Adoption and Business Value of Mobile Retail Channel:

A Dependency Perspective on Mobile Commerce

by

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ABSTRACT

Forrest Research estimated that revenues derived from mobile devices will grow at an annual rate of 39% to reach $31 billion by 2016. With the tremendous market growth, mobile banking, mobile marketing, and mobile retailing have been recently introduced to satisfy customer needs. Academic and practical articles have widely discussed unique features of m-commerce. For instance, hardware constraints such as small screens have led to the discussion of tradeoff between usability and mobility. Needs for personalization and entertainment foster the development of new mobile data services. Given distinct features of mobile data services, existing empirical literature on m-commerce is mostly from the consumer side and focuses on consumer perceptions toward these features and their adoption intentions. From the supply side, limited data availability in early years explains the lack of firm-level studies on m-commerce. Prior studies have shown that unclear market demand is a major reason that hinders firms' adoption of m-commerce. Given the advances of smart phones, especially the introduction of the iPhone in 2007, firms recently have started to incorporate various mobile information systems in their business operations. The study uses mobile retailing as the context and empirically assesses firms' migration to this new sales venue with a unique cross-sectional dataset. Despite the distinct features of m-commerce, m-Retailing is essentially an extended arm of e-Retailing. Thus, a dependency perspective is used to explore the link between a firm's e-Retail characteristics and the migration to m-Retailing. Rooted in the innovation diffusion theory, the first stage of my study assesses *the decision of adoption* that indicates whether a firm moves to m-Retailing and *the extent of*

adoption that shows a firm's commitment to m-Retailing in terms of system implementation choices. In this first stage, I take a dependency perspective to examine the impacts of e-Retail characteristics on m-Retailing adoption. The second stage of my study analyzes conditions that affect *business value* of the m-Retail channel. I examine the association between system implementation choices and m-Retail performance while analyzing the effects of e-Retail characteristics on value realization. The two-stage analysis provides an exploratory assessment of firm's migration from e-Retailing to m-Retailing.

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Chapter 1

INTRODUCTION

Mobile commerce (or m-commerce) is an emerging subset of e-commerce that refers to the use of wireless devices to conduct e-commerce activities over the mobile network and the Internet (OECD, 2007). Ushered in by the advances of smart phones like iPhones and other mobile devices, m-commerce has been experiencing tremendous growth over the past few years. According to the Forrester Research (2011), m-commerce was estimated to have generated $6 billion in revenues in 2011; the upward trend will likely continue, projected at an annual growth rate of 39% to reach $31 billion by 2016.

Since mobility relaxes the constraints of time and space, and it leads to new value propositions (Balasubraman et al., 2002), researchers have widely discussed unique features of mobile devices that are different from those of other consumer electronics products. Examining the nature of mobile services, Varshney and Vetter (2002) and Tiwari et al. (2006) identify and classify several important mobile information systems such as mobile banking, mobile retailing, and mobile office. Despite the enormous sales potential of m-commerce, limitations of hardware and concerns for privacy and security associated with mobile devices impose new challenges on the adoption and success of m-commerce (Tarasewich et al., 2002). The rapid growth rate and corresponding challenges of m-commerce raise a practical need to examine how firms respond to the emerging mobile sales channel. However, prior literature on m-commerce has focused on customers' acceptance of and responses to mobile data services. Most studies to date have used psychometric models (i.e., survey-based approaches) to articulate the behavioral intentions of consumers. Few studies have examined antecedents and consequences of m-commerce at the organizational level. Conducting firm-level analysis is crucial for managers to better understand whether and what associations exist among organizational characteristics, choices of mobile information systems, and business outcomes.

Driven by practical and academic needs, my dissertation empirically assesses firms' migration from e-Retailing to m-Retailing. In the context of my study, m-Retailing refers to the selling of goods and services over mobile networks to consumers. Grounded on the innovation diffusion theory and IT innovation literature, the study examines firms' adoption decisions as well as the extent of adoption, and extends to business value of m-Retailing. While IT innovation research has predominantly focused on the adoption decision (Zhu and Kraemer, 2005), the innovation diffusion theory suggests that a firm's innovation adoption is a two-stage model consisting of an initiation stage for making adoption decisions and an implementation stage for employing innovations. It is only recently that researchers have started to recognize and forestall the pro-innovation assumption that is inherently made in the prior literature and that presumes innovations would be beneficial to all potential adopters at all times. To address the deficiency resulting from this pro-innovation assumption, Fichman (2004) and Zhu and Kraemer (2005) urge researchers to explore *whether, when* and *how* firms acquire performance benefits from innovation adoption.

The dependency view is reflected in the notion that m-Retailing is an extended arm of e-Retailing and essentially shares many of its features, functions, and underlying capabilities. Most existing studies stress distinct attributes of m-commerce in order to contrast from e-commerce and identify its specific drivers of success. The emphasis on their differences is understandable but should not be restrictive. Some conceptual frameworks have also been proposed to illuminate the tight link between e-commerce and m-commerce (e.g., Wu and Hisa, 2004; Okazaki, 2005) and the authors encourage researchers to further explore this link, either theoretically or empirically.

So far, very few empirical studies on m-commerce in the IS literature have looked into how structures in the e-commerce landscape impact the behavior and performance of the m-commerce initiatives. Among the exceptions, Wei and Ozok (2005) illustrate the link by analyzing functions between e-Ticketing and m-Ticketing websites of 27 major airlines. Lin (2012) instead assesses the link from the customer side and shows that customers' perceived e-service quality has influences on m-service quality and m-loyalty. Motivated by the call for investigation into link between e-commerce and m-commerce and by the limited empirical evidence available, this dissertation attempts to address the following research questions:

- How do firms migrate from e-Retailing to m-Retailing?
- What are the influences of firms' e-Retail characteristics on their m-Retailing adoption?
- How do firms realize business value from their adoption of m-Retailing?

The first part of my empirical analysis addresses two related ways through which firms embrace the m-Retail channel: adoption and the extent of adoption. The adoption refers to the decision of whether a firm moves to the m-Retail channel. The extent of adoption shows a firm’s commitment to m-Retail channel and thus reflects the extent to which a firm chooses to invest in system functions of the m-Retail channel. These two adoption measures complement each other. While the adoption decision indicates a firm’s behavior in a dichotomous manner, the extent of adoption quantifies a firm’s level of involvement in m-Retailing.

System functions are the medium to engage online customers. Firms need to consider system implementations that take into account the unique features and hardware limitations of mobile devices, and make appropriate technological investments to maximize consumer shopping experiences and in turn generate revenues. Existing studies on m-commerce are mostly conducted from the customer perspective, and a majority of these individual-level analyses emphasize user-related factors such as the need for personalization. Some exceptions have explored service-related factors such as system quality (e.g., Lee et al., 2009). Since these exceptions are still at the individual level and related to customer perceptions, the dissertation aims to extend the literature to the firm-level analysis by focusing on firms’ extent of adoption in terms of system implementation choices.

From a dependency perspective, I explore the influences of a firm’s e-Retail characteristics on its m-Retail adoption decision and extent of adoption. Specifically, I examine the e-Retail dependency from both operation and customer dimensions. Operating characteristics such as technology competency, firm types and economies of scale are discussed in the IT innovation literature. In the research context, I explore a firm’s accumulated e-Retail resources through measures of e-Retail functions, e-Retailer types, and e-Retail market share. A firm's resources related to customer demand and preferences, however, are rarely considered in the literature. In this study, I examine how greater demand from younger populations (Anckar and D'Incau, 2002) and customer preferences for small order value due to security concerns, short duration of usage occasion, and hardware constraints of mobile devices (Shankar and Balasubramanian, 2009) take effect through e-Retail shopper age and e-Retail order value.

The second part of my empirical analysis tackles the pro-innovation assumption inherent in the literature (Fichman, 2004) by examining specific conditions leading to business value generated from the m-Retail channel. Extending the dependency viewpoint, I examine the influences of e-Retail characteristics on the performances of the mobile sales channel. In addition, I examine the impacts of a firm's extent of adoption (i.e., system implementation choices) on the value of the m-Retail channel.

Using a cross-sectional dataset of e-Retailers in the U.S. and European markets, I find that firms' migration to m-Retailing in terms of adoption, extent of adoption, and value realization are closely related to its e-Retail characteristics. The finding suggests that firms with advantages of operating resources regarding technology competency to provide digitalized services, economies of scale, and physical outlets tend to grasp at market opportunities enabled by m-Retailing and hence are more likely to adopt m-Retailing. After adoption, those firms with an operational edge are also willing to invest more in system development. Interestingly, in order to capitalize on the young generation who use mobile data services extensively and to maximize the conversion rate of small-value orders that fit with the nature of instant shopping in m-commerce, adopting firms with younger e-Retail shopper age and smaller e-Retail order value also engage more in system development.

Business value provides justification for IT innovation adoption. Firms with strong operating resources in e-Retailing, such as experiences in providing digitalized services, accumulated reputation of service quality from e-Retail markets, strong market establishment in e-Retailing, and physical outlets, are found to be leaders in m-Retailing as well. Retail chains, however, have lower conversion rate on average. Firms with e-Retail characteristics that match with customer preferences of the m-Retail channel can benefit from their existing e-Retail resources. Firms with smaller e-Retail order value are found to have higher m-Retail conversion rate. Firms with younger e-Retail shopper age are associated with higher m-Retail sales and traffic. Firms, however, need to be aware of the economic dimensions and ramifications of the two customer-oriented e-Retail resources. Due to the income effect, a firm with high e-Retail shopper age is found to have a higher conversion rate. Because of the price effect, a firm with larger e-Retail order value is found to have higher sales. Finally, a firm’s extent of adoption in terms of information functions and mobile applications is positively related to m-Retail performances.

The rest of the dissertation is organized as follows. Chapter 2 provides a review of the relevant literature. Chapter 3 presents the theoretical framework and research hypotheses, which are followed by data description and variable definitions in Chapter 4. The estimation methodologies, data analysis, and empirical results are presented in Chapter 5. Chapter 6 discusses the findings obtained from the two different stages of analysis. I conclude by deriving implications and specifying limitations and hence potential topics for future research in Chapter 7.

Chapter 2

LITERATURE REVIEW

2.1 M-Commerce

Clarke (2001) summarizes value propositions for m-commerce in four dimensions: ubiquity, localization, personalization, and convenience. Each dimension is associated with a group of mobile applications that manifest the specified value proposition, such as mobile payments for convenience and mobile advertising for personalization. Anckar and D'Incau (2002) identify five distinct value contexts of mobile data services in terms of time-sensitivity, location-based services, spontaneity, entertainment needs, and efficiency needs. Aside from opportunities, limitations of small screens, low-resolution displays, bandwidth, connection instability, and vulnerability in information security are also recognized for mobile devices and well discussed in the m-commerce literature (e.g., Tarasewich et al., 2002; Siau and Shen, 2003; Lee and Benbasat, 2003).

Abundant empirical studies on m-commerce have been conducted from consumers' perspectives. Mostly, researchers use survey methods to explore consumers' perceptions about unique features of mobile data services and mobile web browsing in general (e.g., Hong and Tam, 2006; Lee et al., 2009). In terms of merchants' perspectives, conceptual frameworks have been proposed to discuss strategic implications of various m-commerce applications for businesses. For example, Balasubraman et al. (2002) describe values of m-commerce applications through a space-time matrix, and argue that values of mobile technologies derive from releasing business activities from time and space constraints. Zhang et al. (2002) identify values of m-commerce for firms by linking mobile consumers to their existing services and creating more contact points with customers via the new mobile sales channel.

Relatively few studies, however, have gone beyond conceptual frameworks to empirically explore m-commerce at the organizational level. Dahlberg et al. (2008) present a thorough literature review on mobile payment research and comment, “Surprisingly, we identified only four papers focusing exclusively on merchant… Merchant adoption had not been studied with quantitative data and surveys.” In the broader context of m-commerce, only two studies (Mallat and Tuunainen, 2008; Guo et al., 2010) empirically examine merchant’s adoption of m-commerce. Frolick and Chen (2004) discuss the immaturity of the mobile market and note that the unclear value propositions of m-commerce have created barriers to merchant adoption. Based on empirical data collected from interviews and surveys, Mallat and Tuunainen (2008) posit that the lack of considerable customer needs is one critical factor that inhibits firms’ adoptions of mobile payment services. Similarly, realizing that travel applications need to be location-aware, Wang and Cheung (2004) conduct in-depth interviews with a group of travel agency CEOs in Taiwan to explore their understanding and acceptance of m-commerce. The authors find that the lack of market demands and unclear perceptions of business values from m-commerce are the two main reasons explaining low adoption rates by that time.

Over time, customer preferences change and mobile technologies evolve. In a recent study by Forrester Research (2011), m-commerce is projected to generate $6 billion in revenues in 2011 and the sales will continue to rise, on average 39% a year, to $31 billion by 2016. Although m-commerce only accounted for 2% of overall e-commerce sales in 2010 (Gibson, 2011), its rapid growth rate suggests a potential to change business models and market structures for players, both big and small, across industries. Considering early innovating firms have started to use various mobile information systems to facilitate business operations and transactions, the dissertation focuses on early implementation of m-Retail channel and aims to explore firms' adoption process as well as the value realization.

2.2 Firm's Adoption of Innovation and Value from Innovation

2.2.1 Adoption of Innovation

In the diffusion of innovation theory, Rogers (2003) proposes a two-stage model to explain the complex process of innovation adoption at the organizational level. The first stage is *initiation* in which organizations make their adoption decisions. In this stage, organizations first identify their problems that trigger requests for innovations (agenda-setting), and then they search for possible solutions (matching). The second stage is *implementation* in which organizations develop and incorporate innovations into their business processes. In the second stage, firms actually implement innovations in their business operations by making necessary adjustments (restructuring), promoting innovations across organizations (clarifying), and finally making innovations part of the regular activities in organizations (routinization). Rogers' two-stage model suggests that a firm's innovation adoption process includes not only the *adoption decision* but also the *extent of adoption* afterwards.

In spite of the two stages identified, IT innovation research has predominantly focused on the first stage of the *adoption decision* and on measures such as "intent to adopt" and "adoption versus non-adoption" (Rogers, 2003; Zhu and Kraemer, 2005). While the initial adoption of an information system is crucial for its diffusion, it is firms' *extent of adoption* of IT innovations that determines its long-term viability and eventual success (Bhattacherjee, 2001; Li et al, 2011). Guinea and Markus (2009) also comment that research on extent of adoption such as continued use has become one of "the most welcome developments" in recent information systems research. In the growing research on extent of adoption, there are two perspectives to measuring extent of adoption. The first stream measures extent of adoption by frequency and diversity of IT innovation usage. For example, Hsu et al. (2006) explore factors explaining firms' EDI usage in terms of percentage of documents exchanged via EDI and number of document types exchanged via EDI. The second stream measures extent of adoption by development of IT innovation. Kowtha and Choon (2001), for instance, examine contextual factors influencing firms' website development from simply providing firm information, to a website capable of handling business transactions, and to a website with backend integration.

In the context of mobile commerce, few empirical studies at the organizational level are found in the literature as discussed earlier in Section 2.1. Exceptions include Mallat and Tuunainen (2008) who examine firms' adoption decisions of mobile payments, and Guo et al. (2010) who study firms' adoption decisions of mobile marketing platforms. Both of the studies are focused on adoption decision. No prior empirical work in major IS publications has explored extent of adoption at the firm level. In this study, I examine firms' adoption decisions as well as extent of adoption of mobile retail channels. Aside from dichotomous adoption decisions, I define extent of adoption in terms of a firm's system implementation choices of its mobile retailing channel.

System functions are the medium to engage online customers. Nevertheless, as discussed in section 2.1, prior literature mostly focuses on individuals' perceptions about the value and limitations of mobile data services. Lee et al. (2009) further point out that a majority of these individual-level studies emphasize demand-side, i.e. user-related, factors such as need for personalization, social influence, and subject norms (Hong and Tam, 2006; Kim et al., 2007; Sheng et al., 2008). Relatively few studies look at supply-side factors such as service-related factors. In addition, among these exceptions, researchers explore *consumers' perceptions* about service-related factors rather than *firms' assessment* of them. The dissertation extends the literature to a firm-level analysis and focuses on firms' incentives to invest in its system functions at different levels.

2.2.2 Value from Innovation

In addition to adoption decision and extent of adoption, a natural follow-up question is how much *business value* is produced from IT innovation adoption. In the end, firms are expected to derive value from adoption of innovations. Yet, adoption in itself cannot guarantee satisfaction or ensure benefits. Instead, appropriate organizational capabilities to manage the innovation, correct configuration of the innovation, learning and experiences accumulated from managing the innovation, and extent of innovation adoption are among the factors influencing value realization for adopting firms. Recently, Fichman (2004) and Zhu and Kraemer (2005) have called for researchers to explicate the link between adoption of IT innovation and business value produced from IT innovation. Fichman (2004) further suggests two promising research opportunities by exploring (1) the relationship between the extent of IT innovation adoption and performance impacts as well as (2) contextual conditions explaining business value produced from IT innovation. I note that the link between adoption of IT innovation and value from IT Innovation also relates to the literature of IT business value. Early work on IT business value focuses on whether IT has positive impacts on firm performance and what benefits such as information access and customer relations are enabled by IT usage (e.g., Brynjolffson and Hitt, 1996). Over time, studies on IT business value have extended to explore complementary or contingency factors that influence business values associated with IT uses (e.g., Brynjolffson and Hitt, 2000). The research inquiry on factors resulting in value from innovation adoption is related to the contingency view of IT business value.

Some prior studies have explored organizational benefits from IT innovations. These studies examine individual applications of IT that are explicitly characterized, or could be potentially qualified, as innovative. The important commonality of these studies is that researchers investigate whether, when and, how firms innovate with IT to realize value. Using both primary and secondary datasets, Zhu (2004) finds that IT infrastructure is critical to enabling e-commerce capabilities which in turn lead to business value for firms. Based on a cross-country sample, Zhu and Kraemer (2005) show that e-business value is positively correlated with back-end system integrations as well as front-end web site functionalities. Whitaker et al. (2007) report that firms with broad IT application deployment and a critical mass of RFID implementation spending tend to perceive early returns from RFID deployments. While the forgoing studies represent efforts to address the pro-innovation assumption in technology adoption literature, no existing studies have empirically assessed business value from mobile information systems and its associated drivers. From a merchant's standpoint, this dissertation fills the gap in the literature by exploring how system implementation choices (i.e., extent of adoption) and other contextual factors affect business value realized from the mobile retailing channel.

2.3 Transition to m-Retailing from an Dependency Perspective

As e-Retailers move to m-Retailing, I adopt a dependency perspective to explore the relationship between e-Retailing and m-Retailing. The dependency perspective indicates that a firm's intentions and initiatives to develop a new capability or adopt a new technology are largely a function of its prior experiences and accumulated resources (Nelson and Winter, 1982; Eisenhardt and Martin, 2000). Abernathy and Clark (1985) classify experiences and resources into operation and customer dimensions. Nelson and Winter (1982) suggest that firms develop routines in response to their experiences and these routines codify the knowledge of the firm. Schumpeter (1950) and Henderson (1993) both argue that established firms are better positioned than new entrants to take advantage of competence-enhancing innovations because established firms have preferential access to their accumulated resources and capabilities. The dependency perspective is rooted in the firm's accumulated resources and sheds light on what sort of response is more likely to occur given the context in which the decision-making process takes place. The dependency perspective has been used to explore firms' product innovations in the photolithographic alignment equipment industry (Henderson, 1993), firms’ migration from EDI to open-standard inter-organizational systems (Zhu et al, 2006), and retailers’ internet adoption in the Netherlands (Boshma and Wltevreden, 2008), among other phenomena studied.

Concerning the adoption and value of m-Retailing, while the use of mobile devices and wireless networks makes m-Retailing different from e-Retailing from technological aspects (Wu and Hisa, 2004), m-Retailing and e-Retailing both involve extensive on-line transactions and are facilitated by front-end and back-end web operations. In fact, m-Retailing is an extended retail format that uses technological innovations to enable cyber-shopping in the wireless domain without dampening the principles of successful e-Retailing (e.g., efficient transaction, reliable fulfillment, etc.). From a dependency perspective, firms with various levels of e-Retail resources tend to respond to m-Retailing differently. The link between e-Retailing and m-Retailing can be a valuable resource to facilitate decision making for both IT managers and online marketers. In response to managers’ interest in knowing how e-commerce affects m-commerce (Okazaki, 2005; Wei and Ozok, 2005; Lin, 2012), I employ a dependency viewpoint to assess the transition from e-Retailing to m-Retailing.

Chapter 3

RESEARCH MODEL

3. 1 Research Framework

As m-Retailing directly extends e-Retailing, I employ a dependency perspective to analyze the association between e-Retailing and m-Retailing. I assess the e-Retail dependency from both operation and customer dimensions. In terms of the operation dimension, I explore a firm's accumulated e-Retail resources through measures of *e-Retail functions*, *e-Retailer types*, and *e-Retail market share*. Regarding the customer dimension, I examine how customer preferences in the m-Retail channel manifest themselves through *e-Retail shopper age* and *e-Retail order value*.

Grounded in the innovation diffusion theory, my dissertation explores the link between e-Retailing and m-Retailing in the contexts of adoption decisions, extent of adoption, and business value. In the first stage of adoption, on top of the dichotomous adoption decision, I analyze the extent of adoption based on firms' system implementation choices. I focus on two distinct features of mobile devices: *information functions* and *mobile application*. The former is critical to m-Retail operations due to hardware constraints of mobile devices and the need for accessing information on the go. Firms have to ensure smooth delivery of information and reduce search costs incurred by technological constraints (e.g., small screen size, slow network speed, etc.). The latter - mobile application - is a unique format that is different from a retail website and requires extra adjustments and development efforts. As some firms choose to stay with mobile websites that can be accessed by any web-enabled mobile devices, numerous companies implement mobile applications in order to make mobile shopping experiences more accessible and interactive. Even though using information functions and mobile application to capture a firm's extent of adoption is not exhaustive, analyzing the two relevant metrics is a useful exercise for managers and researchers to clearly understand mobile Retailer's extent of adoption at a granular level of system implementation choices.

In the second stage of value assessment, I posit that e-Retail dependency also affects m-Retail performance. In addition, since system designs are the medium to engage customers' participation, I examine firms' choices of system development denoted by features of mobile devices (i.e., extent of adoption) to study influences of these functions on m-Retail performance. I empirically analyze three related performance measures in sales, traffic and conversion rate. While the sales measure is a commonly used performance criteria (e.g., Zhu and Kraemer, 2005), traffic and conversion rates are also important but less frequently studied in online retailing (Grewal et al., 2004). In the following section, I explicitly hypothesize the associations between each factor and adoption as well as value realization (see Figure 1).

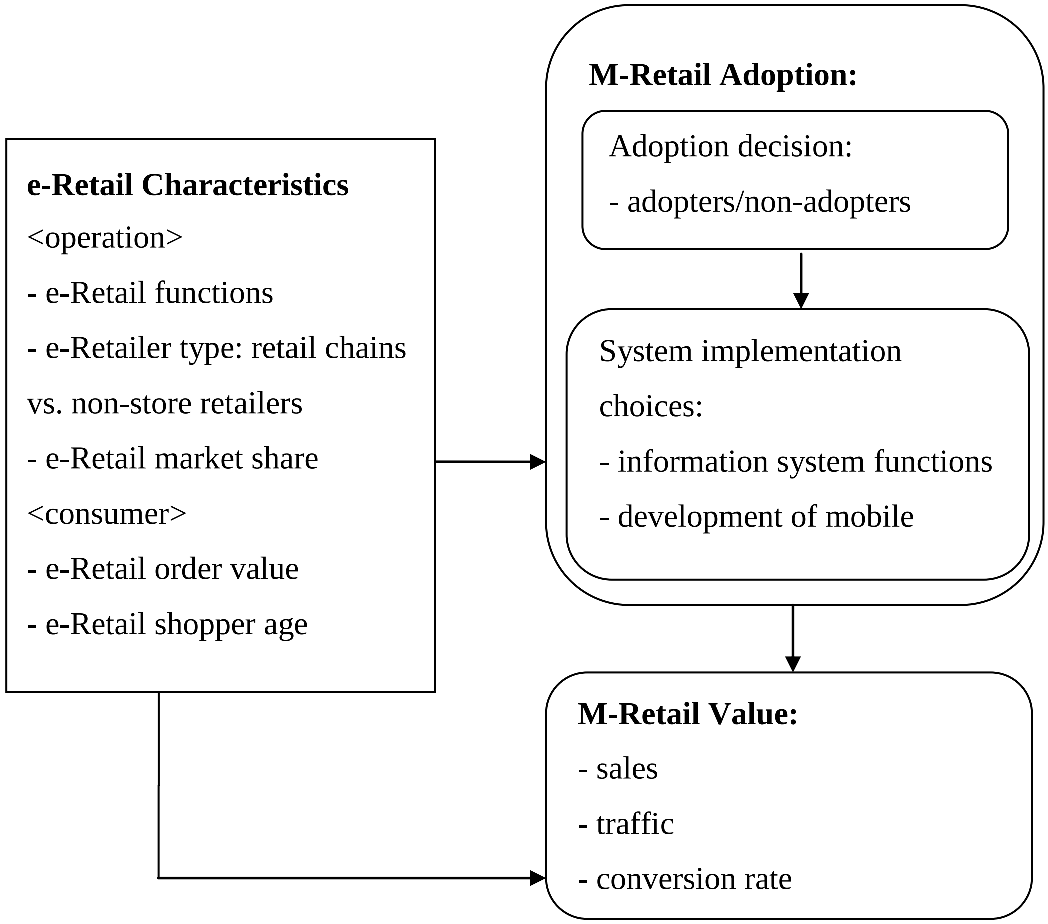

Figure 1. Research Framework of m-Retailing Adoption and Value

3.2 Hypotheses

Front-end functionality is the technology enabler of a firm's digitalized services. Zhu and Kraemer (2002) classify a firm's e-commerce front-end functions into four digitalized services dimensions: information, transaction, customization, and supplier support. Alternatively, Voss (2003) defines a three-layer model that categorizes digitalized services into foundational functionality, customer-centered functionality, and value-added functionality. These front-end functions are among the critical determinants of firm's technology competence to provide digitalized services. Zhu et al. (2004) and Zhu and Kraemer (2005) find a significant correlation between front-end functions and e-Business value in financial and retail industries, respectively.

As m-Retailing involves digitalized services through wireless networks, firms with strong e-Retail functionality are expected to utilize their e-Retailing experiences to facilitate the development of their mobile retail channels. Wei and Ozok (2005) develop a list of functions that support online ticketing processes from leading e-commerce websites and they use the list to evaluate 27 major airlines' mobile ticketing websites. They find a significant level of similarity in functions between e-Ticketing and m-Ticketing websites of these airlines. According to Cam Fortin, the Director of Business Development at Wine.com, one of the critical success factors that drive mobile site implementation outcome is the established web functions the firm has been able to accumulate from its e-commerce website (Minnick, 2012). Thus, a technologically competent firm with better e-Retail functions is more likely to adopt m-Retailing and invest more in system development (extent of adoption).

Besides, firms with comprehensive e-Retail functions are considered to be more technologically innovative. According to the e-service model by Voss (2003), those firms build upon their foundational functions and further expand to value-added ones. Hence, e-Retailers with stronger front-end functions and greater innovativeness are more likely to migrate to m-Retailing, which delivers a new channel to serve customers. Given their inclination to proactively offer technology-enabled services, those innovative firms are also more willing to invest in advanced system design such as development of mobile applications. Finally, customers derive their perceived e-service quality based on e-Retailers' front-end functions (Heim and Field, 2007). Since perceived service quality can be transferred from one channel to another, customers may use a firm's m-Retail channel because they have favorable perceived service quality in its e-Retail channel (Lin, 2012). Therefore, firms with well-established front-end functionality can benefit from their accumulated reputation of service quality in e-Retailing to achieve superior performance in m-Retailing. Taken together, I hypothesize the effect of e-Retail functionality on m-Retail adoption as follows:

H1: Firms' e-Retail functions are positively associated with their adoption decisions of mobile retail channel.

H2: Firms' e-Retail functions are positively associated with their extent of adoption of mobile retail channel.

H3: Firms' e-Retail functions are positively associated with their performances of mobile retail channel (sales, traffic, and conversion rate).

Among different types of e-Retailers, retail chain is the store-based e-Retailer with potential cross-channel synergies between virtual and physical channels (Berman and Thelen, 2004; Xia and Zhang, 2010). For example, JCPenney, Walgreens, and Office Depot have increased customer visits to their physical outlets by tightening the cooperation between their web sites and physical stores, such as allowing online inventory data lookup for each store location and online prescription pickup at the chosen physical store (Gulati and Garino, 2000; Porter, 2001; Berner, 2007). In addition, with physical outlets, retail chains can provide online customers with a free option of "ship to store." Moreover, some retail chains upgrade the option with additional convenience. Shoppers can buy products online, schedule a pickup time, and have employees meet them curbside with their purchased goods (Tuttle, 2012). Product return is another critical concern in online retailing because returns occur more frequently in Internet retailing than in traditional retailing (Xia and Zhang, 2010). The store format also allows retail chains to provide the service of "return to store," which helps retail chains build advantages in e-Retail operations (Vishwanath and Mulvin, 2001).

Since m-Retailing involves online transactions with wireless networks, retail chains can extend such store-based synergies from e-Retailing to m-Retailing. Both options of in-store pickups and return/exchange are also applicable to m-Retailing, perhaps even to a greater extent due to mobility and physical proximity enabled by mobile devices. The new mobile channel also brings extra traffic to physical outlets. Customers can browse and check out products through mobile sites at anytime from anywhere, especially when they receive location-based services like promotions and advertisements on such platforms as iAd and AdMob. Afterwards, they can go to the physical outlets nearby to touch and feel products and to make sure they fit with their taste or size. Alternatively, after browsing products on their mobile devices, customers can go to physical outlets and purchase the products right away without waiting for deliveries (The Economist, 2012). This combination of location and mobility fulfills the so-called "instant gratification" that is said to characterize the Millennial and younger generations.

Overall, when compared with other non-store e-Retailers (i.e., catalog retailers, web-only retailers, and manufacturers), retail chains with their physical store presence are in a better position to create cross-channel synergies when they step into the mobile channels. Therefore, retail chains are hypothesized to be more likely to adopt an m-Retail channel (adoption decision) and invest more in system development (extent of adoption) to exploit the potential of this new sales channel. Because of the aforementioned synergies, retail chains are also expected to enjoy higher m-Retail sales, traffic, and conversion rate.

H4: Compared with the other firm types, retail chains are more likely to adopt mobile sales channel.

H5: Compared with the other firm types, retail chains invest more in m-Retailing platforms (extent of adoption).

H6: Compared with the other firm types, retail chains have better performances of mobile sales channel.

E-Retail market share represents a firm’s relative size/scale in the product category. In order to achieve a significant size/scale in a product market, a firm needs to acquire and deploy corresponding resources and capabilities. For example, Grewal et al. (2004) argue that economic reward alone is not a strong enough incentive to maintain a stable customer base online when competition is only a click of mouse or a touch of screen away. Instead, reliable order fulfillment and customer trust are two equally important drivers for determining the success of online transactions. The former increases online customer satisfaction and the latter reduces perceived risks associated with online transactions. Zhu (2004) and Zhu and Kraemer(2005) use survey methods to evaluate firms in the retail industry and find that firms with tight electronic integration of back-end infrastructures, such as inventory and order fulfillment, are found to have better e-Retail and overall financial performances. Hulland et al. (2007) find that e-Retailers' brand management and customer service capabilities are positively associated with their e-Retail performances. Since a mobile retail channel extends e-Retailing and represents the next generation of online shopping platform, these core e-Retail capabilities are critical to the success of m-Retailing as well. Arguably, firms can extend their e-Retail advantages into the m-Retail arena by leveraging their existing organizational e-commerce competencies.

I thus hypothesize that firms with significant e-Retail market share and accumulated resources are inclined to take initiatives to adopt m-Retail channels. In addition, firms' extents of adoption can vary with their system implementation choices. Firms that perceive more benefits accumulated from e-Retail channels have incentives and resources to offer more advanced m-Retail system functions. Finally, firms can benefit from the experiences and capabilities acquired from e-Retail channels and achieve better performances in m-Retail channels.

H7: Firms' e-Retail market shares are positively associated with their adoption decisions of mobile retail channel.

H8: Firms' e-Retail market shares are positively associated with their extent of adoption of mobile retail channel.

H9: Firms' e-Retail market shares are positively associated with their performances of mobile retail channel (sales, traffic, and conversion rate).

According to a survey of 117 firms with mobile retail channels, 56% of them report that their average dollar amount of orders received through this channel is less than $75 dollars (Brohan, 2011). One possible explanation for the small order value is customers' security concerns for mobile transactions. Customers' perception of security uncertainty about mobile commerce has been found to affect their trust (Siau and Shen, 2003) as well as usages of mobile data services (Yun et al., 2011). As a result, customers tend to make purchases with small order values to reduce the potential risk. In addition, due to hardware constraints of mobile devices and the typically short duration of usage occasion, m-commerce to a great extent is about spontaneous and instant shopping (Anckar and D'Incau, 2002). In other words, when using the m-Retail channel, customers tend to buy products that involve instant decisions without significant information search and price comparison (Shankar and Balasubramanian, 2009). Transactions with small order values satisfy these spontaneous buying criteria.

Since m-Retailing is an extended form of e-Retailing, customers' purchase patterns such as order quantities for specific products and firms' product/service offerings are not substantially different between the two channels. According to the earlier discussion about security concerns, hardware constraints, and spontaneous purchasing, a firm with low average order value in e-Retailing is likely to sell products that better fit with the mobile retail channel. Thus, those firms should have more incentives to adopt m-Retailing and further deploy advanced system features on the mobile platform. Regarding firms' performances in the m-Retail channel, I expect to observe a similar association between low average order value in e-Retailing and strong performances in m-Retailing. I thus posit the following hypotheses regarding e-Retail order value:

H10: Firms' e-Retail order values are negatively associated with their adoption decisions of mobile retail channel.

H11: Firms' e-Retail order values are negatively associated with their extent of adoption of mobile retail channel.

H12: Firms' e-Retail order values are negatively associated with their performances of mobile retail channel (sales, traffic, and conversion rate).

Demographic characteristics such as age and gender have been identified as key factors that drive IT adoption and usage (e.g., Morris and Venkatesh, 2000; Mitchell and Walsh, 2004). In the mobile commerce context, Anckar and D'Incau (2002) conduct a consumer survey in Finland and report that customer willingness to use mobile data services is higher for the younger generations. In a more recent survey conducted by National Retail Federation (2010), 26.8% of American adults with a smart phone report use of these devices to research or make holiday purchases, and that number jumps to 45% among young adults from 18 to 24 years of age. Based on these surveys, young adults are found more likely to opt into the mobile retail channel. Progressive Grocer (2012) reports that young adults have stronger brand preferences compared with their friends and families. Moreover, the young generation tends to influence their peers' purchase decisions and hence bring additional customers to a retailer through word-of-mouth and referrals. From the firm's perspective, offering the mobile retail channel is a sensible and viable strategy to improve shopping convenience and win over young consumers.

Given the evidence that young adults make up a significant proportion of potential m-Retailing patrons, a firm is likely to adopt and invest more in the mobile retail channel when *the average age of its existing e-Retail shoppers* is young. For a firm with a relatively young e-Retail consumer base, it is expected that these existing young shoppers are also willing to experience the m-Retail channel offered by the firm. This carryover effect is likely to take hold in on-line retailing as customer loyalty is found to be higher online than offline (Shankar et al., 2003). Considering young consumers' willingness to use the new mobile channel and the carryover effect, I expect firms with *younger average age of existing e-Retail shoppers* to have better performances in the mobile retail channel.

H13: Firms' e-Retail average shopper ages are negatively associated with their adoption decisions of mobile retail channel.

H14: Firms' e-Retail average shopper ages are negatively associated with their extent of adoption of mobile retail channel.

H15: Firms' e-Retail average shopper ages are negatively associated with their performances of mobile retail channel (sales, traffic, and conversion rate).

In prior e-commerce literature, the availability and quality of relevant information has been identified as a key driver of online transactions success. Customers express greater satisfaction when an e-commerce website provides detailed product information (Palmer, 2002). Zhu and Kramer (2002) also find that on-line firms outperform competitors if they possess better information capability (e.g., providing customers with useful information). The notion of information capability is even more important in the context of m-Retailing (Venkatesh et al., 2003). While mobility and ubiquitous computing encourage customers' adoption and firms’ implementation of m-commerce, mobility/ubiquity also comes at a price when customers need to endure hardware limitations such as small screen and relatively low connection speed. These hardware constraints of mobile devices raise the need for efficient and effective information delivery so that customers can have easy access to useful product/service information.

Zhou (2011) finds that system qualities in terms of stability, navigation and layout have influences on customers’ satisfactions with mobile websites. Halladay (2011) argues that convenient product search capability is among the critical success factors of the m-Retail channel. These factors (e.g., layout, search, etc.) are closely related to information display and delivery. Thus, when firms choose to implement m-Retailing, they must manifest information capability through effective and reliable mobile system design. Specifically, m-Retailers cultivate information capability by developing system functions that can meet customers’ information requirements and accommodate the technical hardware constraints mentioned above. Zhu and Kraemer (2002) define information capability in terms of provision of product information online, search capability, availability of product review, and product support. Accordingly, I examine information capability by looking into system features that fall into the four dimensions they define. As discussed earlier, the importance of information capability is paramount for m-Retailing. Creating and deploying an array of system functions that elevate information capability is expected to enhance customer participation and satisfaction and eventually can create more business value.

H16: Firms that develop mobile websites with advanced information capability through system features are more likely to have better performances of mobile retailing channels (sales, traffic, and conversion rate).

Formats of m-Retail channels include mobile websites as well as mobile applications. While the former is similar to e-commerce websites, the latter is a unique feature in the m-commerce context. Compared with mobile websites, mobile applications have the advantage of providing more interactive user experiences (Chandra, 2011). For example, Pizza Hut provides a mobile application that allows customers to virtually build their pizzas and place orders (Butcher, 2009). Amazon offers a mobile application that enables customers to scan products in-store, compare prices on the spot, and sends purchase promotions to customers who checked items through the application (AisleBuyer, 2012).

The key utility of mobile applications comes from interactivity, which facilitates two-way communication between customers and merchants. In the e-commerce literature, interactivity has been found to be a driver of online transactions success (Palmer, 2002). Srinivasan et al. (2002) find that interactivity is an important antecedent of customer loyalty, which in turn has positive impacts on word-of-mouth and willingness to pay. Since m-Retailing is essentially another form of online retailing, interactivity also yields leverage that forward-looking firms should consider to capitalize on (Piccoli et al., 2004). Provision of mobile applications indicates a better and smoother interactive environment which helps bring in more customers and more sales revenue. I hypothesize the following:

H17: Firms that choose to implement mobile applications are more likely to show better performances of mobile retailing channels (sales, traffic, and conversion rate).

Chapter 4

DATA AND VARIABLES

4.1 Adoption

As one major focus of the study is to explore the dependency between e-Retailing and m-Retailing, I use U.S. Top 500 e-Retailers as the sample for the first stage of adoption study. The data set is collected from Top 500 Guide published by Internet Retailer, a monthly national business magazine. The Top 500 Guide provides an annual ranking of the largest e-Retailers in the United States and Canada based on annual online sales. To develop its annual ranking, Internet Retailer collects a retailer's sales data for its e-commerce channel from the company. When the company does not provide sales figures, Internet Retailer estimates sales data based on traffic, assumed conversion rate, and average order value. Traffic data of a retailer's e-commerce is collected from the company or from third-party agencies if the company does not reveal figures. Two firms comSource Inc. and Nielson Online are the agencies responsible for e-commerce traffic. Retailers have opportunities to review and respond to their estimates.

According to the survey conducted by Shop.org (2010), 80% of retailers still do not have clearly defined operations strategies for m-commerce. Since firms have just started to build their m-Retail channels, I look at the cross-sectional data set of top e-Retailers from Internet Retailer in 2010. Among these 500 firms, there are 161 firms who already had adopted m-Retail channels in 2010. Yet, due to missing data of variables, the data set for estimation consists of 456 firms and among them 152 are adopters. The firms in the sample are either retail chains or other non-store e-Retailers including catalog retailers, manufacturers, and web-only retailers. The firms also belong to one of the following thirteen product markets: apparel/accessories, automotive parts/accessories, books/music/video, computers/electronics, flowers/gifts, food/drug, hardware/home improvement, health/beauty, housewares/home furnishings, jewelry, mass merchant, office supplies, specialty/non-apparel, sporting goods, and toys/hobbies. Table 1 provides descriptions about distributions of adopters and non-adopters of firms.

Table 1. Description of adopting and non-adopting firms

Adoption Decision	Firm Type	Count	Example
Adopting Firms (*N*=152)	Retail chain	67	Best Buy
	Other non-store e-Retailers	85	1800Flowers.com
Non-adopting firms (*N*=304)	Retail chain	73	Ann Taylor
	Other non-store e-Retailers	231	Boston Apparel Group

For the adoption study, the dependent variable *m-Retail adoption* is dichotomously defined as adopters and non-adopters. I also define extent of adoption based on firms' system implementation choices. By combining with another data source, Internet Retailer's Mobile Commerce Top 300 in 2011, I collect data on system implementation choices regarding development of mobile applications (*mobile application*) and product information navigation and presentation (*count of information functions*) for adopting firms. The Mobile Commerce Top 300 is a recently-published annual ranking of mobile sales channels for firms across retailing, hotel and airline industries.

Two system implementation choices serve as dependent variables to represent a firm's extent of adoption. Because of missing data, samples of the two variables are 98 (*mobile application*) and 141 (*count of information functions*) firms, respectively. *Mobile application* is a dummy variable that takes the value of 1 for firms with mobile applications and 0 otherwise. I operationalize a firm's ability to provide product information through m-Retail system functions by following the metric proposed by Zhu and Kramer (2002). The authors define four dimensions of information capability as provision of product information, search capability, availability of product reviews, and product support. C*ount of information functions* is the sum of m-Retail system functions aligned with these four dimensions (see Table 2).

Table 2. Classification of Information System Functions

Information Capability (Zhu and Kramer, 2002)	System Functions
Provision of Product Information	- Alternate image - Multiple hero shots - Featured products - Product image
Search Capability	- Site search - Advanced site search - Slidebar of products - Barcode scan
Availability of Product Review	- Customer reviews
Product Support	- Contact us form

Independent variables reflect e-Retail characteristics. The variable, *e-Retail function*, represents the intensity of a firm's ability to provide digitalized services through system functions relative to its peers, and I use the estimation method by Tsai et al. (2012). I first take the ratio of 1 (if the firm has the feature) over the total number of firms that have the same feature and sum up such ratios for 60 features (Appendix A shows the complete list of e-Retailer functions). This ratio sum number is then normalized to show a firm's relative advance compared with peers. In other words, a firm's e-Retail function is represented by Z score with consideration of average and variations of peers. *Retail chain* is a dummy variable and takes the value of 1 for retail chains and 0 for others. The variable, *e-Retail market share,* represents the percent of a firm's e-Retail sales to total sales of the product market. I use *e-Retail order value* and *e-Retail shopper age* to reflect the extent to which a firm is susceptible to the specifics of the m-Retail channel. Since consumers tend to make small purchases in the m-Retail channel, *e-Retail order value* is used to measure the average dollar amount of orders that customers place through the e-Retail channel. As young population is more likely to use mobile data services, *e-Retail shopper age* is used to indicate the average age of customers who make purchases through the e-Retail channel.

Control variables include differences between public and private firms as well as market competition. *Public firm* is a dummy variable reflecting whether the firm is publicly traded. Public firms are believed to have access to resources such as financial capital more easily (Srinivasan and Moorman, 2005). *Market competition* is the variable to reflect the competitive level of a market where a firm operates. The variable is operationalized by Herfindahl-Hirschman index (HHI) of a firm's e-Retail product market for the model of adoption decision and by the percent of e-Retailers in a product market that have adopted the mobile retail channel for the models of extent of adoption (Krishnan, 2005; Zhu et al., 2003). Table 3 lists the variables and their summary statistics and Table 4 shows the correlation matrix of variables.

Table 3. Variable Description and Summary of Statistics for Adoption Study

Variable	Description	Mean	S.D.	Min	Max
Adoption Decision: Dependent Variable (*N*=456)					
M-commerce Adoption	Dummy variable, 1 for adopters and 0 for non-adopters	0.3333	0.4719	0	1
Independent Variable					
E-Retail Function	Intensity of the firm's ability to provide digitized services through e-Retail system functions	-0.0196	0.9503	-2.0524	4.0068
Retail Chain	Dummy variable, 1 for retail chains and 0 otherwise	0.3070	0.4617	0	1
E-Retail Market Share	Percent of a firm's e-Retail sales to total sales of the product market	0.0304	0.0701	0.0004	0.6056
E-Retail Order Value	Average dollar value of purchases made through the e-Retail channel	192.71	217.58	8	1800
E-Retail Shopper Age	Average age of e-Retail shoppers	40.147	2.5180	34	47.1
Control Variable					
Public Firm	Dummy variable, 1 for public firms and 0 otherwise	0.2917	0.4550	0	1
Market Competition	Herfindahl-Hirschman index (HHI) of an e-Retail product market	0.1346	0.1101	0.0298	0.3822
Extent of Adoption: Dependent Variable (N_{info}=141, *and* N_{app}=98)					
Count of Information Functions	Count of the system functions designed to provide product information	5.1560	1.4846	1	9
Mobile Application	Dummy variable, 1 for firms with mobile applications and 0 otherwise	0.5612	0.4988	0	1

Control Variable (only variables different from those of adoption decision are listed)					
Market Competition	Percent of e-Retailers in a product market adopting m-Retail channel	37.843	15.195	14.58	66.67

Table 4 Correlation Matrix for Adoption Study

Variable	1	2	3	4	5	6	7
E-Retail Function	1.000						
Retail Chain	0.114	1.000					
E-Retail Market Share	0.175	0.080	1.000				
E-Retail Order Value	-0.036	-0.098	0.072	1.000			
E-Retail Shopper Age	0.022	-0.151	0.082	-0.008	1.000		
Public Firm	0.091	0.305	0.255	0.014	-0.085	1.000	
Market Comp.	0.127	0.002	0.219	0.037	0.253	-0.017	1.000

4.2 Value

To construct the data set for the second stage of value study, I collect m-Retail performance data from Internet Retailer's Mobile Commerce Top 300 in 2011. Mobile Commerce Top 300 provides an annual ranking of mobile sales channels for firms across retailing, hotel and airline industries. Internet Retailer collects sales data for a firm's m-commerce channels from the company. When the company does not provide sales figures, Internet Retailer estimates sales data based on traffic, assumed conversion rate, and average ticket. Traffic data of a firm's m-commerce channels is collected from the company or from a third-party agency if the company does not reveal figures. Ground Truth is the third-party agency responsible for estimating m-commerce traffic. Retailers have opportunities to review and respond to their estimates.

From the top 300 m-commerce firms, I find 100 firms are also listed in U.S. Top 500 e-Retailers Guide and thus I have data of their e-Retail characteristics. In addition, I find another 37 firms listed in Internet Retailer's Top300 Europe Guide for e-Retailers. Top 300 Europe Guide is another annual ranking published by Internet Retailer which provides data and ranking for the largest e-Retailers in Europe. Overall, the data set contains 137 firms from U.S. and various countries from Europe.

The firms in the sample are either retail chains or other non-store e-Retailers including catalog retailers, manufacturers, and web-only retailers. The firms also belong to one of the following thirteen product markets: apparel/accessories, automotive parts/accessories, books/music/video, computers/electronics, flowers/gifts, food/drug, hardware/home improvement, health/beauty, housewares/home furnishings, jewelry, mass merchant, office supplies, specialty/non-apparel, sporting goods, and toys/hobbies. Since m-Retailing is still in its early developing stage, the data collected is cross-sectional for the year of 2011. I only consider a firm's performance of mobile sales channel to keep inter-firm comparisons on an equal footing. In other words, I only measure performance of the "mobile retail" segment of each firm. Table 5 provides descriptions of m-Retailers in the sample.

Table 5. Description of m-Retailers

M-Retailer Type	**Counts**	**Examples**
Retail chains	76	Target
Other non-store e-Retailers	61	1800Flowers.com
Product Market of m-Retailers	**Counts**	**Examples**
Mass merchant	24	Macy's
Apparel/accessories	46	H&M
Automotiveparts/accessories	1	Halfords
Books/music/video	6	Follett Higher Education Group
Computers/electronics	15	Best Buy
Flowers/gifts	3	1800Flowers.com
Food/drug	4	Walgreen
Hardware/home improvement	4	The Home Depot
Health/beauty	6	Sephora
Housewares/home furnishings	5	Brookstone
Jewelry	2	Blue Nile
Office supplies	3	Staples
Specialty/non-apparel	9	Musician's Friend
Sporting goods	7	Recreational Equipment Inc
Toys/hobbies	2	ToysRUs

I measure performances of a firm's mobile sales channels in sales, traffic, and m-Retail conversion rate. The variable *m-Retail sales* represent the natural logarithm of a firm's total mobile sales for the year. *M-Retail traffic* is measured as the natural logarithm of average monthly number of unique visitors to the mobile sales channel and it reflects the traction of mobile site to attract potential paying customers. *M-Retail conversion rate* captures the percentage of visitors who make purchases. Similar to the adoption study, I explore the influences of the following e-Retail characteristics on m-Retail performances: *e-Retail function, retail chain, e-Retail market share, e-Retail order value*, and e-*Retail shopper age*.

In addition, I examine the influences of the two m-Retail system implementation choices: development of mobile application and a firm's ability to provide effective product information through system functions. *Mobile application* is a dummy variable and takes the value of 1 for an adopting firm that chooses to implement a mobile application and 0 otherwise. The variable *information capability* reflects the intensity of a firm's ability to provide accurate information through system functions relative to the peers. I first take the ratio of 1 (if the firm has the feature) over the total number of firms that have the same feature and sum up such ratios for 10 features. This ratio sum number is then normalized to show a firm's relative advance compared with the peers in terms of information capability (Tsai et al., 2012).

In terms of control variables, I include differences between public and private firms, market competition, and differences between U.S. and European markets. Similar to the adoption study, *public firm* and *market competition* are included in the model. Because firms included in the value study are in the U.S. and European markets, *country* is also included as a dummy variable to control for geographic differences between the two markets. It takes the value of 1 for the U.S. and 0 for European countries. Table 6 lists the variables and their descriptions, and Table 7 shows the correlation matrix of variables. The data sample for the sales performance has 137 firms, and that for the traffic performance and for conversion rate has 135 firms respectively. The variable, *e-Retail shopper age*, is only available for firms in the U.S. market, and thus data samples of models with this variable included are down to 98 firms for m-Retail sales and 97 firms for traffic and conversion rate. Accordingly, the correlation between variables of e-Retail shopper age and country in the correlation matrix is missing.

Table 6. Variable Description and Summary of Statistics for Value Study

Variable	**Description**	**Mean**	**S.D.**	**Min**	**Max**
M-Retail Sales	Natural logarithm of total mobile sales (thousands)	7.9969	1.7551	4.1057	14.509
M-Retail Traffic	Natural logarithm of average unique visitors	11.699	1.6768	8.0564	16.499
M-Retail Conversion Rate	Percent of visitors who make purchases	1.6418	1.3613	0.26	12.5
E-Retail Function	Intensity of the firm's ability to provide digitized services through e-Retail system functions	0.6209	1.1625	-1.6808	4.6251
Retail Chain	Dummy variable, 1 for retail chains and 0 otherwise	0.5547	0.4988	0	1
E-Retail Market Share	Percent of a firm's e-Retail sales to total sales of the product market	6.2981	10.547	0.05	60.6
E-Retail Order Value	Average dollar value of purchases made through the e-Retail channel	175.36	129.18	32	924.6
E-Retail Shopper Age	Average age of e-Retail shoppers	39.824	2.6354	34	46.3
Information Capability	Intensity of the firm's ability to provide accurate information through system functions	0.0611	2.4635	-3.0893	7.9018
Mobile Application	Dummy variable, 1 for firms with mobile applications and 0 otherwise	0.5036	0.5018	0	1

Public Firm	Dummy variable, 1 for public firms and 0 otherwise	0.4672	0.5007	0	1
Market Competition	Percent of e-Retailers in a product market adopting m-Retail channel	34.033	14.869	7.69	66.67
Country	Dummy variable, 1 for firms in U.S. and 0 otherwise	0.7299	0.4456	0	1

Table 7 Correlation Matrix for Value Study

Variable	1	2	3	4	5	6	7	8	9	10
E-Retail Function	1.000									
Retail Chain	.089	1.000								
E-Retail Market Share	.145	.019	1.000							
E-Retail Order Value	-.003	-.190	.034	1.000						
E-Retail Shopper Age	.162	-.187	.204	-.102	1.000					
Info. Cap.	.067	.124	.148	-.012	-.148	1.000				
Mobile App.	.082	-.008	.073	-.232	.025	.093	1.000			
Public Firm	-.114	.191	0.106	-.095	.003	.310	.344	1.000		
Market Comp.	.003	-.163	-.116	-.111	.076	.061	.188	.240	1.000	
Country	-.180	-.115	-.037	-.010	--	.062	.152	.240	.428	1.000

Chapter 5

DATA ANALYSIS AND RESULTS

5.1 Adoption

For the adoption study, I explore both dichotomous adoption decision and extent of adoption. For the dichotomous adoption model, I use the logit regression for estimation. The logit function characterized probability of a firm to adopt m-Retail channel is expressed as:

$$P(y_i = Adoption|\, \boldsymbol{X}_i) = \frac{\exp(\boldsymbol{X}_i\gamma)}{1+\exp(\boldsymbol{X}_i\gamma)}$$

where y_i represents a firm's m-Retail adoption decision and $\boldsymbol{X_i}$ is the vector for independent variables. The logit transformation is used to represent a firm's adoption decision as linear function of independent variables. The estimation model employed to study adoption decision of m-Retailing is specified as follows:

$$\text{Logit}[P(y_i = Adoption)] = \ln\left(\frac{P(y_i = Adoption \mid \boldsymbol{X}_i)}{P(y_i = Non-Adoption \mid \boldsymbol{X}_i)}\right)$$

$$= \gamma_0 + \gamma_1 * ERetailFunction_i + \gamma_2 * RetailChain_i + \gamma_3 * ERetailMarketShare_i + \gamma_4 * ERetailOrderValue_i + \gamma_5 * ERetailShopperAge_i + \gamma_6 * PublicFirm_i + \gamma_7 * MarketCompetition_i + \varepsilon_i$$

In terms of extent of adoption, dependent variables include the number of system functions related to information capability (*count of information functions*) and development of mobile applications (*mobile application*). Due to the nature of data, the former is estimated by count data method and the latter is estimated by logit model. The general form of research model employed to study the two system implementation choices is specified as follows:

$$ExtentofAdoption_i = \pi_0 + \pi_1 * ERetailingFunction_i + \pi_2 * RetailChain_i + \pi_3 * ERetailMarketShare_i + \pi_4 * ERetailOrderValue_i + \pi_5 * ERetailShopperAge_i + \pi_6 * PublicFirm_i + \pi_7 * MarketCompetition_i + \varepsilon_i$$

For the discrete dependent variables (i.e., *count of information functions*), I employ the count data regression for estimation. The data set has two issues: under-dispersion and zero truncation. The issue of under-dispersion indicates that the data set has the distributional characteristic (i.e., mean less than variance) that requires a more flexible model than Poisson regression. Poisson regression is the common model used for count data analysis. Yet, one distinct feature of Poisson distribution is equi-dispersion assumption, i.e., the mean of data distribution equal to the variance. Violation of the assumption, either over-dispersion or under-dispersion, indicates a mismatch between specified distribution and observed relationship of explanatory variables and event counts of interest. In addition, the estimated parameter values will be more dispersed than they should be due to a systematic error of an incorrect functional form introduced in the model (Kauffman et al., 2012). Because of the restricted assumption, the Poisson distribution has its practical limitation.

Zero truncation is another important issue that requires additional adjustments of the specified distribution. Zero truncation occurs when the dependent variable is in integer form but there are no zeros observed (Kauffman et al., 2012). Instances include the number of songs that music lovers download from a streaming website and the number of information system functions m-Retailers decide to implement as in the case of my study.

To account for under-dispersion and zero-truncation observed in the count data of information system functions, I apply a general form of Poisson distribution called the zero-truncated Conway-Maxwell-Poisson (COM-Poisson) distribution (Shmueli e t al., 2005; Sellers and Shmueli, 2010). The functional form of the distribution is

$$f(y_i \mid \lambda, \nu) = \frac{\lambda^{y_i}}{(y!)^{\nu} Z(\lambda, \nu)} \Big/ (1 - \frac{1}{Z(\lambda, \nu)})$$

where y_i is a firm's count of system functions, $\lambda > 0$, $\nu \geq 0$, and $Z(\lambda, \nu) = \sum_{j=0}^{\infty} \frac{\lambda^j}{(j!)^{\nu}}$.

Accordingly, the regression model that specifies a count dependent variable *y* to explanatory variables $\boldsymbol{X}$ is in loglinear form: $\log \lambda = \boldsymbol{X}' \beta$ (Sellers and Shmueli, 2010). The parameters of β are estimated by the maximum likelihood method.

Table 8 reports the estimation results for the adoption study. Model 1 is for adoption decision. Model 2 and Model 3 are for extent of adoption (i.e., *count of information functions* and *mobile application*). For the adoption decision, I refer to coefficient estimates in Model 1. Coefficient estimates of *e-Retail function* (γ_1 = 0.6359, *p*-value = 0.000), *retail chain* (γ_2 = 0.5471, *p*-value = 0.019), and *e-Retail market share* (γ_3 = 0.0430, *p*-value = 0.073) supports hypotheses. The results reveal that a firm with better e-Retail functions to provide digitalized services (H2), a retail-chain type of e-Retailer (H5), or/and a firm with stronger e-Retail performance in terms of market share (H8) is more likely to adopt the mobile retail channel.

For extent of adoption, I refer to coefficient estimates in Model 2 (information function) and Model 3 (mobile application). For development of information functions, I find that coefficient estimates of *e-Retail market share* (π_3 = 1.3314, *p*-value = 0.021) and *e-Retail shopper age* (π_5 = -0.0240, *p*-value = 0.000) support hypotheses. This indicates that a firm with better e-Retail performance in market share (H8) or/and younger average e-Retail shopper age (H14) is likely to invest more in system development of the m-Retail channel in terms of information capability. For development of mobile application, the results of Model 3 reveal that coefficient estimates of e-Retail functions (π_1 = 0.4385, *p*-value = 0.040) and e-Retail order value (π_4 = -0.0076, *p*-value = 0.001) support hypotheses. This suggests that a firm with better e-Retail function (H2) or/and lower e-Retail order value (H11) is likely to invest more in system development of the mobile retail channel in terms of mobile applications. Finally, I note that the control variable of *public firm* is significant and positive in all the three models.

Table 8. Estimation Results for Adoption Study

Constructs	Model 1 (Binary Adoption Decision)	Model 2 (Information Functions)	Model 3 (Mobile Application)
E-Retail Function	0.6359*** (0.1316)	0.0203 (0.0590)	0.4385** (0.2132)
Retail Chain	0.5471** (0.2322)	0.1908 (0.1317)	-0.7219 (0.5520)
E-Retail Market Share	0.0430* (0.0239)	1.3314** (0.6449)	0.0234 (0.0456)
E-Retail Order Value	-0.0003 (0.0004)	-0.0003 (0.0003)	-0.0076*** (0.0022)
E-Retail Shopper Age	-0.0633 (0.0456)	-0.0240** (0.0063)	-0.0819 (0.0957)
Public Firm	0.7344** (0.2449)	0.3693** (0.1423)	1.7554*** (0.5002)
Market Competition	0.4187 (1.0572)	0.0002 (0.0047)	0.0081 (0.0215)
Sample Size	456	141	98
Pseudo R-squared	0.1350	0.3893	0.2081
Standard errors in parentheses; *** for $p < 0.001$, ** for $p < 0.05$, * for $p < 0.1$			

5.2 Value

The research model used to study performances of mobile sales channel in the second stage of value study is specified as follows:

$$PerformanceMetric_i = \beta_0 + \beta_1 * ERetailFunction_i + \beta_2 * RetailChain_i + \beta_3 * ERetailMarketShare_i + \beta_4 * ERetailOrderValue_i + \beta_5 * ERetailShopperAge_i + \beta_6 * InformationCapability_i + \beta_7 * MobileApplication_i + \beta_8 * PublicFirm_i + \beta_9 * MarketCompetition_i + \beta_{10} * Country_i + \varepsilon_i$$

The parameters β_0 to β_{10} are to be estimated. The subscripts i index the firm and ε stands for the error terms. The dependent variable of performance metric includes *sales*, *traffic* and *conversion rate*. In testing for multicollinearity, I checked the variance inflation factor (VIF) for all independent variables and confirmed that all of the VIFs are below 10 (Greene, 2008). Sales and traffic models are estimated using robust OLS regression as Wooldridge (2006) suggests that the heteroskedasticity-robust regression is valid irrespective of non-constant variance for the error terms. Because the distribution of conversion rate is right-skewed (see Figure 2), I apply the gamma generalized linear model (GLM) and estimate the model using the maximum likelihood method.

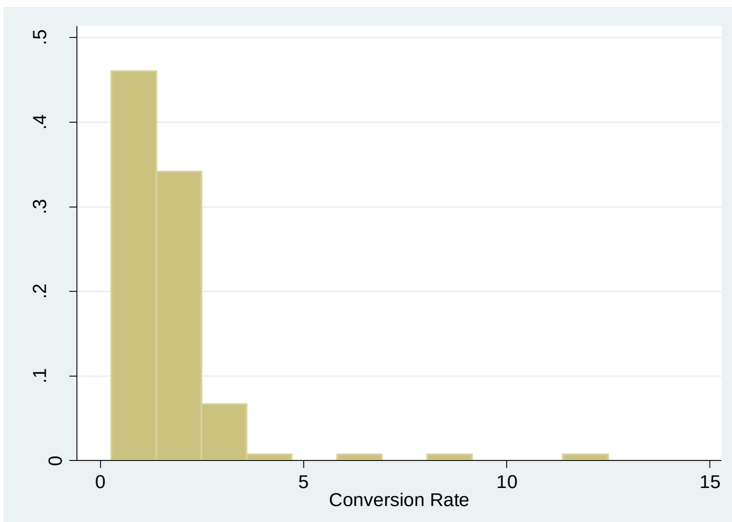

Figure 2. Histogram of Conversion Rate (*N*=137)

Table 9 reports the estimation results for factors that influence performances of mobile retail channel. Models 1 and Model 2 show results for mobile sales, Model 3 and Model 4 for mobile traffic, and Model 5 and Model 6 for mobile conversion rate. Because sample sizes of models with the variable of e-Retail shopper age included are reduced, hypothesis testing excluding the shopper age variable is based on models with full samples. Model 1 (sales), Model 3 (traffic), and Model 5 (conversion rate) are models with full samples and with the variable of *e-Retail shopper age* excluded. Model 2 (sales), Model 4 (traffic) and Model 6 (conversion rate) are models with the variable of *e-Retail shopper age* included.

To test Hypothesis H3, I refer to the coefficient estimate for *e-Retail function*. For the model using mobile sales as the performance metric, the coefficient estimate is positive and significant for Model 1 (β_1 = 0.1835, *p*-value = 0.073). Similar result is observed for Model 3 using mobile traffic as the performance metric (β_1 = 0.2085, *p*-value = 0.083). The coefficient estimate, however, is insignificant for the model using conversion rate as the performance metric. These results reveal a positive correlation between e-Retail functions and m-Retail performances using mobile sales and traffic as performance metrics. To test Hypothesis H6, I refer to the coefficient estimate for *Retail Chain.* For Model 1 (sales), the coefficient estimate is positive and significant (β_2 = 0.3835, *p*-value = 0.074). Model 3 also shows a positive and significant association for *Retail Chain* with m-Retail traffic (β_2 = 0.5427, *p*-value = 0.023). Contrary to the hypothesis, a negative and significant coefficient estimate is found using the performance metric of conversion rate (β_2 = -0.3506, *p*-value = 0.019). The estimation results indicate that retail chains are found to have better m-Retail sales and traffic but lower conversion rate compared with other types of e-Retailers.

To test Hypothesis H9, I refer to the coefficient estimate for *e-Retail market share.* For the model using mobile sales as the performance metric, the coefficient estimate is positive and significant for Model 1 (β_3 = 0.0661, *p*-value = 0.000). Similar results are observed for models using mobile traffic and conversion rate as the performance metrics. For Model 3 (traffic), the coefficient estimate is positive and significant (β_3 = 0.0460, *p*-value = 0.000), and same is for Model 5 using conversion rate as the performance metric (β_3 = 0.0351, *p*-value = 0.012). The result supports Hypothesis H9 and indicates that a positive correlation exists between a firm's e-Retail market share and its m-Retail performance. To test Hypothesis H12, I refer to the coefficient estimate for *e-Retail order value.* For Model 5 (conversion rate), the coefficient estimate is negative and significant (β_4 = -0.0012, *p*-value = 0.000). This result supports Hypothesis H12 and indicates a negative association between a firm's e-Retail order value and its m-Retail conversion rate. For Model 1 (sales), the coefficient estimate is, nevertheless contrary to the hypothesis, positive and significant (β_4 = 0.0018, *p*-value = 0.008).

To test Hypothesis H15, I refer to the coefficient estimate for *e-Retail shopper age.* For Model 2 (sales), the coefficient estimate is negative and significant (β_5 = -0.0958, *p*-value = 0.039). Model 4 also shows a negative and significant association for *e-Retail shopper age* with m-Retail traffic (β_5 = -0.0885, *p*-value = 0.078). The estimation results provide support for Hypothesis H15 and suggest that a negative correlation between e-Retail shopper age and m-Retail performances using mobile sales and traffic as performance metrics. Nevertheless, the coefficient estimate for Model 6 using the metric of conversion rate is positive and significant (β_5 = 0.0602, *p*-value = 0.043).

To test Hypothesis H16, I refer to the coefficient estimate for *information capability*. For Model 1 (sales), the coefficient estimate is positive and significant (β_6 = 0.1281, *p*-value = 0.004). Similar result is observed for Model 3 using traffic as the performance metric (β_6 = 0.1340, p-value = 0.003). The result supports Hypothesis H16 and indicates that a positive correlation exists between information functions of the m-Retail channel and a firm's m-Retail sales as well as its traffic. To test Hypothesis H17, I examine the coefficient estimate for *mobile application*. The coefficient estimate is positive and significant for Model 1 using sales as the performance metric (β_7 = 0.5311, p-value = 0.033) and for Model 5 using conversion rate as the performance metric (β_7 = 0.2476, p-value = 0.077). Table 10 summarizes the results for the adoption and value studies.

Table 9. Estimation Results for Value Study

Constructs	**Model 1 (Sales)**	**Model 2 (Sales)**	**Model 3 (Traffic)**	**Model 4 (Traffic)**
E-Retail Function	0.1835* (0.1015)	0.2744** (0.1160)	0.2085* (0.1194)	0.3718** (0.1399)
Retail Chain	0.3835* (0.2125)	0.5337** (0.2655)	0.5427** (0.2360)	0.6544** (0.2840)
E-Retail Market Share	0.0661*** (0.0125)	0.0727*** (0.0138)	0.0460*** (0.0123)	0.0478*** (0.0139)
E-Retail Order Value	0.0018** (0.0006)	0.0010 (0.0009)	-0.0007 (0.0007)	-0.0013 (0.0009)
E-Retail Shopper Age	--	-0.0958** (0.0458)	--	-0.0885* (0.0496)
Information Capability	0.1281** (0.0437)	0.1025** (0.0481)	0.1340** (0.0441)	0.1324** (0.0504)
Mobile Application	0.5311** (0.2466)	0.4805 (0.3136)	0.3028 (0.2533)	0.2629 (0.3116)
Public Firm	0.8326*** (0.2462)	0.7791** (0.3272)	0.7051** (0.2642)	0.6297* (0.3586)
Market Competition	0.0355*** (0.2515)	0.0411*** (0.0096)	0.0310*** (0.0087)	0.0346*** (0.0096)
Country	-1.3933*** (0.2515)	--	-1.2151*** (0.2700)	--
Sample Size	137	98	135	97
R-squared	0.5413	0.6017	0.4521	0.5395
Standard errors in parentheses; *** for $p < 0.001$, ** for $p < 0.05$, * for $p < 0.1$				

Constructs	**Model 5 (Conversion Rate)**	**Model 6 (Conversion Rate)**
E-Retail Function	-0.0697 (0.0724)	-0.1955*** (0.0454)
Retail Chain	-0.3506** (0.1492)	-0.1988 (0.1337)
E-Retail Market Share	0.0351** (0.0139)	0.0333** (0.0141)
E-Retail Order Value	-0.0012*** (0.0003)	-0.0014*** (0.0003)
E-Retail Shopper Age	--	0.0601** (0.0297)
Information Capability	0.0146 (0.0221)	0.0177 (0.0210)
Mobile Application	0.2476* (0.1402)	0.2455** (0.1277)
Public Firm	0.1059 (0.1496)	0.0533 (0.1648)
Market Competition	0.0085 (0.0055)	0.0115** (0.0054)
Country	-0.3733* (0.2179)	--
Sample Size	135	97
R-squared	0.4472	0.5995
Standard errors in parentheses; *** for $p < 0.001$, ** for $p < 0.05$, * for $p < 0.1$		

Table 10. Summary Results of Hypotheses

Variable	Adoption	Extent of Adoption	Value
e-Retail Function	H1: supported	H2: supported for development of application	H3: supported for sales and traffic
e-Retailer Type	H4: supported	H5: not supported	H6: supported for sales and traffic but opposite for conversion rate
e-Retail Market Share	H7: supported	H8: supported for information functions	H9: supported
e-Retail Order Value	H10: not supported	H11: supported for development of application	H12: supported for conversion rate but opposite for sales
e-Retail Shopper Age	H13: not supported	H14: supported for information functions	H15: supported for sales and traffic but opposite for conversion rate
Information Capability	--	--	H16: supported for sales and traffic
Development of Mobile Application	--	--	H17: supported for sales and conversion rate

5.3 Robustness Check

For Model 1 on binary adoption decision in Table 6, I examine a firm's adoption status in 2010 irrespective of timing of adoption. It is possible that the propensity of adoption is different each year. With specific information of adoption years for 106 adopting firms, Figure 3 depicts the Kaplan-Meier curve of the adoption probability for 422 e-Retailers in the U.S. market from 2007 to 2010.

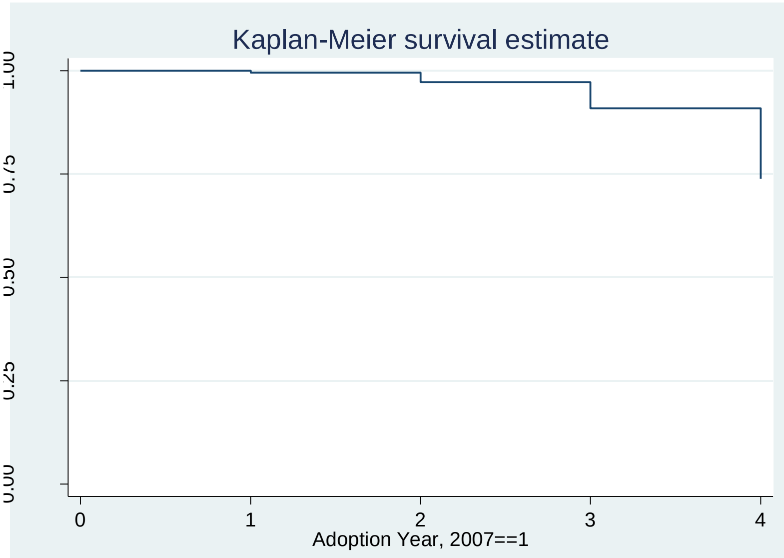

Figure 3. Kaplan-Meier Adoption Probability (from 2007 to 2010)

I use a logit model with year dummies to incorporate the discrete time effect of adoption in different years (Rabe-Hesketh and Skrondal, 2008). I note that data on factors explaining a firm's adoption decision is cross-sectional in 2010. Since the time period is short and the variables of e-Retail function, retail chain, e-Retail market share, e-Retail order value, and e-Retail shopper age are less likely to change dramatically in four years, I assume the same values for the data of a firm across the four years. Still, because of this constant values assumption for these independent variables, this robustness check is deemed not perfect but informative. The estimation model employed to study adoption decision with timing of adoption included (*d*1-*d*3) is specified as follows:

$$\text{Logit}[P(y_i = Adoption)] = \ln\left(\frac{P(y_i = Adoption \mid \boldsymbol{X}_i)}{P(y_i = Non-Adoption \mid \boldsymbol{X}_i)}\right)$$

$= \lambda_0 + \lambda_1 * ERetailFunction_i + \lambda_2 * RetailChain_i + \lambda_3 * ERetailMarketShare_i +$

$\lambda_4 * ERetailOrderValue_i + \lambda_5 * ERetailShopperAge_i + \lambda_6 * PublicFirm_i + \lambda_7 *$

$MarketCompetition_i + \lambda_{8\text{-}10} \sum_1^3 d_j + \varepsilon_i$

Table 11 presents the results for this robustness check. Consistent with the results in Model 1, coefficient estimates of *e-Retail function* (λ_1 = 0.6385, *p*-value = 0.000), *retail chain* (λ_2 = 0.7321, *p*-value = 0.005), and *e-Retail market share* (λ_3 = 0.0438, *p*-value = 0.002) are found to be positively associated with a firm's adoption decision. While treating the year of 2010 as the base year, the three year dummies are observed as negative and significant (λ_8 = -4.3206, *p*-value = 0.000, λ_9 = -2.7439, *p*-value = 0.000, λ_{10} = -1.5044, *p*-value = 0.000). This indicates that adoption propensity varies and increases across years.

Table 11. Robustness Check for Binary Adoption Model

Var.	E-Retail Fun.	Retail Chain	E-Retail Market Share	E-Retail Order Value	E-Retail Shopper Age	Yr-07	Yr-08	Yr-09
Cof.	0.64*** (0.11)	0.73** (0.26)	0.04** (0.01)	-0.00 (0.00)	-0.04 (0.05)	-4.32*** (0.77)	-2.74*** (0.39)	-1.50*** (0.27)
Sample size: 1443; Pseudo R-squared: 0.2778 Standard errors in parentheses; *** for *p* < 0.001, ** for *p* < 0.05, * for *p* < 0.1								

Chapter 6

DISCUSSION

The study conducts an exploratory analysis of firms' migration from e-Retailing to m-Retailing. Grounded in the path dependency perspective, I propose and test a research model to assess how a firm's e-Retail characteristics impact adoption decision, extent of adoption, and business value of m-Retailing. The research model also takes into account the influence of extent of adoption on value realization from the IT innovation being studied, i.e., the mobile Retail channel. In this chapter, I will discuss in detail the empirical results of the proposed model.

6. 1 Adoption

For the *binary adoption model,* I find that the three factors related to e-Retail operational competence (i.e., e-Retail function, e-Retailer type, and e-Retail market share) are significant determinants of adoption decision. An unexpected finding is that no significant impact on adoption decision is found associated with the two factors related to customer preferences (i.e., e-Retail order value and e-Retail shopper age). Although I hypothesize that firms with smaller order value or younger shopper age would have incentives and hence be more likely to adopt m-Retailing, the results suggest that operating resources are sufficient to distinguish adopters from non-adopters. Instead of discounting the influence of customer preferences on a firm's adoption altogether, a more appropriate interpretation is that due to the recent emergence of m-commerce, firms are inclined to quickly grasp at the additional sales opportunities if they have either technological competence (i.e., comprehensive e-Retail functions to provide digitalized services) or strong market performance in their specialized field (i.e., high market share and economies of scale/scope). That is, as firms sense that they have operational edge to fuel channel expansion and move ahead of competitors, they are willing to enter the new market channel even when their order value or shopper age may not fit best with mobile Retailing. For example, despite the wide range of shopper age their customers may show, retail chains as a group are still more likely to adopt m-Retailing simply because they see chances of creating cross-channel synergies between e-Retailing and m-Retailing in terms of in-store pickups, exchange and return, etc. The nature of mobility also enhances their location advantages as customers can browse mobile sites at anytime from anywhere, choose to go to physical outlets nearby to check out a product to ensure its fit, and purchase the product on the spot without having to wait for delivery. The significance of the three operation-related factors and the non-significance of the two customer-related factors in the adoption decision are interesting and reflect the subtle dependency relationship between e-Retailing and m-Retailing.

On top of the adoption decision, my study further examines a firm's extent of adoption in terms of its system development in mobile Retailing. As I focus on the sample of adopting firms and continue to assess the impacts of e-Retail characteristics on extent of adoption, their impacts observed here are different from those in the binary adoption model. While operating resources seem to be sufficient to differentiate adopters from non-adopters, factors related to customer preferences are found able to explain an adopting firm's involvement and commitment in terms of system development. With respect to operation-oriented factors, a firm's e-Retail market share and complementary resources to support m-Retail operations have significant effects on the development of information functions among adopters. I also find that technologically innovative/competent firms with more e-Retail functions are more likely to deploy mobile applications. Different from the results of the adoption decision model, the customer dimension comes into play. E-Retail shopper age is significantly associated with firms' implementation of information functions. Similarly, I find that firms with smaller e-Retail order value have greater odds of implementing mobile applications. Since spontaneous shopping decisions are more likely to take place when order value is small, firms are incentivized to develop mobile applications that can stimulate instant or impulsive shopping.

To sum up, while operation-related factors still have effects on the extent of adoption, the empirical evidence suggests that customer-related factors now have impacts on the extent of adoption which do not manifest in the adoption decision. This difference in observations associated with customer-related factors is understandable. Even though firms with operational edge may enter the mobile domain simply for the sake of expansion, eventually they need to allure and satisfy customers to sustain the new mobile sales channel. Therefore, their system implementation choices must be driven by or related to customer preferences. As such, firms will be able to capitalize on the younger generation who use mobile data services extensively and to maximize the conversion of potential small-value orders. With that said, operating resources still have non-negligible impacts on extent of adoption. The finding makes practical sense since firms in a better position (i.e., high market share) or with technology competence (i.e., more e-Retail functions) are expected to be more capable of trying out mobile system features. Taken together, the significant influences of operation- and customer-related factors on extent of adoption suggest support for the dependency perspective.

6. 2 Value

To empirically assess the link between innovation-related variables and the value of an IT innovation, the study demonstrates influences of a firm's e-Retail characteristics and extent of adoption on value realization from adopting the m-Retail channel. In support of the dependency perspective, the empirical analysis shows that a firm's e-Retail characteristics have substantial influences on m-Retail performance in addition to their impacts on m-Retail adoption decision and extent of adoption. I also find that firm's extent of adoption of the new channel, i.e., the two system implementation choices, are significant determinants of business value in m-Retailing. Regarding value of m-Retailing, my study focuses on three performance metrics -- sales, traffic, and conversion rate. While these metrics are related, influences of e-Retail characteristics and extent of adoption on each metric can be different. Overall, effects of explanatory factors on sales and traffic are similar. Interestingly, I find that conversion rate exhibits a different pattern from that of sales and traffic.

All the three operation-oriented factors (i.e., e-Retail function, e-Retailer type, and e-Retail market share) are significantly associated with firms' performance in the mobile domain. On the one hand, e-Retail function indicates a firm's technology competency to provide digitalized services. On the other hand, when customers have good perceptions about a firm's e-service quality driven by e-service functions, customers tend to build their perceived m-service quality of the firm based on their prior perceived e-service quality (Lin, 2012). Accordingly, the positive influence of e-Retail functions suggests that firms can capitalize on experiences and expertise in providing digitalized services and on accumulated perceived e-Retail service quality to boost mobile Retail sales and increase traffic volume.

In addition, I find that e-Retail market share is positively related to m-Retail sales, traffic, and conversion rate. These strong effects simply support the argument that complementary resources to support a firm's economies of scale in the e-Retail market can be leveraged in the m-Retail channel. Finally, due to their physical presence, retail chains have higher m-Retail sales and traffic compared with other non-store-based firms. Interestingly, on average retail chains exhibit lower conversion rates. While customers browse products through m-Retail channels on the go, they may choose to visit physical outlets nearby to check for product fit and/or to purchase on the spot to avoid delivery waiting and hence enjoy instant gratification. As a consequence, some mobile visitors are diverted to physical outlets and perform transactions there, causing lower conversion rates of the mobile Retail channel for retail chains.

While operation-related factors can differentiate between adopters and non-adopters as discussed in section 6.1, the two customer-oriented characteristics (i.e., e-Retail order value and e-Retail shopper age) are critical determinants of mobile Retail performance. Essentially, a firm can benefit from its inherent resources when its e-Retail characteristics fit with customer preferences of m-Retail channel. For instance, I find that firms that are associated with smaller e-Retail order value have higher m-Retail conversion rate. This is understandable since customers tend to prefer purchases with small order values in m-Retailing due to security concerns and the nature of instant shopping. Given the fact that young generation is the primary customer base of m-Retailing, I also find that a firm with younger e-Retail shopper age allures more m-Retail traffic and attains higher sales. The aforementioned findings are consistent with hypotheses, but there is an economic dimension of the two customer-oriented resources that needs to be taken into account. When purchase quantities of two orders are equivalent, the order with higher value (i.e., price effects) creates higher sales revenue. This explains the finding that firms in our sample with large e-Retail order value also have high m-Retail sales (assuming product offerings of a retailer are similar for both e-Retailing and m-Retailing). In addition, shopper age and purchasing power in most cases are positively correlated. A customer at the age of 30 generally has higher purchasing power than a customer at the age of 15 does. This provides a possible explanation for the positive association between a firm's e-Retail shopper age and conversion rate in the mobile sales channel when more mature customers with higher incomes are more likely to place an order than their younger counterparts.

Finally, I find that the two system implementation choices representing a firm's extent of adoption (i.e., information functions and mobile application) also have substantial impacts on m-Retail performance. Per information functions, a firm's information capability of the m-Retail channel is positively associated with its mobile sales and traffic. Effective and speedy delivery of product/service information is an especially important system design consideration in m-Retailing given hardware constraints and customer needs for accessing information when they are in motion or on the run. In addition, mobile application is positively related to m-Retail sales and conversion rate, given that mobile applications create a more interactive and facile shopping environment that better fulfill customer needs.

Chapter 7

CONCLUSION

Prior studies have suggested that multichannel retailers can outperform single-channel competitors because their customers are more likely to spend money, revisit the store, and repeat product purchases (Kumar and Venkatesan, 2005). The emergence of m-Retailing creates a unique opportunity for e-Retailers to exploit multichannel formats and further fulfill customer needs. Using a cross-sectional dataset of e-Retailers in the U.S. and European markets, my study provides empirical evidence to probe the transition from e-Retailing to m-Retailing.

Distinct features and unique value propositions of mobile data services are discussed widely both in academia and practice. Nevertheless, m-Retailing is essentially an extended arm of e-Retailing. The dissertation shows that firms' migration to m-Retailing in terms of adoption, extent of adoption, and value realization is closely related to their e-Retail characteristics. The finding suggests that firms with advantages of operating resources regarding technology competency to provide digitalized services, economies of scale, and physical outlets tend to grasp at market opportunities offered by m-Retailing and thus are more apt to adopt m-Retailing. After adoption, those firms with operational edge are also willing to invest more in system development. Interestingly, in order to capitalize on the young generation who use mobile data services extensively and to maximize the conversion rate of small-value orders that fit with the nature of instant shopping in m-commerce, firms with younger e-Retail shopper age and smaller e-Retail order value also engage more in system development. The finding provides useful information for technology vendors and promoters to identify potential adopters for initial set-up and to target adopters for additional value-added services in the mobile domain.

Business value provides justification for IT adoption. Firms with strong operating resources in e-Retailing, such as experiences and expertise in providing digitalized services, accumulation reputation of service quality from e-Retail market, strong market establishment in e-Retailing, and physical outlets, are found to be leaders in m-Retailing as well. Retail chains, however, are found to have lower conversion rate on average. The silver lining is that for retail chains, lower conversion rate of the m-Retail channel may not be unfavorable after all when mobile visitors can help with sales of physical outlets, thus leading to cross-channel synergies. Contrarily, pure on-line retailers are more vulnerable to low conversion rates since they rely solely on the virtual channel for their business. Different firm types need to consider weighing and balancing performance metrics differently.

Firms with e-Retail characteristics that fit with customer preferences of the m-Retail channel can benefit from their existing e-Retail resources. Firms with smaller e-Retail order value are found to have higher m-Retail conversion rate. Firms with younger e-Retail shopper age are associated with higher m-Retail sales and traffic. Firms, however, need to be aware of economic dimension and interpretations of the two e-Retail customer-oriented resources. Due to the income effect, a firm with higher e-Retail shopper age is found to have a higher conversion rate. Because of the price effect, a firm with larger e-Retail order value is found to have higher sales. While firms benefit from the fit between their e-Retail characteristics and the nature of m-Retailing (e.g., low order value, and young shoppers), they should consider marketing and promotion plans to leverage the economic dimension (i.e., price effect and income effect) and to fully exploit the sales potential.

Finally, proper system implementation is also relevant to the success of m-Retailing. In addition to information functions that address hardware constraints and short-duration usage, mobile application is found associated with higher m-Retail conversion rate. While some firms may still choose to utilize the website as the main format for m-Retailing, the empirical finding on conversion rate provides information for firms' decisions on developing mobile application.

My study makes several distinct contributions to the literature. First, most existing empirical studies on m-commerce focus on customers' perceptions of the new sales channel. Discussions on firms' strategic decisions and business value from m-commerce are mainly derived from conceptual frameworks or case studies, hence lacking empirical evidence to validate the assertions. Complementing existing literature, my paper presents an empirical assessment of firms' migration to the new channel based on secondary data analysis.

Second, while some prior studies use survey data to explore firms' adoption of mobile information systems, my analysis contributes to the literature by looking beyond the conventional dichotomy of "adoption versus non-adoption" and by incorporating firms' extent of adoption and business value into the research framework. As IT innovation diffusion involves not only initiation but routinization (Rogers, 2003), I explore a firm's extent of adoption in terms of system implementation choices. Unlike the aggregate usage frequency of IT innovation, system implementation choices provide a more detailed and granular view on extent of adoption. This level of analysis is more realistic and relevant to firms' actual decision making. Nevertheless, this requirement increases complexity of data collection and analysis. In the emerging m-commerce research stream, the study serves as a launching pad to explore a firm's extent of adoption in terms of two distinct features of mobile data services. Future research can extend the work by providing a theoretical framework to assess a firm's system implementation choices regarding mobile information systems.

The business value is deliberately examined in response to the call for linking innovation-related variables to performance impacts by Fichman (2004). The empirical findings indicate that a firm's organizational factors in terms of e-Retail characteristics and its extent of adoption in terms of system implementation choices influence business value of adopting the IT innovation (i.e., m-Retail channel). In particular, I incorporate the comparatively under-studied conversion rate as one performance metric (Johnson et al., 2004). The pattern of conversion rate is found to be different from those of sales and traffic. For example, while retail chains are found to have higher mobile sales and greater traffic volume compared with other non-store firms, their conversion rates are on average lower than others' due to traffic redirection to physical outlets. Future research on this conversion rate metric will be interesting and fruitful.

Third, previous research on m-commerce has mainly focused on its distinct features and new value propositions (Clarke, 2001; Lee and Benbasat, 2003). Since m-Retailing still involves extensive online transactions, my study complements existing literature by exploring the dependency relationship between e-Retailing and m-Retailing to elaborate on the inner workings among the associated constructs. While there are conceptual studies addressing the link between e-commerce and m-commerce, my dissertation contributes to the literature by empirically assessing this link. Specifically, I examine the dependency relationship from two dimensions: resources related to business operations and those related to customer preferences. While firm-level analysis inclines to focus on operation-related resources, the dimension of customer demand is often ignored by most firm-level studies (Witt, 2001). My study fills the literature gap by incorporating customer preferences into the research model and empirically testing their effects on adoption and value. While I find that operation-related capabilities largely determine firms' participation in the IT-enabled sales channel, I also show that characteristics related to customer preferences are no less important than operating resources in terms of their contribution to the success of m-Retailing.

Finally, when it comes to measuring extent of adoption in terms of system functions, counted observations are commonly collected. The often-used Poisson count data model is too restrictive as it only allows for no-dispersion (i.e., variance equal to mean). I introduce a generic count data model that accommodates over-, no-, or under-dispersion. I also account for the issue of zero-truncation given that an adopting firm at least has one system function. Empirical IS researchers who intend to explore a firm's system implementation choices or need to deal with count data modeling may find the Conway-Maxwell Poisson regression model employed in this study useful.

Given its exploratory nature, my study has several limitations, many of which are due to data unavailability and hence can be addressed by future research when more data become available. First, the cross-sectional research design to some extent limits the ability to make causal inference. I made endeavors to address the limitation by performing the robustness check of my adoption decision model, in which I have specific adoption years for 106 firms from 2007 to 2010. Yet, the robustness analysis is still confined by the unavailability of panel data for independent variables. A better understanding about causes and effects of adoption decisions will require longitudinal analysis. If longitudinal data become available, a temporal diffusion and business value analysis will derive more insights. Second, the dimensions I assess are by no means exhaustive. For instance, learning externalities or bandwagon effects may exist and hence affect other firms' decisions to adopt mobile Retailing. Future research can explore to what extent a firm's adoption is influenced by prior adopters. A follow-up study can also address what types of firms are prone to influences of prior adopters. The above discussion, however, depends on data availability of temporal history of firms' adoption.

Third, the sample of firms is composed of the top 500 e-Retailers list in the U.S. and the top 300 e-Retailers in Europe. This seeming bias is the challenge that empirical researchers usually encounter as firm-level data is mostly available for large and/or public firms. Nonetheless, the sample still has fair generalizability given that the top 500 e-Retailers make up 75% of total e-Retail sales in the U.S. market and hence can explain the behaviors of firms that account for the lion's share of the market. Last, practitioners have started to recognize and discuss the potential cannibalization between e-Retailing and m-Retailing as mobile devices such as tablets make mobile shopping less constrained by hardware limitations. However, it is difficult to assess the cannibalization issue under this cross-sectional setting. Alternatively, since currently e-Retail and m-Retail markets are both still in growing stages, a plausible case is that firms with growing e-Retail sales would also enjoy m-Retail sales growth, leading to an increase in overall sales. In addition, the result shows that traffic to the m-Retail channel may bring transactions to physical stores. In this context, cannibalization may not be such a concern as the addition of m-Retail channel to the multichannel mix enables retailers to interact with customers constantly, and improves overall sales. Future research can extend the focus to the performance of the firm as a whole, preferably with data across years. Doing so will enhance our understanding of the overall impact of the extra m-Retail channel and contribute to the literature of multichannel management.

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APPENDIX A

E-RETAIL FUNCTION LIST

360 degree spin	Microsites	Widges
Affiliate program	Mouseover	Wish list
Auction	Online circular	Zoom
Blogs	Online gift certificates	Account status/History
Catalog quick order	Outlet center	Buy online/Pick up in store
Color swatching	Pre-orders	Click to call
Coupons/Rebates	Product comparisons	Currency converter
Customer reviews	Product customization	Estimated shipping date
Daily/Seasonal specials	Product ratings	Express checkout
Dynamic imaging	Product recommendations	Free return shipping
E-mail a friend	Product wikis	Live chat/E-mail
Enlarged product view	Registry	Order confirmation
Frequent buyer program	RSS feed	Order status
Frequently asked questions	Site personalization	Pre-paid labels
Gadgets	Social networking	Rain checks
Guided navigation	Store locator	Real-time inventory check
Interactive catalog	Syndicated content	Ship to multiple addresses
Interactive kiosks	Top sellers	Shipping costs calculator
Mapping	Videocasts	Shipment tracking
Mash-ups	What’s new	Toll-free number