Exploring the Effects of Aggregate Review Characteristics on Mobile Application Adoption

Completed Research Paper

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Abstract

This study investigates how potential adopters of mobile applications utilize online review systems to inform their perceptions on the application's technology characteristics and thus inform their eventual adoption decision. Informational cascades and herding behavior theories are combined with the Innovation Diffusion Model and the Theory of Planned Behavior (TPB) to develop a research model. The review characteristics of aggregate review valence, overall rating, and review volume are related to the perceived technology characteristics of relative advantage, compatibility, and complexity. These, in turn, use the TPB as a lens to tie it all to the behavioral intention to adopt the mobile application. An online survey yielded 448 responses for analysis. The results yield some important insights and raises new questions for future evaluation.

Keywords: Adoption, Innovation Diffusion Theory, Informational Cascades, Herding Behavior, Theory of Planned Behavior, Mobile Applications, Online Product Reviews

Introduction

Mobile Applications and M-Commerce

As Information Technology (IT) and the Internet are transforming people's lives in numerous ways, online e-commerce is booming. In recent years, the market share of mobile devices and smart phones based on 3G and 4G LTE networks is seeing a sharp increase. Devices such as iPod, iPad, and iPhones, or wearable technologies such as Google Glasses and Samsung's smart watch, appear to have similar adoption patterns as those of new fashion trends (Sun, 2013). As a result, various mobile applications (commonly referred to as "mobile apps") based on those devices and smart phones are becoming the mainstream. According to Lessin and Ante (2013), users are estimated to spend two hours with their apps on a daily basis. Besides the use of mobile apps in daily life, such as comparing price, activity reservation, social networking, and entertainment, mobile apps are increasingly being used by professionals, such as health care monitoring (Ee-May Fong & Wan-Young Chung, 2013), aviation planning (Dy, 2013), and worker safety enhancement (Alam & Hamida, 2014). Consequently, like never before, individual users and businesses have access to those various choices which are increasing rapidly in variety on the market. The nature of the mobile app business is characterized by the fact that success, and a flood of money, can arrive practically overnight (MacMillan, Burrows, & Ante, 2009).

This "app economy" is creating more opportunities and fortunes for businesses and entrepreneurs and is changing the way people conduct businesses. Apple and Google's app stores offer over 700, 000 apps each. The overall revenue from app stores is expected to reach $25 billion by 2013, with 62% increase in the year of 2013, according to Garner Inc. (Lessin & Ante, 2013). It is projected that the next trend on the web lies in the intersection of three areas: apps, web services, and small online payments from consumers. Apps are not viewed as a product but rather an ongoing service that users tap into and pay in small increments (MacMillan et al., 2009). Apple's App Store was launched in 2008; at the time it was launched, it was the first on the market (MacMillan et al., 2009). Currently, the number of apps is growing at a faster speed, resulting in a sharp increase of available apps on the virtual shelves of online shops such as Apple's App Store, Google's Android Market, Research In Motion's BlackBerry App World, and Microsoft's app store for Windows Phone. According to Ovum Consulting, the number of apps sold in these stores may reach 18.7 billion in 2014, while the figure in 2008 was 491 million (Kharif, 2009). Mobile app startups are rivaling traditional game and software companies. The money infused into apps is triggered by people's belief that the smartphones and mobiles devices are reshaping the tech world (MacMillan et al., 2009). It is projected that some of the app publishers will become large brand names. The booming of apps has attracted some high-profile investors as well. Companies generate revenue from selling apps, distributing advertisement in their apps, and from selling digital goods used in the apps. Apple's app store generated $10 billion sales revenue in 2013, which is higher than all the previous years combined since its launch in 2008 (Frizell, 2014). While the mobile app market is seeing sharp growth, "the bar is so high to build something that is special and valuable and easy to use." App developers are being more selective in what to build and how to promote their apps (Lessin & Ante, 2013). Research on the mobile app area is promising as more knowledge concerning the dynamics within the area should benefit both app-oriented businesses and individual users.

Besides the aforementioned apps, game makers are also striving to gain a larger user base on all available technology platforms. One of the major targets would be apps on the mobile platforms. Facebook, with more than 1 billion mobile users as of April 24, 2014 (McDuling, 2014), would be the primary target in this sector. Apple's App Store has more than 500 million users as of June 4, 2013 (Hughes, 2013). In addition to gaming apps, mobile shopping, content, social media, communications, and productivity tools are also attracting more attention. Among thousands of new apps, many are targeted at consumers but there are also tools available for businesses. For instance, Salesforce.com has apps to help executives conduct customer relationship management from an iPhone or BlackBerry. The tasks people used to do primarily on their desktops are now increasingly being done on mobile devices (MacMillan et al., 2009).

Characteristics of Mobile Applications and Information Overload

Mobile apps are characterized by having a large and increasing number of competing products. One main reason of the success of Apple's iPhone can be attributed to their ability to provide more software choices than their competitors (MacMillan et al., 2009). With the wide range of choices available for a certain type of product, the customer is overwhelmed with numerous choices and associated sources of information. As a result, it causes the problem of information overload.

In mobile application adoption, due to the overwhelming number of choices, users lack time to evaluate those products and make comparisons. This makes it difficult to reach well-informed decisions to adopt a particular product (Duan, Gu, & Whinston, 2009). Therefore, when a user needs to make a quick decision, it is difficult to evaluate the product or service due to the large number of available choices and large amount of information related to them. In this case, previous theories, such as the Technology Acceptance Model (TAM) (Davis, 1989; Davis, Bagozzi, & Warshaw, 1989), the Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1975), the Theory of Planned Behavior (TPB) (Ajzen, 1991) and Information Diffusion Theory (IDT) (Rogers, 2003; Moore & Benbasat, 1991) need adaptation to address new issues in mobile application adoption. These issues include a users' lack of time and experience in evaluating the product, and other factors influence users' adoption decisions. Therefore, while using the previous theories as a basis, we need to seek new approaches to examine the decision process of users trying to adopt such mobile applications.

Online Review and Its Effect on Users' Adoption Intention

It is widely agreed that online information search is valuable. It has been reported that looking for product information online is the most important predictor of product adoption (Bellman, Lohse, & Johnson, 1999). The main reason is that an adopter feels it is very important to learn about the specification of the product, to evaluate possible alternatives, to know the requirements, and to gain enough knowledge to make well informed decisions (Pavlou & Dimoka, 2006). If word-of-mouth (WOM) is relevant to online sales, firms need to learn about these factors in order to maximize their success (Y. Liu, 2006).

For online e-commerce sites with a wide range of products and services, online customer reviews are increasingly available. Such customer reviews serve as an important supplement along with other information on the electronic storefronts, such as expert reviews, product descriptions, and some automatically generated content by recommendation systems (Mudambi & Schuff, 2010). Online product reviews generated by consumers who have experienced the product have become a main source for consumers to evaluate a product before purchasing (Hu, Liu, & Zhang, 2008). Duan et al. (2009) suggested that in the information cascades theory, there is a more complicated relationship between online user reviews and product adoption than previously suggested in research. Therefore, it is necessary to examine the effects of online reviews in the adoption decision-making process in a more depth.

Herd Behavior and Informational Cascade

Informational cascades are identified as a special case of herd behavior in Duan et al.'s (2009) study. They stated that informational cascades take place when an adopter makes a decision without referring at all to their own private information. Cascades happen when the perceived herd information becomes more salient than private information causing some individuals to join the herd. These additional individuals make the herd information appear even more important (due to herd growth) and even more join the herd and a cascade begins (Sun, 2013). The cascade, therefore, represents an explanation of herd behavior. In a herd behavior, all the adopters make an identical decision and they may or may not ignore their private information (Smith & Sorensen, 2000). Duan et al. (2009) empirically studied informational cascades among online customers and analyzed the influence of online product information on adopters' informational cascades behavior. In their result, they found that informational cascades play an important role in adopters' decision-making. To be specific, Duan et al. (2009) found that informational cascades have a significant influence on decision-making for online users. In informational cascades, people make decisions sequentially by simply observing their predecessors' actions without examining their decision-making process or information sources. This situation sometimes has a strong influence resulting in consumers simply imitating others' behaviors while ignoring their own private information.

In Bikhchandani et al.'s (1992) research, they defined informational cascades as a situation "when it is optimal for an individual, having observed the actions of those ahead of him, to follow the behavior of the preceding individual without regard to his own information" (Bikhchandani et al., 1992). Duan et al.'s (2009) major objective was to study the effect of herd behavior in the adoption process of software programs. They systematically studied two major sets of unique characteristics of informational cascades. One is the impact of digital product ranking variation on the adoption decision. The other one is the different impact of customer reviews on products with different levels of popularity (Duan et al., 2009). Their results showed that there are more complicated relationships between digital product reviews and consumer adoption decisions and they indicated that such relationships need to be further investigated as previous literature lacks coverage on this issue (Duan et al., 2009). While Duan et al.'s theory provided a plausible explanation on consumers' adoption behaviors for online software programs, it also has its drawbacks as mentioned above.

Some research has identified herd behavior in IT and digital product adoption though further research is necessary (Sun, 2013). Duan et al. (2009) developed the informational cascades theory to address the situation when a decision maker faces multiple competing products and needs to make a choice. In their theory, they articulate that there are two sources of information for the decision maker. One source is the decision maker's private information based on knowledge of the products or reading about the products. However, his/her private information is often limited or imperfect, thus he/she perceives a certain level of uncertainty in evaluating the true value of a product. The other source is the information derived from other users' adoption decisions. Typically, the decision maker takes consideration of the two sources of information together to make the best decision (Duan, Gu, & Whinston, 2009). During this process, potential adopters face both the issues of product uncertainty and effort needed in searching for quality information when making adoption decisions.

Most IT adoption processes are hindered by various degrees of information asymmetry. Hence, informational cascades have a great potential in changing the dynamics of IT competition and diffusion (Li, 2004). The informational cascades theory can also be applied to situations where many choices of products are available (Banerjee, 1992; Bikhchandani, Hirshleifer, & Welch, 1992; Chamley, 2004). Therefore, the informational cascades theory appears to be an appropriate approach in studying mobile app adoption, where there are multiple products available to choose from in most cases.

Meanwhile, informational cascades have its negative effects. For popular products, informational cascades tend to occur; for less popular products, people may refer to online reviews more. As a result, informational cascades are less likely to occur. When informational cascades do occur, it may be misleading, resulting in the adopter rejecting a superior product. That is because a high number of adoptions on a certain product tends to give potential adopters an impression that the product is popular, and there is no further information given. Therefore, making ranking information available for customers to trigger informational cascades may deteriorate customer benefits (Duan et al., 2009). Therefore, in the context of mobile app adoption, considering both review volume and aggregate review valence is important to fully understand adopters' decision-making.

Mobile Applications as Experience Goods

In both Zhu and Zhang's (2010) and Duan et al.'s (2009) research, they distinguished the different influences of online reviews on different product types. Zhu and Zhang's (2010) study showed that consumer online reviews have more influences for less popular games, while Duan et al. (2009) found that online reviews have little impact on users' adoption decisions on the most popular products and have an increasingly positive impact for lower ranking products. Nelson (1970) divided products into search goods and experience goods. In his study, he defined search goods to be the type of goods where customers are able to obtain information on product quality before purchasing, and experience goods are those that require sampling or purchase in order to evaluate product quality (Nelson, 1970). An example of an experience good in mobile apps might be an email client. While some judgments about the software may be made from the experiences of others, whether the app will work with the specific server and email configurations the individual is saddled with can often not be truly evaluated without a trial. Therefore, online product reviews likely do not have a uniform impact across all types of products, but rather, there will be a moderating effect of product type when consumers refer to online reviews to make adoption decisions.

Research Objective

As has been discussed above, there is much that needs further investigation in the general area of how review systems are used by consumers. Mobile computing is arguably one of the areas that need special scrutiny due to its fast growing nature as well as the important effects of this new product category on society in general.

The primary motivation for this research is to explore how online product reviews are utilized by potential adopters to determine important product characteristics that should, in turn, lead to a decision as to whether or not to adopt the product. Mobile apps were chosen as the product category due to an identified need to explore the general adoption behaviors in this category. Furthermore the characteristics of mobile apps may make informational cascades, herding behavior, and by extension online reviews more important than in most other products. There has been some limited research in the area of mobile app adoption (Al-Jabri & Sohail, 2012; Chen, Meservy, & Gillenson, 2012; Verkasalo, Lo´pez-Nicola´s, Molina-Castillo, & Bouwman, 2010; Yang, 2013) and there has been some additional research in herding behavior and IT adoption (Sun, 2013; Walden & Browne, 2009); however, no research has been found that study herding behavior in mobile app adoption. The results of this research should be useful to information systems researchers exploring the mechanisms of adoption for new classes of information technologies on the individual level. Additionally, the Internet can be considered a very large and complex information system. One output of this system is information in the form of online product reviews. Therefore this research also relates to the understanding of how a specific type of information system output is utilized for decision-making by the users of that information system (mobile device owners using online review sites in this context). This further helps define what information characteristics give these reviews the greatest utility within this type of decision-making.

Development of the Research Model

The research model (see Figure 1) focuses on the effects of online reviews on perceived technology characteristics such as relative advantage, compatibility, and complexity. These technology characteristics are in turn viewed as antecedents to the well-known Theory of Planned Behavior (TPB) Model. As such, the TPB simply serves as a lens to view the effects of the technology characteristics on the 'planned behavior' of technology adoption. We are primarily interested in the relationship between technology characteristics and the antecedents of behavioral intention in the TPB. As the TPB has already been extensively studied we will not spend time discussing the well-researched paths internal to the TPB (shown in dashed lines in our model). The technology characteristics were chosen from the Innovation Diffusion Theory (IDT) first developed by Rogers (2003). IDT identifies five characteristics of innovations believed to impact innovation adoption. The two additional characteristics we are not utilizing are trialability and observability. It was determined that choosing a subset of the IDT that would be the most logically affected by reviews would aid in reducing the model complexity. For this reason it was determined that relative advantage, complexity, and compatibility would be the perceived characteristics most logically influenced by reviews. Review content is associated far more with these three characteristics than the others and even if some reviews rarely mention issues pertaining to trialability and observability, these characteristics are primarily determined through other means. Whether a trial version is available is usually prominently listed in the product description and the decision-maker really needs to determine their own level of observability as this may differ significantly between individuals due to life contexts.

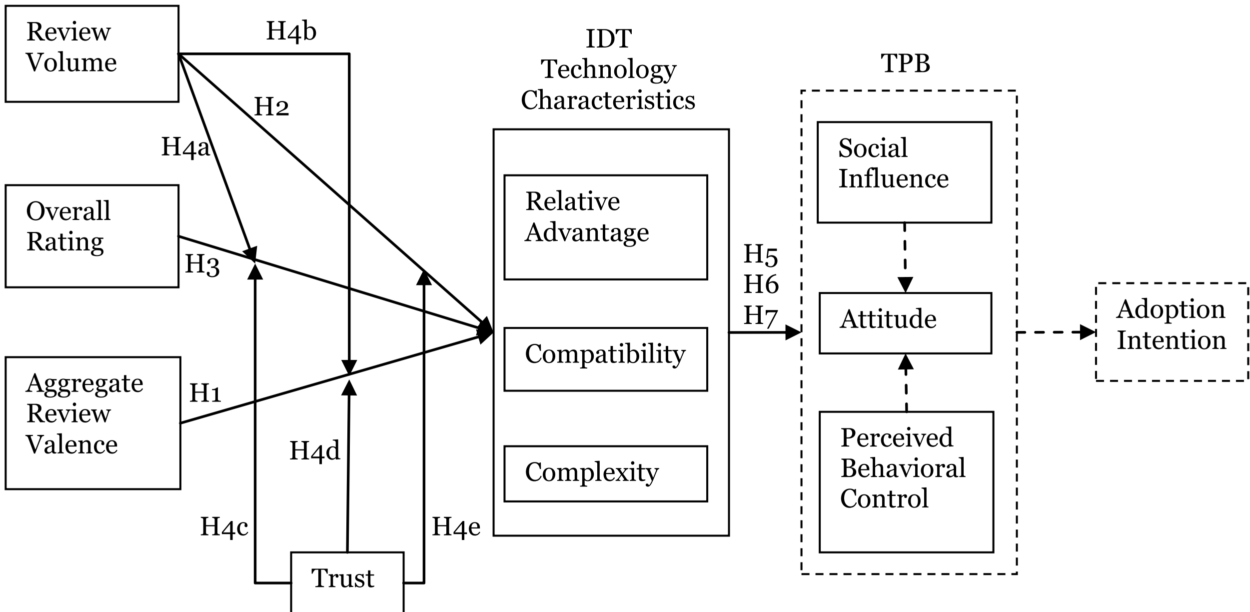

Figure 1. Research Model

Hypothesis Development

When consumers are trying to make adoption decisions on a mobile application, they go through a process of comparing price and evaluating product quality (Hu et al., 2008). Online reviews are recognized by both researchers and practitioners as an important source to learn about a product. Duan et al. (2009) suggested that word of mouth (WOM) volume has a positive influence on product sales. They also suggested WOM valence (the positiveness or negativeness of the communication) also influence consumers' perceptions toward a product and their eventual purchase decision. In this study, we use aggregate review valence, a similar concept as WOM valence, to refer to the overall perception of the positiveness of online reviews. We also define review volume as the number of reviews available on a product. Typically, a higher review volume indicates a product is popular among adopters.

In Rogers' (2003) innovation diffusion theory, he defines relative advantage as the degree to which adopters perceive an innovation to be better than the idea it supersedes. Also, Goodhue & Thompson (1995) developed the task-technology fit model, in which it is argued that a technology has to be a good fit for a specific task in order to achieve good performance. In Rogers' (2003) work, he used the term compatibility to refer to the extent to which an innovation is perceived to be consistent with the need of an adopter. In innovation diffusion research, technology complexity has been a major obstacle for technology adoption and easy-to-use technologies is an important factor to influence adoption decisions (Katz & Aspden, 1997) .

It follows that, if a potential adopter perceives valence as positive, they will likely have a more positive perception of the application and of its relative advantage and compatibility, and a lower perception of complexity. Similarly, a greater number of reviews leads potential adopters to believe it is a popular application and, following herding behavior arguments previously discussed, should lead to similar improved perceptions of the application and IDT characteristics studied.

In this research, we adapt Rogers' relative advantage, compatibility and complexity to measure the quality of a mobile application over other similar applications. Therefore, following the above discussion, we propose hypotheses as follows:

> *H1a. There is a positive relationship between aggregate review valence (ARV) and perceived relative advantage (RA) of a mobile application.*

H1b. There is a positive relationship between aggregate review valence (ARV) and perceived compatibility (CP) of a mobile application.

H1c. There is a negative relationship between aggregate review valence (ARV) and perceived complexity (CX) of a mobile application.

H2a. There is a positive relationship between review volume (RV) and perceived relative advantage (RA) of a mobile application.

H2b. There is a positive relationship between review volume (RV) and perceived compatibility (CP) of a mobile application.

H2c. There is a negative relationship between review volume (RV) and perceived complexity (CP) of a mobile application.

Information overload refers to the situation when users are facing an amount of information that exceeds their ability to consume within a certain time period (Liang & Xue, 2009b). When a user faces an information overload problem, the user seeks to reduce the amount of information in order to reduce the efforts in finding the target (Liang et al., 2006). Following the principle of least effort (Zipf, 1949), Liang et al. (2006) find that information seekers will attempt to use minimum effort in obtaining information. They are willing to accept lower quality or quantity of information to minimize their search effort. In this research, overall rating is similar to the 'star rating' on a product. More stars indicate higher product quality or popularity. Although this is an objective measure that could be used directly, it should be noted that in behavioral studies such as this, the perceived value is what is of importance. Therefore, we do not employ the star rating directly but rather measure the decision-makers' perception of the relative strength of the rating. The overall rating is similar to aggregate review valence in that it is a measure of the positiveness of the reviews. There is a distinction between them that the overall rating can be found in seconds while aggregate review valence is developed by reading reviews. Following the definitions of overall rating and discussions on relative advantage, compatibility and complexity, we propose:

H3a. There is a positive relationship between overall rating (OR) and perceived relative advantage (RA) of a mobile application.

H3b. There is a positive relationship between overall rating (OR) and perceived compatibility (CP) of a mobile application.

H3c. There is a negative relationship between overall rating (OR) and perceived complexity (CX) of a mobile application.

In Surowiecki's (2005) book, he used examples to show that in a group of people with diverse backgrounds and sufficient number of members, the averaged decision will be more accurate than any individual's decision in the group (Surowiecki, 2005). His argument is that people try to make their best decisions based on their knowledge, but they are always using imperfect information. However, when all the decisions of the group members are averaged out, it is most likely that the errors cancel out, thus reaching a highly accurate estimation of the real value. It follows that the more reviews available on a product, the more accurate the overall rating of the product. In this research, review volume refers to the number of reviews available. Due to the possibility of information overload (Eppler & Mengis, 2004), decision-makers may rely on overall rating to judge the quality of a product to save time. In addition, when there are a lot of reviews, the decision-maker would likely have more confidence that the reviews truly reflect the opinions of other consumers. If there are more reviews available, it could reinforce the effect of aggregate review valence and overall rating on people's technology perceptions. Therefore, we hypothesize as follows:

H4a. Review volume has a positive moderating effect on the relationships between overall rating and technology perceptions (relative advantage ($H4a_i$), compatibility ($H4a_{ii}$), complexity ($H4a_{iii}$)) of a mobile application.

H4b. Review volume has a positive moderating effect on the relationships between aggregate review valence and technology perceptions (relative advantage ($H4b_i$), compatibility ($H4b_{ii}$), complexity ($H4b_{iii}$)) of a mobile application.

There is a large body of research that acknowledges that trust is important in an online environment (Pavlou, 2003). Trust has been studied in many different contexts. In Pavlou and Fygenson's (2006) study, trust is studied as an antecedent of perceived behavioral control. Trust also plays an important role in the technology adoption process. According to McKnight et al. (2002), disposition to trust is the degree to which a person relies on others across various situations. When an adopter is interested in a mobile application, the adopter tends to either refer to online reviews or people they trust. It is likely that as the propensity to trust increases, the effects of online reviews increase as well. In other words, they trust that the reviewers are expressing their honest opinions to a greater degree than someone with a low propensity to trust. Therefore, moderating effects of trust on the relationships between review characteristics and technology characteristics might also be observed.

H4c. Trust has a positive moderating effect on the relationships between overall rating and technology perceptions (relative advantage ($H4c_i$), compatibility ($H4c_{ii}$), complexity ($H4c_{iii}$)) of a mobile application.

H4d. Trust has a positive moderating effect on the relationships between aggregate review valence and technology perceptions (relative advantage ($H4d_i$), compatibility ($H4d_{ii}$), complexity ($H4d_{iii}$)) of a mobile application.

H4e. Trust has a positive moderating effect on the relationships between review volume and technology perceptions (relative advantage ($H4e_i$), compatibility ($H4e_{ii}$), complexity ($H4e_{iii}$)) of a mobile application.

Previous literature suggests that high relative advantage leads to forming a behavioral intention to adopt (Choudhury & Karahanna, 2008). In addition, the linkage between attitude and behavioral intention is also well established (Fishbein & Ajzen, 1975). However, the relationship between perceived technology characteristics and attitude needs to be examined. Rogers (2003) defined relative advantage as the extent to which a product is superior to other alternatives. Goodhue & Thompson (1995) argued that a technology has to be a good fit for a specific task to be adopted. In this research, compatibility is employed to reflect the extent to which a mobile application is a good fit for a potential adopter's task. Complexity is defined by Rogers (2003) as the extent to which a technology is hard to learn and use. Typically, users prefer a technology that is easy to use (Davis, 1989; Katz & Aspden, 1997). Therefore, we hypothesize that:

H5a. There is a positive relationship between relative advantage (RA) and attitude (ATT) towards a mobile application.

H5b. There is a positive relationship between compatibility (CP) and attitude (ATT) towards a mobile application.

H5c. There is a negative relationship between complexity (CX) and attitude (ATT) towards a mobile application.

Social influence is defined as an individual's perception of important others' beliefs that the individual should engage in a particular behavior (Venkatesh, Morris, Davis, & Davis, 2003). There is evidence that members in a social network, such as family, relatives, friends, and peers may have a positive influence on a person's innovation behavior (Childers & Rao, 1992; Valente, 1995). The subjective norms which guide an individual's behavior will be influenced by their most salient referents (Taylor & Todd, 1995b). Social influence is found to be the immediate predictor of behavioral intention in previous literature (Davis, 1989).

There are two types of social influence: informational influence and normative influence (Karahanna et al., 1999). These two types of influence better explain the reason people adopt a mobile application. When people try to adopt a mobile application, they are potentially influenced by both informational influence and normative influence. While normative influence relates to doing what others expect us to do, informational influence is exerted by a belief that someone has more information than the decision-maker and they conform to the others' actions as a result. We are testing the influence of the technology characteristics on social influence primarily to see if the reviewer's opinions are mediated by the technology characteristics so that changes in these characteristics might affect more than just the attitude towards adopting the technology. Perhaps when conclusions on the technology characteristics were derived to a certain extent from others' opinions (online reviews) the level of the perceived characteristic may influence the person's belief that others would support them taking the adoption action. More positive perceived technology characteristics may also lead to higher levels of social influence due to consistency motifs. That is, a decision-maker's perception of whether a person whose opinion they value would be more likely to want them to engage in behavior that they already have concluded is positive (based on their perceived characteristics of the technology). Previous literature also shows ample evidence that higher social influence will lead to increased adoption intention (Ajzen, 1991) in many but not all technologies. Following the above discussion on technology perceptions and social influence, we propose the following hypotheses:

> *H6a. There is a positive relationship between relative advantage (RA) and social influence (SI) on a mobile application.*
>
> *H6b. There is a positive relationship between compatibility (CP) and social influence (SI) on a mobile application.*
>
> *H6c. There is a negative relationship between complexity (CX) and social influence (SI) on a mobile application.*

Perceived behavioral control (PBC) is a key factor in e-commerce context, and the antecedents of PBC need to be empirically examined (Pavlou & Dimoka, 2006). Ajzen (1991) defined perceived behavioral control as people's perceptions on how easy or difficult it is to perform a behavior that they are interested in. In some other literatures, perceived behavioral control is defined as an adopter's perception of the extent he/she meets the requirements to perform the behavior of interest (Ajzen, 1991; Hsieh et al., 2008). We are interested in examining the relationships between technology perceptions and perceived behavioral control, as well as the relationships between PBC, attitude, and adoption intention. Complexity and compatibility would logically be important determinants of perceived behavioral control. The more complex something is the less likely a person is to believe they can perform the behavior correctly. Likewise, if something is not compatible with other parts of the decision-maker's life then they may perceive it as more difficult to perform due to those incompatibilities. Relative advantage is less obvious as a determinant of PBC. However, if the decision-maker believes the technology has substantial advantages they may estimate their ability to perform the behavior to be greater due to an increased desire to make it work.

> *H7a. There is a positive relationship between relative advantage (RA) and perceived behavioral control (PBC).*
>
> *H7b. There is positive relationship between compatibility (CP) and perceived behavioral control (PBC).*
>
> *H7c. There is a negative relationship between complexity (CX) and perceived behavioral control (PBC).*

Methodology

Instrument Development

Dillman et al.'s (2009) book on designing and deploying surveys is a commonly used standard. Therefore, to maximize the validity and reliability of the instrument and to maximize response rates, this standard was followed. Most of the survey questions were based on validated survey questions in previous research. For a few survey questions that could not be found in previous research, indicators were constructed initially through discussions with experienced researchers. After developing the instrument, several rounds of reviews were conducted. First several university faculty members with knowledge in the area were asked to review the questionnaire. A pilot study was then conducted in a class with 50 students from a business college. This was used for a preliminary analysis and ensuing revision on the survey questionnaire. Based on the rounds of reviews and revising, validity of the instruments was improved.

Population and Data Collection

An online survey was employed. Three waves were conducted by sending out three email messages to the survey population. The population employed for this study was students over 18 years old at a large public university in the Great Lakes area of the United States. Students were thought to be an accessible and reasonable population for study. Students are generally more technology savvy and have substantial experience with mobile apps. It is believed that the way reviews are employed by students would not differ widely from the general population. However, the incidence of use is undoubtedly higher in the student population and there are other differences so some limitations concerning generalizability are justified. A total of 4251 respondents received and opened the survey, a total of 997 responded to the survey. A total of 512 respondents finished the survey. There were 64 respondents who do not have a mobile device or have not used mobile apps before. Therefore, we used 448 responses for data analysis.

Results

Overall Model Fit

PLS-SEM was the primary statistical tool utilized. The specific software employed was SmartPLS 2.0 (Ringle, et al., 2005). The model testing includes measuring the convergent validity, discriminant validity, and reliability. Reliability is measured by composite reliability and Cronbach's alpha is also reported for those more familiar with its usage. For composite reliability, most values are greater than 0.9, the lowest value is 0.85. The cutoff score for composite reliability is 0.7 (Nunnally, 1978). Therefore, the model has good reliability according to the cutoff score.

Average Variance Extracted (AVE) is a good indicator of convergent validity. AVE values greater than 0.5 are considered to be good indications for convergent validity. The AVE value for most latent variables (LVs) are greater than 0.7. Relative advantage has the lowest AVE in the model of 0.59 which is still well above the benchmark of 0.5. Overall, the AVE values show good convergent validity of the model constructs.

To ensure discriminant validity, the square root of AVE has to be greater than the correlations of that LV and any other LVs in the model. This analysis showed no issues with discriminant validity.

In addition, R^2 values for the dependent variables indicate the explanatory power of the model. Referring to Figure 2, for Adoption Intention (AI), 51.5% of the variance is explained by the model. Additionally, 56.5% of the variance of Attitude (ATT), 54.6% of the variance of Social Influence (SI), 10.6% variance of Complexity (CX), 46.9% of the variance of Perceived Behavioral Control (PBC), 27.4% of the variance of Relative Advantage (RA) is explained, and 28.5% of the variance of Compatibility (CP) is explained.

Multicollinearity was also tested for. Variance Inflation Factors (VIF) are commonly employed to explore potential problems with multicollinearity. In order to obtain the VIF scores, latent variance scores were used in a regression analysis. Most the VIFs were found to be under 3, with only 2 VIFs over 3 (ARV 3.597 and RV 3.267). Previous research has suggested that a VIF score under 4 is acceptable while others propose 10 as a rule of thumb (O'Brien, 2007). Even under the more conservative cutoff, multicollinearity does not seem to be problem in this data.

	AVE	Composite Reliability	R Square	Cronbach's Alpha
AI	0.718774	0.938137	0.514978	0.919341
ARV	0.855091	0.946526		0.915209
ARV*TRUST	0.826399	0.986184		0.984971
ATT	0.718533	0.910675	0.565419	0.869205
CP	0.661163	0.884849	0.285371	0.823974
CX	0.763258	0.927730	0.106490	0.895345
OR	0.766651	0.942415		0.923237
OR*TRUST	0.746772	0.986602		0.985813
PBC	0.810444	0.944719	0.468680	0.921810
RA	0.593611	0.853326	0.274161	0.771842
RV	0.788272	0.917738		0.865172
RV*ARV	0.850543	0.980844		0.978063
RV*OR	0.795386	0.983126		0.981595
RV*TRUST	0.743242	0.977445		0.975240
SI	0.748708	0.937010	0.546242	0.915652

Table 1. Average Variance Extracted, Reliability, and R^2 for Latent Variables

Hypotheses Testing and Discussion

Figure 2 shows the path coefficient and significance for the hypotheses developed earlier. The figure appears more complex than the research model since each separate path is enumerated while in the research model (Figure 1) groups of latent variables were allowed to share common paths. Each section of the model is discussed in the following sections.

The Effect of Online Review Characteristics on Technology Characteristics

Review volume (RV), aggregate review valence (ARV) and overall rating (OR) are the three perceived aggregate review characteristics that are posited to affect the perceived technology characteristics investigated (from the IDT) of relative advantage (RA), compatibility (CP) and complexity (CX). A summary of this testing is available in Table 2.

Aggregate review valence shows a significant positive relationship with compatibility and a significant negative relationship with complexity, both at $p<=0.001$ level. The findings support the hypotheses and indicate that when a decision-maker perceives the aggregate set of reviews to have a more positive valence then they are also likely to perceive it as being less complex and more compatible with how they function. Interestingly, the ARV was not found to have a significant effect on relative advantage. It is difficult to suggest why this might be so without further research but it may be that, when considering mobile app adoption, review content is overshadowed by other review factors. The only review characteristic that does seem related to relative advantage is review volume. As this may be perceived as a measure of the app's popularity, this might overshadow other considerations concerning online reviews, including what the reviews actually say. It would seem that potential adopters do form a perception of the aggregate review valence as the other hypotheses using this construct show it to be a significant antecedent. Taken as a whole, a conjecture that can be made concerning all three results would be that potential adopters read reviews more because they have complexity and compatibility concerns but are willing to let a measure of popularity dictate how they perceive the overall advantage of the app over similar apps that may be available.

Hypothesis	Path Coefficients	Significance
H1a$^{(+)}$: ARV → RA	0.072	n.s.
H1b$^{(+)}$: ARV → CP	0.235	P<=0.001
H1c$^{(-)}$: ARV → CX	-0.463	P<=0.001
H2a$^{(+)}$: RV → RA	0.372	P<=0.001
H2b$^{(+)}$: RV → CP	0.095	n.s.
H2c$^{(-)}$: RV → CX	0.107	n.s.
H3a$^{(+)}$: OR → RA	0.024	n.s.
H3b$^{(+)}$: OR → CP	0.156	P<=0.05
H3c$^{(-)}$: OR → CX	0.074	n.s.

Table 2. Results of Hypothesis Testing for Review Characteristics as Antecedents

Review volume is significantly related to only the relative advantage perceived technology characteristic. The finding supports the hypothesis that review volume is positively related to relative advantage. As potential adopters perceive the app to have a larger number of reviews they perceive the relative advantage of the app to be greater. As discussed above, review volume is the only review characteristic that is significantly related to relative advantage. It was suggested that review volume is an indication of app popularity. With the monetary investment being generally very low or free, perhaps potential adopters rarely read many reviews and base their perceptions more on the number of reviews. As noted previously, people tend to choose the restaurant that has more customers if there are two restaurants next to each other (Duan et al., 2009). This is also consistent with Zhu and Zhang's (2010) study that shows that consumer online reviews have more influences for less popular games as well as with Duan et al. (2009) who found that online reviews have little impact on users' adoption decisions on the most popular products. When compatibility and complexity are an issue, however, potential adopters may pay more attention to review content and ratings. This may explain why aggregate review valence and overall rating are not related to relative advantage while they are each related to one or both of compatibility and complexity.

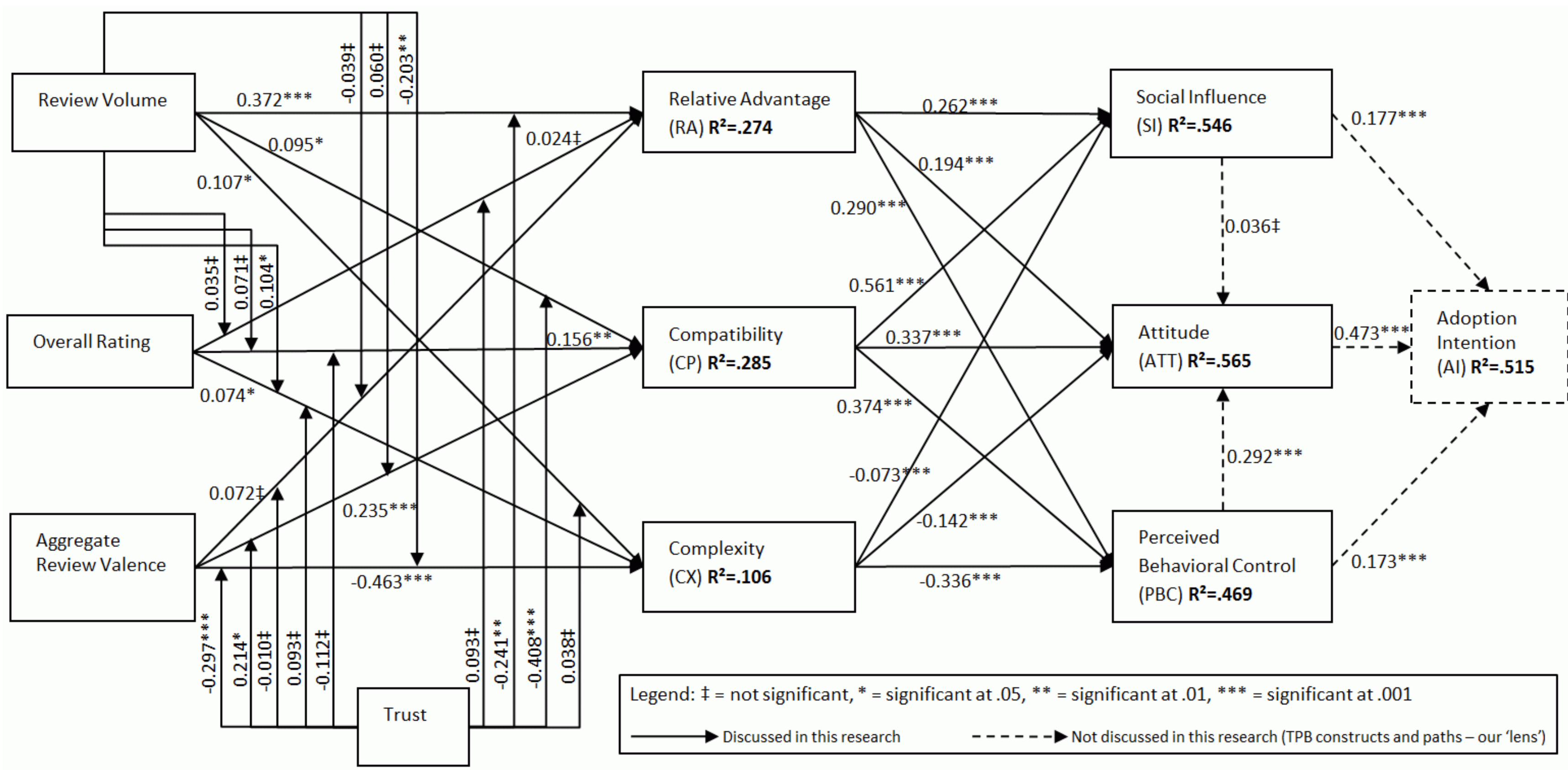

Figure 2. Path Coefficients and Significance

Overall rating is positively related with compatibility, which suggests that potential adopters perceive that higher overall ratings are consistent with app compatibility. A relatively high star rating would imply that many of the individuals reviewing it must find it to be compatible to rate it highly. However, overall rating is not related to relative advantage and complexity. This is somewhat perplexing, especially concerning relative advantage, because the star rating was assumed to be used by potential adopters as a measure of the overall quality of the app. It would be reasonable to assume that this would then translate into a positive relationship to relative advantage. Without further research this is only conjecture but it may be that overall rating serves as a sort of qualifier. It is generally the first indicator that a potential adopter may see and it may be that they use this to determine if they will even consider the app. This would cause all low rated apps to be discarded before they are really perceived as candidates. The remaining highly rated apps are then evaluated on other measures such as review volume and, for more concerning and technical issues such as complexity, review content (which we measure as aggregate review valence). This behavior would make the overall rating seem less important to the decision-maker when making their final choice between apps as it was used earlier in the process as a first-pass screener.

Moderating Effects of Trust and Review Volume

In this study, we also considered the moderating effect of trust on the relationships of review characteristics (review volume, overall rating, aggregate review valence) and IDT factors (relative advantage, compatibility, complexity). Besides the moderating effect of trust, the moderating effect of review volume on overall rating and aggregate review valence are also studied.

A quick view of Table 3 shows that most of the hypothesized moderating relationships were not supported. Additionally, two of the four significant moderating effects are also not supporting of their hypotheses due to the effect being in the opposite direction from what was hypothesized. The two supported moderator hypotheses are associated with moderating the relationship of aggregate review valence on complexity. Both review volume and trust negatively moderate this relationship (it increases the effect by making the negative relationship more negative). Looking at review volume as the moderator supports that the effect of aggregate review valence on complexity increases as review volume increases. This would make sense since a greater number of reviews should give the decision-maker more confidence in the accuracy of the aggregated reviews. Similarly, trust as the moderator supports the same as trust levels increase. As the decision-maker is more willing to trust the reviewers, the importance of aggregate review valence should increase. The reason that aggregate review valence is only moderated in its relationship to complexity may be related to the previous argument that the review content is generally only accessed (read) when there are concerns over issues that individual reviewers may be able to shed some light on – like complexity.

The moderating effects that are in the opposite direction as what was hypothesized may also yield some interesting insights. Trust negatively moderated review volume's relationships to both relative advantage and compatibility. It was thought that an increased propensity to trust would make all of the information gleaned from the review system more salient to the decision-maker since they would generally trust the reviews. The opposite result may show that review volume is a substitute for trust. An increased review volume would also lend more credibility to the aggregate reviews. Therefore, a person who has a high propensity to trust may not require a high review volume before trusting what the reviews are disclosing. Alternatively, they may not rely on reviews at all (or at least to a lesser extent) due to a propensity to trust the developer to produce a good product.

Hypothesis	Path Coefficients	Significance
H4a1(+): RV*OR → RA	0.035	n.s.
H4a2(+): RV*OR → CP	0.071	n.s.
H4a3(-): RV*OR → CX	0.104	n.s.
H4b1(+): RV*ARV → RA	-0.039	n.s.
H4b2(+): RV*ARV → CP	0.06	n.s.
H4b3(-): RV*ARV → CX	-0.203	P<=0.05
H4c1(+): OR*TRUST → RA	0.093	n.s.
H4c2(+): OR*TRUST → CP	-0.112	n.s.
H4c3(-): OR*TRUST → CX	0.103	n.s.
H4d1(+): ARV*TRUST → RA	-0.01	n.s.
H4d2(+): ARV*TRUST → CP	0.214	n.s.
H4d3(-): ARV*TRUST → CX	-0.297	P<=0.01
H4e1(+): RV*TRUST → RA	-0.241	P<=0.01
H4e2(+): RV*TRUST → CP	-0.408	P<=0.001
H4e3(-): RV*TRUST → CX	0.038	n.s.

Table 3. Results of Hypothesis Testing for Moderating Effects

Relationships between Perceived Technology Characteristics and TPB Factors

This part of the model confirms the effect of relative advantage, compatibility, and complexity on social influence, perceived behavioral control and attitude (see Table 4). Each hypothesis was supported. The relationship between the technology characteristics and attitude is fairly straightforward. As the perceptions of these technology characteristics improve, it would make sense that the attitude toward adopting the app would improve as well. The relationship between complexity and perceived behavioral control is also straightforward since it is logical that increased complexity leads to more difficulties in using the app. The relationship between compatibility and perceived behavioral control is similar but less obvious. The more compatible something is with the rest of your life, the easier it would be to implement it due to fewer conflicts. The effects of technology characteristics on social influence were hypothesized, in part, because of potential consistency issues in respondents. It is likely that the higher the decision-maker rates the app on these technology characteristics, the more they would expect the people whose opinion they respect to approve of them adopting it. This leaves us with the relationships between relative advantage and compatibility with perceived behavioral control. It was thought these were the least likely to have a significant relationship due to the only logical connection being that an increased perception of the app's relative advantage and compatibility would increase the decision-maker's desire to be able to effectively implement it (measured by perceived behavioral control) rather than their actual ability to do so. Unless other factors that have not been identified are in play, it would seem that these results do suggest that the *desire* to have control over a behavior may be sufficient to increase the respondent's estimation of their *ability* to have control over that behavior.

Hypothesis	Path Coefficients	Significance
H5a(+): RA → ATT	0.194	P<=0.001
H6a(+): RA → SI	0.262	P<=0.001
H7a(+): RA → PBC	0.29	P<=0.001
H5b (+): CP → ATT	0.337	P<=0.001
H6b(+): CP → SI	0.561	P<=0.001
H7b(+): CP → PBC	0.374	P<=0.001
H5c(-): CX → ATT	-0.142	P<=0.001
H6c(-): CX → SI	-0.073	P<=0.05
H7c(-): CX → PBC	-0.336	P<=0.001

Table 4. Results of Hypothesis Testing for Technology Characteristics as Antecedents

Conclusions

As an exploratory study it is not surprising that our results have raised some additional questions that may need to be studied at a later point. Specifically, there were several instances where our results did not match our hypotheses. Although we offered some conjectures as to why this might be, further study is warranted before coming to any firm conclusions. This study did also yield some important insights into how reviews may be used in this context. One of the most interesting results showed that review content is not always the most meaningful element in a review system. Review volume seems to be more important when reaching conclusions on relative advantage for instance. It was suggested this is so because review volume is a proxy for app popularity. Another insight is that when review content does become important it may be due to concerns the potential adopter has over technical issues such as complexity. It is proposed that these uncertainties are what leads potential adopters to read some of the reviews when they may not read any if they have no specific concerns. Conversely, without these concerns they focus on indications of popularity such as review volume. Next, the overall (or 'star') rating has the least impact of any of the review characteristics studied. We suggest that the reason for this is that overall rating may be used as an initial screener for candidates for adoption. Since all of the app's that the potential adopter then considers formally have relatively high ratings, its importance is diminished in the final stage of the process. Finally, when it comes to perceived behavioral control, our findings suggest that having the *desire* to be able to accomplish the tasks seems to increase the person's perceived *ability* to do so.

The results of this study, as well as related future research, have implications for information systems research and practice. Why people or organizations adopt and use information technologies (such as mobile apps) is one of the most studied areas in information systems. This research strives to begin to fill a void concerning herding behavior and mobile app adoption. The psychological processes that lead to adoption as well as phenomena that seem to short-circuit them (such as herding behavior) are still a fundamental question in behavioral information system research. Understanding how herding behavior and other such processes work can potentially aid organizations in creating viable business models for innovations they produce. Additionally, organizations can potentially use this information to create positive herding behaviors within their own organizations. Finally, designers of review systems and similar web applications can better understand how the information outputs of their system, the reviews, are utilized. This can be used to begin discussions concerning the information quality of these review systems.

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