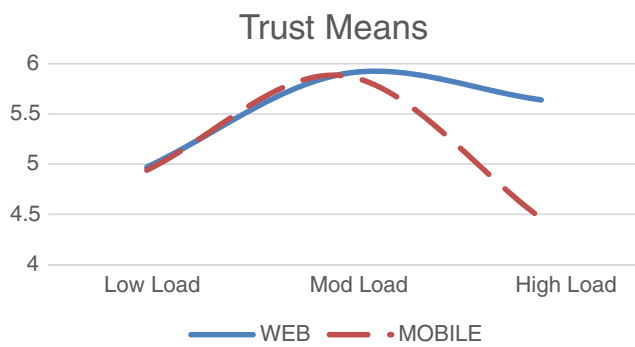
review length and consumer outcomes, by suggesting that the relationship is not linear (more information yielding better outcomes), but rather curved, with information overload coming into play and reducing outcomes when information load is too high. We also demonstrate that the influence of information load is more substantial when the user is using a mobile device, and their information processing capacity is reduced.

Our findings are instructive to eWOM and mobile computing researchers, as they extend the extensive

eWOM paradigm into a new and increasingly relevant field: that of mobile computing. Importantly, our findings indicate a difference in the way that consumers process information when reading reviews on a mobile device than they did the traditional e-commerce context, which has been studied for years. This suggests that extant e-commerce behavioural (and eWOM in particular) models may not hold in the mobile computing context, and many such models should be reevaluated in a mobile context. While some research has viewed the

**Table 5** Results of Repeated Measures Analysis

| Source           | Measure | Type III SoS | <i>df</i> | Mean Sq. | F      | Sig.   |
|------------------|---------|--------------|-----------|----------|--------|--------|
| Info. Load       | Trust   | 9.659        | 2         | 8.30     | 6.445  | 0.008  |
|                  | PI      | 13.154       | 2         | 6.577    | 79.941 | 0.003  |
| InfoLoad*Context | Trust   | 54.773       | 2         | 27.386   | 36.545 | <0.001 |
|                  | PI      | 31.147       | 2         | 17.074   | 12.720 | <0.001 |

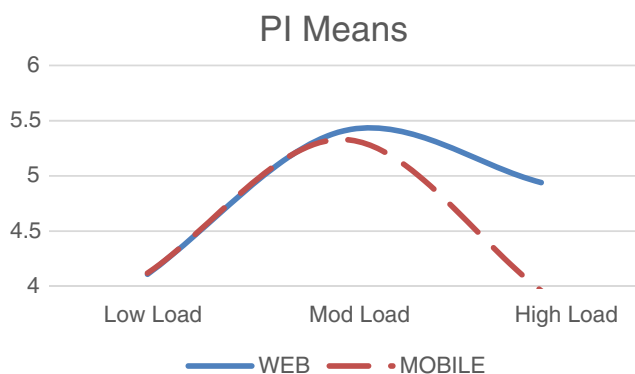


**Fig. 2** Means for trust across information load manipulations

mobile platform as an extension of existing sales channels (e.g. Schmidt-Rauch and Schwabe 2014), our findings suggest that existing e-commerce channels may be less effective if the consumer is using a mobile device.

Our findings raise other new questions as well. For example, we demonstrated that the diminutive effect of information load was stronger in the mobile context, which leads us to question whether the inflection point differs in mobile vs. web contexts as well. Since the current study only examined three levels of information load, and actual reviews vary substantially more, pinpointing the inflection point of the inverted U was impossible. Other questions we posit going forward include: do internet self-efficacy and mobile computing self-efficacy (Keith et al. 2015) play a role in one's ability to process information load? If so, do individuals who have high internet self-efficacy but low mobile self-efficacy experience a stronger diminutive effect of information load in a mobile context than individuals who have both high internet self-efficacy and high mobile self-efficacy? Also, what is the influence of information load in reviews on willingness to pay for hotel rooms?

In addition to extending the mobile computing and eWOM paradigms as described above, this study carries implications for review system administrators, as it suggests that interface sensitive review platforms should prioritize reviews with lower, but not very small, information load for mobile consumers,



**Fig. 3** Means for PI across information load manipulations

while providing moderate-high information load reviews to web users.

Finally Patil and Bagade (2012) point out that a number of individuals seek to influence consumers by exploiting the anonymous nature of online review systems and creating fake product reviews, to make a product seem more appealing, or in some cases to make a product seem less appealing. Our finding that extensive reviews curtail purchase intention could imply that reviewers who seek to negatively affect sales of products or services might flood review systems with extensive reviews, thus consuming the cognitive resources of the consumer so that those resources cannot be applied to considering legitimate reviews.

## Conclusion

The trend toward mobile computing is underway in a number of information processing contexts. Several researchers have questioned the extent to which the shift in devices matter to users. Following Lee and Benbasat (2004) we demonstrate that difference in navigation and the ability to foster focus between the web and mobile context have an impact on an important information processing outcome. In this study, we conducted a simulation-based experiment aimed at understanding one difference between information processing in a web-based vs mobile computing environment: information overload. Specifically, we developed a model, founded upon e-commerce, information processing and eWOM research which suggests that consumers reading online reviews will be better able to overcome the limitations associated with information overload when using a web-based review system rather than a mobile review system. This study extends the emerging yet important mobile information processing paradigm while also bringing e-commerce, particularly eWOM research into the mobile realm. Our findings that 1) there is an inverted U-shaped relationship between information load and both trust and purchase intention, and that 2) the diminutive effect of excessive information is more pronounced in the mobile context raises a number of new questions for e-commerce researchers to explore.

**Acknowledgments** An earlier version of this study was presented at the 2015 Wuhan International Conference on e-Business in June 2015 (Furner et al., 2015b). The version presented at the conference was a theory paper and did not report results.

## Appendix

**Table 6** Text of the three reviews

| Review             | Text   |
|--------------------|--|
| Low Info Load      | I stayed here for 3 days in November, 2013. The location is very good, as you can walk to the tower. The room is small, and expensive, but worth it. The staff is friendly, and the breakfast is good.   |
| Moderate Info Load | <p>My spouse and I stayed here for 3 nights in November of 2013, as part of a 2 week European vacation to celebrate our anniversary. This was our first time in Paris, and we were not sure what to expect.</p> <p>The location was very good, it was a 15 min walk to the Eiffel Tower, which you could see from the lobby. The neighborhood felt very safe, and there were plenty of restaurants and cafés within 1 block of the hotel.</p> <p>As is common in Europe, the rooms were somewhat small, but it wasn't a problem for us. You might find yourself side-shuffling to squeeze between the dresser and the bed, and you can definitely hear the shower from the bedroom. Since we didn't spend too much time in the room, it fulfilled its purpose, as a convenient home base, that allowed to us to enjoy Paris without wasting too much time commuting each day.</p> <p>The hotel is expensive. It was at least 100 euros per night more than any other hotel we had stayed at on our trip. Internet was 10 euro extra, and the restaurant was overpriced. Fortunately, we were a short walk to a number of more reasonable establishments. I recommend the Crepe Vine, 2 buildings south of the hotel. Even with the high price, I do believe that this hotel was a smart choice for us.</p> <p>The staff were very friendly and knowledgeable. We started each day by asking the person at the front desk what to do, and they always responded with a smile and several excellent suggestions. They knew us by name after the second day, and really made us feel welcome.</p> <p>The rate does include a complimentary breakfast for two. This was a true joy: delicate and flavorful sweet pastries, rich, pressed coffee and a variety of fresh fruits served from 6:00–8:30 each morning.</p>  |
| High Info Load     | <p>In November 13, 2013 my spouse Terri and I were visiting England and France for the first time. We had booked our room at the Eiffel Tower hotel via trip advisor 2 weeks prior. We considered five hotels, including the Oh La La Downtown, Hôtel de Centre-ville, Grande Ville de Villégiature and Meilleure Ville de Parisienne. Given our budget, it really came down to the Eiffel Tower Hotel and the Oh La La. They very similar in terms of location, not too far but not too close to the attractions, and also similar in terms of price. We found that the reviews for the Oh La La were slightly less positive. Some reviewers noted problems with the quality of the furnishings, while others noted the staff being less focused on customer satisfaction. The reviews for the Eiffel Tower Hotel were also mixed, but on the whole, fewer potential problems were identified. Ultimately, Terri and I decided to go with the Eiffel Tower Hotel.</p> <p>We arrived around 3:00 on November 7, 2013. We were able to check in relatively painlessly, and were in our room before 3:15. The Bell Boy, Jean Marc, was very polite and handled our heavy suitcases with care, so I gave him a 10 euro tip. We checked out around 10:30 on November 11, worried that we might miss our 1:00 flight back to the US.</p> <p>The hotel itself is quaint, situated less than 1KM from the Eiffel Tower. With traffic lights, it takes between 15 and 20 min to walk to the tower. From the lobby, you get a nice view of the tower, however our room was on the other side of the building. The building is a nineteenth century office building that had been repurposed as a hotel in 1987. The external aesthetics are distinctively French, and match the architecture and ascetics of the neighborhood perfectly.</p> <p>The neighborhood itself is also very good. There are some parts of Paris that you would want to avoid, however we never felt unsafe where we stayed. Other guests seemed to include well-to-do tourists (some with children) and businesspeople, all of whom walked with confidence and engendered a sense of safety. Being so close to the Eiffel Tower, there was a noticeable, but not distracting police presence. We spent our mornings at Café Frapper à la Tête, which has a very bold and full bodied press style coffee for 4 Euros. Terri and I would have 2 cups each before departing directly for the Eiffel Tower. We liked the coffee here more than the coffee at our hotel.</p> <p>I do have to complain that the rooms were pretty small. I know this is common in Europe, and particularly in central metro areas. But it was a noticeable issue. There is almost no buffer area between the bed (I'm not sure what size it was, but the two of us barely fit) and the wall on either side. You could barely squeeze between the foot of the bed and the dresser (which was tiny too), and you could hear all of the activity in the bathroom from the bed (there was nowhere else to go in the room, there is no couch, chair or desk). There is barely enough room in the bathroom to stand at the sink, and there is no tub, only a small walk in style shower in which you really are not able to move. Luckily, the weather was nice and we were able to enjoy the outdoor attractions, and only used the room minimally. The real benefit is the location, allowing us to start early and stay out late.</p> <p>The hotel is expensive. Including tax, we had to pay 350 Euro per night just for the room. We didn't park, but if you wanted to, parking would cost another 100 Euro, and internet costs 10. There is a mini-bar in the room (it is above the night stand, since there is so little space). A bottle of water from the mini-bar is 6 Euro and a tiny bottle of cheap wine is 15. We got our water from the café on the same block for 1.5 euro. So if you are willing to play it smart and avoid the add-ons, like we did, this hotel is a great choice.</p> <p>The hotel has a restaurant: Bistro Eiffel. The menu looks very good, but it is out of our price range. Lunch starts at 70 Euro, and dinners can exceed 200 Euro per entree. There are number of great restaurants on the same block, including the reasonably priced and delightful bakery (Le petit déjeuner) with pasterys, sandwiches and soups in the 12–20 Euro range (1 block west). Also check out the Crepe Vine, two buildings south, with 20–25 Euro lunch crepes, with delectable sliced meats and cheeses. We usually stopped here for dinner on the way back, sometimes as late as 11:00 PM. The are one of the few places in the area that is open until 2:00, but is not a nightclub or bar. During the day, the Crepe Vine gets lots of tourists and business people, but late, particularly on weekends, I hear that the crowd changes to party people looking for a quick snack.</p> <p>We were happy with our treatment by the hotel staff. We were first greeted by the bell boy, Jean Marc, who opened our taxi door and helped us with our suitcases, and held them for us during check in. He showed us to the check in counter, where Maria greeted us</p> |

**Table 6** (continued)

| Review | Text  |
|--------|---|
|        | <p>with a genuine, warm smile. Maria explained the hotel's layout and amenities in good detail. Our room was ready when we got there. Jean Marc then showed us to our room. We also had a good experience with Fanette, the concierge. She sat at a small booth near the main entrance (complete with city maps and business cards for local restaurants), and each time we approached her, she greeted us with a smile and provided us with a great deal of useful information about the area. We must have gotten advice from her 10 times during our 3 night stay. Jean Mark, Maria and Fanette had each learned our names by the time we left. Overall, the staff are very customer centric, which I have found to be a rarity in Europe.</p> <p>We enjoyed the complimentary breakfast (maximum of 2 free breakfasts per room), the hours were very good for us, and I imagine that they are agreeable to business travelers as well (6:00–8:30 during the week). Breakfast is buffet style, and is located in the hotel's restaurant (Bistro Eiffel). The atmosphere is somewhat more fancy and stuffy than we are used to, but in the mornings, there is enough commotion and activity to make you feel comfortable. The coffee was a little strong for my taste, but French pressed coffee is like that. Orange juice and bagged tea was also available. Terri went to town on the pastries, particularly the bichon au citron and the éclair (they must have had six different types of éclair, and they changed each morning). There was also a good assortment of fruit (apples, oranges and bananas in a basket, as well as blueberries, sliced strawberries, cantaloupe and honeydew). We each took 2 gougère to munch on at Café Frapper à la Tête. Really, it is more like a dessert than a breakfast, but we were not complaining.</p> <p>If we were to take another trip to Paris, we would choose the Eiffel Tower Hotel again.</p> |

**Table 7** Measures for outcome variables

| Variable           | Text   | 7-Point Likert Scale Minimum   | 7-Point Likert Scale Maximum |
|--------------------|--|--------------------------------|------------------------------|
| Trust              | Please indicate the extent to which you trust this reviewer  | I distrust this reviewer a lot | I trust this reviewer a lot  |
| Trust              | Please indicate how comfortable you feel acting based on the information provided by this reviewer   | Not comfortable at all         | Very comfortable             |
| Trust              | Please indicate how comfortable you feel relying on this reviewer's advice   | Not comfortable at all         | Very comfortable             |
| Purchase Intention | Based on only this review (ignoring any previous reviews about this hotel that you have read) how likely are you to book a room at the Eiffel Tower Hotel? | Very unlikely                  | Very likely                  |

## References

- Ackoff, R. L. (1967). Management misinformation systems. *Management Science*, *14*(4), 147–156.
- Agnew, J. R., & Szykman, L. R. (2005). Asset allocation and information overload, the influence of information display, asset choice, and investor experience. *Journal of Behavioral Finance*, *6*(2), 57–70.
- Albert, L. J., Aggarwal, N., & Hill, T. R. (2014). Influencing customer's purchase intentions through firm participation in online consumer communities. *Electronic Markets*, *24*(4), 285–295.
- Bartikowski, B., & Walsh, G. (2014). Attitude contagion in consumer opinion platforms: posters and lurkers. *Electronic Markets*, *24*(3), 207–217.
- Berger, C. R. (1979). Beyond initial interaction: uncertainty, understanding, and the development of interpersonal relationships. *Language and Social Psychology*, 122–144.
- Botha, R. A., Furnell, S. M., & Clarke, N. L. (2009). From desktop to mobile: Examining the security experience. *Computers & Security*, *28*(3–4), 130–137. doi:10.1016/j.cose.2008.11.001.
- Browne, J., Drego, V. L., & Petterson, J. (2012). *Mobile interactive design agencies emerge*. Retrieved from Forrester Research database. <https://www.forrester.com/report/Mobile+Interactive+Design+Age+ncies+Emerge/-/E-RES60272>.
- Buhalis, D. (2003). *eTourism: information technology for strategic tourism management*. London: Pearson Education.
- Carroll, J. M. (2000). Five reasons for scenario-based design. *Interacting with Computers*, *13*(1), 43–60.
- Chervany, N. L., & Dickson, G. W. (1974). An experimental evaluation of information overload in a production environment. *Management Science*, *20*(10), 1355–1344.
- Cheung, M., Luo, C., Sia, C., & Chen, H. (2009). Credibility of electronic word-of-mouth: information and normative determinants of online consumer recommendations. *International Journal of Electronic Commerce*, *13*(4), 9–38.
- Csikszentmihalyi, M. (1977). The ecology of adolescent activity and experience. *Journal of Youth and Adolescence*, *6*, 181–202.
- Dellarocas, C., Zhang, X., & Awad, N. (2007). Exploring the value of online product reviews in forecasting sales: The case of motion pictures. *Journal of Interactive Marketing*, *21*(4), 23–45.
- Dellarocas, C., Gao, G., & Narayan, R. (2010). Are consumers more likely to contribute online reviews for hit or niche products? *Journal of Management Information Systems*, *27*(2), 127–157.
- Eppler, M. J., & Mengis, J. (2004). The concept of information overload: A review of literature from organization science, accounting, marketing, MIS, and related disciplines. *The Information Society*, *20*(5), 325–344.
- Furner, C. P., Racherla, P., & Zhu, Z. (2012). Uncertainty, trust and purchase intention based on online product reviews: An introduction to an international study. *International Journal of Networking and Virtual Organizations*, *11*(3–4), 260–276.

- Furner, C. P., Racherla, P., & Babb, J. (2014). Mobile application stickiness (MASS) and mobile interactivity: A conceptual model. *The Marketing Review*, 14(2), 163–188.
- Furner, C. P., Racherla, P., & Babb, J. (2015a). What we know and do not know about mobile app usage and stickiness: A research agenda. *International Journal of E-Services and Mobile Applications*, 7(3), 48–69.
- Furner, C. P., Zinko, R. A., & Zhu, Z. (2015b). The influence of information overload on the development of trust and purchase intention based on online product reviews in a mobile vs. web environment: a research proposal. Proceedings of the Wuhan International Conference on e-Business, Wuhan, PR China (p. 245–252). AIS.
- Gao, H., & Liu, D. (2014). Relationship of trustworthiness and relational benefit in electronic catalog markets. *Electronic Markets*, 24(1), 67–75.
- Gastwirth, J. L., Gel, Y. R., & Miao, W. (2009). The impact of Levene's test of equality of variances on statistical theory and practice. *Statistical Science*, 343–360.
- Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in Online Shopping: An Integrated Model. *MIS Quarterly*, 27(1), 51–90.
- Hair, J. F. (2009). *Multivariate data analysis* (7th ed). New York: Prentice Hall International.
- Hu, N., Liu, L., & Zhang, J. (2008). Do online reviews affect product sales? The role of reviewer characteristics and temporal effects. *Information Technology and Management*, 9(3), 201–214.
- Jacoby, J., Speller, D. E., & Berning, C. K. (1974). Brand choice behavior as a function of information load: Replication and extension. *Journal of Consumer Research*, 33–42.
- Jarvenpaa, S. L., & Staples, D. S. (2001). Exploring perceptions of organizational ownership of information and expertise. *Journal of Management Information Systems*, 18(1), 151–183.
- Jeong, M., & Lambert, C. U. (2001). Adaptation of an information quality framework to measure customers' behavioral intentions and use of lodging Web sites. *International Journal of Hospitality Management*, 20(2), 129–146.
- Juliana, S., Elia, P., Tan, C. H., & Phang, C. W. (2013). Addressing the personalization-privacy paradox: An empirical assessment from a field experiment on smartphone users. *MIS Quarterly*, 37(4), 1141.
- Keith, M., Babb, J., Lowrey, P., Furner, C. P., & Abdullat, A. (2015). The role of mobile-computing self-efficacy in consumer information disclosure. *Information Systems Journal*, 25(6), 637–667.
- Kugler, L. (2014). Keeping online reviews honest. *Communications of the ACM*, 57(11), 20–23.
- Lee, Y. E., & Benbasat, I. (2004). A framework for the study of customer interface design for mobile commerce. *International Journal of Electronic Commerce*, 8(3), 79–102.
- Lee, J., Lee, J. N., & Shin, H. (2011). The long tail or the short tail? The category-specific impact of eWOM on sales distribution. *Decision Support Systems*, 51(3), 466–479.
- Lipowski, Z. (1975). Sensory and information inputs overload: behavioral effects. *Comprehensive Psychiatry*, 16(3), 199–221.
- Liu, Y. (2006). Word of mouth for movies: its dynamics and impact on box office revenue. *Journal of Marketing*, 70(3), 74–89.
- Liu, Y., & Sutanto, J. (2012). Buyers' purchasing time and herd behavior on deal-of-the-day group-buying websites. *Electronic Markets*, 22(2), 83–93.
- Liu, S. H., Liao, H. L., & Chen, C. H. (2013). Marketing for remote area using an experience-based tourism website destination. *International Journal of Services Technology and Management*, 19(4/5/6), 294–303.
- Ludwig, S., Ruyter, K., Friedman, M., Brügggen, E. C., Wetzels, M., & Pfann, G. (2013). More than words: The influence of affective content and linguistic style matches in online reviews on conversion rates. *Journal of Marketing*, 77(1), 87–103.
- Malhorta, N. K. (1984). Reflections on the information overload paradigm in consumer decision making. *Journal of Consumer Research*, 10(4), 436–440.
- Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An integrative model of organizational trust. *Academy of Management Review*, 20(3), 709–734.
- Meier, R. L. (1963). Communications overload: proposals from the study of a university library. *Administrative Science Quarterly*, 521–544.
- Mudambi, S., & Schuff, D. (2010). What makes a helpful online review? A study of consumer reviews on Amazon.com. *MIS Quarterly*, 34(1), 185–200.
- Park, D.-H., & Kim, S. (2008). The effects of consumer knowledge on message processing of electronic word-of-mouth via online consumer reviews. *Electronic Commerce Research and Applications*, 7(4), 399–410. doi:10.1016/j.elerap.2007.12.001.
- Park, D.-H., & Lee, J. (2008). eWOM overload and its effect on consumer behavioral intention depending on consumer involvement. *Electronic Commerce Research and Applications*, 7(4), 386–398. doi:10.1016/j.elerap.2007.11.004.
- Patil, M. S., & Bagade, A. (2012). Online Review Spam Detection using Language Model and Feature Selection. *International Journal of Computer Applications*, 59(7), 33–36.
- Pintrich, P. R., & De Groot, E. V. (1990). Motivational and self-regulated learning components of classroom academic performance. *Journal of Educational Psychology*, 82(1), 33.
- Potts, C. (1995). *Using schematic scenarios to understand user needs*. Paper presented at the Proceedings of the 1<sup>st</sup> conference on Designing Interactive Systems: Processes, Practices, Methods, & Techniques, University of Michigan (p. 247–256). ACM.
- Qiu, L., Pang, J., & Lim, K. H. (2012). Effects of conflicting aggregated rating on eWOM review credibility and diagnosticity: The moderating role of review valence. *Decision Support Systems*, 54(1), 631–643.
- Racherla, P., & Friske, W. (2012). Perceived 'usefulness' of online consumer reviews: An exploratory investigation across three services categories. *Electronic Commerce Research and Applications*, 11(6), 548–559.
- Razali, N. M., & Wah, Y. B. (2011). Power comparisons of shapiro-wilk, kolmogorov-smirnov, lilliefors and anderson-darling tests. *Journal of Statistical Modeling and Analytics*, 2(1), 21–33.
- Realmuto, G., Begleiter, H., Odencrantz, J., & Porjesz, B. (1993). Event-related potential evidence of dysfunction in automatic processing in abstinent alcoholics. *Biological Psychiatry*, 33(8–9), 594–601.
- Rhee, H. T., & Yang, S.-B. (2015). How does hotel attribute importance vary among different travelers? An exploratory case study based on a conjoint analysis. *Electronic Markets*, 25, 211–226.
- Richins, M. L. (1983). Negative word-of-mouth by dissatisfied consumers: a pilot study. *The Journal of Marketing*, 68–78.
- Schmidt-Rauch, S., & Schwabe, G. (2014). Designing for mobile value co-creation—the case of travel counselling. *Electronic Markets*, 24(1), 5–17.
- Serino, C. M., Furner, C. P., & Smatt, C. S. (2005). Making it personal: How personalization affects trust over time. Paper presented at the Proceedings of the 38th Hawaii International Conference on System Sciences.
- Sotiriadis, M. D., & van Zyl, C. (2013). Electronic word-of-mouth and online reviews in tourism services: the use of twitter by tourists. *Electronic Commerce Research*, 13(1), 103–124.
- Stantchev, V., & Tamm, G. (2012). Reducing information asymmetry in cloud marketplaces. *International Journal of Human Capital and Information Technology Professionals (IJHCITP)*, 3(4), 1–10.
- Tan, W. T., & Thoen, W. (2000). Toward a generic model of trust for electronic commerce. *International Journal of Electronic Commerce*, 5(2), 61–74.
- Vera-Baquero, A., Colomo Palacios, R., Stantchev, V., & Molloy, O. (2015). Leveraging big-data for business process analytics. *The Learning Organization*, 22(4), 215–228.

- Vicente, K. J. (2000). HCI in the global knowledge-based economy: designing to support worker adaptation. *ACM Transactions on Computer-Human Interaction*, 7(2), 236–280.
- Vollmann, T. E. (1991). Cutting the Gordian knot of misguided performance measurement. *Industrial Management & Data Systems*, 91(1), 24–26.
- Wang, Y. S., Lin, H. H., & Luarn, P. (2006). Predicting consumer intention to use mobile service. *Information Systems Journal*, 16(2), 157–179.
- Webster, J., Trevino, L. K., & Ryan, L. (1994). The dimensionality and correlates of flow in human-computer interactions. *Computers in Human Behavior*, 9, 411–426.
- Whitehead, J. C., Groothuis, P. A., & Blomquist, G. C. (1993). Testing for non-response and sample selection bias in contingent valuation: analysis of a combination phone/mail survey. *Economics Letters*, 41(2), 215–220.
- Wilson, J. W., & Carry, L. R. (1969). Homogeneity of regression. Its rationale, computation and use. *American Educational Research Journal*, 80–90.
- Wurman, R. S. (2001). *Information Anxiety*. Indianapolis, IN: Macmillan.
- You, W., Xia, M., Liu, L., & Liu, D. (2012). Customer knowledge discovery from online reviews. *Electronic Markets*, 22(3), 131–142.
- Zhang, X., Luo, J., & Li, Q. (2012). Do different reputation systems provide consistent signals of seller quality: a canonical correlation investigation of Chinese C2C marketplaces. *Electronic Markets*, 22(3), 155–168.

Reproduced with permission of copyright owner.  
Further reproduction prohibited without permission.