From PC to Mobile: Drivers of Mobile Commerce Adoption

Completed Research Paper

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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.

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.

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; Thorpe, 1956).

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.(1998)'s field experiment shows that intentions remain as an significant predictor for behavior only 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., 2007). 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., 2005). 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.

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.

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.

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.

Table 1 summarizes the advantages and disadvantages of m-commerce comparing to the stationary 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.

Table 1. Advantages and disadvantages of m-commerce compared to e-commerce

Advantage and Disadvantage		**Rationale**
Advantage	Ubiquity	• Ubiquity of the mobile Internet
	Easy and quick to access	• Readiness of mobile devices to access the Internet
Disadvantage	Hard to browse, collect information and make complex interactions	• Low user interfaces and usability in general • Transitive nature of mobile Internet usage
	Higher risk perception	• Limited product information collection • New distribution channel

Research Hypotheses

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.*

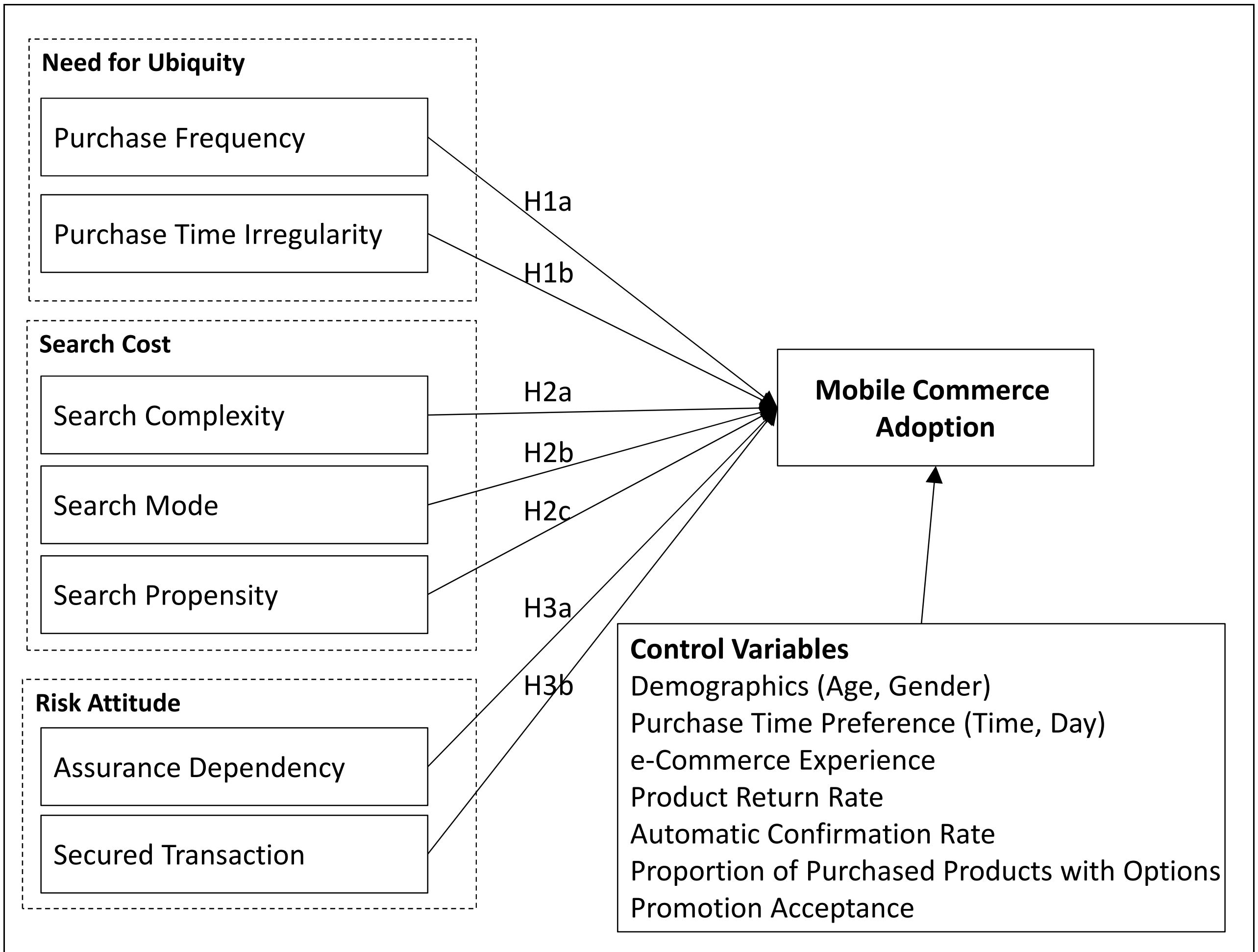

Figure 1. An Empirical Model on M-commerce Adoption

Search cost

Mobile devices usually offer a lower level of user interfaces, resulting in higher search costs than PCs. Thus, consumers who have an online shopping pattern requiring more extensive search, such as purchasing multi-items or multi-categories at the same time, would face significantly higher search costs on mobile devices than in a traditional e-commerce environment. Similarly, given that clicking on display ads is much easier than typing-in or browsing on a mobile device (Lee and Benbasat, 2003), online consumers who prefer to click on display ads for product search would incur lower search costs, compared to those who prefer to type in keywords or browse categories, and thus would be more likely to adopt m-commerce. In addition, consumers who are thorough (visiting multiple pages) in searching for products online would find it more difficult to do the same on a mobile device – the mobile Internet is harder to browse and collect comprehensive product information. Hence, we propose:

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.*

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.*

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

Risk attitude

Consumers' perceived value of product purchase under uncertainty would vary, according to their risk preference. For those who have higher risk-aversion, the value lowered by the perceived risk would be greater for the same amount of uncertainty. With the limited information collection in mobile and the newness of the channel would pose uncertainty when purchasing. Given that mobile transactions can be considered as more uncertain compared to traditional online transactions, e-commerce users who seek secured transactions (and hence, who are more risk-averse than those who do not) are less likely to adopt m-commerce. In addition, we conjecture that those who seek assurance (e.g., price-matching guarantees and minimum-quality guarantees) are more risk-averse, and are thus less likely to adopt m-commerce. Hence, we propose:

H3a (Secured Transaction): *E-commerce users who value secured transactions more highly are less likely to adopt m-commerce.*

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

Data and Method

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 4 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.

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 3 summarizes the variables and measures we have used to test the hypotheses.

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. Table 2 summarizes the variables and measures we use to test the hypotheses.

Table 2. Key Variables and Measures

Hypotheses	Key Variables	Measures
H1a	Purchase Frequency	-Mean of the time gap (milliseconds) between the current transaction and the last transaction (FQ)
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)

Control variables

We need to control several variables that might affect the m-commerce adoption to get valid results. First, we have interpreted CR as a proxy for the risk-aversion in our hypotheses. However, it might represent the other traits such as the preference of receiving messages from the website or less seclusion concerns (Hui and Png, 2006). In order to control the possibility, we input a promotion message acceptance variable (CPA), which is a dummy variable whether to accept an opt-in promotion from the commerce site or not. Second, some products, such as clothes or USB memory, need additional inputs such as color or size to purchase. These product options might make the purchasing more complicated. In order to control the complexity per purchase, we employ an option selection variable (COS), which is a proportion of the number of transactions which had required additional options to the total number of transactions. Third, online consumers sometimes forfeit their rights to confirm transaction and receive rewards (additional points) from the site. This behavior might cloud the effects of the cost-benefit calculus. So, we input a proportion of the number of transactions of forfeiting the right to the total number of transactions (CSF) as a control variable. Fourth, consumers who have more experiences of returning products are expected make a conservative purchase decision. Therefore, the experiences of product return might also affect the risk preferences. We input the proportion of transactions of returned products to the total number of transactions (CPR) in our model to control the possible effect. Fifth, we have discussed the role of purchase habit earlier on the m-commerce adoption. However, not only online purchase patterns but also the channel usage itself can be under the influence of habit. This phenomenon of channel usage inertia is reported in marketing literature (Ansari et al., 2008; Falk et al., 2007) and especially dominant at the early stage of channel choice (Valentini et al., 2011). Therefore, we need to control the transaction experiences on the pre-existing e-commerce channel. Two variables, total order prices (CTO) and total number of transactions (CTN), were initially selected to control the channel usage inertia, but CTN was dropped at the final analysis due to the high correlation with NI. Sixth, we control demographics like age (CAG) and gender (CGD) since they are known to be correlated with IT adoption (Venkatesh et al., 2003). Lastly, to consider consumers' shopping preferences on time and day, we input each consumer's online transaction distribution by time and day.

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 survival analysis technique.

We employ a Cox proportional hazard (PH) model to test our hypotheses (Cox, 1972). Like other survival analysis techniques, a Cox-proportional hazard model focuses on *time to event*. While other parametric hazard models assume the hazard function to take a particular shape such as the Weibull or log-logistic, the Cox PH model has an advantage of placing no restrictions on the shape of the baseline hazard. The Cox PH model is also known as one of the most general and robust regression models (Li et al., 2010).

We know the exact time when the mobile channel was launched, and our data cover the periods both before and after the launch of the mobile channel. Therefore, our data are right-censored in that we know the start time (that is, all subjects enter the study at the same time), but we cannot observe those who have adopted m-commerce beyond our data collection period or those who never adopted m-commerce. None of our subjects dropped out or got lost during the sample period. Also, our sample is independently censored data, since our data period is independent of the event times. Furthermore, m-commerce adoption is a one-time event, and all of our independent variables, including the control variables, are not time varying. Thus, we can implement the simplest form of the Cox PH model without concerns of the left-censoring issue or model specification. The Cox PH model is expressed as,

$$\lambda(t; \mathbf{Z}) = \lambda_0(t)e^{\beta \mathbf{Z}}$$

where $\lambda(t; \mathbf{Z})$ is a hazard function, $\mathbf{Z}$ is a vector of explanatory variables and β is a vector of the parameter to be estimated. The Cox PH model is a product of two quantities. The first part, $\lambda_0(t)$, is the baseline hazard function and signifies the underlying hazard for subjects with all explanatory variables $Z_1, \ldots, Z_n$ equal to 0. Note that the ratio of the hazard function and the baseline hazard function, $\lambda(t; Z)/\lambda_0(t)$, does not depend on time, t. Therefore, the ratio should remain constant over time. This proportionality is the main assumption of the Cox PH model, and we need to check the proportionality assumption.

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.

Before we interpret the analysis results, we check the proportionality of the Cox PH model. We test for a non-zero slope in a generalized linear regression of the scaled Schoenfeld residuals on functions of time. A non-zero slope can indicate a violation of the proportional hazard assumption. All major explanatory variables hold proportionality. Among control variable, however, CGD and a day dummy (Thu) seem not to be proportional. Since they are not the primary covariate of interest, therefore, we stratify the Cox model by two groups based on the control variable (Female vs. Male, Thu vs. the others) and re-run each model without the awkward variables. Each analysis result was consistent with the main result, so we could interpret the analysis result.

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.

Table 3. Estimation Results based on the Cox Proportional Hazard Model

Dependent Variable = Time to adopt m-commerce, Log likelihood = = -34487.965 ($p < 0.001$)

Independent Variables			**Coef.**	**z**	**Hypothesis Testing**
Need for Ubiquity	*H1a: Purchase Frequency*	FQ	-2.31e-11	-4.710***	Supported
	H1b: Purchase Time Irregularity	TF	0.098	7.720***	Supported
		TP	0.070	3.630***	
Search Cost	*H2a: Search Complexity*	MI	-0.042	-3.570***	Supported
		MC	-1.193	-7.570***	
	H2b: Search Mode	PD	1.353	18.680***	Supported

	H2c: Search Propensity	TS	-0.017	-9.470***	Supported
Risk Aversion	*H3a: Secured Transaction*	CR	-0.545	-10.630***	Supported
		AL	-0.414	-8.730***	
	H3b: Dependence on Assurance	PA	0.357	3.970***	Rejected
		QA	0.229	2.310*	
Control Variables					
Online Shopping Experience		CTO	-1.18e-06	-2.620**	
Promotion Acceptance		CPA	0.204	5.750***	
Transaction with Option		COS	0.104	1.080	
Automatic Confirmation		CSF	-0.085	-1.620	
Product Return		CPR	-2.735	-0.820	
Demographics		CAG	-0.040	-16.740***	
		CGD	0.185	4.910***	
Shopping Preference on Day of Week (base: Saturday)		Sun	0.071	0.370	Overall effect of day of week $\chi^2_{(6)} = 14.54$ Prob. > $\chi^2 = 0.0242$
		Mon	-0.200	-1.090	
		Tue	-0.186	-1.010	
		Wed	0.191	1.050	
		Thu	0.103	0.550	
		Fri	-0.377	-1.810	
Shopping Preference on Time of Day (base: 23h)		00h	-0.305	-1.130	Overall effect of time of day $\chi^2_{(23)} = 74.73$ Prob. > $\chi^2 = 0.0000$
		01h	-0.357	-1.180	
		02h	-0.002	0.000	
		03h	0.297	0.710	
		04h	0.433	0.870	
		05h	0.751	1.370	
		06h	0.771	1.630	
		07h	-0.076	-0.160	
		08h	-0.152	-0.410	
		09h	-0.306	-0.990	
		10h	-0.920	-3.180**	
		11h	-0.740	-2.740**	
		12h	-0.644	-2.350*	
		13h	-0.366	-1.440	
		14h	-0.320	-1.230	
		15h	-0.312	-1.180	
		16h	-0.445	-1.690	

	17h	-0.333	-1.230	
	18h	0.187	0.700	
	19h	0.377	1.420	
	20h	-0.476	-1.740	
	21h	0.387	1.600	
	22h	-0.272	-1.080	

$^{***}p<0.001$; $^{**}p<0.01$; $^{*}p<0.05$

Why does this happen? These assurances usually displays 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.

Among the control variables, the coefficient for Total Order Prices (CTO) was significant and negative, which signals that channel use inertia exists in the use of stationary Internet when transiting to mobile, even though the two channels are similar in the sense that the products and prices offered are identical. Age (CAG) was significant and negatively correlated with m-commerce adoption, that is, younger e-commerce users are positively associated with m-commerce adoption. Gender (CGD) showed positive coefficient, which means male users are positively associated with adopting m-commerce. This result is consistent with the previous literatures on technology adoption that man is more likely to adopt new technology than woman. Promotion opts-in tendency (CPA) was significant and positively associated with the adoption. Lastly, both the purchase time and day preferences of e-commerce users show overall significances.

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 except H1b. That means, the need for ubiquity plays a weak role in explaining the weekend adoption. M-commerce adopters who are too busy to shop on weekdays and shop mostly on weekends might make the coefficients insignificant, since they have no need for ubiquitous shopping (because they are so busy).

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 4. Robustness Checks

Robustness Check	Sample	Size (No. of Adopters)	Purpose	Task	Result
1	Sample 2	29,213 (3,441)	Re-run the same model on a different sample	Re-run the same model on sample 2 and compare coefficients	No significant difference
2	Sample 3	29,198 (3,436)	Predict on a different sample using the main model result	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	Significant positive correlation between the hazard rate and the actual adoption
3	Sample 4	29,283 (3,506)	Explore the weekends effect on m-commerce adoption	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.	Hypotheses regarding need for ubiquity were not significant for the weekend adopters.
	Sub-sample 1 (weekdays)	28,512 (2,735)			
	Sub-sample 2 (weekends)	26,538 (761)			
4	Sample 4	29,283 (3,506)	Explore the time effect on m-commerce adoption	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	No significant difference
	Sub-sample A (8:00-15:59)	27,275 (1,498)			
	Sub-sample B (16:00-23:59)	27,255 (1,478)			
	Sub-sample C (24:00-7:59)	26,307 (530)			

Table 5. Prediction Results on Sample 3												
	Hazard Rate Percentile											
	70	80	90	91	92	93	94	95	96	97	98	99
No. of Adopters	1095	732	375	347	318	283	250	212	180	146	114	71
No. of Units	8774	5848	2924	2632	2339	2047	1754	1462	1169	877	584	292
Accuracy	12.48%	12.52%	12.83%	13.2%	13.60%	13.83%	14.25%	14.50%	15.40%	16.65%	19.52%	24.32%

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.

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