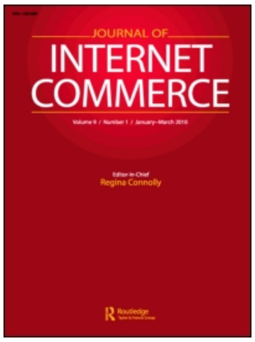

Journal of Internet Commerce

Routledge
Taylor & Francis Group

ISSN: 1533-2861 (Print) 1533-287X (Online) Journal homepage: http://www.tandfonline.com/loi/wico20

Determinants of App Stores Continuance Behavior: A PLS Path Modelling Approach

Sajad Rezaei, Milad Kalantari Shahijan, Muslim Amin & Wan Khairuzzaman Wan Ismail

To cite this article: Sajad Rezaei, Milad Kalantari Shahijan, Muslim Amin & Wan Khairuzzaman Wan Ismail (2016) Determinants of App Stores Continuance Behavior: A PLS Path Modelling Approach, Journal of Internet Commerce, 15:4, 408-440, DOI: 10.1080/15332861.2016.1256749

To link to this article: http://dx.doi.org/10.1080/15332861.2016.1256749

JOURNAL OF INTERNET COMMERCE
2016, VOL. 15, NO. 4, 408–440
http://dx.doi.org/10.1080/15332861.2016.1256749

Routledge
Taylor & Francis Group

Determinants of App Stores Continuance Behavior: A PLS Path Modelling Approach

Sajad Rezaei[a], Milad Kalantari Shahijan[b], Muslim Amin[c], and Wan Khairuzzaman Wan Ismail[d]

[a]Taylor's Business School, Taylor's University, Subang Jaya, Selangor Darul Ehsan, Malaysia; [b]UTM Razak School of Engineering and Advanced Technology, Universiti Teknologi Malaysia (UTM), Kuala Lumpur, Malaysia; [c]Department of Management, College of Business Administration, King Saud University, Riyadh, Saudi Arabia; [d]UTM International Business School (UTM IBS), Universiti Teknologi Malaysia, Kuala Lumpur, Malaysia

ABSTRACT

Prior research has mostly examined the satisfaction, intention, and behavior of users toward technology and systems in general, and little research has been dedicated to understanding apps commerce and app stores. Drawing upon the extended model of IT continuance and theory of information overload as a theoretical foundation, the aim of this study is to examine consumer satisfaction, continuous intention, and behavior toward apps shopping. A total of 347 valid questionnaires were collected from experienced consumers with app stores to statistically test the theoretical model using the partial least squares path modelling approach, a structural equation modelling technique. The results show that apps self-efficacy, post-usage usefulness, disconfirmation, facilitating conditions, perceived information overload, apps satisfaction, and apps continuance intention can be used to predict and explain 75.7% of variance in consumer's continuance behavior in using app stores. The negative and positive causal relationship between constructs, managerial implications, and limitations are discussed.

KEYWORDS

App store; apps commerce; continuous behavior; continuous intention; extended model of IT continuance; theory of information overload

Introduction

The advent of e-commerce and associated technologies have opened an effective gate for firms (Kauffman and Walden 2001; Hill, Beatty, and Walsh 2013; Peng and Lai 2014) to implement a strategic channel expansion and to offer products and services to target consumers (Lee, Cha, and Cho 2012; Ström, Vendel, and Bredican 2014; Nagar 2016). Apps technologies (Cloud Applications), as a part of cloud computing, provide a platform that companies are struggling to adopt into their business activities (Marston et al. 2011; Oliveira, Thomas, and Espadanal 2014). Apps technologies create effective functions to hold consumer interest (Song et al. 2014). From the consumer's

CONTACT Sajad Rezaei mmg.sajad@gmail.com Taylor's Business School, Taylor's University, Lakeside Campus, No. 1, Jalan Taylor's, Subang Jaya, Selangor Darul Ehsan 47500, Malaysia.
Color versions of one or more of the figures in the article can be found online at www.tandfonline.com/wico.

viewpoint, new technologies such as apps empower them by providing wider access to helpful information relating to particular products and services in the retail setting (Bellman et al. 2011; Hsu and Lin 2014; Kang, Mun, and Johnson 2015; Wang, Malthouse, and Krishnamurthi 2015). Specifically, apps, such as mobile apps, which are available for laptops, iPads, and smartphones, increase consumers' awareness toward products, prices, and price promotions (Grewal et al. 2012; Rosenbloom 2013). Recent studies have begun to refer to mobile applications as apps in the business domain (Lin and Chen 2013) and education (Bishop 2012), and several studies have evaluated consumer's shopping behavior toward shopping using apps (Bellman et al. 2011; Wang et al. 2015). Despite the fact that smartphone users mostly use apps for their shopping experience and related activities, a few empirical assessments have considered the app store as a distinct platform.

There are several categories of apps available for customers. Approximately 48% of smartphone owners shop for apps on a weekly basis, and users spend an average of 81 minutes a day using apps (Budd and Vorley 2013). The most significant element in the use of cell phones for the purpose of getting access to information has been the emergence of apps (White 2010). Apps are available at apps stores for mobile phones, smartphones, tablets, and even PCs which are available in a variety of handheld forms such as on smartphones or other portable devices (Song et al. 2014). Hsu and Lin (2014) referred to mobile apps as the software for smartphones that facilitate productivity and information repossession for users. Examples of apps services include mobile banking, mobile payment, mobile news, mobile shopping, and mobile gaming and entertainment. In reference to the e-commerce definition (Zwass 1996 3), which is "the sharing of business information, maintaining business relationships, and conducting business transactions by means of telecommunications networks," apps commerce is a series of business efforts in utilizing apps for the distribution of information, sustaining and conducting relationships, communications, and transactions within an individual organization. Accordingly, this study defines app store as a platform that enables users to search for goods and services, read reviews, compare prices, and accomplish transactions using apps (Cloud Applications). Lazada apps, Groupon apps, LivingSocial apps, Zara apps, eBay apps, and Amazon apps are some examples of apps retailing or app stores that are currently available for customers on both smartphones and PCs. Perhaps apps are attractive to customers (Lu 2014; Song et al. 2014) and are gaining popularity due to technological innovations, and business and user demands (Hsu and Lin 2014; Sipior, Ward, and Volonino 2014; Wang et al. 2015).

Furthermore, the advancement of IT enables consumers to understand the offerings of firms, while their satisfaction is not enough in itself to sustain the long-term connection with the firm (Song et al. 2014). Continuance intention has been used by marketing and information system (IS) research in order to evaluate technology acceptance, continued use, or intention. The notion of self-efficacy is significant in order to enable firms to realize how each person can promptly create new mechanisms in terms of skill, technology acceptance, and usage (Torkzadeh and Van Dyke 2002). E-store satisfaction, like traditional stores, is not only obtained from customer satisfaction with the goods purchased. Accordingly, studies (Al-Maghrabi and Dennis 2011; Lin, Chen, and Fang 2011; Wang and Chiang 2009) have shown that acquiring new customers costs five times more than keeping the current ones. The intention of users toward the continued use of an IS is related to users' satisfaction levels as well as post-usage usefulness (PUU) (Hossain and Quaddus 2011). Positive disconfirmation is the over-efficiency that can relate to satisfaction, while the negative type of disconfirmation leads to under-efficiency that has lower overall satisfaction. Likewise, high expectation may lead to high disconfirmation, and a low expectation or low perceived usefulness may reduce the continuance use intention. According to Limayem, Khalifa, and Frini (2000), facilitating conditions are significant in encouraging individuals to act on their intention to shop on the Internet. Considerably, information overload may avert system users from devoting full mental capacity to system usage. As a result, information overload makes consumers confused (Kasper, Bloemer, and Driessen 2010) and leads to feelings of being confused and overwhelmed (Karani, Fraccastoro, and Shelton 2013).

The aim of this study is to examine consumers' continuance intention and behavior toward apps retail by integrating the extended model of IT continuance and the theory of information overload. Therefore, the hypothesis development is formulated along with the literature review in the following section. After the hypotheses are developed and the model is established, the study discusses the methodology and procedures used in this study, followed by the results and empirical findings. At the end, we shall describe the conclusion and implications as well as recommendations for future research directions. This study contributes to the literature by examining users' continuous intention and behavior toward apps commerce, a new phenomenon of e-commerce.

Theoretical background and hypotheses development

Continuance intention has become a significant topic in the context of IS. In order to illustrate consumers' continuous intention and behavior toward app stores, this research proposes an integrative model based on the extended model of IT continuance constructs (i.e., disconfirmation, PUU, satisfaction, self-efficacy, facilitating conditions, continuance intention, and continuance behavior) and the information overload theory construct (i.e., perceived information overload). The extended model of IT continuance (Bhattacherjee, Perols, and Sanford 2008) originated from the expectation disconfirmation theory (EDT) (Oliver 1980) and post-acceptance theory of IS continuance

(Bhattacherjee 2001). The EDT explains users' continuance behaviors according to external motivations, for instance, usefulness and satisfaction. The IT continuance model explains individuals' intention to continue using information and communication technology, and proposes that initial acceptance would lead to user's continuance decision (Hsu and Lin 2014). The extended model of IT continuance posits that IT self-efficacy, disconfirmation, facilitating conditions, PUU, satisfaction, and continuance intention drive IT continuance behavior.

With respect to the fast progress of IT and IS, information overload is considered to be an issue in which users perceive obstacles in performing given activities, especially among online users. In addition to the extended model of IT continuance constructs, the perceived information overload construct has been integrated in order to propose a model in app stores and to examine consumers' continuous intention and behavior toward apps. The theory of information overload is considered to be one of the major theories in explaining user satisfaction (Liang, Lai, and Ku 2006). The information overload concept has attracted considerable attention in consumer behavior and the IS context (Jacoby 1984), as the notion of information overload refers to a negative or series of problematic results (Klausegger, Sinkovics, and "Joy" Zou 2007; Bawden and Robinson 2009; Stanton and Paolo 2012). The theory of information overload was introduced by Jacoby, Speller, and Kohn (1974) to explain the consumer shopping decision process. This theory proposed that a series of negative information and errors might result in a user's frustration or confusion. Information overload is defined as "a state in which too much information leads to a generalized state of anxiety and/or confusion, or an inability to make a decision regarding a specific problem" (Lueg 2014 9). Perceived information overload might happen when the information received by users becomes a source of inconvenience and causes harassment to the users instead of assistance when the information is potentially helpful. Figure 1 depicts the theoretical research model.

Apps continuance intention and behavior

It is important to understand users' continuance behavior (Hsu and Lin 2014). Bhattacherjee (2001) was one of the first scholars who clearly explained the actual discrepancy of continuance behaviors and IS acceptance, and related assumptions in consumer continuance behavior. Continuance behavior is defined as "the continued usage of IS by adopters, where a continuance decision follows an initial acceptance decision" (W.-S. Lin 2011, 141). In other words, continuance behavior is defined as a user's intention to continue or discontinue using a system which tracks on prior acceptance decision. Continuance intention is a person's tendency in order to use services in the post-acceptance stage (Hu et al. 2009). A high degree of continuance intention

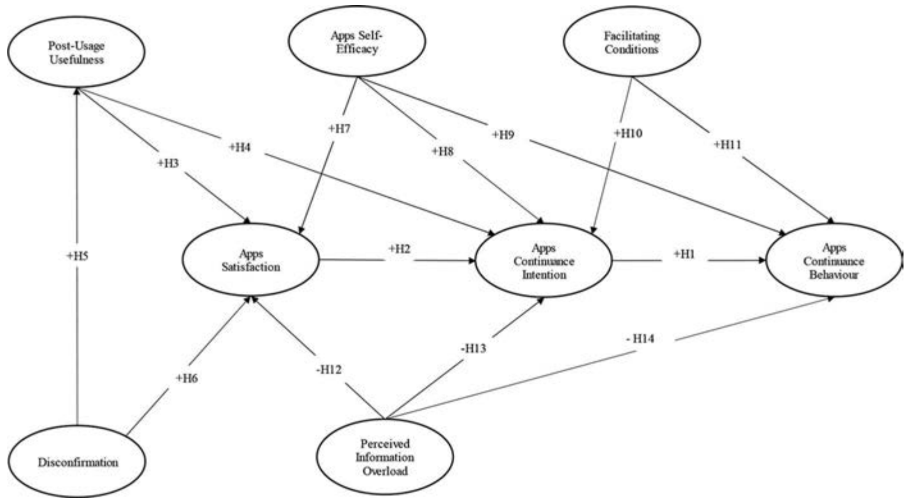

Figure 1. Theoretical research model.

refers to the fact that the program, system, or product is designed and performs well (Lin et al. 2011), and as a result, the users can proceed for more applications and perhaps use that particular website or app for more of the assigned task.

A higher consumer continuance tendency shows a subjective willingness to purchase online. Several factors, such as time saving, advantages of price, ease of use, and comfort could have an impact on the customer's continuance intention toward a system in general. Similarly, studies have stressed that continuance intention plays an important role in the online environment (Wang and Chiang 2009). Noticeably, studies regarding IS continuance have claimed that IS continuance behavior is related to the intention to continue using an IS positively (Limayem, Hirt, and Cheung 2007). Likewise, continuance behavior is significantly affected by IT continuance intention (Bhattacherjee et al. 2008; Hsu and Lin 2014). In social networking sites or online shopping websites, users' continuance intention could be driven by the personal interaction and communication developed offline as well as the information and system itself. Studies have claimed that a key element in order to explain continuance behavior is spontaneous behavior, which is a crucial component in illustrating continuance behavior (Bellman et al. 2011). Therefore, the researchers hypothesize the following:

H1. There is a positive relationship between apps continuance intention and apps continuance behavior.

Apps satisfaction

The expectation confirmation model was proposed by Oliver (1977, 1980) for the purpose of examining customers' profound satisfaction and repeated decision-making processes. Satisfaction can be defined as "an affective consumer condition that results from a global evaluation of all the aspects that make up the consumer relationship" (Flavián, Guinalíu, and Gurrea 2006, 4). Nevertheless, satisfaction is the total assessment of the relationship with the vendor and cannot be the outcome of a particular transaction, and is shown to be key in attracting and retaining consumers (Bhattacherjee 2001). Customer satisfaction is a rivalry element and one of the greatest indexes for a firm's profit related with the return on investment, and is believed to influence consumers' purchasing processes. The economic outcomes of apps satisfaction would be illustrated when customers are satisfied in the long run. Sivadas and Baker-Prewitt (2000) asserted that customer satisfaction or even dissatisfaction as an affective or cognitive response appears as a reaction to an individual or extended collection of services. Similarly, satisfaction is an efficient and emotional reaction to a particular experience of retail (Teo and Lim 2001), such as app stores.

Likewise, scholars have asserted that IS continuance behavior can be predicted by satisfaction (Bhattacherjee 2001). Bellman and colleagues (2011) argued that mobile apps have a positive impact on consumers' attitudes toward branded apps. User satisfaction with apps would result in "pleasurable fulfilment" of the system (Song et al. 2014). Scholars believe that satisfaction can be advanced via shopping experience. Interestingly, a customer's perception of satisfaction is an objective that is achieved through buying and utilizing products and services; thus, purchase satisfaction indicates an achievement. apps users' satisfaction with businesses might enhance the customers' satisfaction level by providing them with such an orientation for product usage. Consumers are more inclined to shape a desirable sense of satisfaction with the shops that provide services virtually and the website that is realized to be helpful in supplying purchasing information. Likewise, according to Currás-Pérez, Ruiz-Mafé, and Sanz-Blas (2013), customer retention can be improved and achieved through the online satisfaction of users with the services. Furthermore, app users usually assess their level of satisfaction regarding a particular experience with services resulting in continuance intention. Therefore, customer satisfaction has a close relationship with continuance intention in a virtual arena (Kang and Lee 2010), and the researchers hypothesize the following:

H2. There is a positive relationship between app satisfaction and app continuance intention.

PUU

Traditionally, perceived usefulness is defined "as the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis 1989, 320). PUU is the level and the perception that the usage of an app store could improve an individual's efficiency and productivity, and provide assistance to make better shopping decisions as well as be useful to the user's total task. The exception confirmation model illustrates the consumers' post-usage expectations by PUU because it has been accredited in most of the IS studies as a solid and silent cognitive belief that specifies the intention of the individual within a period of time. Usefulness could be considered to be a significant individual cognition and perception that may occur at the pre- and post-usage level, and influences the overall user intention and behavior. PUU is considered to be the long-term belief integrated from previous usefulness. Thus, in order to enhance the level of usefulness, an individual user (e.g., a mobile user) is being influenced by various mobile services and applications.

Mobile apps that synthesize the interactivity of design factors may improve the users' experiences and steer toward satisfaction (Bellman et al. 2011). Noticeably, most retailers provide their customers with smartphone apps and in-store mobile services as the shopping assistant systems for the purpose of shopping and comfort (Kang et al. 2015). With any IS usage, the interchange of costs and benefits has a significant impact on continuance intention. Usefulness and performance are closely related to each other. Moreover, empirical studies regarding usefulness indicated the need to prepare quick, efficient, and helpful comments for users at a suitable level, which clearly leads to a positive attitude of users toward the electronic system. Moreover, when PUU perception is more consistent with long-term usage, it will be a powerful influence on long-term usage (Bhattacherjee et al. 2008). Productivity, as a component of PUU, is created mainly of elements that are associated with whether the system has augmented the efficiency, usefulness, and easiness of interacting with people, as well as the quality. Thus, the researchers hypothesize the following:

H3. There is a positive relationship between PUU and apps satisfaction.

H4. There is a positive relationship between PUU and apps continuance intention.

Disconfirmation

Disconfirmation is the cognitive collation among predictive expectations, such as the desires, needs, and norms, and what the consumer actually achieves in terms of products and services (Gorla and Somers 2014). Disconfirmation reflects "the discrepancy between an individual's perceptions of a product or service's performance and his or her expectation levels" (Hsu, Chiu, and Ju 2004, 769). A previous study (Kim 2013) has claimed that consumer pre-expectations have a positive relationship with negative disconfirmation in that higher expectations are less likely to be exceeded by performance perception. On the other hand, perceived high performance is more likely to surpass consumer pre-expectation, which results in positive disconfirmation. According to Riquelme and Román (2014), the higher prevalence of negative outcome is the result of falling below expectations, whereas positive perception equates to exceeding expectations in which both disconfirmation sides are related to the initial expectations of product performance.

Hsu and Lin (2014) argued that confirmation is positively related to satisfaction and purchase intention for paid mobile apps. In fact, relatively, user satisfaction and continuance usage can be led by positive disconfirmation and confirmation (Hsu and Lin 2014). Disconfirmation is influenced positively by service performance during and after the consumption experience period because higher performance will raise the expectations and lead to positive confirmation, and finally satisfaction. Additionally, in relation to expectations, this is just the anticipation of utilizing the usefulness system, which improves job performance, productivity, and work quality. Rosen, Karwan, and Scribner (2003) argued that disconfirmation is the most immediate precursor to satisfaction, which occurs from the differences among previous expectations and the real performance. Furthermore, the effects of disconfirmation vary across different products/services (retail offering), degrees of expectations, and involvement in the usage of apps. Moreover, studies have claimed that disconfirmation is an emergent construct influencing PUU (Mettler 2012), and it would progress the effectiveness and also raise the productivity level. Likewise, confirmation as well as expectation are crucial elements of satisfaction and continuance intention (K.-M. Lin 2011). Therefore, the researchers hypothesize the following:

H5. There is a positive relationship between disconfirmation and PUU.

H6. There is a positive relationship between disconfirmation and apps satisfaction.

Apps self-efficacy

Self-efficacy as a construct originates from social cognitive theory (Bandura 1986, 1997), and it has attracted significant attention because it plays an important role in creating individual desire performance. Self-efficacy is "the belief that one has the ability to perform a particular action and besides, it has been indicated to be associated with an individual's performance in computer training and technology acceptance" (Igbaria and Iivari 1995, 588). In addition, self-efficacy raises the level of individual endeavors, and regulates a person's perseverance and their effort whenever they face challenges. Greater perceived self-efficacy would result in people having greater intention or desire to accept the suggested practices, such as an app store.

In other words, Internet self-efficacy implies the "self-assessment of the ability to organize and execute Internet-related activities that elicit the desired results" (Kuo et al. 2014, 37). Studies regarding the gender issues in technology usage found that those users who considered learning computers as being valuable and useful will have positive self-efficacy beliefs (Vekiri and Chronaki 2008). According to Torkzadeh, Chang, and Demirhan (2006), when the degree of self-efficacy is higher, the performance achievement would be enhanced; thus, people with high self-efficacy are proactive and work longer compared to those with low self-efficacy. Prior experience is significant in order to characterize the self-efficacy related to computers; for example, students will obtain more knowledge and experience with their computers (Salanova et al. 2000). Likewise, a previous study about the relationship between technology use and self-efficacy (Shank and Cotten 2014) revealed that youths with greater self-efficacy might engage with computers more than their less efficacious counterparts.

Kuo and colleagues (2014) claimed that individuals with poor self-efficacy would be reluctant to socialize using virtual systems to get help due to having low confidence. Moreover, a study (Kang and Lee 2014) regarding the self-customization of the online service environment found that self-efficacy has a significant effect on the continuance intention, which posits that a powerful sense of self-efficacy increases the degree of motivation and the likelihood of the approach behavior. A keen interest to take risks and explore as well as solve problems by using apps (Kim and Glassman 2013; Akhter 2014) would be related to self-efficacy. Individuals with greater self-efficacy will have more self-confidence about their capability to obtain various objectives on the Internet. Moreover, they are more inclined to undertake hard tasks to become experts rather than avoid them. In spite of this, those people who have high self-efficacy can set higher objectives for themselves and put forth intense effort to understand the objectives. In addition, those who have slightly low self-efficacy will obtain the original objective and will become attached to it. Additionally, individuals who spend more time on the Internet are more inclined to achieve higher scores for self-efficacy and improve their communication as well as general self-efficacy toward the Internet. Self-efficacy is the strongest antecedent of satisfaction, so self-efficacy affects satisfaction continuance intention and behavior. Therefore, the researchers hypothesize:

H7. There is a positive relationship between apps self-efficacy and apps satisfaction.

H8. There is a positive relationship between apps self-efficacy and apps continuance intention.

H9. There is a positive relationship between apps self-efficacy and apps continuance behavior.

Facilitating conditions

Traditionally, facilitating conditions have been considered in IS research as a construct; thus, in the Internet environment, researchers have selected measures, such as a good understanding of the Internet and inexpensive access to the Internet to assess facilitating conditions (Pallud and Straub 2014). Facilitating conditions are defined as "the degree to which one believes that organizational and technical resources are available" (Bhattacherjee et al. 2008, 20). In other words, the facilitating conditions are the elements that are solely available in the environment that have an impact on an individual's propensity to carry out a task. A study regarding "online tax filing and payment system" figured out that the increase in facilitating conditions toward Taiwan's e-government services will lead to the increase in perceived behavioral control, positively (Hung, Chang, and Yu 2006). Nevertheless, they can have full control over the Internet in order to do/not do shopping or use particular apps, and perhaps they can use it whenever they need to. A study that examined the predictors of m-commerce adoption (Chong 2013) claimed that facilitating conditions are an important construct. According to Liu and Forsythe (2011), one of the facilitating condition factors is Internet usage, which is part of the process of post-usage of the virtual channel; thus, accessibility to the Internet provides a facilitating condition for virtual purchasing.

Moreover, the purpose of patronizing the Internet market amid facilitating conditions should illustrate the great user interface, which comprises searching, ease of access, and navigation. Similarly, a confirmatory study emphasized that intention is positively influenced by facilitating conditions. Another empirical study illustrated that perceived behavioral control toward technology-related information adoption is affected by the perceived facilitating resource conditions, such as money and time (Hung, Ku, and Chang 2003). Scholars have examined the purpose of "adoption and non-adoption of mobile banking in Ghana" and illustrated that facilitating conditions assist in supplying the services, raising the perception of usefulness and user self-confidence for mobile banking, which consequently leads to rising usage (Crabbe et al. 2009). Therefore, the researchers hypothesize:

H10. There is a positive relationship between facilitating conditions and apps continuance intention.

H11. There is a positive relationship between facilitating conditions and apps continuance behavior.

Perceived information overload

The concept of perceived information overload refers to the negative effects caused by excessive information resulting in user dissatisfaction, and discontinuous intention and behavior toward the system. It is important to understand the influence of information overload on consumers when the interaction among consumers and marketers occurs in an online environment (Lee and Lee 2004). Increasingly, and especially in the domain of non-work-related information processing, apps are being developed to address information overload (Pentina and Tarafdar 2014). Likewise, information overload on the Internet may prevent individual users from scrutinizing information in detail (Zhang et al. 2014). Hsiao (2009) argued that consumers might receive plenty of messages from other users and consumers that would distract their attention and which may cause a sense of information overload. Some market segments, such as aged consumers, are more vulnerable to perceived information overload compared to the younger segments. Consequently, retailers should design efficient review mechanisms because many users will experience information overload. A higher degree of Internet use is related to a higher degree of interpersonal trust and lower levels of information overload; therefore, consumers will have adversity in order to acquire information (Pentina and Tarafdar 2014).

In an organizational setting, the results of an empirical survey depicted that information overload would lead to employee job dissatisfaction (Bawden and Robinson 2009) and stress (Klausegger et al. 2007). In a consumer setting, because high quality information is required for decision processing (e.g., shopping) compared to the physical ability to process the particular IS task, information overload requires a great deal of attention. Both information overload and the lack of information would lead to customer dissatisfaction. A customer's decision and perception highly depend on the quality of information. People will face problems with information overload when the particular system has a huge amount of information, which makes the user confused due to complicated information (Liang et al. 2006; Shang, Chen, and Chen 2013). Likewise, consumer confusion can occur when the amounts of information-based decisions are increased and perhaps when the information received is similar, complex, and too ambiguous.

According to the information overload theory, satisfaction with the system would be enhanced when the content and information is perceived as adequate by consumers/users based on their interests (Liang et al. 2006). Sufficient information plays a significant role in improving the consumers' shopping decisions. Based on the theory of information overload, whenever the perception of information overload increases, consumers must strive more to process the information, thus the decision would be poor and less effective (Lee and Lee 2004; Nagar 2016). A study on online travel websites indicated that information overload would lead consumers to be confronted by too many alternatives in virtual shops and put the consumers in a difficult situation when they are trying to decide which is better (Shang et al. 2013). Stanton and Paolo (2012) argued that information overload influences consumer confidence in terms of shopping orientation for apparel products. In addition, a study has shown that the difficulty that arose from information overload and the lack of clarity in the system make users rely on those cues that can indicate information credibility (Zhang et al. 2014). Similarly, those consumers who become confused under information overload cannot decide easily, and it is hard for them to make shopping decisions (Nagar 2016). In addition, it can lead to a decrease in the consumers' confidence, which affects their capability to make better decisions (Klausegger et al. 2007; Wang and Shukla 2013), and it leads the consumers to a less satisfied state of mind. Hence, information overload contributes to the negative consequences for consumers in making decisions (Kasper et al. 2010), and as a result, the literature suggested that information overload would cause consumer confusion and lead to feelings of being overwhelmed and stressed (Liang et al. 2006; Stanton and Paolo 2012; Karani et al. 2013). Therefore, the researchers hypothesize:

H12. Perceived information overload negatively influences apps satisfaction.

H13. Perceived information overload negatively influences apps continuance intention.

H14. Perceived information overload negatively influences apps continuance behavior.

Research method

To empirically and statistically examine the proposed theoretical research model (Figure 1) and the hypothesized relationships, a cross-sectional data collection approach using the quantitative method was conducted. The survey was designed to target apps shoppers who have had an experience with apps retailers to determine consumer continuance intention and behavior. Accordingly, an online questionnaire was designed in two sections. The first section captures the respondent's demographic characteristics, such as gender, age, education, monthly income, and ethnicity. Table 1 depicts the frequency of the respondents' demographic characteristics. Since the study targets apps shoppers, a question was designed to ensure that the study sample represents respondents who have experienced apps retailing; thus, a question was appended to capture the information regarding the apps retail used by respondents. As shown in Table 1, the respondents have purchased products from and have experience with apps retailers, such as Lazada apps, Groupon apps, LivingSocial apps, Zara apps, eBay apps, Amazon apps, and other retailers.

Content and face validity

Further, the second part of the questionnaire was considered to capture information regarding the research constructs, to statistically test the model. The information in the second section was used to empirically test the model

Table 1. Demographic characteristics of respondents.

Profile	Characteristics	%
Gender	Male	46.1
	Female	53.9
Age	≤19	7.2
	20–29	35.2
	30–39	39.2
	≥40	18.4
Education	PhD	4.9
	Master	28.8
	Degree	40.9
	Diploma	23.1
	Others	2.3
Monthly income	≤RM1000[a]	14.7
	RM1001–RM2000	30.3
	RM2001–RM3000	27.1
	RM3001–RM4000	15.9
	≥RM4001	12.1
Ethnicity	Malay	34.6
	Chinese	49.9
	Indian	9.5
	Others	6.1
Experience with apps retailing	Lazada apps	13.3
	Groupon apps	22.5
	LivingSocial apps	21.6
	Zara apps	19.6
	eBay apps	12.7
	Amazon apps	6.9
	Other apps retail	3.5

[a]RM3.25 = USD1.

for the measurement and structural model. To measure the research constructs and ensure content validity, the measurement items selected for the constructs were taken from previous studies in the context of IS and retailing. Appendix A shows the measurement scales and sources. In consumer research studies and survey methodologies, researchers proposed a set of indicators to measure a latent construct. Content validity is "the degree to which the elements of an assessment instrument are relevant to and representative of the targeted construct for a particular assessment purpose" (Haynes, Richard, and Kubany 1995, 238). There is a consensus in the methodological literature that content validity involves two distinct phases including through careful theoretical conceptualization-related to domain analysis, and the evaluation of the relevance of the scale's content through expert assessment (Polit and Beck 2006). Based on the research patterns and proposed framework in this study, the questionnaire items are adopted based on previous related studies to ensure that content validity is established. In addition, face validity, which is closely related to content validity, and is often considered to be an aspect of it, was considered. "Face validity has been defined as reflecting the extent to which a measure reflects what it is intended to measure" (Hardesty and Bearden 2004, 99). Following the guidelines of previous studies (Babin and Burns 1998; Bruner, Hensel, and

James 2001), before the questionnaire was distributed and data collected, careful consideration was given to the face validity of the proposed measurements of the constructs. First, three experts were consulted regarding the areas of the anticipated dimensions, and secondly, a focus group was selected to further explore whether the research constructs were reasonable and meaningful from a shopper's point of view. Subsequently, the hypothetical structure attained a high degree of face validity, and the study further proceeded with distribution of the questionnaire, a pretest ($N = 21$), and pilot test ($N = 131$). Therefore, after the pretest was conducted, and the questionnaire was amended based on consumers' feedback, a pilot test was successfully undertaken, following which we distributed the questionnaire for actual study.

Sample size adequacy for PLS-SEM analysis

In IS and social science research, Chin (1998) argued that the adequacy of sample size depends on power analysis. To determine an adequate sample size to test the model using PLS-SEM analysis, power analysis (Chin 2010) was considered both before and after data collection. Prior to data collection, to compute and determine the necessary sample size, "A-Priori Sample Size Calculator for Structural Equation Models" (Soper 2015) was used. The results imply that the recommended minimum sample size is 108 observations/cases (given: anticipated effect size = 0.3, desired statistical power level = 0.8, number of latent variables = 8, number of observed variables = 31, probability level = 0.05). In addition, the rule of thumb power analysis recommends a minimal sample size of 100 to 130 cases according to the model with the largest number of predictors. Accordingly, following Gefen, Straub, and Boudreau (2000), since PLS-SEM is less affected by small sample sizes, "at least 10 times the number of items of the most complex construct" is required to set an adequate sample size. Apps continuance intention (ACI) is the model with the largest number of predictors (i.e., five predictors including PUU, apps satisfaction, apps self-efficacy, facilitating conditions, and perceived information overload); thus, 50 cases were determined to be the minimal requirement to conduct statistical analysis. For the purpose of this study, out of the 400 questionnaires distributed among the target population, 351 questionnaires were collected. Out of the 351 questionnaires received, 4 were not properly completed. Thus, a total of 347 valid questionnaires were used to empirically test the model for measurement and structural model using PLS-SEM. Once the data were collected, principal components analysis, which is an exploratory statistics analysis, was considered. The extraction sum of square loading results imply that more than one construct exists in the model, and the Kaiser-Meyer-Olkin (KMO), which is a measure of sampling adequacy, shows a value of 0.844, thereby confirming an adequate sample size. Furthermore, the Cronbach's alpha values and average variance extracted (AVE) values (see

Table 2), and post-hoc power analysis for the rejected hypothesis (PUU → ACI) imply that the dataset is adequate (i.e., data are statistically powerful to detect the degree of significant effect). Thus, the statistical procedure results show adequate dataset and power.

Missing values treatment

In social and behavioral science, missing values are defined as "a pervasive problem in sample surveys" (Little 1988, 287) and cause serious problem in the analyses of multivariate data analysis (Schafer and Olsen 1998; Rezaei and Ghodsi 2014) such as SEM. Using SPSS software, before the data were

Table 2. Construct validity and outer *T*-statistics.

Construct	Items	Outer weights or loadings	AVE[a]	Composite reliability[b]	Cronbach alpha	Outer *T*-statistics[c]
ACB[d]	ACB1	0.923	0.845	0.942	0.908	73.813
	ACB2	0.911				52.296
	ACB3	0.924				58.169
ACI	ACI1	0.815	0.675	0.862	0.759	29.571
	ACI2	0.820				33.598
	ACI3	0.829				34.365
ASE	ASE1	0.772	0.691	0.899	0.851	28.506
	ASE2	0.852				35.196
	ASE3	0.846				37.599
	ASE4	0.852				35.920
DISC	DISC1	0.861	0.768	0.930	0.899	50.257
	DISC2	0.888				61.841
	DISC3	0.895				57.428
	DISC4	0.860				41.991
FC	FC1	0.872	0.715	0.882	0.801	38.305
	FC2	0.847				38.354
	FC3	0.817				40.113
PIO	PIO1	0.846	0.613	0.905	0.873	31.768
	PIO2	0.725				21.865
	PIO3	0.708				16.550
	PIO4	0.797				24.233
	PIO5	0.794				23.516
	PIO6	0.820				29.154
PPU	PUU1	0.850	0.692	0.900	0.851	43.842
	PUU2	0.846				38.126
	PUU3	0.855				41.946
	PUU4	0.774				26.868
SAT	SAT1	0.836	0.664	0.887	0.830	36.413
	SAT2	0.860				46.587
	SAT3	0.747				23.703
	SAT4	0.812				27.998

[a]AVE = (summation of the square of the factor loadings)/{(summation of the square of the factor loadings) + (summation of the error variances)}.
[b]Composite reliability (CR) = (square of the summation of the factor loadings)/{(square of the summation of the factor loadings) + (square of the summation of the error variances)}.
[c]*t* values: *t* value 2.58 (sig. level = 1%). From the outer *t* statistics, a set of "actionable strategies" based on the sizes of the exogenous construct item weights is interpreted.
[d]ACB = apps continuance behavior; ASE = apps self-efficacy; DISC = Disconfirmation; FC = Facilitating conditions; PIO = Perceived information overload; SAT = Satisfaction.

analysed in SEM, the expectation maximization (EM) algorithm (Little 1988; Rezaei 2015) was performed to impute and handle missing values. The EM is an iterative processing method in which all other constructs and items relevant to the construct of interest are taken into account to predict the values of the missing data (Graham et al. 1997). First, using SPSS, EM was performed to ensure that values are missing completely at random (MCAR) according to Little's chi-square statistic. The Little's MCAR test shows that $\chi^2 = 198.165$, degrees of freedom = 180, and significance level = 0.168, indicating that the missing data were completely at random. Therefore, subsequently, the EM algorithm was performed in order to handle the missing values in the dataset before proceeding to data analysis.

Non-response bias and common method variance (CMV)

Non-response bias and common method bias are two major types of bias in survey methods, and researchers should consider these threats to validate the results and the generalizability of the research findings. Non-response bias is defined as "a systematic and significant difference between those who respond to a survey and those who do not in terms of characteristics central to the research focus" (Lewis, Hardy, and Snaith 2013, 240–41), while common method bias is due to the single survey method used in collecting data or responses from the target population (Podsakoff et al. 2003; MacKenzie and Podsakoff 2012). Accordingly, common method bias was considered following guidelines (two steps) proposed by previous studies (Podsakoff et al. 2003; MacKenzie and Podsakoff 2012). First, at the survey design stage, the researchers avoided acquiescence biases, scale length, common scale formats, item priming, common rate, and item characteristic effects. Second, statistical techniques, such as Harman's single-factor test (Harman 1976) and the structural model marker-construct technique, were conducted. Thus, the statistical finding depicts that common method bias is not a concern in this study. Furthermore, in order to ensure that non-respondents bias is not a threat in this study, continuum of resistance theory (Lin and Schaeffer 1995) analysis and procedures were performed. The results of an analysis of known demographic characteristics (see Table 1), wave analysis (early and late response), and comparing the key constructs of the study (i.e., PUU, disconfirmation, satisfaction, continuance intention, and behavior) imply that there are no significant differences among groups. Therefore, empirical assessment depicts that non-respondents bias is not an intimidation in this study.

PLS-SEM analysis method

Based on the research objectives, SEM enables researchers to test or modify theories and models (Anderson and Gerbing 1982). The SEM technique is a great advantage over first-generation methodologies (Fornell and Larcker 1981; Henseler, Ringle, and Sinkovics 2009; Hair, Ringle, and Sarstedt 2011; Henseler et al. 2014) in IS research (Chin 1998; Gefen et al. 2000; Chin, Marcolin, and Newsted 2003), which integrates various statistical processes simultaneously for parameter assessment and hypothesis testing. As a variance-based SEM (VB-SEM), the PLS statistical approach (Wold 1975) and its methodology (Lohmöller 1989) have gained tremendous attention in IS, marketing, and consumer behavior research (Sarstedt 2008; Henseler et al. 2009; Reinartz, Haenlein, and Henseler 2009; Hair et al. 2011). The maximum likelihood (MLE) method (Jöreskog 1970) for confirmatory factor analysis, a covariance-based SEM (CB-SEM), is a suitable method when researchers intend to test a theory and relationships based on measurement errors. While CB-SEM only focuses on measurement errors or a set of model parameters, PLS-SEM enables researchers to assess indicators/items and causal relationships among latent constructs (Reinartz et al. 2009). VB-SEM and CB-SEM start with a theory or a set of theories and concepts (Reinartz et al. 2009; Hair et al. 2011; Hair et al. 2012) that share the same roots and functions (Hair et al. 2012). Notwithstanding, CB-SEM requires a hard and fixed assumption of a theory, whereas VB-SEM is more flexible (Henseler 2010); thus, PLS-SEM is preferred over CB-SEM if the purpose of study is "an extension of an existing structural theory" (Hair et al. 2011, 144). While CB-SEM focuses on the inconsistency among the estimations and sample to minimize the covariance matrices between constructs, PLS-SEM maximizes the variance of the endogenous latent constructs (Hair et al. 2012). PLS is based on the component construct concept (suitable for explaining complex relationships) (Sarstedt 2008) and does not need strong assumptions, such as distributions, normality, and sample size (Sarstedt 2008; Henseler et al. 2009; Henseler 2010; Vinzi, Trinchera, and Amato 2010). In testing a complex model, CB-SEM would obtain biased results and fail to adequately produce a robust path among constructs (Hair et al. 2012). In addition, PLS is an advantage when the primary concern of the analysis is prediction accuracy (Sarstedt 2008; Reinartz et al. 2009; Hair et al. 2011; Henseler et al. 2014). PLS is also suitable for exploratory and confirmatory research (Gefen et al. 2000) in the assessment of complex and large relationships (many indicators and constructs) and models (Chin et al. 2003; Sarstedt 2008). PLS does not provide fit indices, such as goodness of fit. In reality, a model with good fit indices would not indicate a good model as fit indices "do not relate to how well the latent variables or item measures are predicted"; instead, fit indices show "how well the parameter estimates are able to match the sample covariance" (Chin 1998, 657). "The PLS algorithm allows each indicator to vary in how much it contributes to the composite score of the latent variable" (Chin et al. 2003, 25). In the IS research stream, because of the robust power for the convergence of parameter estimations, researchers largely perform PLS for confirmatory testing where MLE is not suitable. Through an empirical comparative study, Reinartz and colleagues (2009) found that VB-SEM is the preferred method over CB-SEM. Thus, VB-SEM has become a more popular and better alternative to CB-SEM (Hair et al. 2012; Henseler et al. 2014).

PLS-SEM analysis includes inner model assessment (measurement model), which evaluates the relationships between the unobserved/latent constructs, while outer model assessment (structural model) assesses the relationships between the latent constructs and their observed indicators (Henseler 2010). According to Henseler and Chin (2010) and Hair and colleagues (2013), the first step in SEM analysis is measurement model assessment; next is the structural model results' assessment (the two-stage approach). The focus of measurement model assessment is to evaluate the causal relations between the indicators/items and validation of the theoretical constructs, while the structural model evaluates the causal relations between the theoretical constructs (Anderson and Gerbing 1982). The PLS path modelling algorithm presents the outer and the inner estimation stages (Vinzi et al. 2010; Hair et al. 2013). In respect of measurement assessment, construct validity is defined as "the extent to which an operationalization measures the concept it is supposed to measure" (Bagozzi, Yi, and Phillips 1991, 421). Further, convergent and discriminant validity are assessed. Convergent validity is defined as "the degree to which multiple attempts to measure the same concept are in agreement," while discriminant validity is defined as "the degree to which measures of different concepts are distinct" (Bagozzi et al. 1991, 425). The structural model assesses R^2 measures and the level and significance of the path coefficients (β) by performing the bootstrapping procedure of 5,000 resamples (Hair et al. 2011). Thus, SmartPLS software (Ringle, Wende, and Will 2005) is used in this study to assess the PLS-SEM analysis.

Results

Measurement model (construct validity)

As discussed, to assess the reflective measurement models using PLS-SEM, construct validity, using outer weights or loadings, composite reliability (CR), convergent validity, and discriminant validity were examined. As depicted in Table 2, all the outer loadings of items are well above the threshold of 0.70, and all constructs have high levels of internal consistency reliability established by the CR values. Secondly, convergent validity was evaluated using AVE, for which the results show that all the AVE values are well above the threshold of 0.5, thereby demonstrating the convergence of the research construct. Figure 2 presents the measurement model including outer loadings along with the β and R^2 values. Furthermore, all the outer t statistics show that the t value is higher than 2.58 (sig. level at 1%). From the outer t statistics,

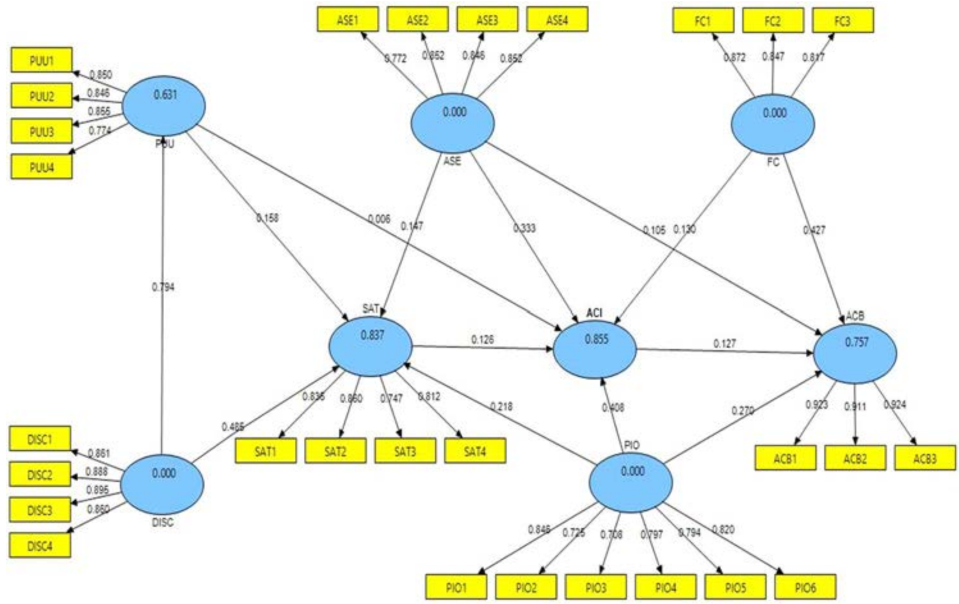

Figure 2. Measurement model (Outer loadings, path coefficient, and R^2).

managers can empirically set "actionable strategies" based on the sizes of the exogenous construct item weights (Hair et al. 2013). For example, from the PUU construct, the *t* statistics for PUU1 = 43.842, which is higher than PUU2 = 38.126, PUU3 = 41.946, and PUU4 = 26.868. Thus, managers should enhance the productivity aspect of apps shopping and address the speed of apps retail in order to influence consumer's continuance intention and behavior. These implications are debated in the discussion section.

To assess construct validity, the discriminant validity between the research constructs was assessed using Fornell and Larcker (1981) and cross-loading criterion. As depicted in Table 3, the off-diagonal values are the square correlations between the latent research constructs, and the diagonal values

Table 3. Discriminant validity (Fornell-Larcker criterion).

Construct[a]	ACB	ACI	ASE	DISC	FC	PIO	PUU	SAT
ACB	**0.845**							
ACI	0.453	**0.675**						
ASE	0.419	0.532	**0.691**					
DISC	0.361	0.511	0.435	**0.768**				
FC	0.597	0.491	0.532	0.413	**0.715**			
PIO	0.335	0.561	0.288	0.513	0.263	**0.613**		
PUU	0.455	0.314	0.317	0.431	0.398	0.158	**0.692**	
SAT	0.377	0.449	0.359	0.446	0.457	0.310	0.491	**0.664**

[a]The off-diagonal values in the above matrix are the square correlations between the latent constructs, and the diagonal values are AVEs.
[b]ACB = apps continuance behavior; ASE = apps self-efficacy; DISC = Disconfirmation; FC = Facilitating conditions; PIO = Perceived information overload; SAT = Satisfaction.

are AVEs. Thus, the Fornell and Larcker criterion shows that discriminant validity between the constructs exists. Furthermore, the loading and cross-loading criterion also shows discriminant validity between constructs, as comparing the loadings across the columns in Table 4 implies that an indicator's loadings on its own construct are in all cases higher compared to all of its cross-loadings with other constructs.

Structural model

Once the measurement model was assessed and the constructs validated, the next step was the assessment of the structural model and their causal relationships. The researchers assessed the structural model of the reflective constructs following the steps and procedures proposed by Hair and

Table 4. Discriminant validity: Loading and cross loading criterion[ab].

Construct[c]	Item	ACB	ACI	ASE	DISC	FC	PIO	PUU	SAT
ACB	ACB1	**0.923**	0.681	0.691	0.583	0.662	0.631	0.640	0.656
	ACB2	**0.911**	0.635	0.501	0.542	0.631	0.560	0.514	0.519
	ACB3	**0.924**	0.612	0.577	0.532	0.508	0.507	0.506	0.630
ACI	ACI1	0.515	**0.815**	0.676	0.643	0.727	0.648	0.640	0.630
	ACI2	0.620	**0.820**	0.637	0.597	0.633	0.537	0.611	0.685
	ACI3	0.652	**0.829**	0.697	0.525	0.688	0.666	0.583	0.575
ASE	ASE1	0.568	0.519	**0.772**	0.538	0.521	0.672	0.583	0.608
	ASE2	0.569	0.690	**0.852**	0.568	0.664	0.616	0.629	0.647
	ASE3	0.561	0.697	**0.846**	0.483	0.501	0.616	0.537	0.566
	ASE4	0.574	0.726	**0.852**	0.593	0.545	0.630	0.631	0.654
DISC	DISC1	0.521	0.613	0.533	**0.861**	0.562	0.632	0.503	0.529
	DISC2	0.494	0.603	0.563	**0.888**	0.551	0.593	0.613	0.670
	DISC3	0.518	0.623	0.586	**0.895**	0.556	0.645	0.644	0.620
	DISC4	0.572	0.662	0.626	**0.860**	0.582	0.639	0.517	0.802
FC	FC1	0.604	0.607	0.655	0.581	**0.872**	0.677	0.608	0.649
	FC2	0.601	0.628	0.572	0.541	**0.847**	0.632	0.618	0.609
	FC3	0.577	0.673	0.651	0.510	**0.817**	0.673	0.575	0.592
PIO	PIO1	0.600	0.560	0.618	0.544	0.615	**0.846**	0.677	0.681
	PIO2	0.559	0.501	0.651	0.493	0.672	**0.725**	0.561	0.571
	PIO3	0.684	0.673	0.699	0.631	0.631	**0.708**	0.613	0.577
	PIO4	0.514	0.620	0.509	0.543	0.570	**0.797**	0.651	0.592
	PIO5	0.565	0.657	0.547	0.517	0.594	**0.794**	0.704	0.521
	PIO6	0.572	0.660	0.548	0.630	0.578	**0.820**	0.723	0.553
PUU	PUU1	0.560	0.632	0.560	0.592	0.565	0.539	**0.850**	0.562
	PUU2	0.561	0.642	0.531	0.640	0.564	0.519	**0.846**	0.645
	PUU3	0.505	0.584	0.529	0.623	0.553	0.629	**0.855**	0.528
	PUU4	0.513	0.738	0.454	0.676	0.670	0.495	**0.774**	0.520
SAT	SAT1	0.598	0.681	0.614	0.655	0.614	0.559	0.633	**0.836**
	SAT2	0.569	0.453	0.648	0.622	0.601	0.524	0.654	**0.860**
	SAT3	0.562	0.659	0.572	0.523	0.570	0.635	0.671	**0.747**
	SAT4	0.524	0.632	0.601	0.601	0.593	0.629	0.651	**0.812**

[a]Bold values are loadings for items, which are above the recommended value of 0.5.
[b]Loading and cross-loading criterion: An indicator's loadings on its own construct are in all cases higher than all of its cross-loadings with other constructs.
[c]ACB = apps continuance behavior; ASE = apps self-efficacy; DISC = Disconfirmation; FC = Facilitating conditions; PIO = Perceived information overload; SAT = Satisfaction.

colleagues (2013). First, the structural model for collinearity was assessed. This step was undertaken to ensure that there are no biased β, the estimations of which might involve significant levels of collinearity among the exogenous constructs. Using the SPSS linear regression option, the analysis shows that all VIF values were well below the threshold of 5.00, thereby demonstrating that multicollinearity is not an issue in this study. Second, the significance and relevance of the structural model relationships were evaluated using the PLS algorithm option. In addition to the structural relationships, researchers examined the significance of the relationship by performing the bootstrapping option of 5,000 resamples. Table 5 depicts the β, which represents the hypothesized relationships between the constructs and their level of significance (t statistics).

As depicted in Table 5, hypothesis 1, which proposes a positive relationship between ACI and apps continuance behavior, is supported with a β of 0.127, standard error of 0.070, and t statistics of 1.826 for the one-tailed test. H2, which implies a positive relationship between satisfaction and ACI, is also supported ($\beta = 0.126$, standard error = 0.048, and t statistics = 2.607). H3, which proposes a positive relationship between PUU and satisfaction, is supported ($\beta = 0.158$, standard error = 0.059, and t statistics = 2.663), while the result does not support H4, which proposes a positive relationship between PUU and ACI ($\beta = 0.006$, standard error = 0.046, and t statistics = 0.126). In addition, H5, which proposes a positive relationship between disconfirmation and PUU ($\beta = 0.794$, standard error = 0.029, and t statistics = 27.424), and H6, which proposes a positive relationship between disconfirmation and satisfaction ($\beta = 0.485$, standard error = 0.042, and

Table 5. Results of hypothesis testing and structural relationships.

Hypothesis	Path	B	Standard error	T statistics[a]	Decision
H1	ACI → ACB[b]	0.127	0.070	1.826*	Supported
H2	SAT → ACI	0.126	0.048	2.607**	Supported
H3	PUU → SAT	0.158	0.059	2.663***	Supported
H4	PUU → ACI	0.006	0.046	0.126	Not supported
H5	DISC → PUU	0.794	0.029	27.424***	Supported
H6	DISC → SAT	0.485	0.042	11.590***	Supported
H7	ASE → SAT	0.147	0.038	3.819***	Supported
H8	ASE → ACI	0.333	0.071	4.714***	Supported
H9	ASE → ACB	0.105	0.058	1.811*	Supported
H10	FC → ACI	0.130	0.055	2.370**	Supported
H11	FC → ACB	0.427	0.061	6.983***	Supported
H12	PIO → SAT	0.218	0.047	4.610***	Supported
H113	PIO → ACI	0.408	0.049	8.244***	Supported
H14	PIO → ACB	0.270	0.077	3.510***	Supported

[a]t values for one-tailed test: *1.645 (sig. level 0.05), **2.326 (sig. level = 0.01), and ***t value 2.576 (sig. level = 0.005).
[b]ACB = apps continuance behavior; ASE = apps self-efficacy; DISC = Disconfirmation; FC = Facilitating conditions; PIO = Perceived information overload; SAT = Satisfaction.

t statistics = 11.590), are supported. Figure 2 presents the measurement model specifications including outer loadings along with the β and R^2 values.

Further, H7, which hypothesizes a positive relationship between apps self-efficacy and satisfaction ($\beta = 0.147$, standard error = 0.038, and t statistics = 3.819), H8, which proposes a positive relationship between apps self-efficacy and ACI ($\beta = 0.333$, standard error = 0.071, and t statistics = 4.714), and H9, which proposes a positive relationship between apps self-efficacy and apps continuance behavior ($\beta = 0.105$, standard error = 0.058, and t statistics = 1.811), are supported. H10, which proposes a positive relationship between facilitating conditions and ACI ($\beta = 0.130$, standard error = 0.055, and t statistics = 2.370), and H11, which suggests a positive relationship between facilitating conditions and apps continuance behavior ($\beta = 0.427$, standard error = 0.061, and t statistics = 6.983), are also supported. Finally, H12, which proposes a negative relationship between perceived information overload and satisfaction ($\beta = 0.218$, standard error = 0.047, and t statistics = 4.610), H13, which proposes a negative relationship between perceived information overload and ACI ($\beta = 0.408$, standard error = 0.049, and t statistics = 8.244), and, H14, which hypothesizes a negative relationship between perceived information overload and apps continuance behavior ($\beta = 0.270$, standard error = 0.077, and t statistics = 3.510), are all supported.

The level of the R^2 values was assessed as another step in evaluating the structural model. The R^2 values of the endogenous latent variables are obtained from the PLS algorithm option. According to Hair and colleauges (2011), an R^2 value for the endogenous latent variable of 0.75 is described as substantial, 0.50 is described as moderate, and 0.25 is considered as weak. As shown in Table 6, the R^2 values for apps continuance behavior = 0.757, for ACI = 0.855, and satisfaction = 0.837 are considered as substantial. Table 6 shows the results of R^2. In addition to the R^2 value assessment, the Q^2value was obtained for the endogenous constructs through the blindfolding procedure. The blindfolding procedure omits a part of the empirical data matrix for the construct that is being examined and then estimates the model parameters (Chin et al. 2003). Table 6 shows the results of R^2 over Q^2. The f^2 effect

Table 6. Results of R^2 and Q^2.

Endogenous latent constructs	R^2	Q^2	Effect size[a]
ACB[b]	0.757	0.624	Large
ACI	0.855	0.578	Large
PUU	0.631	0.431	Large
SAT	0.837	0.555	Large

[a]Assessing predictive relevance or effect size (Q^2): Value effect size: 0.02 = Small; 0.15 = Medium; 0.35 = Large.
[b]ACB = apps continuance behavior; ASE = apps self-efficacy; DISC = Disconfirmation; FC = Facilitating conditions; PIO = Perceived information overload; SAT = Satisfaction.

Table 7. Results—β, f2 and q2.

	ACB			ACI			PUU			SAT		
ACB	β	f^2 effect size	q^2 effect size	β	f^2 effect size	q^2 effect size	β	f^2 effect size	q^2 effect size	β	f^2 effect size	q^2 effect size
ACI	0.127	0.078	0.001									
ASE	0.105	0.060	0.000	0.333	0.169	0.102				0.147	0.098	0.01
DISC							0.794	0.362	0.155	0.485	0.242	0.114
FC	0.427	0.223	0.102	0.130	0.098	0.024						
PIO	0.270	0.115	0.089	0.408	0.228	0.124				0.218	0.104	0.092
PUU				0.006	0.000	0.000				0.158	0.0890	0.003
SAT				0.126	0.050	0.001						

Note. Assessing q^2 and f^2 effect size: Value effect size: 0.02 = Small; 0.15 = Medium; 0.35 = Large.

size was assessed to measure the impact of a specific exogenous construct on its designated endogenous construct. Table 7 shows the f^2 values against q^2. Finally, in examining the structural model, the predictive relevance including the q^2 effect size are presented in Table 7.

Discussion

This study attempts to investigate consumers' continuous intention and behavior toward app stores grounded by the extended model of IT continuance and the theory of information overload. Understanding consumers' continuous intention and behavior is important because continued usage applies a central positive impact on the propensity of virtual communities. Literature has shown that acquiring new customers costs five times more than keeping the current customers. Theoretically and practically, integrating a set of positive constructs along with negative constructs would lead to a better understanding of consumers' continuous intention and behavior toward a system. It is considered to be a crucial rivalry element and one of the greatest indexes for the firm's profit, and is significantly related to return on investment. In addition, one of the IS continuance behavior constructs would be users' satisfaction, which was empirically examined in this research. This study reveals that continued intention has a strong and significant effect on continued behavior. Furthermore, usefulness can be considered to be a significant individual cognition that influences the intentions and behavior at the pre- and post-usage level. Consumers' post-usage expectations and PUU are important in app stores, and it has been shown in most of the IS studies to be the solid and salient cognitive belief that specifies the intention of the individual. In addition, positive disconfirmation would lead to apps shoppers' perception of delighted efficiency that relates to satisfaction, while the negative type of disconfirmation leads to inefficiency, which results in lower overall satisfaction. In fact, PUU and confirmation has a robust influence on consumers' continuous intention and behavior related to apps performance, both during and after the consumption experience period because higher performance will boost the expectations and lead to positive confirmation, and finally satisfaction. In addition, the notion of self-efficacy is significant in order to assist apps retailer or app stores to realize how each person can promptly create new mechanisms and develop great skill regarding the shopping decision process. Noticeably, the apps users with a high degree of self-efficacy might experience a better interaction with apps retailer. Individuals with greater self-efficacy will have more self-confidence about their capability to obtain various objectives in surfing apps, as they have a keen interest to take risks and explore as well as solve problems by using related applications. Similarly, apps users with a high degree of self-efficacy are proactive and intend to spend longer time on apps stores than those with low self-efficacy.

Moreover, this study found that facilitating condition has a positive impact on consumers' continuance intention and behavior, while perceived information overload has a negative impact on consumer satisfaction, continuance intention, and behavior toward apps retail. Facilitating conditions is significant in encouraging apps users and individuals to act on their intention to shop on the Internet or from apps retail. Furthermore, facilitating conditions have been mentioned in IS research as being an important construct, especially in the Internet environment. Researchers have selected measures, such as a good understanding of the Internet and inexpensive access to the Internet, to assess the facilitating conditions. In literature, it was stressed that superior Internet market should be provided amid facilitating conditions that would illustrate and emphasize it, in spite of user interface demand, and this comprised searching, ease of access as well as navigation. Information overload has become a phenomenon that causes people to suffer and perhaps confront serious obstacles. Therefore, perceived information overload occurs on apps retail when the information received causes inconvenience instead of being helpful. The practical implications are discussed as follows.

Managerial implications

Technology is a mechanism which enables customers to have more control over and access to a vast pool of information about company offerings. To be competitive, firms have created apps in order to assist customers to modify the products based on their interests. Thus, a new phenomenon of e-commerce emerges, which is apps commerce. As suggested above, to avoid negative perceived information overload on apps usage, managers should effectively manage apps retail in the way that consumers could find the product information they need. Table 2 shows that the retail product information

(PIO1: t statistics = 31.768) significantly contributes to perceived information overload. In addition, there should not be too much information about retail products stored on apps that could burden consumers in handling the information. Consumers should be able to effectively handle all the retail product information on apps. If there is too much retail product information on the apps, consumers will have difficulty in acquiring all the information. Moreover, consumers should be able to find a large amount of the retail product information on the apps relevant to their needs. Accordingly, managers should minimize the negative impact of perceived information overload by assuring consumers that the retail product information on the apps retail are suited to their needs to make buying decisions.

Although PUU has a positive impact on satisfaction, it does not influence consumer's continuance intention. Managers should still consider the usefulness of apps retailing. To enhance the usefulness of apps retail, managers should enhance the productivity aspect of consumers' shopping, such as make their shopping faster. In addition, using apps for shopping should improve the performance of the shopper, such as make their shopping better than what they might experience from other channels. Using apps retail for shopping should make consumers more effective in helping them make better shopping decisions; thus, they should find the apps to be useful for shopping. The current statistical assessment shows that disconfirmation strongly and positively influences PUU and satisfaction. In order to enhance the positive impact of disconfirmation, using the apps retail should improve consumers' performance much more than they had initially expected, and using the apps stores should improve their effectiveness and productivity much more than they had initially expected. In addition, managers should be aware that in order to enhance the positive impact of disconfirmation on PUU and satisfaction, consumers' experience using the apps retailers should greatly exceed their initial expectations.

Furthermore, consumers' self-efficacy and facilitating conditions are two important individual factors that influence apps usage satisfaction, continuance intention, and behavior; hence, managers should be aware of these factors. Consumers with high levels of self-efficacy can perform shopping using apps even without other help if they have adequate time to complete the shopping. Importantly, managers should realize that consumers should be able to perform shopping using apps and only using online help for reference. Accordingly, shoppers should be confident in their ability to perform shopping using apps retails. There are several ways to facilitate conditions in the apps commerce environment. Consumers should have access to the resources, such as a dedicated computer terminal, which is needed to access the apps retailers; they should be able to use apps retailers whenever and however they want; and they should have full control over their use or non-use of apps retailers.

Limitations and future research avenues

This research has some limitations despite its contribution to the current understanding of the new phenomena of e-commerce, which is apps commerce. First, this study was undertaken from the retail consumers' point of view. Future research should generalize the findings of this study by adopting the proposed model (Figure 1) in other contexts, such as banking and education. Second, the results are limited to Malaysian consumers' usage experience with apps retailers. Future research should generalize the findings of this study across countries. Third, since this study is considered to be one of the first attempts toward understanding apps commercing and apps retailing, future research should use the traditional marketing and IS theories in understanding individuals' apps satisfaction, continuance intention, and behavior.

References

Akhter, S. H. 2014. Privacy concern and online transactions: The impact of Internet self-efficacy and Internet involvement. *Journal of Consumer Marketing* 31 (2):118–25. doi:10.1108/jcm-06-2013-0606.

Al-Maghrabi, T., and C. Dennis. 2011. What drives consumers' continuance intention to e-shopping? Conceptual framework and managerial implications in the case of Saudi Arabia. *International Journal of Retail & Distribution Management* 39 (12):899–926. doi:10.1108/09590551111183308.

Anderson, J. C., and D. W. Gerbing. 1982. Some methods for respecifying measurement models to obtain unidimensional construct measurement. *Journal of Marketing Research* 19:453–60. doi:10.2307/3151719.

Babin, L. A., and A. C. Burns. 1998. A modified scale for the measurement of communication-evoked mental imagery. *Psychology & Marketing* 15 (3):261–78. doi:10.1002/(sici)1520-6793(199805)15:3<261::aid-mar4>3.3.co;2-x.

Bagozzi, R. P., Y. Yi, and L. W. Phillips. 1991. Assessing construct validity in organizational research. *Administrative Science Quarterly* 36:421–58. doi:10.2307/2393203.

Bandura, A. 1986. *Social foundations of thought and action*. Englewood Cliffs, NJ: Prentice Hall.

Bandura, A. 1997. *Self-efficacy: The exercise of control*. New York, NY: Macmillan.

Bawden, D., and L. Robinson. 2009. The dark side of information: Overload, anxiety and other paradoxes and pathologies. *Journal of Information Science* 35 (2):180–91. doi:10.1177/0165551508095781.

Bellman, S., R. F. Potter, S. Treleaven-Hassard, J. A. Robinson, and D. Varan. 2011. The effectiveness of branded mobile phone apps. *Journal of Interactive Marketing* 25 (4):191–200. doi:10.1016/j.intmar.2011.06.001.

Bhattacherjee, A. 2001. Understanding information systems continuance: An expectation-confirmation model. *MIS Quarterly* 25 (3):351–70. doi:10.2307/3250921.

Bhattacherjee, A., J. Perols, and C. Sanford. 2008. Information technology continuance: A theoretic extension and empirical test. *Journal of Computer Information Systems* 49 (1):17–26.

Bishop, B. W. 2012. Analysis of reference transactions to inform library applications (apps). *Library & Information Science Research* 34 (4):265–70. doi:10.1016/j.lisr.2012.06.001.

Bruner, G. C., P. J. Hensel, and K. E. James. 2001. *Marketing scales handbook*. Chicago: American Marketing Association.

Budd, L., and T. Vorley. 2013. Airlines, apps, and business travel: A critical examination. *Research in Transportation Business & Management* 9:41–49. doi:10.1016/j.rtbm.2013.08.004.

Chen, Y.-C., R.-A. Shang, and C.-Y. Kao. 2009. The effects of information overload on consumers' subjective state towards buying decision in the Internet shopping environment. *Electronic Commerce Research and Applications* 8 (1):48–58.

Chin, W. 2010. How to write up and report PLS analyses. In *Handbook of partial least squares*, ed. V. Esposito Vinzi, W. W. Chin, J. Henseler, and H. Wang 655–90. Heidelberg, Berlin: Springer.

Chin, W. W. 1998. Commentary: Issues and opinion on structural equation modeling. *MIS Quarterly* 22 (1):7–16.

Chin, W. W., B. L. Marcolin, and P. R. Newsted. 2003. A partial least squares latent variable modeling approach for measuring interaction effects: Results from a Monte Carlo simulation study and an electronic-mail emotion/adoption study. *Information Systems Research* 14 (2):189–217. doi:10.1287/isre.14.2.189.16018.

Chong, A. Y.-L. 2013. Predicting m-commerce adoption determinants: A neural network approach. *Expert Systems with Applications* 40 (2):523–30. doi:10.1016/j.eswa.2012.07.068.

Crabbe, M., C. Standing, S. Standing, and H. Karjaluoto. 2009. An adoption model for mobile banking in Ghana. *International Journal of Mobile Communications* 7 (5):515–43. doi:10.1504/ijmc.2009.024391.

Currás-Pérez, R., C. Ruiz-Mafé, and S. Sanz-Blas. 2013. Social network loyalty: Evaluating the role of attitude, perceived risk and satisfaction. *Online Information Review* 37 (1):61–82. doi:10.1108/14684521311311630.

Davis, F. D. 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly* 13:319–40. doi:10.2307/249008.

Flavián, C., M. Guinalíu, and R. Gurrea. 2006. The role played by perceived usability, satisfaction and consumer trust on website loyalty. *Information & Management* 43 (1):1–14. doi:10.1016/j.im.2005.01.002.

Fornell, C., and D. F. Larcker. 1981. Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research* 18:39–50. doi:10.2307/3151312.

Gefen, D., D. W. Straub, and M.-C. Boudreau. 2000. *Structural equation modeling and regression: Guidelines for research practice*. Communications of the Association for Information Systems: CiteSeer.

Gorla, N., and T. M. Somers. 2014. The impact of IT outsourcing on information systems success. *Information & Management* 51 (3):320–35. doi:10.1016/j.im.2013.12.002.

Graham, J. W., S. M. Hofer, S. I. Donaldson, D. P. MacKinnon, and J. L. Schafer. 1997. Analysis with missing data in prevention research. In *The science of prevention: Methodological advances from alcohol and substance abuse research*, ed. K. J. Bryant, M. Windle, and S. G. West, 325–366. Washington, DC: American Psychological Association.

Grewal, D., A. L. Roggeveen, L. D. Compeau, and M. Levy. 2012. Retail value-based pricing strategies: New times, new technologies, new consumers. *Journal of Retailing* 88 (1):1–6. doi:10.1016/j.jretai.2011.12.001.

Hair, J. F., G. T. M. Hult, C. Ringle, and M. Sarstedt. 2013. *A primer on partial least squares structural equation modeling (PLS-SEM)*. Thousand Oaks, CA: Sage Publications.

Hair, J. F., C. M. Ringle, and M. Sarstedt. 2011. PLS-SEM: Indeed a silver bullet. *Journal of Marketing Theory and Practice* 19 (2):139–51.

Hair, J. F., M. Sarstedt, C. M. Ringle, and J. A. Mena. 2012. An assessment of the use of partial least squares structural equation modeling in marketing research. *Journal of the Academy of Marketing Science* 40:414–33. doi:10.1007/s11747-011-0261-6.

Hardesty, D. M., and W. O. Bearden. 2004. The use of expert judges in scale development: Implications for improving face validity of measures of unobservable constructs. *Journal of Business Research* 57 (2):98–107. doi:10.1016/s0148-2963(01)00295-8.

Harman, H. H. 1976. *Modern factor analysis*. Chicago, IL: University of Chicago Press.

Haynes, S. N., D. Richard, and E. S. Kubany. 1995. Content validity in psychological assessment: A functional approach to concepts and methods. *Psychological Assessment* 7 (3):238–47. doi:10.1037//1040-3590.7.3.238.

Henseler, J. 2010. On the convergence of the partial least squares path modeling algorithm. *Computational Statistics* 25 (1):107–20. doi:10.1007/s00180-009-0164-x.

Henseler, J., and W. W. Chin. 2010. A comparison of approaches for the analysis of interaction effects between latent variables using partial least squares path modeling. *Structural Equation Modeling* 17 (1):82–109. doi:10.1080/10705510903439003.

Henseler, J., T. K. Dijkstra, M. Sarstedt, C. M. Ringle, A. Diamantopoulos, D. W. Straub, D. J. Ketchen, J. F. Hair, G. T. M. Hult, and R. J. Calantone. 2014. Common beliefs and reality about PLS: Comments on Rönkkö and Evermann (2013). *Organizational Research Methods* 17:182–209. doi:10.1177/1094428114526928.

Henseler, J., C. M. Ringle, and R. R. Sinkovics. 2009. The use of partial least squares path modeling in international marketing. In *Advances in international marketing*, ed. R. R. Sinkovics and P. N. Ghauri vol. 20, 277–320. Bingley: Emerald.

Hill, W. W., S. E. Beatty, and G. Walsh. 2013. A segmentation of adolescent online users and shoppers. *Journal of Services Marketing* 27 (5):347–60. doi:10.1108/jsm-10-2011-0157.

Hossain, M. A., and M. Quaddus. 2011. The adoption and continued usage intention of RFID: An integrated framework. *Information Technology & People* 24 (3):236–56. doi:10.1108/09593841111158365.

Hsiao, M.-H. 2009. Shopping mode choice: Physical store shopping versus e-shopping. *Transportation Research Part E: Logistics and Transportation Review* 45 (1):86–95. doi:10.1016/j.tre.2008.06.002.

Hsu, C.-L., and J. C.-C. Lin. 2014. What drives purchase intention for paid mobile apps? An expectation confirmation model with perceived value. *Electronic Commerce Research and Applications* 14:46–57. doi:10.1016/j.elerap.2014.11.003.

Hsu, M. H., C. M. Chiu, and T. L. Ju. 2004. Determinants of continued use of the WWW: An integration of two theoretical models. *Industrial Management & Data Systems* 104 (9): 766–75. doi:10.1108/02635570410567757.

Hu, P. J. H., S. A. Brown, J. Y. Thong, F. K. Chan, and K. Y. Tam. 2009. Determinants of service quality and continuance intention of online services: The case of eTax. *Journal of the American Society for Information Science and Technology* 60 (2):292–306. doi:10.1002/asi.20956.

Hung, S.-Y., C.-M. Chang, and T.-J. Yu. 2006. Determinants of user acceptance of the e-government services: The case of online tax filing and payment system. *Government Information Quarterly* 23 (1):97–122. doi:10.1016/j.giq.2005.11.005.

Hung, S.-Y., C.-Y. Ku, and C.-M. Chang. 2003. Critical factors of WAP services adoption: An empirical study. *Electronic Commerce Research and Applications* 2 (1):42–60. doi:10.1016/s1567-4223(03)00008-5.

Igbaria, M., and J. Iivari. 1995. The effects of self-efficacy on computer usage. *Omega* 23 (6):587–605. doi:10.1016/0305-0483(95)00035-6.

Jacoby, J. 1984. Perspectives on information overload. *Journal of Consumer Research* 10: 432–35. doi:10.1086/208981.

Jacoby, J., D. E. Speller, and C. A. Kohn. 1974. Brand choice behavior as a function of information load. *Journal of Marketing Research* 11 (1):63–69. doi:10.2307/3150994.

Jöreskog, K. G. 1970. A general method for analysis of covariance structures. *Biometrika* 57 (2):239–51. doi:10.2307/2334833.

Kang, J.-Y. M., J. M. Mun, and K. K. Johnson. 2015. In-store mobile usage: Downloading and usage intention toward mobile location-based retail apps. *Computers in Human Behavior* 46:210–17. doi:10.1016/j.chb.2015.01.012.

Kang, Y. J., and W. J. Lee. 2014. Self-customization of online service environments by users and its effect on their continuance intention. *Service Business* 9:1–22. doi:10.1007/s11628-014-0229-y.

Kang, Y. S., and H. Lee. 2010. Understanding the role of an IT artifact in online service continuance: An extended perspective of user satisfaction. *Computers in Human Behavior* 26 (3):353–64. doi:10.1016/j.chb.2009.11.006.

Karani, K. S., K. Fraccastoro, and J. Shelton. 2013. The effect of order of prices on customers' confidence levels. *Journal of Management & Marketing Research* 13:1–10.

Kasper, H., J. Bloemer, and P. H. Driessen. 2010. Coping with confusion: The case of the Dutch mobile phone market. *Managing Service Quality* 20 (2):140–60. doi:10.1108/09604521011027570.

Kauffman, R. J., and E. A. Walden. 2001. Economics and electronic commerce: Survey and directions for research. *International Journal of Electronic Commerce* 5:5–116.

Kim, J. B. 2013. Understanding the repurchase abandonment process of consumers in the online environment: Integrating dissatisfaction and distrust. *Journal of Internet Commerce* 12 (2):154–94. doi:10.1080/15332861.2013.817863.

Kim, Y., and M. Glassman. 2013. Beyond search and communication: Development and validation of the Internet self-efficacy Scale (ISS). *Computers in Human Behavior* 29 (4):1421–29. doi:10.1016/j.chb.2013.01.018.

Klausegger, C., R. R. Sinkovics, and H. "Joy" Zou. 2007. Information overload: A cross-national investigation of influence factors and effects. *Marketing Intelligence & Planning* 25 (7):691–718.

Kuo, Y.-C., A. E. Walker, K. E. Schroder, and B. R. Belland. 2014. Interaction, Internet self-efficacy, and self-regulated learning as predictors of student satisfaction in online education courses. *The Internet and Higher Education* 20:35–50. doi:10.1016/j.iheduc.2013.10.001.

Lee, B. K., and W. N. Lee. 2004. The effect of information overload on consumer choice quality in an on-line environment. *Psychology & Marketing* 21 (3):159–83. doi:10.1002/mar.20000.

Lee, J., M. S. Cha, and C. Cho. 2012. *Online service quality in social commerce websites contemporary research on E-business technology and strategy*, 335–51. Berlin, Germany: Springer.

Lewis, E. F., M. Hardy, and B. Snaith. 2013. An analysis of survey reporting in the imaging professions: Is the issue of non-response bias being adequately addressed? *Radiography* 19 (3):240–45. doi:10.1016/j.radi.2013.02.003.

Liang, T.-P., H.-J. Lai, and Y.-C. Ku. 2006. Personalized content recommendation and user satisfaction: Theoretical synthesis and empirical findings. *Journal of Management Information Systems* 23 (3):45–70. doi:10.2753/mis0742-1222230303.

Limayem, M., S. G. Hirt, and C. M. Cheung. 2007. How habit limits the predictive power of intention: The case of information systems continuance. *MIS Quarterly* 31 (4):705–37.

Limayem, M., M. Khalifa, and A. Frini. 2000. What makes consumers buy from Internet? A longitudinal study of online shopping. *IEEE Transactions on Systems, Man, and Cybernetics - Part A* 30 (4):421–32. doi:10.1109/3468.852436.

Lin, H.-F., and C.-H. Chen. 2013. An intelligent embedded marketing service system based on TV apps: Design and implementation through product placement in idol dramas. *Expert Systems with Applications* 40 (10):4127–36. doi:10.1016/j.eswa.2013.01.034.

Lin, I.-F., and N. C. Schaeffer. 1995. Using survey participants to estimate the impact of non-participation. *Public Opinion Quarterly* 59 (2):236–58. doi:10.1086/269471.

Lin, K.-M. 2011. E-learning continuance intention: Moderating effects of user e-learning experience. *Computers & Education* 56 (2):515–26. doi:10.1016/j.compedu.2010.09.017.

Lin, W.-S. 2011. Perceived fit and satisfaction on online learning performance: An empirical study Edutainment Technologies. In *Educational games and virtual reality/augmented reality applications*, ed. M. Chang, W.-Y. Hwang, M.-P. Chen, and W. Müller, 139–46. Berlin, Germany: Springer.

Lin, K.-M., N.-S. Chen, and K. Fang. 2011. Understanding e-learning continuance intention: A negative critical incidents perspective. *Behaviour & Information Technology* 30 (1):77–89. doi:10.1080/01449291003752948.

Little, R. J. A. 1988. Missing-data adjustments in large surveys. *Journal of Business & Economic Statistics* 6 (3):287–96. doi:10.1080/07350015.1988.10509663.

Liu, C., and S. Forsythe. 2011. Examining drivers of online purchase intensity: Moderating role of adoption duration in sustaining post-adoption online shopping. *Journal of Retailing and Consumer Services* 18 (1):101–09.

Lohmöller, J.-B. 1989. *Latent variable path modeling with partial least squares*. Heidelberg: Physica-Verlag.

Lu, J. 2014. Are personal innovativeness and social influence critical to continue with mobile commerce? *Internet Research* 24 (2):134–59. doi:10.1108/intr-05-2012-0100.

Lueg, C. P. 2014. Characteristics of human perception and their relevance when studying information behavior. *Journal of Documentation* 70 (4):562–74. doi:10.1108/jd-05-2012-0064.

MacKenzie, S. B., and P. M. Podsakoff. 2012. Common method bias in marketing: Causes, mechanisms, and procedural remedies. *Journal of Retailing* 88:542–55. doi:10.1016/j.jretai.2012.08.001.

Marston, S., Z. Li, S. Bandyopadhyay, J. Zhang, and A. Ghalsasi. 2011. Cloud computing – The business perspective. *Decision Support Systems* 51 (1):176–89.

Mettler, T. 2012. *Post-acceptance of electronic medical records: Evidence from a longitudinal field study*. Orlando, FL: ICIS.

Nagar, K. 2016. Drivers of E-store patronage intentions: Choice overload, internet shopping anxiety, and impulse purchase tendency. *Journal of Internet Commerce* 15 (2):97–124. doi:10.1080/15332861.2016.1148971.

Oliveira, T., M. Thomas, and M. Espadanal. 2014. Assessing the determinants of cloud computing adoption: An analysis of the manufacturing and services sectors. *Information & Management* 51 (5):497–510. doi:10.1016/j.im.2014.03.006.

Oliver, R. L. 1977. Effect of expectation and disconfirmation on postexposure product evaluations: An alternative interpretation. *Journal of Applied Psychology* 62 (4):480–86. doi:10.1037//0021-9010.62.4.480.

Oliver, R. L. 1980. A cognitive model of the antecedents and consequences of satisfaction decisions. *Journal of Marketing Research* 17:460–69. doi:10.2307/3150499.

Pallud, J., and D. W. Straub. 2014. Effective website design for experience-influenced environments: The case of high culture museums. *Information & Management* 51 (3):359–73. doi:10.1016/j.im.2014.02.010.

Peng, L., and L. Lai. 2014. A service innovation evaluation framework for tourism e-commerce in China based on BP neural network. *Electronic Markets* 24 (1):37–46. doi:10.1007/s12525-013-0148-0.

Pentina, I., and M. Tarafdar. 2014. From “information” to “knowing”: Exploring the role of social media in contemporary news consumption. *Computers in Human Behavior* 35:211–23. doi:10.1016/j.chb.2014.02.045.

Podsakoff, P. M., S. B. MacKenzie, L. Jeong-Yeon, and N. P. Podsakoff. 2003. Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology* 88 (5):879–903. doi:10.1037/0021-9010.88.5.879.

Polit, D. F., and C. T. Beck. 2006. The content validity index: Are you sure you know what's being reported? Critique and recommendations. *Research in Nursing & Health* 29 (5): 489–97. doi:10.1002/nur.20147.

Reinartz, W. J., M. Haenlein, and J. Henseler. 2009. An empirical comparison of the efficacy of covariance-based and variance-based SEM. *International Journal of Research in Marketing* 26 (4):332–44. doi:10.1016/j.ijresmar.2009.08.001.

Rezaei, S. 2015. Segmenting consumer decision-making styles (CDMS) toward marketing practice: A partial least squares (PLS) path modeling approach. *Journal of Retailing and Consumer Services* 22:1–15. doi:10.1016/j.jretconser.2014.09.001.

Rezaei, S., and S. S. Ghodsi. 2014. Does value matters in playing online game? An empirical study among massively multiplayer online role-playing games (MMORPGs). *Computers in Human Behavior* 35:252–66. doi:10.1016/j.chb.2014.03.002.

Ringle, C. M., S. Wende, and A. Will. 2005. SmartPLS 2.0. www.smartpls.de.

Riquelme, I. P., and S. Román. 2014. The influence of consumers' cognitive and psychographic traits on perceived deception: A comparison between online and offline retailing contexts. *Journal of Business Ethics* 119 (3):405–22. doi:10.1007/s10551-013-1628-z.

Rosen, L. D., K. R. Karwan, and L. L. Scribner. 2003. Service quality measurement and the disconfirmation model: Taking care in interpretation. *Total Quality Management and Business Excellence* 14 (1):3–14. doi:10.1080/14783360309703.

Rosenbloom, B. 2013. Functions and institutions: The roots and the future of marketing channels. *Journal of Marketing Channels* 20 (3–4):191–203. doi:10.1080/1046669x.2013.803423.

Salanova, M., R. M. Grau, E. Cifre, and S. Llorens. 2000. Computer training, frequency of usage and burnout: The moderating role of computer self-efficacy. *Computers in Human Behavior* 16 (6):575–90. doi:10.1016/s0747-5632(00)00028-5.

Sarstedt, M. 2008. A review of recent approaches for capturing heterogeneity in partial least squares path modelling. *Journal of Modelling in Management* 3 (2):140–61. doi:10.1108/17465660810890126.

Schafer, J. L., and M. K. Olsen. 1998. Multiple imputation for multivariate missing-data problems: A data analyst's perspective. *Multivariate Behavioral Research* 33 (4):545–71. doi:10.1207/s15327906mbr3304_5.

Shang, R.-A., Y.-C. Chen, and S.-Y. Chen. 2013. The effects of the number of alternative products and the way they are presented on the consumers' subjective statuses in online travel sites. *Behaviour & Information Technology* 32 (7):630–43. doi:10.1080/0144929x.2011.572185.

Shank, D. B., and S. R. Cotten. 2014. Does technology empower urban youth? The relationship of technology use to self-efficacy. *Computers & Education* 70:184–93. doi:10.1016/j.compedu.2013.08.018.

Sipior, J. C., B. T. Ward, and L. Volonino. 2014. Privacy concerns associated with smartphone use. *Journal of Internet Commerce* 13 (3–4):177–93. doi:10.1080/15332861.2014.947902.

Sivadas, E., and J. L. Baker-Prewitt. 2000. An examination of the relationship between service quality, customer satisfaction, and store loyalty. *International Journal of Retail & Distribution Management* 28 (2):73–82. doi:10.1108/09590550010315223.

Song, J., J. Kim, D. R. Jones, J. Baker, and W. W. Chin. 2014. Application discoverability and user satisfaction in mobile application stores: An environmental psychology perspective. *Decision Support Systems* 59:37–51. doi:10.1016/j.dss.2013.10.004.

Soper, D. 2015. A-Priori Sample Size Calculator for Structural Equation Models [Software].

Stanton, J. V., and D. M. Paolo. 2012. Information overload in the context of apparel: Effects on confidence, shopper orientation and leadership. *Journal of Fashion Marketing and Management* 16 (4):454–76. doi:10.1108/13612021211265854.

Ström, R., M. Vendel, and J. Bredican. 2014. Mobile marketing: A literature review on its value for consumers and retailers. *Journal of Retailing and Consumer Services* 21:1001–02. doi:10.1016/j.jretconser.2013.12.003.

Teo, T. S., and V. K. Lim. 2001. The effects of perceived justice on satisfaction and behavioral intentions: The case of computer purchase. *International Journal of Retail & Distribution Management* 29 (2):109–25. doi:10.1108/09590550110382039.

Torkzadeh, G., J. C.-J. Chang, and D. Demirhan. 2006. A contingency model of computer and Internet self-efficacy. *Information & Management* 43 (4):541–50. doi:10.1016/j.im.2006.02.001.

Torkzadeh, G., and T. P. Van Dyke. 2002. Effects of training on Internet self-efficacy and computer user attitudes. *Computers in Human Behavior* 18 (5):479–94. doi:10.1016/s0747-5632(02)00010-9.

Vekiri, I., and A. Chronaki. 2008. Gender issues in technology use: Perceived social support, computer self-efficacy and value beliefs, and computer use beyond school. *Computers & Education* 51 (3):1392–404. doi:10.1016/j.compedu.2008.01.003.

Vinzi, V. E., L. Trinchera, and S. Amato. 2010. PLS path modeling: From foundations to recent developments and open issues for model assessment and improvement. In *Handbook of partial least squares*, ed. V. Esposito Vinzi, W. W. Chin, J. Henseler, and H. Wang, 47–82. Berlin, Germany: Springer.

Wang, J.-C., and M.-J. Chiang. 2009. Social interaction and continuance intention in online auctions: A social capital perspective. *Decision Support Systems* 47 (4):466–76. doi:10.1016/j.dss.2009.04.013.

Wang, Q., and P. Shukla. 2013. Linking sources of consumer confusion to decision satisfaction: The role of choice goals. *Psychology & Marketing* 30 (4):295–304. doi:10.1002/mar.20606.

Wang, R. J.-H., E. C. Malthouse, and L. Krishnamurthi. 2015. On the go: How mobile shopping affects customer purchase behavior. *Journal of Retailing* 91:217–34. doi:10.1016/j.jretai.2015.01.002.

White, M. 2010. Information anywhere, any when: The role of the smartphone. *Business Information Review* 27 (4):242–47. doi:10.1177/0266382110390651.

Wold, H. 1975. *Path models with latent variables: The NIPALS approach*. New York, NY: Academic Press.

Zhang, L., T.-Q. Peng, Y.-P. Zhang, X.-H. Wang, and J. J. Zhu. 2014. Content or context: Which matters more in information processing on microblogging sites. *Computers in Human Behavior* 31:242–49. doi:10.1016/j.chb.2013.10.031.

Zwass, V. 1996. Electronic commerce: Structures and issues. *International Journal of Electronic Commerce* 1:3–23. doi:10.1080/10864415.1996.11518273.

Appendix: Measurement items

	Research construct	Measurement items[a]
1	Perceived Information Overload (PIO)[ab]	PIO1 I had no idea about where to find the retail product's information I needed on this app. PIO2 There was too much information about retail products on this app so that I was burdened in handling it. PIO3 I could not effectively handle all of the apps retail products information. PIO4 Because of the numerous apps retail products information, I had difficulty in acquiring all the information. PIO5 I found that only a small part of the apps retail products information was relevant to my need. PIO6 I was not certain that the apps retail products information fitted my needs for making a buying decision.
2	PUU[a]	PUU1 Using apps for shopping will increase my productivity (e.g., make my shopping faster). PUU2 Using apps for shopping will not improve my performance (e.g., make my shopping better). ® PUU3 Using apps for shopping will make me more effective (e.g., help me make better shopping decisions). PUU4 I will find the apps to be useful for shopping.
3	Disconfirmation (DISC)[a]	DISC1 Using the apps retail improved my performance much more than I had initially expected. DISC2 Using the apps retail improved my productivity much more than I had initially expected. DISC3 Using the apps retail improved my effectiveness much more than I had initially expected. DISC4 My experience with using the apps retailers greatly exceeded my initial expectations.
4	Apps Self-Efficacy (ASE)[a]	ASE1 I can perform shopping using apps even if there is no one around to help me. ASE2 I can perform shopping using apps if I have adequate time to complete my shopping. ASE3 I can perform shopping using apps and using only online help for reference. ASE4 I am not confident in my ability to perform shopping using apps retailers.®
5	Facilitating Conditions (FC)[a]	FC1 I have access to the resources (e.g., a dedicated computer terminal) needed to use the apps retailers. FC2 I can use apps retailers whenever and however I want. FC3 I have full control over my using or not using apps retailers.
6	Satisfaction (SAT)[a]	How do you feel about your overall experience of using the apps retailers: SAT1 Very dissatisfied … Very satisfied SAT2 Very displeased … Very pleased SAT3 Very frustrated … Very contented SAT4 Absolutely terrible … Absolutely delighted
7	ACI[a]	ACI1 I intend to continue using the apps for shopping. ACI2 I intend to continue using apps for processing more shopping. ACI3 I intend to continue using apps for more of my shopping responsibilities.
8	Apps Continuance Behavior (ACB)	ACB1 Number of times you currently use apps retail per week: 0 | 1–3 | 4–6 | 7–9 | 10–12 | Other : _____ ACB2 Number of apps retail that you currently use: 0 | 1 | 2 | 3 | 4 | 5 | Other (specify): _____ ACB3 Percentage of your requests in using apps retail currently: 0% | 1–10% | 11–20% | 21–30% | 31–40% | Other: ______

[a]7-point scales anchored by “strongly disagree” to “strongly agree.”
[b]®: Reverse coding: Reverse code items and measurement items for PIO were recoded prior to data analysis.
Source: ACB, ACI, ASE, DISC, FC, PUU, SAT from Bhattacherjee (2001); PIO from Chen, Shang, and Kao (2009).