FROM ONLINE TO MOBILE: LINKING CONSUMERS’ ONLINE PURCHASE BEHAVIORS WITH MOBILE COMMERCE ADOPTION

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Abstract
With the growing popularity of mobile commerce (m-commerce), it becomes vital for both researchers and practitioners to understand consumers’ mobile commerce adoption behavior. In this study, we empirically investigate the drivers of consumers’ mobile commerce adoption behavior based on a cost and benefit framework. Based on consumers’ browsing and purchase behaviors at the e-commerce site before the addition of mobile commerce channel, we constructed behavioral proxy variables which capture the underlying cost and benefit of mobile commerce channel relative to the pre-existing e-commerce channel.

We collected two large datasets from of a large e-marketplace in South Korea that introduced m-commerce to its existing e-commerce offering in 2011. Based on the analysis of browsing and purchase behaviors of 29,283 subjects over a period of 28 months, we find that the need for ubiquity plays a significant role in the m-commerce adoption decision. The two proxies for ubiquity need—Purchase frequency and Purchase time irregularity—were found to have a positive impact on m-commerce adoption. The results also suggest that search cost influences the decision to adopt m-commerce. Specifically, we find that the consumers who search multi-item or categories at a time, engage in active search, and conduct thorough search, are less likely to adopt m-commerce. Finally, the results show that the risk preference of the consumer is related to the adoption decision. Risk aversion, as measured by the two proxies—Reliance on secure log-in system, and Need for receiving confirmations—lowers the likelihood of m-commerce adoption. These results highlight the importance of the unique features of mobile platform in influencing the consumers’ adoption of m-commerce. We discuss the implications of our findings for academics and practitioners.

Keywords: adoption, mobile commerce, empirical analysis, cost-benefit framework, search pattern, ubiquity, risk preference.
INTRODUCTION

With the prevalence of mobile devices and the ubiquity of mobile networks, consumers are increasingly using the mobile channel to purchase products and services. US mobile commerce sales were predicted to reach $4.9 billion in 2011, and will account for $163 billion in sales by 2015 (ABI Research, 2010). The Mobile Gross Merchandise Volume (GMV) of eBay, for example, was expected to reach nearly $5 billion in revenue for 2011, more than double from the past year (Sullivan, 2011). Amazon also recently announced that mobile devices generated US $1 billion in sales, 3.5% of its net sales during the same 12-month period (Patel, 2012).

Several factors are driving the growth of mobile commerce (m-commerce hereafter). First, access to the mobile Internet has become easier and cheaper. Mobile devices such as smartphones and tablet PCs, which are designed to increase usability on the mobile Internet, have gained widespread popularity. Statistics show that smartphone adoption grew 50% during each of the past two years (eMarketer, 2011). Mobile Internet prices across various wireless Internet technologies are falling, and that trend is expected to continue (Harbor Research, 2010). Mobile Internet traffic worldwide, accordingly, rose to 5.02% in June 2011, up from 1.82% in March 2010 and has doubled within the past year (Sullivan, 2011). Second, companies and retailers are increasingly considering m-commerce as a new venue for future growth; thus, their corresponding efforts are also lifting m-commerce. As web traffic via the mobile Internet accounts for over 10% of the traffic, more retailers are creating mobile sites enabled for m-commerce (Patel, 2011). Google, for example, has recently acquired Motorola Mobility in a move to expand its influence over the m-commerce industry. Third, new transaction technologies, such as Near Field Communication and Mobile Wallet technology, are making mobile transactions much easier and more convenient. Gap, for instance, has recently adopted Google Wallet, which lets consumers easily pay for products with its mobile shop (Johnson, 2011).

Two main characteristics distinguish m-commerce from traditional e-commerce. First, due to the ubiquity of the mobile Internet, m-commerce facilitates anytime, anywhere transactions. Second, relatively less time spent per visit and less complex navigation is expected on m-commerce webpages—small screens and low usability may hamper long and complex use of the m-commerce channel. This is also due to the transitory nature of using mobile Internet. The ESPN mobile web page, for example, records about 12 minutes per visit on average, which is much less than the dot-com page, and is mostly driven by simple tasks, such as score-checking and fantasy sports (Walsh, 2011).

Despite the increasing significance of the m-commerce market and the differences between e-commerce and m-commerce, there is a paucity of empirical research on m-commerce, mainly due to the unavailability of necessary data. We contribute to this nascent research area by examining how consumers’ e-commerce search and purchase behaviors influence their m-commerce adoption based on a large dataset from a major Korean e-marketplace. Our panel dataset contains detailed transaction data before and after the launch of the mobile channel. This provides us with a unique opportunity to measure consumers’ search and purchase patterns on the e-commerce channel and their subsequent m-commerce adoption based on their actual behavior rather than their perceptions. In our study, m-commerce adoption refers to an e-commerce user’s first-time usage of the mobile channel to purchase products. Based on consumers’ product search and purchase behaviors on the e-commerce site prior to the launch of the mobile channel, we construct variables that capture the underlying costs and benefits of the mobile channel relative to the traditional online channel.

Using a Cox proportional hazard model, we find the following results. First, e-commerce users who have a greater need for ubiquitous shopping are more likely to adopt m-commerce. Specifically, those who shop more frequently and irregularly are more likely to adopt m-commerce. Second, e-commerce users with shopping patterns incurring higher search costs are less likely to adopt m-commerce. Those who tend to purchase multi-items or multi-categories at a time and those who tend to search for products across multiple pages are less likely to adopt m-commerce, while those who tend to click on display ads rather than search with keywords or browse categories to purchase products are more likely to adopt m-commerce. Third, e-commerce users who are more risk-averse for transactions are less likely to adopt m-commerce.
Our study has several important implications. First, this paper is among the first to examine m-commerce adoption based on a unique large-scale panel dataset which features the introduction of the mobile channel in the middle of the sample period. Second, linking m-commerce (a new system) adoption with the usage patterns in e-commerce (a pre-existing system) is novel. Our behavioral measures can be more reliable compared to self-reported perceptual measures typically used in the adoption literature. Third, our model can provide online retailers with a better understanding of who is more (and less) likely to adopt a mobile channel based on the data readily available from their internal database. Online retailers can target customers more effectively for their newly established mobile channel by utilizing our findings.

2 LITERATURE REVIEW

This section is composed of three pieces. The first two parts are about the theories the paper is based on, and the last part is the brief review on the research stream on the mobile commerce.

2.1 Theory of Habit

We conjecture that prior online shopping patterns would affect the mobile commerce adoption either directly or indirectly. In this subsection, we briefly explain how it works based on the theory of habit.

Habit is a behavioral pattern of human beings in that the same decision is repeated over and over again, as the former decision with a desirable outcome reinforces or increases the probability of the same choice over the next decision. Habits are defined differently based on the perspective as a positive relation between past and current behavior (Becker, 1992) or a causal mechanism to predict future behavior, not merely a set of correlated events (Hodgson, 2004). In fact, this tendency of behavior has been widely studied in a variety of forms, such as habitual voting in political science (Plutzer, 2002; Fowler, 2006), brand loyalty or RFM analysis in marketing (Bawa, 1990; Chaudhuri and Holbrook, 2001; Jeuland, 1979; Rust and Chung, 2006), inertia in criminology (Felson et al., 1998) and animal habit in zoology (Guhl, 1968).

There are still debates about the process of habit formation, but a widely accepted theory is that habit is formed by a learning process (Jog et al., 1999; Mandar et al., 1999; Mittal 1988; Yin and Knowlton, 2006). As a part of the learning process, habits can be strengthened by a positive reinforcement (Mowrer and Jones, 1945). Not only external rewards, such as money or gifts, but also intrinsic rewards including satisfaction or positive feeling as a consequence of behavior or selection, can be regarded as a positive reinforcement (Lally et al., 2009). Brand loyalty, for example, can result from satisfaction obtained from the consumption of the brand (Bawa, 1990). Once brand loyalty has been formed, a consumer would minimize costs of thinking which are required in the information processing to choose a brand among alternatives and routinize her behavior (Bawa, 1990).

We cannot easily change our habit. That is the reason why a habit can be a powerful predictor for future behavior (Aarts et al., 1998). Several experiment results indicate that habit is a stronger predictor of behavior than intentions (Landis et al., 1978; Verplanken et al., 1998). In the domain of travel mode choices, Verplanken et al.'s (1998) field experiment shows that intentions remain as an explanatory power for behavior when habit is weak, whereas intentions have no predictable power for behavior when habit is strong. When it comes to continued usage of information systems, habit limits the explanatory power of intentions in terms of predicting IS continuance behavior (Limayem et al., 2001). In fact, Limayem et al.(2001) suggests a habit-intention model and argues that a lot of variance of IS usages can be explained by habit.

Past consumption habits are an important determinant of present consumption patterns (Pollack, 1970). By the way, as Hull wrote “functional equivalence of stimuli plays an important role in bringing it about that habits established under certain stimulus conditions will function with little or no delay in new situations having nothing whatever as objective stimuli in common with the conditions under which the habit was originally formed.” (Hull, 1934, p. 35), habit can be transferred to a new situation which is carrying similar stimulus to the original (Upshur, 1962). If aspects of the performance context do not change significantly, a habit continues to survive in a new environment (Wood et al.,
Furthermore, a habit is known as a significant determinant to a post-IT adoption (Ye and Potter, 2001). Therefore, we can expect an online purchase pattern would be passed on and continue to play a critical role, especially in the early stage of mobile purchasing behavior.

Specifically, our exploratory analysis on online purchasing behaviors shows that online consumers are largely varying in terms of shopping patterns, such as the number of purchasing items at a time, shopping frequency and preferred search behaviors to purchase products. For example, some online consumers have a more tendency to click displays to purchase products, while others search products by typing in a brand name or a product name. These shopping patterns before the introduction of mobile channel are expected to influence the adoption of m-commerce when the mobile channel becomes available.

2.2 Cost-Benefit Calculus

We look into the effects of cost-benefit calculus on the m-commerce adoption with the rational choice theory. Rational choice theory, which is rooted in utility theory in economics, is an approach used by social scientists to understand human decision-making. According to the rational choice theory, a person (or an animal) makes choices in a way to maximize the total utility within a given choice set and information. The rational choice theory has been widely adopted in a various fields of studies, such as economics, sociology, psychology, zoology, political science and marketing, and explains human behaviors in a concise way (Green, 2002; Herrnstein, 1990).

Rational choice theory views, coupled with the baseline assumptions that human wants more rather than less of a good, and all the available resources to maximize the utility are scarce, any social exchange relationship such as firm and consumer as an economic exchange relationship where all parties try to make cost-effective decisions. Therefore, mobile users would also follow the calculus of (expected) costs and benefits when adopting m-commerce.

Coupled with the characteristics of m-commerce comparing to the traditional e-commerce, consumers with a certain shopping pattern or propensity might benefit by adopting the m-commerce. In other words, each consumer in a different context might face a different cost-benefit calculus for the m-commerce adoption. For example, due to the ubiquity of the m-commerce, consumers who shop frequently and irregularly would benefit from the m-commerce adoption, while the others would benefit less.

2.3 Research Stream on Mobile Commerce

At first, we briefly review the current research stream on m-commerce. A few behavioral studies have been conducted in the domain of m-commerce. Wu and Wang (2005) proposed the revised technology acceptance model (TAM) by integrating innovation diffusion theory, perceived risk and cost into the original TAM and found empirical evidence that perceived risk, cost, compatibility and perceived usefulness have significant impact on the intention to use m-commerce. Mallat et al. (2009) also suggested the extended TAM model by incorporating compatibility, mobility and use context into the original model. Their work emphasizes mobile use context in terms of places and time is an important determinant for the intention to use m-commerce.

These types of behavioral research based on the technology adoption theory have greatly advanced our knowledge in the domain; however it is the time to take a different angle to improve practicality of the research and to nurture our knowledge into the next stage. Since the early works of Davis(1986) and Davis(1989), many behavioral studies focused on the role of internal perceptions of an individual, such as perceived ease of use, perceived usefulness, subjective norm, motivation and so forth, to explain an information technology adoption behavior systematically in a various of contexts, all-encompassing from e-commerce, Internet banking, telecommunications service, software, and education to medical technology. However, technology adoption theory has been criticized, despite its frequent use, especially about its practicality. Benbasat and Barki suggest that “we need to identify the antecedents of the beliefs contained in adoption models in order to benefit practice” (Benbasat and Barki, 2007). We also need to identify antecedents of IT adoption that are measured beyond
perceptions, specifically objective measure, where possible, to improve the practicality (Davis and Kotteman 1994). In sum, it is the time to take a fresh look at the adoption behavior to advance IT adoption research to the next stage (Bagozzi, 2007; Benbasat and Barki, 2007).

In this study, we identify consumers’ traditional e-commerce usage patterns and characteristics affecting the m-commerce adoption on econometric basis. We do believe that this new empirical approach to the adoption problem can not only complement our knowledge on the IT adoption, but also stimulate adoption research stream.

Meanwhile, recent researches conducted in the domain of mobile Internet are also related to the study. Ghose and Han (2011) examine whether there is a positive or negative interdependence between the mobile-phone-based content generation behavior and the content usage behavior. They found out that there is a negative temporal interdependence between content generation and usage. Their study is among the first econometric studies which explore factors driving user behavior on the mobile Internet. Their evidences of resource constraint on mobile users’ behaviors which can vary across users are consistent with our cost-benefit framework in the sense that m-commerce adoption would depends on the benefit and cost involved in the decision which would be different across users’ characteristics and their purchase behaviors. Ghose et al. (2012) compare users’ behaviors between the traditional online and mobile channels. According to them, the rank is turned out to have higher effects on mobile than online when clicking contents, which imply higher search cost is involved in mobile search than online search. Since product search is a prerequisite step to purchase products (Pavlou and Fygenson, 2006), higher search cost in mobile is expected to affect the m-commerce adoption.

3 RESEARCH MODEL

In this section, we derive research hypotheses based on theory of habit, rational choice theory and several related literature. Before we derive our hypotheses, we abridge the advantages and disadvantages of m-commerce comparing to the traditional e-commerce in the following subsection. They would be the basic assumptions on our study, and mostly stem from the current mobile Internet usage characteristics.

3.1 Background

Table 1 summarizes the advantages and disadvantages of m-commerce comparing to e-commerce. First, due to the ubiquity of the mobile Internet, we can enjoy anytime and anywhere shopping through mobile. M-commerce provides us with this ubiquitous shopping experience. Second, mobile is easy and quick to access, but hard to browse. We can access the Internet on mobile devices by pushing one or two buttons without a need to, for example, wait for computer-booting to access the stationary Internet. Furthermore, with a prior setting of login credential, we can also access the personal m-commerce page without a need to type-in our login credentials. However, because of the small screens and low usability in general, consumers who want to browse many products and collect detailed information might be reluctant to do the tasks on mobile. Transitive nature of mobile Internet usage might hamper products browsing and information gathering, too. Lastly, because of the above disadvantages, information collection about products would be limited on mobile. Moreover, since the m-commerce is relatively new, consumers might feel unfamiliar with the m-commerce. As a result, consumers might perceive higher risk when purchasing products on mobile than stationary.
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<th>Advantage and Disadvantage</th>
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<td><strong>Advantage</strong></td>
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<td>Ubiquity</td>
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<td>Easy and quick to access</td>
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<td><strong>Disadvantage</strong></td>
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<td>Hard to browse, collect</td>
<td>Low user interfaces and usability in general</td>
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<td>Higher risk perception</td>
<td>Limited product information collection</td>
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<td>New distribution channel</td>
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Table 1. Advantages and disadvantages of m-commerce compared to e-commerce

3.2 Need for Ubiquity

The ubiquity of a wireless network provides an ideal environment for anytime, anywhere shopping. Especially for those who frequently purchase online, the ubiquity of m-commerce can be more important and beneficial. As a result, we expect that online consumers with a tendency to shop online more frequently will be more likely to adopt m-commerce. Also for e-commerce consumers who show a large amount of shopping time variance (i.e., whose shopping time tends to vary quite a bit from one day to another), the ubiquity benefits of m-commerce will be greater. For example, a consumer who has a tendency of shopping at the regular time, name 7 p.m. after work, might not have a special need to access mobile shops, while a consumer who has a tendency of shopping irregularly, followed by the unexpected needs to purchase products, could exploit the benefit of m-commerce to which time and location are irrelevant. Hence, we propose:

H1a. (Purchase frequency): E-commerce users shopping online more frequently are more likely to adopt m-commerce.

H1b. (Purchase time irregularity): E-commerce users shopping online more irregularly are more likely to adopt m-commerce.

3.3 Search Cost

Consumers continue searching for a better product until the marginal cost of searching exceeds the marginal benefit (Hoque and Lohse, 1999). The mobile Internet device usually offers a lower level of user interfaces. As a result, the user interfaces hamper collecting information significantly (Zhang, 2007). Under the reasonable assumption that the marginal search cost in a mobile device is larger than that of online, consumers who have a shopping habit of high search costs, such as purchasing multi-items or multi-categories at the same time would face a significant search cost on mobile devices. Furthermore, not only high search costs but also more interactions with mobile devices are expected when purchasing multi-products at a time. Therefore, consumers with this tendency of transactions would be less likely to adopt a mobile commerce.

H2a. (Search Complexity): E-commerce users who tend to purchase multi-items or multi-categories at a time are less likely to adopt m-commerce.

We can access mobile Internet easily and instantly whenever and wherever we want. Meanwhile, there are three ways in product search to purchase online: 1) clicking display ads, 2) typing in keywords, and 3) browsing categories. The former is passive, less-interactive and might be impulse, while the two latter are active, more-interactive, and associated with planned purchasing. Mobile channel is more aligned with this passive and impulse purchasing, since mobile Internet is easier and quicker to access. Furthermore, clicking displays is much easier than typing-in or browsing on mobile (Lee and Benbasat, 2003). Therefore, online consumers who are in favor of clicking displays would feel less-burden to continue the operation with mobile devices, and would be more likely to adopt mobile commerce accordingly. On the other hand, due to the small screens and low usability, consumers who type-in keywords or browse categories to purchase products and collect detailed information might be reluctant to do the tasks on mobile. As a result, consumers who are more prone to pushed display ads would be more liable to adopt mobile commerce. We call the three way as
“search mode” where active search mode is defined as searching using keywords or browsing categories and passive search mode is defined as using display ads.

**H2b. (Search Mode):** E-commerce users who tend to click on display ads rather than type in keywords or browse categories to search for products are more likely to adopt m-commerce.

In addition, consumers who are meticulous in searching products online would feel difficulty in continuing the nature on mobile, since mobile is hard to browse and collect product information. Therefore, they are less likely to adopt mobile commerce.

**H2c. (Search Propensity):** E-commerce users who tend to search for products more thoroughly are less likely to adopt m-commerce.

![An empirical model on m-commerce adoption](image)

### 3.4 Risk Attitude

The transitory nature of using mobile Internet and low usability of mobile devices would hamper mobile users in collecting product information. The limited user experiences of mobile Internet can aggravate the problems of the information gathering and processing when purchasing mobile. The limited information collection in mobile can elevate the uncertainty when purchasing mobile. Furthermore, since the mobile channel is newly introduced into the market and, consequently, the successful mobile transactions around e-commerce users are not reported enough, the (perceived) uncertainty regarding transaction in mobile would be higher than online for the same product. Meanwhile, coupled with the fact that most consumers show a risk-averse pattern when purchasing products, the uncertainty involved in product purchasing lowers the value assessment of products (Castano et al., 2008; Peracchio and Tybout, 1996). Therefore, the situation of limited information collection or the newness of the mobile channel impedes mobile adoption.

Consumers’ perceived values on product purchase under uncertainty would vary by their risk preference. For those who have higher risk-aversion, the value lowered by the perceived risk would be higher for the same amount of uncertainty. We can regard e-commerce users who seek secured transactions as more risk-averse than who don’t. Therefore, e-commerce users who seek secured transactions are less likely to adopt mobile commerce.
H3a. (Secured Transaction): E-commerce users who value secured transactions more highly are less likely to adopt m-commerce.

The vast amount of information available on the Web is a burden for online users to process (Duan et al., 2009). When it comes to online shopping, not only attributes of alternatives such as price and quality, but also attributes of services such as delivery and security need to be considered to make a purchase. The burden from processing information might cause information overload and turn people off from online shopping (Ahuja et al., 2003). That is the reason why many online vendors have implemented sophisticated tools to assist shoppers in their purchase decisions (Häubl and Trifts, 2000).

One of the most popular ways to relieve the burden of consumers to process a large amount of information is presenting an assurance. Many online vendors offer an assurance on price (price matching guarantee) or an assurance on quality (minimum quality guarantee) to help decisions of those who put much weight on the value attribute. With the price matching guarantee, for instance, online consumers who care much for the price can easily make a purchase decision.

By purchasing the assured deals, we can alleviate our worries on the uncertainty involved in the product quality and price. Therefore, those who seek the assured deals might be regarded as more risk-averse than who don’t.

H3b. (Dependence on Assurance): E-commerce users who tend to seek assurance are less likely to adopt m-commerce than others.

4 DATA AND METHOD

4.1 Data Description

We used two large datasets randomly drawn from the database of a large e-marketplace in South Korea that had initially provided online channel only and launched mobile channel later. The two datasets contain detailed information on customers, products and transactions, and cover the periods before and after the launch of the mobile channel. Dataset 1 contains the demographic variables of 30,000 users who have never purchased in mobile and their all online transaction variables during more than two years (March 2009—June 2011). The total number of 1,454,803 transactions is in dataset 1. Dataset 2 contains the demographic variables of 30,000 users who have purchased mobile at least once and their all online and mobile transaction variables for the same period. The total number of 1,179,159 online transactions and the total number of 106,189 mobile transactions are in dataset 2.

To explore m-commerce adoption issues, we stratified-sampled several times from both datasets based on the m-commerce adoption rate of the population (the adoption rate of the e-marketplace at that time). All samples contain the demographic variables of 30,000 users and their all online and mobile transactions. To derive e-commerce shopping patterns, we used the data until May 20, 2011, eleven days before the mobile channel launch, since purchase decisions near the mobile channel launch may have been affected by the launch event. By using data before the mobile channel launch to derive the variables which capture search and shopping patterns, we can avoid the potential endogeneity issue. A total of 29,283 subjects and their 540,883 online transaction records are left for the derivation of behavioral measures of online search and purchase.

Note that the number of subjects is different from that of the sample initially drawn. That is because we ruled out some subjects and their all transactions from the sample. First, we excluded business consumers, since they show a significant different shopping pattern from individual consumers in terms of purchasing volume and frequency. Second, we let off those who transacted less than or equal to three times in online. Our independent variables root in prior online purchasing behaviors, but their online purchasing patterns couldn’t be decided due to the lack of records.

We use several other samples to validate our analysis results. First, we run the same model on a different sample (sample 2), and compare the analysis results with those from the main sample. Second, we predict possible mobile adopters using the other sample (sample 3) and compare them...
with real adopters. Third, to explore the effects of the time and day when the m-commerce has been adopted, we split the adopter group in the sample by the (groups of) time and day on which the m-commerce is adopted, and compare the results from each sub-sample. Details will be discussed in the latter part of the paper.

4.2 Variables

We constructed behavioral proxy variables from the consumers' browsing and purchase behaviors at the e-commerce site before the addition of m-commerce channel. Table 2 summarizes the variables and measures we have used to test the hypotheses.

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<th>Hypotheses</th>
<th>Key Variables</th>
<th>Measures</th>
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<tr>
<td>H1a</td>
<td>Purchase Frequency</td>
<td>Mean of the time gap (milliseconds) between the current transaction and the last transaction (FQ)</td>
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| H1b | Purchase Time Irregularity | -Mean of the difference in purchase time of the day between the current transaction and the last transaction (TF)  
-Standard deviation of the difference in purchase time of the day between the current transaction and the last transaction (TP) |
| H2a | Search Complexity | -Proportion of the transactions involving multi-items (MI)  
-Proportion of the transactions involving multi-categories (MC) |
| H2b | Search Mode | -Proportion of the transactions initiated by clicking on display ads rather than typing in keywords or browsing categories to search for products (PD) |
| H2c | Search Propensity | -Mean of the display rank of transactions (TS). Display rank is calculated based on the location of the display. If a product is listed at the top of the first search result page, the display rank is 1; the rank value is greater for products listed lower. |
| H3a | Secured Transaction | -Proportion of transactions including order confirmation requests either through email or text messages (CR)  
-Use of a safer log-in system (AL) |
| H3b | Dependence on Assurance | -Proportion of transactions with price-matching guarantees (PA)  
-Proportion of transactions with minimum-quality guarantees (QA) |

Table 2. Key variables and measures

At first, in terms of pattern for the purchase frequency (H1a), the mean of the purchase time gap (milliseconds) between the current transaction and the last transaction (FQ) was selected. Note that FQ measures the time gap; therefore a smaller value of FQ means more frequent online shopping. Two variables were selected for the purchase time irregularity (H1b), the mean of the difference of purchase hour between the current transaction and the last transaction (TF), and the standard deviation of the difference of purchase hour between the current transaction and the last transaction (TP). For a consumer who transacted online 3 times and the purchase times are 3 p.m., 5 p.m. and 10 p.m., respectfully, for example, then the TF will be (2+5)/2=3.5, and the TP will be 2.121, the square root of (2-3.5)^2+(5-3.5)^2.

For the transaction complexity (H2a), we initially selected total of four variables, mean of number of items per transaction (NI), proportion of the number of transactions of multi-items to the total number of transactions (MI), mean of number of categories per transaction (NC), and proportion of the number of transactions of multi-categories to the total number of transactions (MC), but 2 variables, MI and NC, were dropped at the analysis because of high correlations with other variables.

To test H2b and H2c, we used two variables, the proportion of the number of clicking display ads rather than typing in keywords or browsing categories to search for products to purchase to the total number of transactions (PD) and the mean of the display rank of transactions (TS). The display rank is calculated based on the location of the display. If a product, for example, is listed at the top of the first search result page then the display rank of the product is 1, and if listed at the bottom or the next search result page, then the rank will be higher. Therefore, TS can be regarded as being associated
with a thorough search tendency. PD shows a high correlation with MC, but variance inflation factor (VIF) was less than 5.0 therefore we included the variable in the final analysis.

We used two variables as proxies for the need for secured transaction (H3a). First, we selected the proportion of the number of order confirmation requests either through email or SMS to the total number of transactions (CR). We can ask for order confirmations to online vendors when we have purchased the products. Then, we can receive a confirmation email or a SMS so that we can assure that the order requests are successfully being processed. We can think that those who had requested order confirmations in most cases put more value on the secured transaction comparing to those who want order confirmations occasionally. Second, we selected the use of a safer log-in system (AL). Many online sites are implementing a safer log-in system, such as a certificate center log-in system. The safer log-in system is designed to reduce the potential risk of identity thefts at the expense of the traditional user-friendly log-in way (e.g. in the form of ID-PW login credential). To use the safer way, users have to install an additional add-in application and wait more time to be logged-in. Therefore, we can regard those who have chosen the safer log-in system as those who value more on the secured transaction than those who haven’t.

Finally, to test H3b, we used two variables, proportion of the number of transactions of price matching guarantee to the total number of transactions (PA) and proportion of the number of transactions of minimum quality guarantee to the total number of transactions (QA) for the assurance variables.

Other than the focal variables, we controlled for several variables that might affect the m-commerce adoption to get valid results. Specifically, we input Promotion Acceptance, Purchase Complexity, Customer Irrationality, Product Return Experiences, Total Order Size and Total Number of Transactions, Demographics, and Shopping Preferences on Time and Day. Due to the page limit, we skip the details on control variables.

4.3 Empirical Method

Our data consists of m-commerce adopters and non-adopters. Furthermore, adopters vary in terms of the adoption time. To capture the nature of adoption time and the characteristics of non-adopters, we employed a cox proportional hazard model. Details on the method are omitted due to the page limit.

5 RESULTS

Table 3 reports the maximum likelihood estimates of the parameters for our model. Note that positive coefficients denote a positive association between the independent variable and the hazard rate. Thus, a positive coefficient indicates faster adoption of m-commerce.

All of the hypotheses except H3b were supported. E-commerce users who shop frequently and irregularly on the e-commerce site are more likely to adopt m-commerce (H1a and H1b), implying that the need for ubiquity plays a significant role in the m-commerce adoption decision. We also find that e-commerce users having shopping patterns involving higher search costs are less likely to adopt m-commerce, which is consistent with our prediction. E-commerce users who tend to purchase multi-items or multi-categories at a time are less likely to adopt m-commerce (H2a). E-commerce users who tend to click on display ads rather than typing in keywords or browsing categories are more likely to adopt m-commerce (H2b), and those who tend to search products thoroughly across multiple pages are less likely to adopt m-commerce (H2c). Finally, the hypothesis on secured transactions (i.e., e-commerce users who put greater value on secured transactions are less likely to adopt m-commerce) (H3a) was supported. However, the hypothesis regarding the dependence on assurance (H3b) was rejected—we find that e-commerce users who tend to seek assurances (price-matching guarantees and minimum-quality guarantees) are more likely to adopt m-commerce, although significance is lower compared to other variables.
Dependent Variable = Time to adopt m-commerce, Log likelihood = -34487.965 (p < 0.001)

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Coef.</th>
<th>z</th>
<th>Hypothesis Testing</th>
</tr>
</thead>
<tbody>
<tr>
<td>Need for Ubiquity</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>H1a: Purchase Frequency</td>
<td>-2.31e-11</td>
<td>-4.710***</td>
<td>Supported</td>
</tr>
<tr>
<td>H1b: Purchase Time Irregularity</td>
<td>0.098</td>
<td>7.720***</td>
<td>Supported</td>
</tr>
<tr>
<td>Search Cost</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>H2a: Search Complexity</td>
<td>-0.042</td>
<td>-3.570***</td>
<td>Supported</td>
</tr>
<tr>
<td>H2b: Search Mode</td>
<td>0.135</td>
<td>18.680***</td>
<td>Supported</td>
</tr>
<tr>
<td>H2c: Search Propensity</td>
<td>-0.017</td>
<td>-9.470***</td>
<td>Supported</td>
</tr>
<tr>
<td>Risk Aversion</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>H3a: Secured Transaction</td>
<td>-0.545</td>
<td>-10.630***</td>
<td>Supported</td>
</tr>
<tr>
<td>H3b: Dependence on Assurance</td>
<td>0.357</td>
<td>3.970***</td>
<td>Rejected</td>
</tr>
</tbody>
</table>

Table 3. Estimation results based on the Cox proportional hazard model

Why does this happen? These assurances usually display at the front of the product search page, and the same to the m-commerce page. Therefore, e-commerce users who seek the assurance information can continue the seeking behavior in mobile relatively easily. On the other hand, e-commerce users who frequently purchase products without the assurances would make the decision based on the information other than the assurances. The additional information seeking tendency might impede the m-commerce adoption, since the transitive nature of mobile Internet usages and lower user experiences compared to stationary make it difficult to search for product details. Therefore, e-commerce users who have a tendency of gathering additional product information other than the assurances are less likely to adopt m-commerce than those who have exploited the benefits of the assurances and make purchase decisions easier. In sum, the assurance seekers might be regarded as more risk-averse users as we postulated before, but the assurances in mobile channel would decrease the need for search (i.e. search cost), and, as a result, the directions could be opposite.

5.1 Robustness Check

We conducted several robustness checks on our main results. Table 4 is the summary of results of the robustness checks. At first, we re-run the same model on a different sample (sample 2), and we got the results with no significant differences. Second, we predicted m-commerce adopters in the sample 3 using the hazard equation derived from the main sample. The hazard rate for each individual is generated with the equation. Then, we check how the e-commerce users with high hazard rate are associated with the actual adoption. Table 5 shows the prediction results on Sample 3. The model predicts 71 real adopters out of the 292 units who are in the 99 percentile of the hazard rate. Accuracy increase dramatically as we lift the percentile. For example, the 99.5 percentile shows the accuracy of 37.50%, and the 99.7 percentile with 56.32%. Note that overall adoption rate in sample 3 is 11.77% (3,436 adopters out of 29,198 users), so we conclude that our model performs well in predicting mobile adopters. Third, to explore whether or not there is a weekend effect on m-commerce adoption, we ran the same model on the subsample 1 and subsample 2, where subsample 1 contains mobile adoptions on weekdays (Mon-Fri), while subsample 2 contains mobile adoption on weekends (Sat-Sun). The results from subsample 1 were consistent with the main results, but the results from subsample 2 were not. Specifically, hypotheses regarding the need for ubiquity were not significant.

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1 Estimation results for the control variables are omitted due to the page limit.
except H1b. That means, the need for ubiquitous shopping plays a weak role in explaining the weekend adoption. Fourth, we ran the same model on the subsample A, B, and C, where A contains mobile adoptions at day (8:00 AM-3:59 PM), B at evening (4:00 PM-11:59PM), and C at night (12:00 AM-7:59AM). We got the each result with no significant differences from the main result.

<table>
<thead>
<tr>
<th>Robustness Check</th>
<th>Purpose</th>
<th>Task</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Re-run the same model on a different sample</td>
<td>Re-run the same model on sample 2 and compare coefficients</td>
<td>No significant difference</td>
</tr>
<tr>
<td>2</td>
<td>Predict on a different using the main model result</td>
<td>Using the coefficients from the main result, generate the hazard rate for each individual in sample 3. Then, see whether the hazard rate is correlated with the actual adoption</td>
<td>Significant positive correlation between the hazard rate and the actual adoption</td>
</tr>
<tr>
<td>3</td>
<td>Explore the weekends effect on mobile commerce adoption</td>
<td>Split the adopters in sample 4 into weekend adopters and weekday adopters, and then run the same model on each of the groups. Compare the coefficients from each analysis result to check the weekend effect</td>
<td>Hypotheses regarding need for ubiquitous shopping were not significant for the weekend adopters.</td>
</tr>
<tr>
<td>4</td>
<td>Explore the time effect on mobile commerce adoption</td>
<td>Split the adopters in sample 4 into three segments based on the adoption time, and then run the same model on each of the groups. Compare the coefficients from each analysis result to check the time effect</td>
<td>No significant difference</td>
</tr>
</tbody>
</table>

Table 4. Robustness Checks on Our Main Results

<table>
<thead>
<tr>
<th>Hazard Rate Percentile</th>
<th>70</th>
<th>80</th>
<th>90</th>
<th>91</th>
<th>92</th>
<th>93</th>
<th>94</th>
<th>95</th>
<th>96</th>
<th>97</th>
<th>98</th>
<th>99</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of Adopters</td>
<td>1095</td>
<td>732</td>
<td>375</td>
<td>347</td>
<td>318</td>
<td>283</td>
<td>250</td>
<td>212</td>
<td>180</td>
<td>146</td>
<td>114</td>
<td>71</td>
</tr>
<tr>
<td>No. of Units</td>
<td>8774</td>
<td>5848</td>
<td>2924</td>
<td>2632</td>
<td>2339</td>
<td>2047</td>
<td>1754</td>
<td>1462</td>
<td>1169</td>
<td>877</td>
<td>584</td>
<td>292</td>
</tr>
<tr>
<td>Accuracy</td>
<td>12.48%</td>
<td>12.52%</td>
<td>12.83%</td>
<td>13.20%</td>
<td>13.60%</td>
<td>13.83%</td>
<td>14.25%</td>
<td>14.50%</td>
<td>15.40%</td>
<td>16.65%</td>
<td>19.52%</td>
<td>24.32%</td>
</tr>
</tbody>
</table>

Table 5. Prediction Results on Sample 3

6 IMPLICATIONS AND CONCLUSION

Our study has several important implications for research and practice. First, this paper is among the first to examine m-commerce adoption based on a large panel dataset. Even though the significance of the m-commerce market has been widely pointed out, empirical research on m-commerce based on a large empirical dataset has been lacking in the literature. This study examined m-commerce adoption based on the two datasets of 60,000 e-commerce users and over 2.5 million of their transactions in online and mobile channels. Second, linking the usage patterns in e-commerce (a pre-existing system) before the launch of the mobile channel and m-commerce (a new system) adoption is novel. In particular, our empirical approach of measuring consumers’ shopping patterns based on consumers’ actual detailed shopping behaviors complements prior adoption studies that have relied on self-reported perceptual measures. Third, we provide new insights by showing that consumers’ habits (formed through e-commerce shopping experiences) and cost-benefit calculus significantly influence the adoption of m-commerce. In particular, our results suggest that m-commerce adoption is affected
by the benefit from ubiquity, one of the major characteristics of the mobile Internet, and the cost from limited product search, which comes from the limited user interfaces of mobile devices. Our model predicts that as mobile technologies advance, m-commerce will be more widely adopted due to improved user experiences in mobile devices. Fourth, we provide empirical evidence that search cost plays a critical role in the mobile environment. Although search cost has been proposed as a key determinant of online consumer behavior, there has been little related empirical evidence in the mobile context, with the exception of Ghose et al. (2012). We make a contribution by showing that search cost significantly influences m-commerce adoption.

On a practical front, our model and results can provide e-commerce firms with a better understanding of their current customers in terms of their propensity to adopt a mobile channel. This understanding, in turn, can help them make a more informed decision on whether or not to launch a mobile channel. Second, our model can help firms predict who is more or less likely to adopt the mobile channel after its launch. Using this information, they can effectively increase the mobile customer base in the early stages by focusing on the customer segment that is more prone to adopt m-commerce. Later, they can use the model to target and provide incentives for the customer segment that is less likely to adopt m-commerce. Of course, the net benefit from increased m-commerce adoption critically depends on whether e-commerce and m-commerce channels are complements or substitutes. We are currently working on another study that examines this issue. Identifying factors affecting m-commerce usage (post-adoption behavior) can be another follow-up research topic. Prior research suggested that determinants or mechanisms for IT adoption might not be the significant determinants for the post-IT adoption. Especially, the feedback after the adoption, such as the satisfaction from m-commerce adoption, can be an important determinant for the future usage. To capture the early usage satisfaction, we might consider early usage transaction results such as transaction confirmation rate, cancellation rate, or exchange or return rate as the proxies. Many of the independent variables in the model also can be considered to be employed in the usage model, since similar logic can be applied to the usage context.

References