ABSTRACT

This study investigates the effect of decision-makers’ characteristics on the level of search effort employed when adopting mobile apps. Mobile apps are different in many aspects from traditional technology; they tend to have a much larger number of alternatives available, they are relatively inexpensive, and are more diversified in complexity. As a result, decision-makers’ may approach the decision of how much time and effort to devote for searching for additional information to inform their mobile app adoption decisions differently than for other technologies. We present a research model to capture the effects of different characteristics on the decision-makers’ level of search effort employed. Our results show that their level of search effort is found to differ based on other personal characteristics such as innovativeness, technological self-efficacy, and resource constraints.

KEYWORDS: Search Effort, Mobile App, Technology Adoption, Adopter Characteristics, and Innovation Diffusion

INTRODUCTION: MOBILE APPS AND M-COMMERCE

In recent years, the market share of mobile devices and smart phones based on 3G and 4G LTE networks is seeing a sharp increase, rapidly shifting the web economy to mobile platforms. Devices such as iPod, iPad, and iPhones, or wearable technologies such as Google Glasses and Apple 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 an average of two hours using their apps on a daily
basis. Mobile apps are used for daily tasks, such as comparing prices, activity reservations, social networking, and entertainment. Additionally, mobile apps are increasingly being used by professionals in health care monitoring (Fong & Chung, 2013), aviation planning (Dy, 2013), and worker safety enhancement (Alam & Hamida, 2014). Consequently, like never before, individual users and organizations have access to these rapidly diversifying app-based options. The nature of the mobile app business is characterized by the fact that success can arrive practically overnight (MacMillan, Burrows, & Ante, 2009) or never at all for the developers.

This “app economy” is creating more opportunities for businesses and entrepreneurs and is changing the way people conduct business. Apple and Google’s app stores offer over 700,000 apps each. The overall revenue from app stores was 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 normal product but rather as an ongoing service that users tap into and pay in small increments (MacMillan et al., 2009). Apple’s App Store was launched in 2008 and 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 an accelerating rate, 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 this app-economy is motivated by the belief that smartphones and mobile 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 business of app development 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 in 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). Further research on the mobile app market is critically needed as more knowledge concerning the dynamics within the area should benefit both app-oriented businesses, developers, and the individual and organizational app users.

In addition to productivity and business app developers, 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 mobile platforms. Facebook, with more than 1 billion mobile users as of April 24, 2014 (McDuling, 2014), is the primary target. Apple’s App Store has more than 500 million users as of June 4, 2013 (Hughes, 2013). Mobile shopping, content, social media, and communications-oriented apps are also attracting more investments. Many of the quickly expanding number of available apps are targeted at consumers or for general business and productivity; however, there are also custom app tools being developed for specific organizations. 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).
During their search for product information of the mobile apps, although they try to reduce their search effort, they also want to reduce uncertainty. During the process of striking a balance between their search effort and reducing uncertainty, the adopters’ characteristics play a significant role on their search efforts. Adopter characteristics are important determinants of whether an adopter is willing to adopt a mobile app. For example, an adopter might adopt a new technology earlier than others if the adopter is more innovative, can tolerate more risks, has more resource slack, has more experience in a certain area, or has more self-efficacy in technology.

RESEARCH QUESTION AND MOTIVATION

App developers and marketers have been very busy creating content that is usually freely provided with the intent of informing potential adopters and generating interest in their app-based product. This sector would be greatly interested in understanding the dynamics of why different potential adopters (customers) vary the amount of time and effort they spend searching for information. Obviously, understanding these and other potential determinants of search effort allows an organization to fine-tune their investments in generating this type of marketing content. For instance, if they are marketing apps that are likely to appeal to individuals with characteristics that suggest they will spend a greater amount of time and effort searching for information, then it would be reasonable to invest significantly in developing rich content since their target audience is more likely to spend the time to view and assimilate this content. Although there are undoubtedly other sources for the variance of search effort, we are specifically interested in what role personal (e.g. innovativeness) and situational (e.g. resource constraint) characteristics of the potential adopters play in determining their level of search effort.

This research endeavors to fill in some of the knowledge desired by these marketers as well as other stakeholders of these app-oriented enterprises. Consequently, the following central research question reflects this and guides the remainder of this research:

*How do adopters’ characteristics influence their level of search effort expended before making a decision on adopting a mobile app?*

ADOPTER CHARACTERISTICS

Besides online reviews and product characteristics, adopter characteristics are important determinants of whether an adopter is willing to adopt a mobile app. For example, an adopter might adopt a new technology earlier than others if the adopter is more innovative, can tolerate more risks, has more resource slack, has more experience in a certain area, or has more self-efficacy in technology. This section reviews the following adopter characteristics: innovativeness, risk tolerance, resource constraints, experience, and technology self-efficacy and concludes with a discussion of search effort.

Innovativeness

Adopters do not all adopt a new technology at the same time. Rather, they adopt a new technology following a time sequence. Therefore, we could categorize adopters who adopt at different times, such as early adopters and late adopters (Rogers, 2003). Some people like to
adopt at the beginning of an innovation, whereas some other people prefer to adopt a technology when it becomes mature and well-known to the public. Early adopters are defined as curious explorers who are willing to try new media (Wohlwend, 2009). Rogers (2003) used the term innovativeness to describe the extent to which an adopter adopts a new technology earlier than others. In this research, we will follow this definition to use innovativeness as an adopter characteristic in mobile app adoption. A person’s knowledge and education is also related to the person’s innovativeness (Damanpour & Schneider, 2009). A person with more education tends to solve a problem with more complex and diverse approaches (Damanpour & Schneider, 2009).

**Risk Tolerance**

Risk tolerance represents how much risk a decision-maker is willing to take on during a particular process, in the present case, the process of deciding whether or not to adopt a mobile app. In addition to transactional risks, app adopters are concerned about their privacy and information security in online transactions, which is a major obstacle for e-commerce in general (George, 2002). Pavlou and Fygenson (2006) define information protection as the user’s belief that an online vendor is capable of protecting the users’ private information. They further state that if a user feels comfortable with the online vendors’ information security measure, they could overcome their psychological barriers in engaging in the transaction. Due to the risk concerns, many online consumers do not trust their vendors when it comes to information exchange (Hoffman et al., 1999).

A recent survey revealed that 72% of users are very concerned about their control over their private information after they have made an online purchase (George, 2002). Since most mobile apps are purchased or downloaded from online, privacy concern is a major issue. Data mining and data warehousing is being exploited like never before due to the availability of the Internet, which poses a great threat to consumers’ private information (Hoffman et al., 1999).

**Resource Constraint**

Pavlou and Fygenson (2006) found a consumer’s level of resources is related to their belief that they can accomplish a task if they decide to engage in it (such as learning how to effectively use a new app). They further specified that consumer resource includes both time resources and monetary resources. Leisure time (a form of resource slack) is found to be a critical factor in engaging in information search activity (Bellman et al., 1999). Available monetary resource is a determinant of product purchasing (Pavlou & Dimoka, 2006). In a mobile app scenario, a potential adopter might face both time constraint and monetary constraint. We combine time and monetary resources as a single construct.

**Experience**

Experience is generally operationalized as a measure of the time engaged in an activity. Experience may also measure the breadth of the activities as well. Experience is often a proxy for expertise since it is much easier to measure than expertise. Experience with the Internet is a factor that determines online transactions (Hoffman et al., 1999). When facing a new information technology (including mobile apps), a person with more knowledge will be more flexible in coping with the complexity of the new technology. This would likely minimize the impact of ease of use issues on their self-efficacy (Hsieh et al., 2008).
Ajzen (1991) has addressed the experience issues in discussions on the theory of planned behavior (TPB). He indicated many researchers advocate that past behavior should have been in the theory of reasoned action (TRA) as an independent variable. Experience can be considered to be an accumulation of past behaviors. The role of experience or past performance has been studied in some literature in MIS area, including in self-efficacy and computer skill training research (George, 2002). Taylor and Todd (1995) also studied experience in a laboratory setting. They found a stronger link between behavioral intention and actual behavior on students who had experience with computers.

**Technology Self-efficacy**

Self-efficacy is defined as a person’s belief that they have the capability to execute a series of actions to achieve a goal (Compeau & Higgins, 1995; Hsieh et al., 2008). According to some earlier literature, it is also defined as a person’s judgment of his/her capability to perform a behavior (Bandura, 1986). Self-efficacy has long been identified as an important factor in perceived behavioral control (Hsieh et al., 2008).

Choudhury and Karahanna (2008) studied efficacy of information acquisition. They defined it as the user’s perception of the online vendor’s ability to provide clear and easy to understand instructions and explanations on a product. They further claim that users differ in their perceptions of efficacy in both offline and online environments in learning about the product.

**Search Effort**

Search effort is regarded to be the perception of the effort required in searching for information about a product. Before consumers make adoption decisions on products on an e-commerce website, they search for the relevant products, compare prices, and evaluate product quality (Hu et al., 2008). Users are often aware of the fact that searching for information costs time and energy and there is a tradeoff between search costs and the benefits of searching for more information (Stigler, 1961). Users can use decision aids or comparison aids (Todd & Benbasat, 1992) and numerical content rating (Poston & Speier, 2005) to reduce cognitive efforts and conserve energy expenditures while improving purchase decision-making (Mudambi & Schuff, 2010). Consumers’ search effort is closely related to their product knowledge (Beatty & Smith, 1987). When decision makers’ own knowledge is inadequate in evaluating the true value of a product, they will refer to their predecessors’ adoption decisions to infer the product’s utility. Such decision makers tend to rationally follow the crowd by ignoring their own noisy information (Duan et al., 2009).

E-commerce adoption is not a monolithic behavior, but rather, is viewed as both acquiring information of the product and purchasing. Most e-commerce research focused on online product purchasing. However, adoption procedure is not monolithic since an adopter needs to search for product information before making purchasing decisions (Pavlou & Dimoka, 2006). The total cost of a product consists of both product cost and the search cost (Nelson, 1970). Search cost can be further divided into physical search and cognitive processing efforts (Mudambi & Schuff, 2010). With a wide range of choices, consumers typically find that there are tradeoffs between effort and accuracy (Johnson & Payne, 1985). Transaction Cost Economics (TCE) was developed by Williamson (1979), there are three variables in TCE, which are asset specificity, uncertainty, and transaction frequency. Williamson contended that firms try to minimize total cost, including production cost and transaction cost, by choosing an optimal approach. Researchers have also adopted TCE to explain both firm-level and individual-level
issues in E-commerce (Hu et al., 2008). Consumers will evaluate transaction cost and select an approach with lower transaction cost when adopting products (Hu et al., 2008). This supports that mobile app consumers will likely include their search costs along with other costs in evaluation of competing products.

RESEARCH MODEL

The research model (Figure 1) focuses on the effects of individual adopter characteristics on their search effort. When online shoppers face a substantial number of sophisticated competing products, they frequently find themselves lacking the knowledge and time to reach the optimal decision in adopting one of them. Before they make adoption decisions on products on an e-commerce website, they search for the relevant product, compare price, and evaluate product quality. Depending on different characteristics such as risk tolerance, self-efficacy, and resource constraint, potential adopters have different perceptions of the need for expending effort in searching for more information on their product adoption decision.

Figure 1. Effects of Adopter Characteristics on Search Effort

HYPOTHESIS DEVELOPMENT

Innovativeness

Rogers' (2003) adopter categories include innovators, early adopters, early majority, late majority, and laggards. Innovativeness refers to the extent to which an adopter adopts an innovation earlier than other adopters (E. M. Rogers, 2003). Therefore, we use innovativeness to describe how early an adopter adopts a mobile app. The earlier an adopter adopts a product, the higher innovativeness the adopter has. Depending on this characteristic, an early adopter might spend less search effort since there is less information available for the new technology. Highly innovative people are also likely to tolerate additional uncertainty, which lowers their motivation to search. Therefore:
H1. There is a negative relationship between innovativeness (IN) of a potential adopter and search effort (SE).

Risk Tolerance

Concern over privacy is often cited as a key reason that stops users from engaging in online transactions (George, 2002). As discussed in the literature review, adopters concerned more about privacy and information security in online transactions are less likely to make a purchase. If they feel more comfortable about an online vendor’s security measures, they are more likely to engage in the online transaction (George, 2002; Hoffman et al., 1999; Pavlou & Dimoka, 2006). Another source of risk is task-technology-fit (Goodhue & Thompson, 1995; Goodhue, 2007). If they purchased a mobile app that does not fit their purpose, they risk a monetary loss while not achieving their goals. Therefore, it is important for a potential adopter to search for more information to avoid paying for an app that does not suit their needs. In other words, if they have less risk tolerance, they are more likely to engage in more search effort. Therefore, the hypothesis is as follows:

H2. There is a negative relationship between risk tolerance (RT) and search effort (SE).

Resource Constraint

According to Pavlou and Fygenson (2006), consumer resources include time resources and monetary resources. ‘Available monetary resources’ is a determinant for product purchasing (Pavlou & Dimoka, 2006). In a mobile app scenario, a potential adopter might face both time constraint and monetary constraint. The term resource constraint is used in this research as an overall construct. If a potential adopter has significant resource constraints, the adopter will be more sensitive to risks, which means he/she will be less tolerant on risks, and will spend more effort in searching. Depending on the level of resource constraint, potential adopters’ risk tolerance and search effort might differ. Therefore, the hypotheses are as follows:

H3. There is a positive relationship between resource constraint (RC) and search effort (SE).

H4. There is a negative relationship between resource constraint (RC) and risk tolerance (RT) of an adopter.

Experience

Hoffman et al. (1999) found that as people’s Internet experience accumulates, the barrier for them to make a transaction lowers. A new Internet user is less likely to engage in an online transaction (George, 2002). It seems the same logic applies to the smart phone and mobile app users. It is likely that the more experiences or knowledge a user has on smart phones or mobile apps, the more capable they are in making a judgment, and thus the less they will rely on external information. In other words, more experienced users will feel more comfortable engaging in purchasing behavior based on their own knowledge. Therefore, we propose the following hypothesis:

H5. There is a negative relationship between experience (EXP) and search effort (SE) on a mobile app.
Technical Self-efficacy

A review of the literature shows self-efficacy is generally defined as the belief in a person’s capability to execute a series of actions to achieve a goal (Compeau & Higgins, 1995; Hsieh et al., 2008). Self-efficacy has long been identified as an important factor in perceived behavioral control (Hsieh et al., 2008). In addition, research also indicates that past performance, or experience, is closely related to an adopter’s self-efficacy in carrying out a new task (Compeau & Higgins, 1995). In mobile app adoption, similar effects of technical self-efficacy on search effort should be observed since the belief that the adopter has the technical expertise to successfully use the app would lower the need perceived need for additional information. Additionally, related experiences would logically lead to a higher perceived self-efficacy. Therefore:

\[
H6. \text{ There is a negative relationship between technical self-efficacy (TS) and search effort (SE).}
\]

\[
H7. \text{ There is a positive relationship between experience (EXP) and technical self-efficacy (TS).}
\]

Perceived Complexity

Complexity is defined by Rogers (2003) as the degree to which a technology is difficult to learn and use. The definition shares similarity with perceived ease of use (PEOU) in the technology acceptance model (TAM) proposed by Davis et al. (1989). In TAM, they defined PEOU as the extent to which a user perceives that a technology can be used with no effort. Rogers (2003) argues that the complexity of an innovation is negatively related to the rate of adoption. He also argues that complexity is a major obstacle in adoption for some new technologies. We use the term perceived complexity to describe the perceived difficulty in learning to use a new app. Consequently, adopters engage in more search effort if they perceive higher complexity. Meanwhile, if an adopter is experienced or has higher technical self-efficacy, they would likely perceive the complexity of the new technology to be lower. According to this argument, We hypothesize:

\[
H8. \text{ There is a positive relationship between perceived complexity (CX) and search effort (SE).}
\]

\[
H9. \text{ There is a negative relationship between tech self-efficacy (TS) perceived complexity (CX).}
\]

\[
H10. \text{ There is a negative relationship between experience (EXP) and perceived complexity (CX).}
\]

METHODOLOGY

This research employs a survey methodology to investigate the hypothesized relationships. There are different modes of survey that can be employed, such as mail, telephone, online, interview. Among those survey modes, respondents might have different preferences for different modes, sometimes a combination of different survey modes is provided to maximize response rate (Dillman, Smyth & Christian 2009). In this research, an online survey was utilized. Given the research goals the most appropriate survey population would be those people who
are likely to use mobile apps. Accordingly the population of interest is app-capable mobile
device owners (predominantly smartphones and tablets). Most of these users are very likely to
be comfortable with online surveys and are likely to have email addresses. In addition,
according to Dillman et al. (2009), there are several advantages of using online surveys. First of
all, online surveys are more cost effective and can reach a greater audience faster and easier.
The cost of sending an online survey is minimal compared to traditional face to face interviews,
mail or telephone-based surveys. Secondly, an online survey offers more convenience and
flexibility to the respondents. Instead of completing a paper survey by hand and mailing it back
to the collector, an online survey can be done with just mouse clicks and a submit button. In
addition, instead of having to make decisions to respond to the survey in a few seconds on the
telephone, respondents have the flexibility to make decisions in a more comfortable way
(Dillman et al., 2009). Finally, online survey tools are readily available with advanced capability
in handling a complex survey questionnaire with skip logic and even multimedia materials.
These advantages of online surveys will generally produce higher response rates and more
accurate response results compared to traditional paper based surveys.

Instrument Development

When designing survey questions, reliability and validity issues need to be considered. There
are a number of sources regarding survey design with the text by Dillman, Smyth, Christian
(2009) being one of the most commonly cited. As the book is widely adopted by researchers for
survey design, we adopted the method for our research. Different ways of constructing
questions, such as the usage of specific words or different way of categorizing questions can
result in significantly different results (Dillman et al., 2009). It is quite challenging to craft the
questions so that the respondents will interpret them as the designer intended. We designed
most of the survey questions based on validated survey questions from previous research. For
a few survey questions that could not be found in previous research, We developed them
through discussions with experienced researchers and examined their validity through a pilot
study. A seven-point Likert scale was used for survey questions.

Instrument Review

After developing the instrument, several rounds of reviews were conducted. First, the
instruments were reviewed by several experienced faculty researchers. Then, a pilot study was
conducted in a class with 50 students from a business college and did a preliminary analysis
and revision on the survey questionnaire. Based on these rounds of reviewing and revising, the
validity of the instruments was improved.

Data Collection

We used mobile app stores, such as Apple’s app store and Android’s marketplace, as our
research context. An online survey was used. We did three waves of data collection by sending
out three rounds of email messages to the survey population. A total of 3996 respondents
received and opened the survey, a total of 1006 responded to the survey. The overall response
rate is 25.18%. A total of 512 respondents finished the survey. Therefore, the usable response
rate is 12.8%. There were 64 respondents who do not have mobile device or have not used
mobile apps before. Therefore, We used 448 responses for our data analysis.
Sample and Survey Distribution

Although we hope to generalize to all mobile device owners, the student population was selected for its cost and accessibility characteristics. In the past decade, emails are increasingly used as a standard communication approach in both organizations and for individuals (Dillman et al., 2009). The survey was distributed to the selected sample population by email. 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 many have substantial experience with mobile apps. It is believed that the way students make mobile app adoption decisions 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. Selecting emails was completed in a pseudo-random process. We randomized students’ initials on their first and last name and then obtained email addresses by searching the student directory with only the student’s initials supplied in the search form. The sample population is discussed in the following section. In the email, the general purpose of the survey was explained and a survey link was provided. The link leads the respondents to the survey webpage to key in their answers. Their answers were stored automatically into a database.

Following Dillman et al. (2009), the questionnaires were sent to the respondents via email. After one week, another reminder was sent. A final reminder was sent after another week with updated information. Incentives, in the form of a drawing for several iTune gift cards, were utilized to improve response rate.

In order to determine if excessive response bias was likely, wave analysis was conducted on the collected data to compare the responses between different waves to see if there are significant differences. This analysis provided no evidence of response bias being present.

Survey Incentive

In order to yield a higher response rate, incentives were used in the survey. Dillman et al. (2009) state that the most effective way to increase response rate is to offer cash incentives of a few dollars. In this research, a total of 3 iTunes gift cards with $100 value on each card were raffled off to the respondents who supplied their email address to enter the drawing. iTunes gift cards are popular for people who use their smart phones to download games and MP3 music. The gift cards were given out to the respondents after the data collection. After data collection finished, a random drawing was made and winners of the gift cards were announced.

There are potential problems with promised incentives as opposed to a cash token sent together with the questionnaire. Research indicates that questionnaires sent with a prepaid cash token yields higher response rate compared to promising rewards will be sent to the respondents after the survey, however, the difference between these two approaches is not substantial (Dillman et al., 2009).

RESULTS

Model Fit

Convergent validity, discriminant validity and reliability were analyzed. Composite reliability was used as a measurement for testing reliability. The cutoff score for composite reliability is
generally considered to be 0.7 (Nunnally, 1978). In Table 1, the composite reliability scores are all above 0.8, therefore, the reliability of the model is good.

For convergent validity, Average Variance Extracted (AVE) scores are used as a measurement. AVE scores over 0.5 reflect good convergent validity. Referring to Table 1, we see that all constructs’ AVE scores are over 0.5. Most of the scores are over 0.6, with only Tech Self-efficacy being 0.54. Therefore, this model has a good convergent validity.

### Table 1. Average Variance Extracted, Reliability, and R² for Latent Variables

<table>
<thead>
<tr>
<th></th>
<th>AVE</th>
<th>Composite Reliability</th>
<th>R Square</th>
</tr>
</thead>
<tbody>
<tr>
<td>CX</td>
<td>0.762366</td>
<td>0.927302</td>
<td>0.018953</td>
</tr>
<tr>
<td>EXP</td>
<td>0.789371</td>
<td>0.918306</td>
<td></td>
</tr>
<tr>
<td>IN</td>
<td>0.635948</td>
<td>0.874510</td>
<td></td>
</tr>
<tr>
<td>RC</td>
<td>0.633848</td>
<td>0.872142</td>
<td></td>
</tr>
<tr>
<td>RT</td>
<td>0.778742</td>
<td>0.913363</td>
<td>0.050941</td>
</tr>
<tr>
<td>SE</td>
<td>0.608122</td>
<td>0.861033</td>
<td>0.485694</td>
</tr>
<tr>
<td>TS</td>
<td>0.539393</td>
<td>0.891126</td>
<td>0.404137</td>
</tr>
</tbody>
</table>

Discriminant validity is tested by referring to the latent variable correlations as shown in Table 2. The values on the diagonal line in the table are the square roots of Average Variance Extracted (AVE) scores. For good discriminant validity, the square root of AVE for a certain latent variable on the diagonal line is compared with the correlations of that LV with any other LVs in the table. By examining the table, we can see that all square roots of AVEs are greater than other correlations. Therefore, this model has adequate discriminant validity.

In addition, R² values for the dependent variables indicate the explanatory power of the model. Referring to Figure 2, 5.1% variance of risk tolerance is explained, 40.4% variance of tech self-efficacy is explained, 48.6% variance of search effort is explained by the model, and 1.9% variance of perceived complexity is explained by the model.

In order to evaluate multicollinearity issues, variance inflation factors (VIFs) were computed. Three regressions were conducted to obtain the VIF scores. The dependent variables used included complexity (CX), tech self-efficacy (TS), and search effort (SE). All the VIF scores are well below the cutoff score of 4 (O’Brien, 2007). Therefore, no significant multicollinearity issues were identified.
Table 2. Latent Variable Correlations for Discriminant Validity

<table>
<thead>
<tr>
<th></th>
<th>CX</th>
<th>EXP</th>
<th>IN</th>
<th>RC</th>
<th>RT</th>
<th>SE</th>
<th>TS</th>
</tr>
</thead>
<tbody>
<tr>
<td>CX</td>
<td>1.00</td>
<td>0.12</td>
<td>-0.51</td>
<td>0.03</td>
<td>0.29</td>
<td>0.66</td>
<td>-0.02</td>
</tr>
<tr>
<td>EXP</td>
<td>0.12</td>
<td>1.00</td>
<td>-0.10</td>
<td>0.07</td>
<td>0.36</td>
<td>0.00</td>
<td>-0.01</td>
</tr>
<tr>
<td>IN</td>
<td>-0.51</td>
<td>-0.10</td>
<td>1.00</td>
<td>-0.46</td>
<td>-0.25</td>
<td>0.63</td>
<td>-0.18</td>
</tr>
<tr>
<td>RC</td>
<td>0.03</td>
<td>0.07</td>
<td>-0.46</td>
<td>1.00</td>
<td>0.51</td>
<td>0.30</td>
<td>0.15</td>
</tr>
<tr>
<td>RT</td>
<td>0.29</td>
<td>0.36</td>
<td>-0.25</td>
<td>0.51</td>
<td>1.00</td>
<td>0.30</td>
<td>0.50</td>
</tr>
<tr>
<td>SE</td>
<td>0.66</td>
<td>0.00</td>
<td>0.63</td>
<td>0.30</td>
<td>0.30</td>
<td>1.00</td>
<td>0.29</td>
</tr>
<tr>
<td>TS</td>
<td>-0.02</td>
<td>-0.01</td>
<td>-0.18</td>
<td>0.15</td>
<td>0.50</td>
<td>0.29</td>
<td>1.00</td>
</tr>
</tbody>
</table>

*Note: Square roots of average variances extracted (AVE’s) are shown on the diagonal.

Hypotheses Testing and Discussion

Figure 2 displays the path coefficient and significance of the completed hypothesis tests. Additionally, all endogenous variables include their variance explained (R2). Abbreviations for the latent variable names are given in parentheses.

Figure 2. Path Coefficients and Significance
Effect of Adopter Characteristics on Search Effort

This research studied the effects of five adopter characteristics on search behavior. The five adopter characteristics being studied are innovativeness (IN), risk tolerance (RT), resource constraint (RC), experience (EXP), and tech self-efficacy (TS). Table below shows the test results of the five characteristics on search effort, as well as the effect of resource constraint on risk tolerance.

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Path Coefficients</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1(·): Innovation → Search Effort</td>
<td>-0.083</td>
<td>P&lt;=0.05</td>
</tr>
<tr>
<td>H2(·): Risk Tolerance → Search Effort</td>
<td>0.073</td>
<td>n.s.</td>
</tr>
<tr>
<td>H3(·): Resource Constraint → Search Effort</td>
<td>0.148</td>
<td>P&lt;=0.05</td>
</tr>
<tr>
<td>H4(·): Resource Constraint → Risk Tolerance</td>
<td>0.226</td>
<td>P&lt;=0.001</td>
</tr>
<tr>
<td>H5(·): Experience → Search Effort</td>
<td>0.034</td>
<td>n.s.</td>
</tr>
<tr>
<td>H6(·): Technical Self-Efficacy → Search Effort</td>
<td>0.024</td>
<td>n.s.</td>
</tr>
</tbody>
</table>

Out of the six hypotheses related to adopter characteristics, three of them were found to be significant. Innovativeness is found to be negatively related to search effort (H1). The finding supports the hypothesis. More innovative adopters spend less time and effort in searching for product information before they adopt a mobile app. These adopters are likely to be “early adopters”, who tend to be more tolerant to uncertainties and have greater interest in trying out new things even if there is little information about the new mobile app. Innovators also tend toward the visionary side of the visionary/pragmatist spectrum. These visionaries rely on their own vision of what the app can do for them rather than demanding the documented benefits often required by the pragmatists. Their own imaginations are often the only justification they require.

Resource constraint is found to be significantly related to search effort (H3), the more resource constraint an adopter has, the more search effort he/she will spend. Monetary constraints will lead potential adopters to spend their money more carefully, which will result in more search effort before adopting a mobile app.

Resource constraint was also found to be significantly related to risk tolerance (H4). As opposed to the hypothesis, resource constraint is positively related to risk tolerance. In other words, the higher constraint on time and money, the more risk tolerance an adopter has in adopting a mobile app. A possible explanation is that if an adopter has limited resources, the adopter will be willing to take more risks simply because he/she has no time to make a well informed decision. This also may be a function of the sample. Perhaps students are more willing take risks (such as opening lines of credit they do not have the income to pay back) the more resource constrained they are because they do not see themselves as perpetually resource constrained (they will pay it back when they graduate and get a job).

In addition, risk tolerance, experience, and tech self-efficacy were found to have no significant effects on search effort (H2, H5, H6). Therefore, we can draw a conclusion that regardless of the experience level, or tech self-efficacy level, adopters’ search effort stays the same, and can be affected by other factors.
Mediating Effect of Technical Self-Efficacy and Perceived Complexity

In addition to the five characteristics of adopters, the mediating effects of technical self-efficacy and perceived complexity were investigated. Even though experience was found to be not significantly related to search effort directly (H5), there is an indirect effect mediated by perceived complexity. By referring to Table 3 it can be seen that the more experience the adopter has, the less complexity the adopter will perceive (H10). This finding is consistent with the hypotheses. Furthermore, the more perceived complexity, the more search effort there will be (H8); this is also consistent with the hypothesis. Therefore, perceived complexity serves as a mediator between experience and search effort. The results also indicate, as hypothesized, that experience is positively related to technical self-efficacy (H7). Meanwhile, technical self-efficacy is not significantly related to perceived complexity (H9).

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Path Coefficients</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>H7(+) : Experience → Technical Self-efficacy</td>
<td>0.636</td>
<td>P&lt;=0.001</td>
</tr>
<tr>
<td>H8(+) : Complexity → Search Effort</td>
<td>0.522</td>
<td>P&lt;=0.001</td>
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<tr>
<td>H9(-) : Technical Self-efficacy → Complexity</td>
<td>0.096</td>
<td>n.s.</td>
</tr>
<tr>
<td>H10(-) : Experience → Complexity</td>
<td>-0.177</td>
<td>P&lt;=0.001</td>
</tr>
</tbody>
</table>

CONCLUSIONS

Adopter characteristics do influence search effort, either directly or through mediators. Rogers (2003) defines an innovative adopter to be those who adopt new technology earlier than others. In a sense, they rely less on online reviews or social factors regarding a product, and they are early adopters because they like trying new things. Our analysis shows that more innovative people spend less effort searching for pertinent information before they adopt a mobile app. Having less slack resources appears to lead to greater search effort. That indicates if an individual has limited resources, such as money, he/she will spend the money more carefully by attempting to gain more information. Therefore, a potential adopter will spend more effort in searching for information before making an adoption decision.

The perception of a more complicated mobile app will lead to more search effort. When a mobile app is less complicated, it will likely attract more users who are not willing to spend time and effort in learning about the mobile app. More experienced users will perceive less complexity on a mobile app. The users might have experience using a similar application before, or the users might have related knowledge in the area the mobile app is targeted. In these cases, users will perceive less complexity. Therefore, perceived complexity works as a mediator between experience and search effort. There are a number of factors that affect search effort. Depending on different product characteristics and adopter characteristics, search effort could differ, and the difference in search effort will affect uncertainty and eventually adoption intention.

Technical self-efficacy is defined as the belief of a person in his/her technical capability in accomplishing a task (Compeau & Higgins, 1995; Hsieh et al., 2008). The analyses show that those who have more experience exhibit more technical self-efficacy. However, technical self-efficacy influences neither perceived complexity nor search effort. It was hypothesized that the higher a person’s belief that they can perform the technical tasks associated with the application,
the lower their perceived complexity of the app would be. Perhaps the respondents adjust complexity relative to other applications. In this way it is possible that someone with either high or low self-efficacy may rate an app’s complexity similarly if they are comparing it to other apps in the genre. It may be rated as complex by the high self-efficacy person because it is more complex than others but they may not perceive it as difficult to use – just more complex.

Practical implications of this study include using this information to fine-tune the type of informational material app designers make available to potential adopters. If the target population is likely to expend low search effort then promotion of that app needs to be in the form of quick, information dense, most likely graphic information. In other words, it should be information that can be gleaned quickly and that the potential adopter does not have to expend much (if any) effort to search for. Potential adopter populations that are more likely to spend time searching for information should be able to find detailed product information, testimonials and reviews, and other detailed content.

REFERENCES


