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Abstract: Online word-of-mouth (WOM) has been studied extensively by electronic commerce researchers, particularly in the realm of online product reviews. As mobile computing becomes more and more common, difference in navigation and the ability to foster focus may lead to changes in the way in which consumers read and react to mobile product reviews compared to online reviews. We use research related to mobile computing limitations, Mobile Self Efficacy and information overload to outlines a study in which two common online review outcomes, trust in the review and purchase intention are evaluated in a mobile environment.
Keywords: Mobile Self Efficacy, Mobile Reviews, Mobile Commerce, Word of Mouth

1. INTRODUCTION

Marketing researchers have long studied the influence of word-of-mouth (WOM), or the sharing of information about product or service experiences between a consumer and their acquaintances. Traditional WOM usually involves a consumer telling their friends and relatives about their feelings of a product that they own or a service that they have received. Online WOM expanded the dynamics of information exchange between consumers in a number of ways. For example, in traditional WOM, the reach of a consumer was limited to their personal network of acquaintances, but with online WOM, enabled on online product review systems, that reach expands to millions of potential consumers. Further, potential consumers have far more information available to them, in the form of reviews from multiple past consumers.

This abundance of information creates challenges for the potential consumer: 1) the consumer is limited in his/her ability to process information, and 2) the consumer must evaluate the veracity of the review based on very little information. These challenges did not exist in the traditional WOM environment: 1) the consumer had less information to consider, as this information only came from those in the potential consumer's personal knowledge sharing network and 2) the consumer would already have established a level of trust or distrust toward the reviewer via past experience with them. For example, online review systems are fraught with reviews generated by entities with a vested interest in the success of a product: reviews can be written by a manufacturer, retailer, or even a competitor [1]. In online WOM, the potential consumer is not able to determine if a review is written by an actual consumer or one of these stakeholders. In traditional WOM, a potential consumer who hears a review of a product from a family member is likely to know if that family member works for the manufacturer, retailer or competitor, and has the ability to use this knowledge in determining the veracity of the review.

More and more people are using mobile devices to meet their computing needs, including information seeking about products and services. Mobile devices and websites differ in a number of important ways, some of which are particularly relevant in the context of online WOM. Mobile browsers and PC based browsers differ in their ability to foster focus as well as dexterity (the ability to control, manipulate and navigate information on a device) [2]. As such, we propose that information seeking for the purpose of reducing uncertainty about products or services is likely to be more difficult and less effective using mobile devices than PCs.

Specifically, consumers in an online interaction space have been shown to suffer from information overload [3]. In this paper, we will argue that mobile devices exacerbate the problems associated with information overload by 1) failing to foster adequate focus for the consumer to process information and 2) frustrating the user due to a lack of dexterity. We will further argue that that this information overload will prevent potential consumers from forming trusting beliefs about the reviews, and subsequently reduce purchase intention. Our first research question follows:

RQ1: In a mobile computing environment, how does information overload influence trust in online product reviews?

Mobile self-efficacy (MSE), or the extent to which an individual reports being confident in their ability to use mobile devices to accomplish tasks has been posited as a way to overcome many of the challenges associated with mobile computing [4]. That is, individuals who score highly on MSE are not only better able to use mobile devices innovatively, but experience better focus and less frustration from the lack of dexterity associated with mobile devices. In this study, we will argue that MSE can reduce the information overload challenges that a mobile computing context. This is the bases of our second research question:

RQ2: In a mobile computing environment, how does MSE influence trust in online product reviews?

This paper proceeds as follows: in the following section, we review relevant literature regarding product selection under uncertainty, WOM, information overload, trust and MSE. Next, we outline our model and hypotheses. We then introduce our proposed methods. A discussion of potential implications of any findings is then presented, and summarizing remarks conclude the paper.

2. LITERATURE REVIEW AND MODEL DEVELOPMENT

In order to evaluate the influence of information overload in online reviews, we develop a model of trust formation and purchase intention, which, consistent with Gefen [5] and Ghose [6], treats trust and purchase intention as central outcomes. This model and hypotheses are discussed below.

Consumers are faced with deciding among multiple competing products or services, and must assess which option will best suit their needs [7]. They must make this assessment with limited information and uncertainty about the products ability to perform under real conditions and over time. Since purchasing a product has a cost, the product selection decision is not trivial. Since the decision is important and wrought with uncertainty, consumers must engage in information seeking activities. Berger [8] identifies active information seeking activities as consumer exerts effort to contact individuals who have information that would reduce their uncertainty, and passive strategies as observing others interact with a product to reduce uncertainty.

In an online environment, passive strategies require less effort, since some consumers post reviews for other consumers to observe, without requiring the potential consumers to put forth effort to contact those with experience with the product. Despite requiring less effort, online reviews present challenges not inherent in an offline environment: there are generally multiple reviews, some of which are less relevant than others, that is, some do not assess the ability of a product to meet the needs of the potential consumer well. This is because the reviewer may have different needs, or may prioritize those needs differently than the potential consumer. Also, online reviews provide less-rich feedback channels than face to face discussions, as potential consumers cannot simply ask synchronous questions of a reviewer. Finally, and of central importance to this study: potential consumers do not have an existing relationship with the reviewer, and have had no basis on which to develop trusting beliefs about the reviewer [5], which can be used as a heuristic to assess the veracity of the information that they provide [9].

Retailers are aware that consumers rely on WOM in their purchase decisions, and strive to develop positive WOM. Some take to the online review systems and pose as consumers of their products as well as their competitors' products in an attempt to influence potential consumers [1]. As such, the importance of developing trusting beliefs before acting on reviews is magnified in an eWOM environment. A number of studies have evaluated the factors that foster trust and purchase intention based on online reviews [e.g. 10].

In this study, we focus on information quality, which has been shown to influence trust and purchase intention in an online review system before [e.g. 11]. For example, Mitchell and Dacin [12] demonstrated that consumers associate reviewer expertise with greater awareness and knowledge of products, and that consumers form these assessments of expertise based on the extensiveness of the review, a finding echoed by Mudambi & Schuff [13] and Mayer et al. [14], who demonstrated a link between the percieved ability of an individual and their trustability. These findings serve as the basis for H1a and H2a, that higher information quality will lead to increased trust and purchase intention.

While the previously mentioned studies have demonstrated links between information quality and a variety of positive outcomes, none have considered that the relationship between information quality and trust might not be linear. That is, information quality might influence trust in a positive way up to a point, after which, the information quality may seem excessive, and lead to a reduction in trust. In this study, we argue that in a mobile computing environment, limitations associated with dexterity and the ability to foster focus make mobile consumers prone to problems associated with information overload, which will in turn reduce trust and purchase intention (H1b and H2b).

Generally, information overload occurs when an individual finds that the perceived cost of processing information is higher than the perceived value the information may create [15]. Information Overload has been studied as a hindrance to decision making in a number of organizational contexts for over 40 years. For example, Chrvany and Dickson [16] demonstrated that information overload caused individuals to make lower quality decisions, have less confidence in their decisions and take longer to arrive at decisions. Information Overload scholars have focused largely on information formatting and summarization, finding that summarization, ease of navigation through information and reduction in choices [7] improves outcomes, but have largely ignored information quality. While information quality has been shown to influence decision making by previous studies [13], it has only been investigated as a beneficial information characteristic, the potential downfalls of excessive information quality have been left largely unstudied. We contend that the mobile computing context is an ideal setting to study information overload, as limitations associated with mobile devices may foster information overload.

An increasing number of individuals are making purchases from their mobile devices [17]. These individuals are largely able to access the same review systems and product review content as those in a web-based environment, however they are doing so using devices which are limited in their ability to foster focus and that are more difficult to navigate [2, 4]. This new way of using different tools to interact with the same information for the same outcome driven task gives rise to a number of questions about how the individual will engage in information processing. In this study, we identify two characteristics of mobile computing that differ from PC computing: Dexterity and the ability to foster focus.

Dexterity refers to the ability to accomplish a task using one's hands [18]. Navigation and input tasks are far more cumbersome on mobile screens than with desktop input devices [2], since the input area is smaller and input controls tend to be closer. While the input devices (fingers) vary in size, they lack the precision of mouse controlled cursers. Mobile applications also vary in their dexterity, Browne et al. [19] demonstrate that apps with a simple layout better facilitate input and navigation, users spend less time completing input and navigation tasks, experience less frustration and stronger feelings of control.

Focus refers to the extent to which an individual can center their attention and other resources on completing a specific task within a limited stimulus field [20]. Webster et al. [21] treat desktops as a limited stimulus field and show that desktop users report feeling mesmerized while completing computing tasks. That is, users are able to devote their attention to the stimulus field provided by desktop screen. In a desktop environment, the user is sitting and working in a task-directed manner usually on a single task. In a mobile environment, the user may or may not be sitting, and may be multitasking: S/he may be walking, participating in a meeting or even driving. As such, the user is not able to focus their attention on the stimulus field provided by the screen, as avoiding objects (walking and driving) or participating (in a meeting) will likely require some attention. As such, mobile devices are not as effective at fostering focus as desktops.

We argue that since mobile devices are not as effective at fostering focus and are more cumbersome to navigate (that is, they are low in terms of dexterity), users will find information processing more challenging, and will experience feelings of information overload when reading a review with a high degree of information quality. In this way, the beneficial effects of information quality on trust and purchase intention will be mitigated. We predict that trust and purchase intention will be higher when information quality is excessive than when it is low, however both trust and purchase intention will be highest when information quality is moderate, because users will experience the benefits of higher information quality for uncertainty reduction without experiencing information overload.

In summary: since information quality is likely to influence increase trust formation and purchase intention, we predict that moderate levels of information quality will influence both trust (H1a) and purchase intention (H2a). However, since mobile devices are more challenging to navigate and do not foster focus as well, we predict that too much information quality will reduce trust (H1b) and purchase intention (H2b) in a mobile environment.

H1: There is a curvilinear relationship between information quality and Trust in online reviews read on a mobile device.

H1a: Subjects are more likely to report trusting moderate levels of information quality in a review, than low levels of information quality.

H1b: Subjects are more likely to report trusting moderate levels of information quality in a review, than excessive information.

H2: There is a curvilinear relationship between information quality and Purchase Intention in online reviews read on a mobile device.

H2a: Subjects are more likely to report intentions to purchase a product, given moderate levels of information quality in a review, than low levels of information quality.

H2b: Subjects are more likely to report intentions to purchase a product, given moderate levels of information quality in a review, than excessive information.

Mobile self-efficacy (MSE) refers to the extent to which an individual reports feeling confident in their ability to effectively use a mobile device to accomplish a task [22]. Bandura [23] is credited with developing the concept of self-efficacy, which he defines as "people's judgments of their capabilities to organize and execute courses of action required to attain designated types of performances" (p. 391). Self-efficacy has been adopted and used in a variety of contexts. Hardin, et al. [24], following Marakas, et al. [25] suggest developing unique self-efficacy constructs for different contexts (such as internet computing, mobile computing, etc.), since self-efficacy in one context (say web-based computing) might not always indicate self-efficacy in another context (mobile computing). Computer self-efficacy has been tied to a number of use outcomes, including reduced technology anxiety [26, 27], innovative use of technology [28-30].

MSE is a relatively new conceptualization of self-efficacy, which reflects capabilities associated with mobile devices which distinguishes them from desktop and web environments. Specifically, Keith et al. [22] identify GPS integration, privacy concerns related to location data accompanied with communication records and contact lists, as well as navigation and search. The authors conduct an experiment in which they demonstrate that MSE has a strong influence on users' perceptions of trust in location-based application vendors as well as structural assurances (such as review systems). They argue that individuals who feel comfortable using mobile devices are better suited to understand the structural assurances and the location based capabilities of apps, and are thus better prepared to make appropriate decisions.

Since MSE in part measures a users' ability to navigate mobile interfaces, and limitations of mobile interfaces exacerbate information overload, those who score high in MSE are predicted to experience less information overload when engaging in mobile computing than those who score low in MSE. Agnew and Skyman [15] find that the way in which investment choices are displayed influence allocation decisions: when search cost in high, participants are more likely to report experiencing information overload and choose the less optimal default choice. However, when the individual is experienced, they are able to better navigate the high-search cost display mode and arrive at more optimal allocations. Following this logic, we predict that MSE will mitigate the challenges associated with processing excessive information on a mobile device, and mitigate the negative portion of the relationship between information quality and both trust and purchase intention.

H3: Mobile self-efficacy moderates the relationship between information quality and trust in online reviews read on a mobile device.

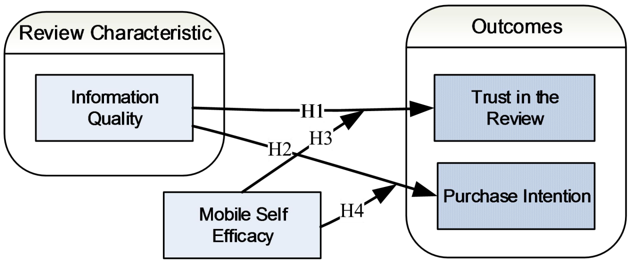

Figure 1. Research model

H4: Mobile self-efficacy moderates the relationship between information quality and purchase intention in online reviews read on a mobile device.

3. METHODS

In order to test our hypotheses, we conducted a simulation-based experiment which required participants to interact with a mock-up of an iPhone display. We chose the hotel industry, because hospitality services are experiential in nature [31], lack the ability to 'try before you buy' and not returnable [32]; and as such, represent high risk purchases that should demand substantial attention when purchasing [11]. Further, the intangibility of the experience should enhance the uncertainty for consumers, increasing their motivation for information search and their need to rely on WOM. This argument for the use of the tourism industry is consistent with Sotiriadis and van Zyle's [33] study on the influence on eWOM via twitter reviews.

In our experiment, subjects were asked to read three reviews for the same hotel, and after each review, they were asked to indicate the extent to which they trust the review (using 3 items), and if they intended to purchase a room. We chose the repeated measures approach not only because it has been used successfully in previous IS studies [e.g. 34] but also because it mirrors a typical use case for an individual making a hotel room purchase decisions: consumers generally read more than one review associated with each product or service.

Our manipulation of information quality consisted of three levels. Each manipulation covered the same 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 value judgment.) in differing levels of detail. Review 1 was very terse and consisted of 39 words, and could be viewed on the iPhone simulator without scrolling. Review 2 was moderate in terms of information quality, contained 311 words and required two full scrolls of the iPhone simulator. Review 3 was very detailed, contained 1,256 words and required 8 and a half full scrolls of the iPhone simulator.

3.1 Subjects

Data were collected from MBA and upper level Management student subjects at a large south-eastern U.S. University. While students are not the only consumers of online reviews, they are expected to have experience in making online purchases [35]. Furthermore, like most MBA programs, work experience was required to enter the program, so although the sample consisted of students, the subjects were also representative of "working adults", a sampling pool that is widely used in organizational research [e.g. 36, 37]. The average age of the subjects was 30.24 years old, with 8.8% of respondents reported themselves as being Black, 85.4% as White, and less than 2% reported themselves as Asian. With respect to gender, 40.3% of respondents indicated that they were female.

3.2 Measures

The subjects were first asked about their demographic information. Then, subjects were told to pretend that they have decided to take a trip to Paris, and are considering hotels. They are informed that they will be asked to read 3 reviews of the same hotel, and asked several questions about their attitudes toward the review after each. Subjects were then presented with a mock-up iPhone screen containing a simulator of the Trip Advisor app displaying the review. If scrolling was necessary, subjects were able to scroll as they read the review. After each review, the subjects were given a series of questions to ascertain their level of intention of purchase, their trust in the review and finally if they chose to read the review in its entirety, scan it, or not read it at all. MSE (adopted from [22]) and Disposition to trust (adopted from [38]) were measured after all three scenarios were completed.

3.3 Results

Using SPS 21, we conducted both a t-test as well as hierarchical moderated multiple regression analyses to test the hypothesized interactions.

Table 1 presents the results of the comparison between manipulations. A T-test confirms Hypotheses 1 and 2, by showing that the second manipulation (moderate information quality) resulted in the highest beta for both trust in the review and purchase intention.

Table 1: Results of the t-test

Dependent Variable	Information Quality	Mean	Std. Deviation	Std. Error Mean	t
	Low IQ	4.64	1.13	0.10	48.54
Trust	Moderate IQ	5.87	0.87	0.07	79.60
	Excessive IQ	5.42	1.28	0.11	50.18
	Low IQ	4.11	1.29	0.11	37.76
Purchase Intention	Moderate IQ	5.36	1.14	0.10	54.29
	Excessive IQ	4.87	1.43	0.12	39.59

N=141

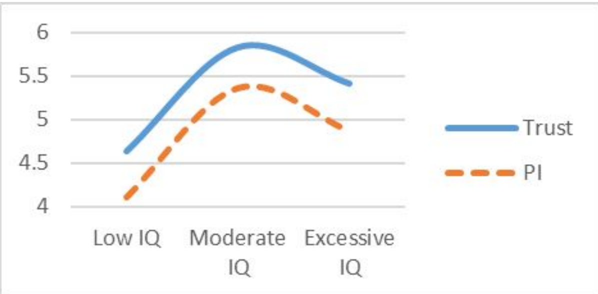

Figure 2. Trust and Purchase Intention across Information Quality

Table 2 shows the means, standard deviations, reliabilities and correlations for the remaining analysis. All variables were shown to be distinct (i.e., correlations < .4) with the exception of the relationship between trust and intent to purchase. This relationship is logical, as they are both related outcomes of the purchasing experience. This correlation will not create an internal validity concern as neither of the correlated variables are predictor variables.

Table 2. Means, Standard Deviations, Reliabilities and Correlations

		M	SD	1	2	3	4	5
1	Age	30.24	6.2	1				
2	Gender			.07	1			
3	Information Quality	5.15	3.53	.09	.17*	0.87		
4	Trust in the Review	4.12	1.44	.11	.21	.28*	0.9	
5	Intent to Purchase	5.53	1.18	.17*	.12	.18*	.72**	1

** significant at p<.01 Note: Reliabilities on the diagonal

* significant at p<.05 Correlations on the lower half

Below, Table 3 shows the regression analysis that was completed after all predictors were standardized and centered. Age and gender were entered in the first step. In the second step, the main effect terms were entered. The final step contained a trust and MSE cross-product term. A significant change in R2 in the third step offers evidence of an interaction effect.

Table 3. Results of the Regression

	Low information quality		Moderate information quality		Excessive information quality	
	Trust	Intent to purchase	Trust	Intent to purchase	Trust	Intent to purchase
Step/Variable	β	β	β	β	β	β
Step 1:						
Age	.12	.10	.21	.16	.14*	.12*
Gender	.10	.05	.12	.09	.17	.16
$AdjR^2$	.01	.00	.00	.00	.04	.04
Step 2:						
Information Quality	.17	.21*	.23*	.31*	.20**	.11*
Mobile Self-efficacy	.12*	.14*	.10*	.17*	.22**	.27**
$\Delta AdjR^2$	.12	.17	.20	.23	.22	.19
Step 3:						
Information Quality x MSE	.10*	.14*	.17*	.22*	.32*	.23*
$\Delta AdjR^2$	.01	.02	.02	.01	.03	.02
F	15.64**	21.78**	27.73**	26.62**	16.23**	25.20**

** significant at p< .01
* significant at P<.05
N=142

The results confirm that MSE does in fact reduce the negative portion of the curvilinear relationship between information quality and both trust and purchase intention, supporting H3 and H4.

4. DISCUSSION

This study was designed to examine two distinct yet related outcomes of online reviews: trust and purchase intention. Our findings supported Hypotheses 1 and 2 and demonstrated an inverted U shape relationship in that individuals would prefer moderate over low or excessive information quality when examining on-line reviews. Hypotheses 3 and 4 focused on the effect that mobile self-efficacy would have on an individual's likeliness to trust (or base a purchase on) a review. As table 3 shows, these hypotheses were supported. Mobile self-efficacy, did, in fact, interact with information quality to increase trust and purchase intention.

This study carries a number of implications for researchers. As mobile computing becomes more ubiquitous, an understanding of how information processing occurs in a mobile context, and differs from the web context becomes increasingly relevant. Our finding that information quality in a mobile context influences how information is processed and feelings of info overload confirms that the differences do exist and opens the door to other questions about information processing differences in mobile computing environments. Further, our finding that MSE serves to mitigate the effect of information overload contributes to the emerging paradigm surrounding MSE [i.e. 22] and highlights the potential of the concept to influence studies of mobile computing.

In addition, our findings carry implications for mobile developers. Since the reviews that people will consume are likely to be written by individuals using a variety of devices (some reviewers will write with a desktop computer, some will use a mobile device), they are likely to vary in terms of information quality. However, since we have shown that consumers working on mobile devices will experience information overload and report lower levels of trust and purchase intention as information quality increases to very high levels, mobile developers for review systems may consider moving longer reviews to the bottom of the list for those consumers who reading the reviews using a mobile device.

5. CONCLUSION

The shift away from PC based computing and toward mobile computing has led to a number of substantial changes in the way that individuals process information. Primary among these changes are new challenges associated with fostering focus and dexterity. In this study, we look at how these challenges influence a common information processing task: reducing uncertainty in a product selection task by reading online product reviews. Further, we argue that these effects are less substantial for individuals who report higher levels of MSE. Findings carry implications for review system developers as well as researchers. In particular, this study raises a question about how individuals in a mobile computing environment differ in their ability to process information while engaging in other tasks.

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