A Study of the Effects of Social Factors and Innovation Characteristics on Search Effort and Uncertainty in Mobile App Adoption

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Abstract
The mobile economy is growing rapidly and creating increasingly diversified digital products available to consumers. Due to the cognitive limitation of adopters, they often face the issue of information overload. In order to cope with such issues, adopters typically utilize other information to reduce their uncertainty before adoption. This study focuses on determinants of uncertainty reduction during the adoption process. We do not study why individuals adopt mobile apps, but rather we are studying what perceptions individuals have on the innovation characteristics and social factors (such as friends who use and like the app) and how those perceptions affect their level of search effort and uncertainty. Innovation diffusion theory, herding behavior theory, information overload theory, and the theory of informational cascades are employed in the development of our research model. Findings from this study provide significant insights for developers and management in the mobile app economy.

1. Introduction
Mobile technologies have significantly changed people’s ways of life and are becoming main stream in diverse sectors of society ranging from organizational operations to personal entertainment. The scale of the mobile economy has also increased sharply in the past few years. As a direct outcome of this mobile economy, the number of mobile apps being developed and downloaded has exploded. Although there is rapidly growing interest in mobile technology, the amount of meaningful research on specific elements of the mobile economy such as mobile app adoption is limited. There is reason to believe that previous research done regarding traditional (non-mobile) software applications is not likely to be generalizable to mobile applications.

Several characteristics of mobile technology differ from traditional technology. These include but are not limited to a large and increasing number of competing alternatives [2], often relatively low cost [17], and a projected shorter time for evaluation due to the low cost [14].

Unlike traditional technology acceptance studies, this study focuses on characteristics that are more pertinent to mobile technology adoption: social characteristics. It also differs from most other traditional adoption research as we seek to understand an intermediate state before either the intention to adopt or usage is initiated. What we seek to address in this research is determining what factors influence the uncertainty around a particular mobile application. Our interest in these outcomes is motivated by a desire to understand how individuals gain the knowledge necessary to make an adoption decision rather than the decision itself.

2. Problem statement and research question
It is widely agreed that online information search is valuable and it has been reported that looking for product information online is the most important predictor of product adoption [5]. The primary impetus 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 [28].

Mobile apps are characterized by having a large and increasing number of competing products that often change frequently. For example, one of the
primary reasons for the success of Apple’s iPhone can be attributed to their ability to provide more software choices than their competitors [22]. With the wide range of choices available for a certain type of product, the customer is overwhelmed with numerous shifting choices and associated sources of information. As a result, it causes the problem of information overload. This refers to the fact that users are facing more information than they can process. This characteristic of frequent change is exemplified in this statement, “You might design a feature [in a traditional software development environment] and not know until two years later whether it was good or people liked it, in apps, you can design a feature in a day and put it in the game the next day.” [22]

In mobile app adoption, due to these overwhelming number of choices, users lack the time to evaluate those products and make comparisons. This makes it difficult to reach well-informed decisions to adopt a certain product [10]. 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. Previous adoption theories, such as the technology acceptance model (TAM) [6][7], focus on users’ adoption of an information technology by considering factors such as ease of use and usefulness. However, in mobile app adoption, potential adopters also face problems such as lack of time and experience in evaluating products, and other factors that may influence users’ adoption decisions. Even when time to evaluate is present it is often difficult for the decision-maker to justify expending the time on an information search for an app that may cost a very small amount of money in comparison to traditional software. This increases the information overload the decision-maker is experiencing since having less time to assimilate whatever information you have available increases the burden.

All of the information overload issues associated with mobile app adoption leads to the question that: if mobile app adopters often have little of their own information, do not have time to assimilate much of the information that may be available due to information overload, and cannot justify much search effort due to low cost/risk then how can they reduce their uncertainty associated with an app being considered? Based on the facts presented in this discussion we offer the informed conjecture that adopters may use ‘Wisdom of the Crowds’ [37] sources to fill in the gaps causing their uncertainty. The sources of this crowd-based supplemental information includes local known sources such as friends, colleagues, family, and other contacts (commonly incorporated into a social influence or social norm construct) as well as more virtual sources such as online reviews. These sources of potential uncertainty reduction form the conceptual basis for the specific social factors (delineated later) we are investigating.

Some of this derived information may be channeled into pertinent information about the application and some may remain as a subjective assessment that the application is either ‘good’ or ‘bad’ without specific knowledge of the characteristics that led to that assessment. This is consistent with the view of social influence in many adoption models (e.g. the UTAUT model [42]). The influence is usually attributed to the belief that others will view their actions positively or negatively [42]. The knowledge that is present about the mobile app itself is studied through use of the innovation characteristics introduced in the innovation diffusion theory (IDT) [32][33].

This leads us to our central research question: What are the effects of social factors and innovation characteristics on search effort and uncertainty in mobile app adoption?

The research model therefore examines the effect of innovation characteristics and social factors on search effort and uncertainty. The role that perceived innovation characteristics and social factors play in influencing search effort and uncertainty need to be studied in more depth.

3. Research background

In the full paper (available from the authors) we include a full theoretical development leading to our research model. However, this forum simply does not allow a discussion of this depth. In summary, we employ information overload theory, herd behavior theory, the informational cascades theory.

**Table 1. Contributing Theories**

<table>
<thead>
<tr>
<th>Theory</th>
<th>Brief Definition</th>
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<tbody>
<tr>
<td>Information Overload</td>
<td>Information overload occurs when the demand for information processing exceeds the capability of an individual to process the information within a certain amount of time [34].</td>
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<tr>
<td>Herd Behavior Theory</td>
<td>Herding depicts a number of social and economic situations, such as financial investment, technology adoption, firms’ strategic decisions, political voting, and dining and fashion trends, in which an individual’s or organization’s decision-making is significantly influenced by others’ decisions [3].</td>
</tr>
<tr>
<td>Informational Cascades</td>
<td>Informational cascades take place when an online user follows the previous adopters’ decision and disregards his own information [10].</td>
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</table>
4. Research model

This paper focuses on social factors that influence the adoption decision of mobile apps. The social factors play an important role in the realm of mobile app adoption. Although research is needed to confirm, it would appear that many apps are now developed with an emphasis on social interactions. Most mobile apps are experience goods. For this type of goods, when making an adoption decision, new adopters rely more on the opinions of previous adopters, as well as people they know, to form an opinion about the mobile app.

This research examines the effect of social characteristics such as social influence, trust, and homophily, as well as innovation characteristics such as trialability, observability, relative advantage and product popularity on search effort and uncertainty. If a mobile app offers a trial version, or if the mobile app is a popular one, that might have some influence in reducing search effort and uncertainty when people make adoption decisions. Additionally, when important others such as friends, relatives, and others recommend the mobile app, it will very likely expedite the adoption decision-making due to social influence and trust. Search effort and uncertainty are known in previous research to be interrelated [25]. Nevertheless, what role social characteristics and product characteristics play in influencing search effort is an understudied area. Figure 1 depicts the research model.

5. Constructs – social factors

5.1 Social influence

The focus of social influence is on the decision-maker’s perception of opinions held by the set of people whose views are important to them [1][11]. These individuals are commonly referred to as ‘important others’ in existing research. Social influence can then be defined as the perception of these individuals’ beliefs that the decision-maker should use the innovation [42]. Social influence is found to be the immediate predictor of behavioral intention in previous literature [6]. In the theory of planned behavior (TPB) [1] social influence is represented as social norm. Despite different labels used in the literature, such social influence indicates that an individual’s behavior is influenced by others’ opinions towards the behavior.

5.2 Homophily

Homophily refers to the degree to which two individuals who interact with each other are similar [33]. There are two types of homophily defined by Lazarsfeld and Merton [19]: status homophily and value homophily. Status homophily is defined by race, sex, age, religion, behavioral pattern, education, and occupation. Value homophily is defined by attitude, value, and beliefs. Value homophily can reflect one’s orientation towards a future behavior [19]. Individuals with a high degree of homophily most likely have similar preferences towards a future behavior, such as adopting the same mobile app.

5.3 Disposition to Trust

Numerous studies have acknowledged the importance of trust in the online environment [27]. The nature of trust in the technology field is still under-researched and not well understood [43].

In McKnight et al.’s study [23], trust is examined in two categories: institutional trust and disposition to trust. Institutional trust refers to the consumers’ perception of structural characteristics of the Internet, such as safety and security. Disposition to trust generally refers to trust in others, which can further influence the individual’s trust towards the online vendors. In our study, we focus on the second type of trust, disposition to trust. This type of trust is embedded in a social environment, which is a major context for mobile apps and social networks.

6. Constructs – innovation characteristics

6.1 Trialability

Trialability is the degree to which a product can be experimented with under certain limitations [32]. Duan et al. [10] contend that online users might treat free-to-try products less seriously since no financial
investments are involved. Their argument is that learning curves and switching costs may be involved which constitute significant cost for adopting these products. They concluded that free-to-try products are not significantly different compared to those products that require purchasing. However, Rogers [32] argues that the trialability of a product is positively related to its rate of adoption. A user wants to be able to try a product before adopting it even if there are many people recommending it [15]. In mobile apps, many products offer a certain level of trialability.

6.2 Observability

Observability is the degree to which an adoption outcome is visible to potential adopters [32]. In a mobile app adoption scenario, the effect of observability is straightforward. In Kebritchi’s [15] research on educational game adoption, it was found that even if there are a lot of recommendations, a user would still like to look at the game before making a decision and others’ recommendations would not affect the user’s adoption decision. When a group of friends get together and showcase their smart phone apps, they observe what apps they have downloaded. If they observe that the app is interesting, it is most likely he/she will also download that app.

6.3 Relative advantage

Relative advantage, according to Rogers’ [32] definition, is the degree to which an innovation is perceived to be superior to its predecessors or competitors. Relative advantage, in this case, is the perceived advantage of a mobile app over other similar apps.

6.4 Product popularity

Zhu and Zhang [44] indicated a strong linkage between popularity and perceived quality of a product. The perceived quality of search goods is reflected by attributes that have an objective nature, while the perceived quality of an experience good is more reflected by subjective attributes dependent on personal taste [25]. Previous studies also showed that potential risk can be minimized if the product being purchased is a popular product [44]. The informational cascades theory indicates product adoption is influenced by relative ranking rather than absolute product sales [10]. Their way of referring product popularity in terms of “relative ranking” of the product is more objective than simply referring to absolute sales.

7. Research model constructs – endogenous variables

7.1 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 [13]. Users are often aware of the fact that searching for information costs time and energy and there is a tradeoff between search costs and benefits of searching for more information [35]. Users can use decision aids or comparison aids [41] and numerical content rating [30] to reduce cognitive efforts and conserve energy expenditures while improving purchase decision-making [25]. Consumers’ search effort is closely related with their product knowledge [4]. 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 [10].

7.2 Uncertainty

Uncertainty refers to the degree to which the future of an environment cannot be accurately predicted due to lack of information. In his classic book, Knight [18] defined uncertainty as “neither entire ignorance nor complete and perfect information but partial knowledge.”

Frequently, a consumer faces the situation of lacking information on product quality, seller quality, and available alternatives when making purchase decisions [25]. The Internet is rich in information that shows other users’ adoption decisions and how popular a product is. This characteristic further facilitates informational cascades [10]. Dimoka et al. [9] defined uncertainty as “the buyers’ difficulty in predicting the outcome of an online transaction due to seller-related and product-related information asymmetry.” In buyer-seller relationships, perceived uncertainty refers to the degree to which the buyer cannot predict the outcome of a purchase decision due to factors related to the seller and product [29]. Uncertainty is the main reason why people tend to imitate others’ actions instead of simply relying on their own information to make a decision [36].
8. Hypothesis development

If a product can be conveniently tried, the adoption rate of the product will be higher [32]. An adopter might hesitate to adopt a mobile app until he/she has a chance to use the app a few times. Once adopters are able to try a mobile app, they will form an idea about the app and whether they need it, even without search for more information or reviews about the app. In that case, the more they are able to experience a mobile app, the less they will have to search for information before they make an adoption decision. Rogers [32] also posits that the observability of an innovation positively influences the adoption rate of the product. We argue that the trialability and observability of a mobile app will reduce the search effort.

H1a. There is a negative relationship between trialability (TR) and search effort (SE).

H1b. There is a negative relationship between observability (OB) and search effort (SE).

In addition, as discussed in previous sections, technology perceptions such as relative advantage and popularity will most likely reduce search effort. The reason being that if a potential adopter perceives a higher relative advantage compared to other products, it will convince them to make a quicker adoption decision because they believe they have no better options. In other cases, if a product is well known from different sources, the potential adopter already has a good amount of knowledge on the product and will likely adopt it without searching for additional information.

Complexity is also an issue that determines how much effort a user will spend in searching for product information. For example, when a user perceives a technology to be complex, the user will spend more time searching for information to learn about the technology in order to reduce the uncertainty caused by complexity. However, in validating the model during analysis (discussed in Section 10) it was discovered that complexity and uncertainty cause excessive multicollinearity to exist in the model. Due to this reason, complexity was dropped from the research model. This leaves us with the following hypotheses:

H1c. There is a negative relationship between relative advantage (RA) and search effort (SE).

H1d. There is a negative relationship between product popularity (PP) and search effort (SE).

Social influence, as defined previously, is an individual’s perception of important others’ beliefs that the individual should use the new innovation [42]. Previous literature emphasizes that others have significant influence because they are important to the individual [1][11][38][39], it is mandatory to use a system [40] due to social pressure [42], or personal image enhancement [24]. In mobile app adoption, an individual might feel it is fashionable to use an app, and that fashion leads the individual to believe that their friends will also support the adoption since the app is consistent with their fashion. In this case, they can adopt a mobile app without spending much time researching.

H2a. There is a negative relationship between social influence (SI) and search effort (SE).

Trust has been studied widely in different contexts [27][23]. As discussed in the literature review, we focus on trust in a social context. According to McKnight et al. [23], disposition to trust is the extent to which a person relies on others across different situations. When trying to adopt a mobile app, people tend to either refer to online reviews or their friends’ experiences with the app.

Trust has been a central construct in economic and social interaction research where uncertainty exists [21]. Detailed discussion can be found in McKnight et al. [23], Pavlou [27], and Pavlou and Fygenson [28]. In the trust literature, it is assumed the consumer lacks control over the vendor, however, trust can help consumers build confidence to rely on the vendor [12]. A higher disposition to trust is likely to decrease search effort since they will be more likely to believe one or a few opinions where those with a lower disposition to trust are likely to seek more information for confirmation. Therefore, we make the following hypothesis:

H2b. There is a negative relationship between disposition to trust (TRUST) and search effort (SE).

In addition, if two individuals have similar backgrounds, they are regarded to have higher degree of homophily. The individuals could be friends, other users who also adopted the app, or reviewers who express similar points of view. Individuals with a higher degree of homophily associated with those whose opinions they have accessed are likely to have more similar tastes and interests in a new product [20]. In this research context, homophily can be easily accessed when the person is known but we also include unknown online reviewers as sources. The decision-maker can often assess the homophily of the online reviewer to some degree based on the content of the review. Therefore,
H2c. There is a negative relationship between homophily (HP) and search effort (SE).

Uncertainty is defined as the degree to which the future of an environment cannot be accurately predicted due to lack of information [29]. Despite the relatively long existence of e-commerce for many years, one major reason that prevents consumers in engaging in online transactions is still the uncertainty issue [29]. Pavlou et al. [29] also introduced three sources of uncertainty: perceived information asymmetry, fears of seller opportunism and information privacy and security concerns. In Luhmann’s [21] research, trust is found to reduce social uncertainty. Trust serves as an absorption resource that helps potential adopters cope with social uncertainty [28]. In our research context, potential adopters reduce the uncertainty they face in several different ways. One approach is to refer to their friends’ opinions and recommendations since they trust them. Another approach is to refer to online peer reviews and further information searches. This search effort would then aid in the reduction of uncertainty. Therefore, our hypotheses are as follows:

H3a. There is a negative relationship between social influence (SI) and uncertainty (UC).
H3b. There is a negative relationship between disposition to trust (TRUST) and uncertainty (UC).
H3c. There is a negative relationship between homophily (HP) and uncertainty (UC).
H4. There is a negative relationship between search effort (SE) and uncertainty (UC).

9. Methodology

In our research, an online survey was utilized. Given our research context, most smartphone users are very likely to be comfortable with online surveys. In addition, according to Dillman et al. [8], there are several advantages of using online surveys including speed, cost, and convenience and flexibility to the respondents. These advantages of online survey will generally produce higher response rates and more accurate response results compared to traditional paper based surveys.

9.1 Survey procedures

When designing survey questions, reliability and validity issues need to be considered. There are a number of literature regarding survey design, such as the book written by Rea and Parker [42]. The book written by Dillman et al. [8] is widely adopted by researchers for survey design. Therefore, to maximize the validity and reliability of the measurements, we followed this standard. We designed most of the survey questions based on validated survey questions in previous research (see Appendix A for items and sources – available from authors). 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. The instrument is available from the authors (due to space limitations).

After developing the instrument, we ran several rounds of reviews. First, we had the instruments reviewed by an experienced information system professor. After that, we had other faculty members review the questionnaire, from several business departments. Then, we ran a pilot study in a class with 50 students from a large state school in Ohio’s College of Business and did a preliminary analysis and revision on the survey questionnaire. Based on the three rounds of reviews and revising, the validity of the instruments was improved.

9.2 Data collection

We used mobile app stores, such as Apple’s app store and Android’s marketplace, as our research environment. Three waves of data collection were employed 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.

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 reviews and other types of social influence are employed by students would not differ widely from the general population. However, the incidence of use is likely 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 first and last name and then obtained the email address on the university directory by the randomized names.

In order to yield a higher response rate, incentives were used in the survey. Dillman et al. [8] state that the most effective way to increase response rate is to offer...
cash incentives of a few dollars. In this research, we provided a total of 3 iTunes gift cards with $100 value on each card. 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 randomly selected respondents after data collection.

10. Analysis

Structural Equation Modeling (SEM) was used in data analysis. More specifically, component based SEM (PLS-SEM) was used. Before employing SEM, the data was examined for careless responses, linearity, multicollinearity, and response bias (using wave analysis). None of these suggested problems existed in these areas.

10.1 Validity

Face and content validity were verified through the survey review process discussed earlier. Construct validity refers to whether a scale measures the unobservable constructs it intends to measure [16].

For convergent validity, we use the Average Variance Extracted (AVE) as a measurement. Most scores with over 0.7, with a few over 0.6, and there is only one score (relative advantage) that is below 0.6 at 0.58. AVE scores over 0.5 indicate good convergent validity. Therefore, the model demonstrates good convergent validity.

For discriminant validity testing, we compared the latent variable correlations to the square roots of Average Variance Extracted (AVE) for each latent variable (LV). For good discriminant validity, we need to ensure the square root of AVE for a certain LV to be greater than the correlations of that LV with any other LVs. Most square roots of AVEs are greater than other correlations. There was an exception in the innovation characteristic of complexity (subsequently dropped from the model) with uncertainty. We also found high multicollinearity between these through examining the variance inflation factors. Several options were attempted to correct for this but in the end it was determined that complexity would be dropped from the research model.

10.2 Reliability

Reliability is the accuracy or precision of a measurement instrument [16]. Composite reliability from the analysis results is used as a measurement for reliability. As aforementioned, the cutoff score for composite reliability is 0.7 [26]. We find most scores for composite reliability are greater than 0.9, with only 1 score for Observability under 0.8 (0.76). Therefore, we conclude that the model has a good reliability.

In addition, R² values for the dependent variables indicate the explanatory power of the model. The variance explained for search effort (SE) is 54.1% and 45.4% of the variance for uncertainty (UC) is explained by the model.

11. Results

The following results were obtained through a PLS-SEM analysis of the model. Figure 2 displays the path coefficients and significances for the hypotheses within the research model.

11.1 Effects of innovation characteristics

In this research, we studied the effect of four innovation characteristics on search effort. The four studied characteristics are trialability, observability, relative advantage, and product popularity. The results of this analysis are summarized in Table 2.

Opposite to our hypothesis, trialability shows a positive significant relationship with search effort (H1a). One possible explanation might be, trying a product is also regarded to be part of the search effort by adopters. When they try a mobile app, they also need to spend time and effort. When developing the hypothesis it was assumed that being able to use the product during a trial would allow the decision-maker to avoid some additional search effort yielding the hypothesized negative relationship. This result seems to imply that the ability to try a product increases the search effort perceived by the decision-maker. Again, this makes conceptual sense if the trial is perceived as additional search effort by the decision-maker.

![Figure 2. Path coefficients and significance for research model](image-url)
Observability has a non-significant negative relationship with search effort (H1b). The direction of relationship is the same as the hypothesis, but not significant. Therefore, being able to observe how the mobile app works does not necessarily result in a lower search effort.

Table 2. Innovation Characteristics and Search Effort

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Path Coefficients</th>
<th>Significance</th>
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<tbody>
<tr>
<td>H1a(-): Trialability→SE</td>
<td>0.199</td>
<td>P&lt;=0.001</td>
</tr>
<tr>
<td>H1b(-): Observability→SE</td>
<td>-0.093</td>
<td>n.s.</td>
</tr>
<tr>
<td>H1c(-): Rel. advantage→SE</td>
<td>0.294</td>
<td>P&lt;=0.001</td>
</tr>
<tr>
<td>H2d(-): Product pop. →SE</td>
<td>-0.024</td>
<td>n.s.</td>
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</table>

Relative advantage has a positive significant relationship with search effort (H1c), which is also opposite to our hypothesis. An adopter might be more interested in learning about a mobile app if it is perceived to have a relative advantage over competing apps. This relative advantage triggered learning process might also be regarded as part of the search effort by the adopters. The more advantage a mobile app is perceived to have, the more interested the potential adopters are in learning about it. The preliminary thinking was that once a decision-maker has concluded that a product has a relative advantage over other products they would be less likely to engage in additional search effort. This result implies the opposite. Potential adopters will expend more effort in searching for information on apps that they view as advantageous.

Product popularity shows a negative non-significant relationship with search effort (H2d). Agreeing with our hypothesis, a more popular product could be well known so less search effort is required in adoption decision-making, but the effect is not significant.

11.2 Effects of social factors

Social influence has a non-significant positive relationship with search effort (H2a). Therefore, even if a friend or family member recommends a mobile app, it will not necessarily reduce the search effort when an adopter tries to make an adoption decision. However, social influence, as hypothesized, will reduce uncertainty (H3a). When an individual observes that their important others are using the mobile app, or recommending the app to the individual, that will most likely be very influential in their decision-making, and most likely reduce their uncertainty. For example, if several friends of an individual all highly recommend a mobile app to the individual, he/she will most likely also adopt the mobile app, and feel certain it will not be wrong to adopt it. However, that does not mean the social influence will make them spend less effort in searching and learning about the app. They still might spend some effort in learning about the app even when friends or important others recommended it.

Trust has a significant negative relationship with search effort (H2b). Therefore, trust in a vendor or the app store will decrease search effort before a user adopts a mobile app. As hypothesized, trust is negatively and significantly related to uncertainty (H3b). The more trust a person has in a vendor or the app store, the less uncertainty the person will have when making adoption decisions. As Pavlou et al. [29] stated, part of the uncertainty in e-commerce comes from fears of seller opportunism and information privacy and security concerns. Trust is found to reduce uncertainty in this context [21]. The reasoning for this finding is, an individual can trust a vendor or the app store, which will reduce their uncertainty caused by their concerns on information security or seller opportunism. The individual will reduce the amount of searching because of more trust.

Table 3. Effects of social influence, trust, homophily on search effort (SE) and uncertainty (UC)

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Path Coefficients</th>
<th>Significance</th>
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</thead>
<tbody>
<tr>
<td>H2a(-): Soc. influence→SE</td>
<td>0.046</td>
<td>n.s.</td>
</tr>
<tr>
<td>H2b(-): Trust→SE</td>
<td>-0.122</td>
<td>P&lt;=0.05</td>
</tr>
<tr>
<td>H2c(-): Homophily→SE</td>
<td>-0.408</td>
<td>P&lt;=0.001</td>
</tr>
<tr>
<td>H3a(-): Soc. influence→UC</td>
<td>-0.181</td>
<td>P&lt;=0.001</td>
</tr>
<tr>
<td>H3b(-): Trust→UC</td>
<td>-0.159</td>
<td>P&lt;=0.001</td>
</tr>
<tr>
<td>H3c(-): Homophily→UC</td>
<td>-0.292</td>
<td>P&lt;=0.001</td>
</tr>
<tr>
<td>H4(-): Search effort→UC</td>
<td>0.451</td>
<td>P&lt;=0.001</td>
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Homophily shows a significant negative relationship with search effort (H2c), which is in support of the hypothesis. Therefore, if other users have similar backgrounds with the potential adopter, they will also share similar preferences with the
adopters. Users tend to be influenced more by similar people when making decisions. Previous research also shows that users will like a product if many other people with similar backgrounds also like the product [20]. In the meanwhile, homophily was found to reduce uncertainty as well (H3c). This proves it again that similar people have similar tastes, thus recommendations from similar people can serve as a good indicator that a mobile app will be a good fit for an individual as well.

Search effort is found to have a positive significant relationship with uncertainty (H4). As a person spends more time in learning about a mobile app and related information through different sources, the behavior indicates the person has more uncertainty.

11. Conclusions

In this study, we found that social factors have effects on people’s adoption decisions through modifying how much search effort they spend in reducing the uncertainty. Social influence is found to significantly reduce users’ uncertainty. By examining the research model, social influence reduces uncertainty. Trust significantly reduces uncertainty. All the findings about social influences lead us to believe the two constructs play very important roles in mobile app adoption. Social influence and trust will reduce uncertainty towards a mobile app.

Innovation characteristics, such as trialability and relative advantage, have significant effects on search effort. Trialability is positively related to search effort. When adopters want to adopt a mobile app, they will try to use the mobile app first, and they regard this trial process to be part of the search effort. Relative advantage of a mobile app increases search effort. When the adopter faces several choices on similar apps, they are more willing to spend time learning about the one with the greatest perceived relative advantage. Homophily is found to be negatively related with search effort. If the potential adopter believes other adopters have similar backgrounds, the potential adopter will spend less search effort to reduce their uncertainty.

Search effort plays a central role in the research model. Our findings confirm that search effort and uncertainty are positively related. If a user spends a lot of effort in learning about a mobile app, it is very likely he/she is not certain about the mobile app.

There are a number of factors that affect search effort. Depending on different innovation characteristics and social influences, search effort could differ, and the difference in search effort will affect uncertainty and eventually adoption intention.

Social influence and trust are found to have no significant relationships with search effort, while the two factors have a significant impact on uncertainty. In other words, social influence and trust do not affect uncertainty through search effort despite the fact that they do have a direct effect on uncertainty. This finding indicates that search effort is related to uncertainty because of product characteristics such as trialability and relative advantage, but not because of social influence and trust. In the research context of this study, social influence and trust are two constructs that could be interesting to investigate to see why they have different effects on the two closely related constructs, search effort and uncertainty.

Based on the findings, there are several suggestions that can be offered to the application vendors and developers. If the potential adopters are offered the opportunity to try a mobile app, it will decrease uncertainty. For management, describing the capabilities of the app more clearly would also increase their sales since it reduces uncertainty of the users. Mobile apps may benefit where applicable by the introduction of social features as social influences decrease uncertainty.

12. Limitations and directions for future research

The primary limitation of this research is the survey population. A student population in a large state university was employed. Student populations have often been used, primarily due to their accessibility, when the population of interest may be more general. This must be considered a limitation and it should be considered whether there are characteristics of a student population that would be expected to meaningfully differ from the general population. In our case, we would argue, the student population may be more likely than the general population to own a mobile device to download apps. However, since you need to be a mobile device user who has at least considered downloading an app to be in the sample. Therefore, this potential bias most likely just caused fewer survey respondents to be rejected. There does not seem to be any obvious logic that would conclude that student users process the adoption decision differently that the general population. This is also an important direction for future research. Replicating this study with randomly selected members of the general population of mobile device/app users would be additionally illuminating.
13. References


