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Consumer Adoption of Offline M-Payment: The Chinese Case

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A B S T R A C T

Purpose: Understanding consumers' preferences and reasons for adopting new particular technology is crucial to provide the available services that create value for stakeholders and consumers. This study researched offline m-payment adoption in the Chinese market based on consumers' point of view. It aims to investigate (1) which key factors determine whether consumers will adopt and use offline m-payments in the Chinese market's context, and (2) whether the individual traits have any moderating effects on consumers' intentions to adopt offline m-payments.
Design/methodology/approach: An empirical research on determinants for offline m-payment adoption has been conducted. The direct influences of the factors determining offline m-payment adoption are explored with an integrated model based on TAM model, the most widely implemented model of user acceptance and utilization of information technology in scientific and technical literature. Perceived usefulness, perceived enjoyment, and habit were used as independent variables. Two important individual traits (self-efficacy and self-expression) were used as moderating variables. Additionally, the perceived ubiquity of consumers, a unique attribute of m-payments, was used as a mediating variable.
Findings: Perceived usefulness, perceived enjoyment, and habit all were found to have a positive effect on behavioral intention. Self-efficacy doesn't moderate the effect consumer's perception of usefulness has on use intention but has a negative moderating effect on the relationship between perceived enjoyment and behavioral intention, as well as between habit and behavioral intention. Additionally, the current study shows that self-expression has no moderating effect on the process of adoption. Finally, the analysis showed that perceived ubiquity is a mediating variable in the relationships between perceived usefulness and behavioral intention and perceived enjoyment and behavioral intention. Third, it may be useful to integrate promotions and targeted ads from merchants.
Research limitations/implications: First implication is that because perceived usefulness and perceived enjoyment positively affect consumers' behavioral intentions to use offline m-payment, service providers should improve the adoption and retention rate by enhancing those perceptions. Second, since perceived ubiquity was found to mediate influence of consumers' perceived usefulness and perceived enjoyment on behavioral intention to use offline m-payments, service providers and retailers should present ubiquitous payment services to consumers, and make consumers realize that by using offline m-payment they can conduct transactions from anywhere at any time by any mobile device. This study has several limitations. First, the research has targeted only offline m-payment adopters. It would be useful to check how factors differ in their importance for adopters and non-adopters. Second, the paper explored the determining factors of offline m-payment adoption only in China. Compare several market ecosystems for better understanding of the differences in characteristics may be useful. Third, the process of adoption may vary depending on which technology was applied. Also, the technical capabilities and preferences of businesses while adopting offline m-payment methods are some of the important factors.
Originality/value: The study contributes to the body of research on adoption of new technologies, and specifically mobile services. From a managerial standpoint, it provides new entrants and service providers with a better understanding of Chinese customers' needs and wants from offline m-payment services.

Keywords: offline mobile payment, habit, self-efficacy, self-expression, perceived ubiquity

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I. Introduction

According to the “Mobile internet users in APAC 2017-2025” research data, in 2019, around 2 billion people were using mobile internet in the Asia Pacific region (Moore, 2021). Thus, user penetration has increased from 45% to 48% in one year. If the number of mobile internet users continues to grow at the same pace, in 2025, there will be 2.7 billion mobile internet users, and the penetration rate will be at 62% (Doan, 2019). Mobile devices provide a multi-sided platform for all kinds of consumers (Miao and Jayakar, 2016). China started late in the mobile payments (m-payments) industry and has relatively less developed technologies in mobile payment fields than, for example, Japan and Korea. In addition, it shows great disharmony in development progress in some regions. Despite all these, China has become the largest smartphone market in the world, with more and more consumers adopting this new technology to facilitate their everyday lives (Amoroso et al., 2012; Miao and Jayakar, 2016).

With the development of the intelligent terminal and mobile internet technology, m-payments have become the most popular application in mobile communication fields. In East Asia, payment platforms such as Alipay, Apple Pay, and Samsung Pay are quickly becoming pervasive. According to the mobile social media platform WeChat’s survey, 92% of people in China’s largest cities and 47% of the rural population use m-payments regularly. Notably, the adoption of mobile payments in China during the COVID-19 helps to reduce the direct and indirect contacts in transactions that, in its turn, allows to maintain social distancing and facilitate stabilization of the social economy (Zhao and Bacao, 2021).

Understanding consumers’ preferences and reasons for adopting new particular technology is crucial to provide the available services that create value for stakeholders and consumers. However, up to now, only a few empirical studies exploring factors influencing m-payments adoption (and especially offline m-payments) by Chinese consumers have been conducted (Zhong et al., 2013; Zhou, 2014). Offline m-payments are payments for goods, services, and bills with a mobile device at a physical point-of-sale (POS) terminal by taking advantage of wireless and other communication technologies (Dahlberg et al., 2008; Li et al., 2014). Offline m-payments are also often called proximity payments. There is a need for further research on the adoption of offline m-payments (proximity payment) by Chinese consumers. This research aims to:

(1) investigate which key factors determine whether consumers will adopt and use offline m-payments in the Chinese market’s context;
(2) investigate whether the individual traits have any moderating effects on consumers’ intentions to adopt offline m-payments;

In this study, the direct influences of the factors determining offline m-payment adoption are explored with an integrated model based on Davis’s TAM model (1989), the most widely implemented model of user acceptance and utilization of information technology in scientific and technical literature (Benbasat and Barki, 2007). This model encompasses core variables of user motivation: perceived ease of use, perceived usefulness, and attitudes toward the technology - that helps to understand how peoples come to acknowledge and utilize new technologies (Kalayou et al., 2020). The model was picked for use in this study because we expect that the constructs and associations described in the modified TAM model are valid to measure the behavioral intention to use offline m-payments.

This study contributes to the body of research on new technologies adoption process, and specifically mobile services. From a managerial standpoint, it provides new entrants and service providers with a better understanding of Chinese customers’ needs and wants from offline m-payment services.

II. Literature review and hypotheses

For this study, was accepted a definition by Dahlberg et al. (2008) that specifies mobile payments as "payments for goods, services, and bills with a mobile device (such as mobile phone, smart-phone, or personal digital assistant by taking advantage of wireless and other communication technologies)".

According to m-payment scenarios, the payments can be divided into remote and proximity m-payments (Li et al., 2014). Remote (i.e., online) m-payments occur when a retailer is remote to consumers. They buy goods or services either through their phones or SMS or directly via a mobile website (using PayPal, credit, or debit cards). In the second case, payment is levied on a consumer's mobile account. Proximity (i.e., offline) m-payments occur when consumers pay using their mobile phone at a physical point-of-sale (POS) terminal. The current study explores the adoption of offline m-payments.

There is a number of research on m-payments (Dahlberg et al., 2015). The earliest academic m-payment adoption research was conducted back in 2003, and many m-payment studies draw on technology acceptance and adoption theories (Taherdoost, 2018). Extant researches, both conceptual and empirical, mainly use the Theory of Reasoned Action (TRA), the Theory of Planned Behavior (TPB), Technology Acceptance Model (TAM), as well as the Diffusion of Innovation (DOI) Theory and the Unified Theory of Acceptance and Use of Technology (UTAUT). As shown in Table 1, the most commonly used theory in previous research on m-payment adoption is TAM. That is because TAM is one of the most reasonable theories (Irani et al., 2009; Lai, 2017). Multiple studies showed that it is reliable and can be used in various contexts of technology adoption (King and He, 2006; Sugandini et al., 2018).

These studies have found several significant factors that positively affect consumers' intentions to adopt m-payments: perceived usefulness and perceived ease of use (Aydin and Burnaz, 2016; Chandra et al., 2010; Keramati et al., 2012; Kim et al., 2010; Schierz et al., 2010; Zhanga et al., 2011), social influence (Mahran and Enaba, 2011; Peng et al., 2011; Schierz et al., 2010; Yang et al., 2012), relative advantage (Lu et al., 2011; Keramati et al., 2012), and trust (Andreev et al., 2012; Chandra et al., 2010; Mallat, 2007; Zhou, 2014). For m-payment services success,

Table 1. Previous Studies on Consumer Adoption of M-Payments

Theory	Sources	Key factors
TRA (Fishbein, 1967; Fishbein and Ajzen, 1975)	Schierz *et al.* (2010), Mahran and Enaba (2011)	Attitude
	Schierz *et al.* (2010), Keramati *et al.* (2012)	Subjective Norm
TPB (Ajzen, 1991)	Mahran and Enaba (2011)	Perceived Behavioral Control
TAM (Davis, 1989; Davis et al., 1989)	Eze *et al.* (2008), Kim *et al.* (2010), Chandra *et al.* (2010), Zhanga *et al.* (2011), Mahran and Enaba (2011), Andreev *et al.* (2012), Keramati *et al.* (2012)	Perceived Usefulness
	Eze *et al.* (2008), Kim *et al.* (2010), Chandra *et al.* (2010), Zhanga et al. (2011), Mahran and Enaba (2011), Andreev *et al.* (2012), Keramati *et al.* (2012)	Perceived Ease of Use
DOI (Rogers, 2003)	Lu *et al.* (2011), Keramati *et al.* (2012)	Relative Advantage
	Kim *et al.* (2010), Schierz *et al.* (2010), Lu *et al.* (2011)	Compatibility
	Keramati *et al.* (2012)	Complexity
	Not found	Trialability
	Lu *et al.* (2011)	Image
UTAUT (Venkatesh *et al.,* 2003)	Peng *et al.* (2011)	Performance Expectancy
	Peng *et al.* (2011)	Effort Expectancy
	Schierz *et al.* (2010), Peng *et al.* (2011)	Social Influence
	Peng *et al.* (2011)	Facilitating Conditions

system security and confidentiality of information are essential (Lu et al., 2011; Yang et al., 2012).

Other studies have also found factors that negatively affect consumers' intentions to adopt m-payments: perceived risk (Peng et al., 2011; Slade et al., 2013; Yan and Yang, 2015; Yang et al., 2012; Zhanga et al., 2011) and perceived cost (Lu et al., 2011; Peng et al., 2011).

Furthermore, some studies have investigated contextual factors and found that such factors as individual mobility (Schierz et al., 2010), different payment scenarios (Goeke and Pousttchis, 2010), and location-based services (Andreev et al., 2012) significantly affect acceptance intentions (Xin et al., 2013).

However, most of these studies were conducted in non-Chinese contexts, and although successful in one country, an m-payment business model may not be applicable in another country (Zhong et al., 2013).

The survey by PricewaterhouseCoopers (PwC) revealed that while Chinese value e-retailing experience more, they value the brick-and-mortar retail experience less than Western consumers (PwC, 2016). Since the offline m-payment scenario (unlike the online e-payment scenario) implies shopping at the physical retail stores, the Chinese shoppers may be more reluctant to adopt it than Western shoppers. Also, the determinants critical for the use decision may differ. For example, the Chinese pay more attention to what other people in their circle think, and the perception of an individual by society is of utmost importance (Hu, 1944). Therefore, self-expression that is "the importance of social expression of identity and self-identification" may interfere in the adoption process (Goldgehn, 2004; Haider et al., 2018). Besides, the existing literature on attitude formation suggests that individual traits influence a user's judgment. One crucial individual trait that may influence a user's judgment is self-efficacy, an individual's belief in his or her capability to perform a given task or behaviors (Bandura, 1995; Jang, 2010). Up to now, hardly any studies have explored the moderating effects of self-efficacy and self-expression on m-payment adoption.

A. Study Ⅰ: The determinants of mobile payment adoption

Study I aims at finding out the key factors which determine if consumers will adopt and use m-payments.

1. Technology acceptance model (TAM)

TAM is an adaption of Ajzen and Fishbein's (1980) general TRA model. Based on a Google scholar report, by the end of October 2019, the original study of Davis et al. (1989) has been cited in 46,529 sources. Since TAM is one of the most widely used and reasonable models for predicting the individual's intention and an act of adoption (Irani et al., 2009; Lai, 2017), this study uses it as an underpinning model.

TAM suggests two main factors that play key roles in the adoption of the new technology: perceived usefulness and perceived ease of use. Perceived usefulness is defined as "the degree to which a potential user believes that using a particular system will enhance his or her job performance." Perceived ease of use is defined as "the degree to which a potential user believes that using a particular system will be free of effort." Ease of use influence behavioral intention only indirectly, while perceived usefulness affects it directly. It implies that perceived usefulness is a stronger determinant than perceived ease of use.

TAM's perceived ease of use has already been assessed as a significant factor influencing consumers' adoption decision-making process in previous research papers (Dahlberg et al., 2015). Therefore, it was decided to exclude perceived ease of use in this study. Also, the attitude factors have been ignored because Cheng and Huang (2013) suggested removing them as not having that much significant influence on behavioral intention. Since the TAM model is used more in the work-related context and organizational context rather than the context of consumer technologies, it is reasonable to include non-utilitarian motivators to investigate consumer's intention to use m-payments (Sun and Zhang, 2006). Thus, perceived enjoyment has been added as the hedonic motivation factor in the original TAM model.

2. Perceived usefulness

Usefulness represents an individual's judgment of how a technology product or its system can effectively help a consumer to perform the purpose and utility of the product (Lee et al., 2011). According to Davis (1989), perceived usefulness is "the degree to which a potential user believes that using a particular system will enhance his or her job performance." Rogers (2003) proposed that individuals are likely to adopt innovations only if these innovations provide a distinct advantage compared to existing ones. Therefore, in the context of m-payment usage, perceived usefulness is the degree to which an individual believes that using m-payment would enhance his or her performance. The ultimate reason for consumers using m-payment is them finding this technology to be helpful for fulfilling their transaction needs and solving their financial issues (Kim et al., 2010).

In a study of mobile ticketing acceptance, Mallat et al. (2009) proved that perceived usefulness has significant direct effects on behavioral intention toward mobile ticketing adoption. Moreover, Kim et al. (2010) argue that perceived usefulness has a direct positive effect on behavioral intention to adopt m-commerce. Therefore, it is hypothesized that:

H1. Perceived usefulness positively affects consumers' behavioral intention to use offline m-payments.

3. Perceived enjoyment

Earlier research has shown that while perceived usefulness is one of the significant determinants for work-related tasks, perceived enjoyment is a significant determinant for entertainment-oriented tasks (Liang and Yeh, 2011).

In the information technology context, perceived enjoyment is the degree to which using a specific system is seen as joyful or pleasurable by a consumer (Davis et al., 1992; Heijden, 2004). The key facets of enjoyment include entertainment, pleasure, recreation, relaxation, and excitement (Lin and Bhattacherjee, 2010; Nysveen et al., 2005).

Enjoyment is broadly used as a construct that evaluates consumer's hedonic experiences (Than et al., 2015). Davis et al. (1992) integrated perceived enjoyment in the original TAM and proposed that it has a significant effect on the adoption intention of word-processing programs. Sun and Zhang (2006) revealed that perceived enjoyment plays a key role in the adoption of user technology and has significant implications, especially for hedonic systems. Gehrt et al. (2007) found that enjoyment positively affects behavioral intention in an online shopping context. In mobile service context too, perceived enjoyment was found to be an important intrinsic motivation for behavioral intention toward using mobile services (Hong et al., 2006). For example, Reychav et al. (2016) suggested that it is a critical factor for hedonic intentions to adopt advanced mobile services. However, although the impact of hedonic motivation on behavioral intention has received support in m-commerce, there has not been much research on perceived enjoyment in the context of m-payment use (Mohan, 2014).

It is expected that when consumers begin using offline m-payment, they put attention to such values as novelty and enjoyment. The greater the enjoyment value mobile payment brings, the greater the customers' adoption intentions. Therefore, the below hypothesis is suggested:

H2. Perceived enjoyment positively affects consumers' behavioral intention to use offline m-payments.

4. Habit

Consumer's habitual behavior is recently receiving more and more attention from scholars of marketing science (Anand and Shachar 2004; Liu-Thompkins et al., 2013; Migdał-Najman et al., 2020; Shah et al., 2014; Wood and Neal, 2009). As an abstract concept, the habit has no objectively "correct" or "incorrect" definitions (Gardner, 2015). According to Butler and Gillian (1995), it is a routine of behavior that is repeated regularly and tends to occur unconsciously. Limayem et al. (2007) defined habit as "the extent to which people tend to perform behaviors automatically because of learning" (p. 705), Kim et al. (2005) likened habit with automaticity, and Nilsen et al. (2012) defined habit as a "behavior that has been repeated until it has became more less automatic, enacted without purposeful thinking, largely without any sense of awareness" (p. 2). Even though, in general, habit was similarly conceptualized by scholars, it is operationalized in two different ways: first, as a repetition of previous behavior; second, as the extent to which the behavior is automatic in an individual's perception (Venkatesh et al., 2012).

Habit is an essential construct in consumer behavior research and is widely used to explain and predict customer behavior because repetition happens in everyone's life. About 45% of consumer behaviors are performed in the same context and almost daily (Neal et al., 2006). On occasions, consumers automatically repeating past behaviors with little regard to specific situations and current goals (Wood and Neal, 2009). Importantly, habit is not only a repeated automatic behavior in specific situations, but it also acts as a determinant of intention to stick to an existing line of behavior (Shiau and Luo, 2012).

Kim and Malhotra (2005) found that habit has a strong impact on predicting behavior regarding future technology use. Generally, because of consumers' entrenched behavior of using traditional payment methods, they may be reluctant to adopt a new method. However, since mobile usage in daily life increasingly grows, in some contexts, customers have already used m-payments, which is a prerequisite to forming the habit. Existing research shows consumers are willing to use a m-payment method to conduct transactions in the context of m-commerce (Khalifa et al., 2012; Lai, 2018).

The issue of whether the habit has a direct effect on behavior or via behavioral intention has been widely argued in previous studies. Thus, the following hypotheses are proposed:

H3. Habit positively affects consumers' behavioral intention to use offline m-payments.

H4. Habit positively affects consumers' behavior to use offline m-payments.

5. Behavioral Intention and Use Behavior

In TAM, the central construct is the intention to use technology. Based on TRA, behavioral intention predetermines the likelihood that an individual will perform a given behavior. Further studies support that there is a significant relationship between behavioral intention and actual use behavior (Cheung and Vogel, 2013; Motaghian et al., 2013). Users first intend and only then use a technology. Thus, "behavioral intention to use becomes the direct estimator of actual use" (Basak et al., 2015, p. 401). However, it determines use behavior only if an individual decides to perform the behavior.

Behavior is affected by some motivators which are a part of behavioral intention. These motivators are "indications of how much the people [are] planning to try and how much effort they are planning to exert in order to perform the behavior" (Ajzen, 1991). It is hypothesized:

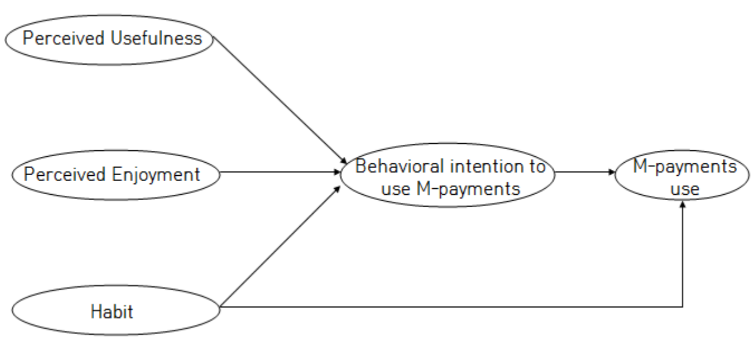

Figure 1. Research Model (Study I)

H5. Behavioral intention positively affects consumers' behavior to use offline m-payments.

6. The mediating effect of perceived ubiquity (additional analysis)

Perceived ubiquity is an individuals' perception about the degree to which mobile wireless technology provides them an uninterrupted personalized connection and communication with other individuals or networks (Kim and Garrison, 2009). Extant studies unanimously agree that ubiquity is the main difference between the mobile Internet and the PC Internet (Kleijnen et al., 2007; Sheng et al., 2008).

The conceptualization of ubiquity in a marketing context can be traced as far back as 2002 (Okazaki and Mendez, 2013). Watson et al. (2002, p. 332) firstly discussed and described ubiquity as synonymous with omnipresence: "not only that they are everywhere but also that they are, in a sense, 'nowhere,' for they become invisible as we no longer notice them."

For consumers, perceived ubiquity is connected to two features of mobile services: time-saving and spatial flexibility (Okazaki et al., 2012). As for time-saving, consumers' evaluation of convenience is affected by two aspects of waiting time: objective time and subjective time (Davis and Vollmann, 1990). In this paper, our view of time saving is similar to Kleijnen et al. (2007) and Okazaki et al. (2012) in a sense that it's close to subjective time. Time-saving as efficiency, in a sense that users incline toward performing mental calculations on how much time can be saved if they the use of a mobile device. As for spatial flexibility, based on contextual mobility, it is defined as a feature of mobile technology which eliminates usual contextual constraints on human interaction allowing to interact across multiple contexts (Kakihara and Sorensen, 2002). In other words, by using wireless networks and mobile terminals, consumers can conduct m-payment transactions at any time from anywhere by any device (Carillo et al., 2017; Yan and Yang, 2015; Zhou, 2013).

To sum, ubiquity is the main advantage of m-payment in comparison with traditional and online payments. It removes the temporal and spatial limitations and enables customers to conduct payments at their convenience, and by doing this, mediates the effect of perceived usefulness or enjoyment on their intention to use m-payment. Therefore, it is hypothesized:

H6. Perceived ubiquity mediates the effect of perceived usefulness on behavioral intention to use offline m-payments.

H7. Perceived ubiquity mediates the effect of perceived enjoyment on behavioral intention to use offline m-payments.

B. Study Ⅱ: The moderating effect of self-efficacy

Study II seeks to find out whether an individual's self-efficacy has a moderating effect on intention to adopt m-payment.

1. Concept of self-efficacy

The existing literature on attitude formation suggests that a user's judgment is influenced by individual traits. One important individual trait that may influence user's judgment is self-efficacy (Jang, 2010).

Self-efficacy is an individual's perception of his or her capability to accomplish a given task or

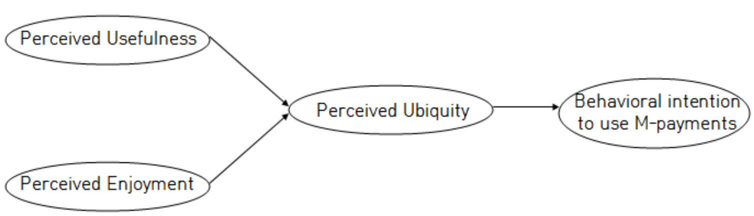

Figure 2. Research Model (Additional Analysis)

behavior. Bandura (1995, p. 2) defined it as "the belief in one's capabilities to organize and execute the courses of action required to manage prospective situations". More precisely, it is a degree to which an individual believes he or she can use his or her abilities to perform a given behavior under certain situations (Snyder et al., 2014).

If a person perceives a certain behavior as beyond his or her capability, he or she is likely not to perform it, even if there is a perceived social demand (Boyd and Vozikis, 1994). Individuals incline to engage in activities in which they have high self-efficacy and tend to avoid being engaged in those in which they have low self-efficacy (Van der Bijl and Shortridge-Baggett, 2002).

2. Sources of self-efficacy beliefs

Four cardinal sources of self-efficacy beliefs are performance outcomes, vicarious experiences, verbal persuasion, and physiological feedback (Bandura, 1982; Wood and Bandura, 1989). These four sources help individuals to determine if they are able to perform a particular behavior.

One of the most important sources of self-efficacy is the performance outcomes - or in other words, experience. Experience, both negative and positive, can affect individual's perceptions of his or her capability to accomplish a given task: if an individual succeeded in accomplishing the task before, then he or she is more likely to feel capable of accomplishing the same or similar task, and vice versa.

Vicarious experience is the one that people learn from other individuals' performances by observing their behavior and comparing our ability with that individuals' abilities (Bandura, 1977). If they observe that someone similar to them has succeeded, it may strengthen their self-efficacy. Similarly, if they observe a failure, it can lower their self-efficacy.

The third way to enhance self-efficacy is verbal persuasion. Self-efficacy is affected by encouragement and discouragement of others because they may give hints of how to evaluate someone's ability to perform the given task (Nawaz and Zeb, 2016).

Lastly, an individual's responses and emotional reactions also matter. Judgments about anticipated performance are based on how positively or negatively aroused people feel when confronted with a task. Importantly, not only external (distraction, risk, etc.) but also general physical condition, personality factors, and immediate affect (mood) may influence arousal (Gist and Mitchell, 1992). When emotions are aroused, people tend to get anxious and expect a negative outcome. In this case, self-efficacy is lowered.

3. Moderating effect of self-efficiancy on relationships between perceived usefulness and behavioral intention, perceived enjoyment and behavioral intention, and perceived habit and behavioral intention

Self-efficacy is "an important determinant of motivation, affect, thought and action" (Grau et al., 2001, p. 64). It often appears in studies as one of the factors influencing customers' perceptions regarding a new technology (Gu et al., 2009; Püschel et al., 2010; Zhou, 2014). However, to date, only few studies focused on the moderating effect of self-efficacy on adoption of mobile technologies, such as m-payment (Jaradat and Faqih, 2014).

Several empirical studies showed that individual's self-efficacy has a significant effect on technology adoption behavior (Suls and Wallston, 2003; Khraim et al., 2011). Customers with higher levels of technology self-efficacy have higher levels of technology use (Laver et al., 2011). Since the m-payment technology operation process is more complex than such of other technologies, self-efficacy is expected to play a pivotal role in customers' decision-making process regarding using m-payments.

Customers with higher levels of self-efficacy are expected to be more engaged, and perceive the features and functions of technology as more pleasurable (Aliakbari, 2015; Yang et al., 2012). Moreover, such customers will have more positive attitudes regarding the usefulness of m-payment than those with low levels. Finally, even if the customer is used to the technology, outcomes of his or her past encounters may affect his or her intention to continually use it. And on the other hand, even if the customer has always paid with a credit or a debit card, the customer's perception regarding the self-ability to use the offline m-payment method will influence use intention. All in all, the level of technology self-efficacy should predict consumers' intentions to use m-payment and affect the strength of the relationships between the variables. Thus, it is hypothesized:

H8. Self-efficacy moderates the effect of perceived usefulness on behavioral intention, such that the effect is stronger for consumers with higher levels of self-efficacy.

H9. Self-efficacy moderates the effect of perceived enjoyment on behavioral intention, such that the effect is stronger for consumers with higher levels of self-efficacy.

H10. Self-efficacy moderates the effect of habit on behavioral intention, such that the effect is stronger for consumers with higher levels of self-efficacy.

C. Study Ⅲ: The moderating effect of self-expression

Study III aims to find out whether an individual's self-expression has a moderating effect on intention to adopt offline m-payment.

Self-expression is an "importance of social expression of identity and self-identification" (Goldgehn, 2004; Haider et al., 2018).

A common human motivation is to aligne how other people view them with how they view themselves (Kokkoris and Kuhnen, 2013). As a result, individuals have a drive to enact their identities by proclaiming who they are (Prentice, 1987), and "we are what we have and possess" (Belk, 1988, p. 76). That means that consumers intentionally or unintentionally regard their possessions as parts of themselves, and a product expresses values beyond instrumental utility (Mittal, 1994). An abundance of marketing research has shown that, frequently, consumers make a choice to buy as a form of self-expression, either expressing "this is what I want to become" or stating "this is who I am" (Johnson and Ein-Gar, 2008; Saenger et al., 2013).

Among others, to display their values and identity to others as well as to themselves, consumers actively use technology products and services (Goh and Sun, 2014; Thorbjørnsen et al., 2007). Nysveen et al. (2005) found a positive relationship between self-expression and consumer adoption intentions of mobile services. M-payment is believed to be one of the value-expressive services that can meet the needs of self-expression since it is likely to be seen as able to materialize and communicate the desired representation of one's self (either of actual or ideal self). Thus, it's expected that in the case of offline m-payment as well desire for self-expression would affect the strength of the effect perceived usefulness, enjoyment, and habit have on use intention. Therefore, the following hypotheses are proposed:

H11. Self-expression positively moderates the effect of perceived usefulness on behavioral intention.

H12. Self-expression positively moderates the effect of perceived enjoyment on behavioral intention.

H13. Self-expression positively moderates the effect of habit on behavioral intention.

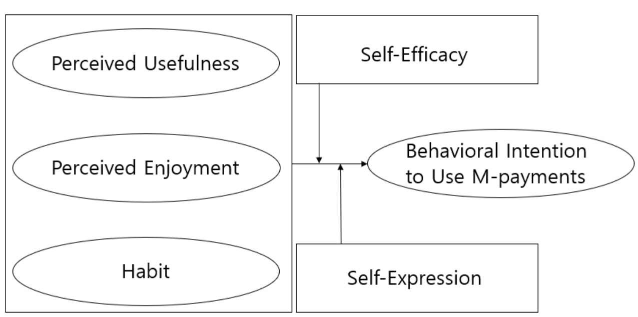

Figure 3. Research Model (Study II & III)

III. Research methodology

A. Measures

The questionnaire was designed to fit the 7-point Likert scale (1=strongly disagree to 7=strongly agree) and consists of 35 items, which were borrowed, and some later modified, from the previous studies. The changes that were made to the survey did not change many of the items' psychometric properties (see Appendix). Detailed information on operational definitions is presented in Table 2.

B. Data collection

The questionnaire was distributed online and offline to Chinese nationals, and a random sampling method was used. First of all, prior to the main survey, a preliminary survey was conducted. Hard copies

Table 2. Operational Definition of the Variables

Construct	Operational Definition	Questions	References
Perceived Usefulness	The degree to which a potential user believes that using a particular system will increase his or her job performance.	1. Generally, I believe that m-payments will be very useful. 2. Using m-payments would enhance my effectiveness in my daily work. 3. Using m-payments will enable me to accomplish my transaction more quickly 4. I believe that using m-payments is more convenient than traditional payment methods.	Davis *et al.* (1989)
Perceived Enjoyment	Consumer's perception of the fun and pleasure derived from using that system.	1. I have fun using m-payments. 2. I think using m-payments is enjoyable. 3. I consider the actual process of using m-payments to be pleasant.	Davis *et al.* (1992), Heijden (2004)
Perceived Ubiquity	An individual's perception of the degree to which mobile wireless technology provides him or her with uninterrupted and personalized communication with other individuals and/or networks.	1. I think I can use m-payments at any time. 2. I think I can use m-payments at any place. 3. Using m-payments makes my life more convenient.	Kim and Garrison (2009), Okazaki *et al.* (2012)
Habit	The extent to which people tend to perform behaviors automatically because of learning.	1. The use of m-payments has become a habit for me. 2. I am addicted to using m-payments. 3. I must use m-payments.	Limayem *et al.* (2007), Nilsen *et al.* (2012), Venkatesh *et al.* (2012)
Behavioral intention	The strength of an individual's intention to perform a specified behavior.	1. I intend to continue using m-payments in the future. 2. I will always try to use m-payments in my daily life. 3. I plan to continue to use m-payments frequently.	Davis *et al.* (1989), Fishbein and Ajzen (1975), Venkatesh *et al.* (2003, 2012)
Use Behavior	A person's actual performance of a given behavior.	1. I often use m-payments at physical stores. 2. I have ever recommended a m-payment service to others.	Davis *et al.* (1989), Venkatesh *et al.* (2003)
Self-Efficacy	An individual's belief in his or her capability to perform a given task or behaviors.	1. I would feel confident that I can use m-payments. 2. I would be able to use m-payments even if there was no one around to show me how to use it. 3. I think that I can use m-payments if someone shows me how to do it first.	Bandura (1986), Yang *et al.* (2012)

were distributed to Chinese students. Then, a self-administered online survey was applied as the data collection method. A total of 430 Chinese individuals participated in this study, and 379 valid questionnaires were used for the analysis. First of all, data with suspected uncertain responses and biases were primarily excluded. Those who had never used offline m-payments before were also excluded.

This study uses various analysis methods to test hypotheses. Theories on the appropriate number of samples vary widely among scholars. However, in the case of the structural equation used for basic hypothesis testing in this study, it is generally accepted that a sample size of 200 or more is preferable in determining statistical power (Kline, 2005).

As for the hypothesis verification method of this study, the whole model has been analyzed using Structural Equation Modeling (SEM). In the case of SEM, it is generally accepted that a sample size of 200 or more is preferable in determining statistical power (Kline, 2005), so the number of 379 samples for analysis can be considered to have statistical power.

Of the total respondents, 160 (42.2%) people are male, and 219 (57.8%) people are female. With 68.3% (n=259) of people between the ages of 20 and 29, people in other age range occupy 31.7% (n=120). Approximately 43.5% of the respondents (n=165) are employees, and 27.2% (n=103) are students. 45.7% (n=173) of the respondents' usage frequency for mobile payments is several times a week. Additional results are shown in Table 3.

IV. Data analysis and results

A. Study Ⅰ: The determinants of m-payment adoption

1. Test of Equation Model.

Structural Equation Modeling (SEM) was used

Table 3. Demographic Analysis

Measure	Items	Frequently	Percentage
Gender	Male	160	42.2%
	Female	219	57.8%
Age	<20	9	2.4%
	20~29	259	68.3%
	30~39	76	20.1%
	40~49	31	8.2%
	>50	4	1.1%
Education Background	Senior high school	19	5.0%
	Junior college	72	19%
	Under-graduate	200	52.8%
	Graduate school	88	23.2%
Usage Frequency	Several times a day	79	20.8%
	Several times a week	173	45.7%
	Several times a month	101	26.7%
	Several times a year	26	6.9%
Most Favorite Payment Habit	M-payments	143	37.7%
	Card payments	144	38.0%
	Cash payments	92	24.3%
	Others	0	0%

to test the equation model. Table 4 shows the fit indices.

2. Path analysis.

Since the path coefficient is 0.45 and the t-value is 10.27, hypothesis that perceived usefulness has a positive effect on behavioral intention (H1) is accepted. The path coefficient of 0.18 and the t-value of 3.58 support our hypothesis that perceived enjoyment has a positive effect on behavioral intention (H2). Also, since the path coefficient is 0.29 and the t-value is 7.14, habit is assumed to have a positive effect on behavioral intention (H3). The path coefficient of 0.67 and the t-value of 17.59 support the statement that habit also has a positive effect on use behavior (H4). Finally, the path coefficient of 0.68 and the t-value of 18.05 prove that behavioral intention has a positive effect on use behavior (H5). In sum, all hypotheses are accepted. Figure 4 displays the results of model testing.

3. The mediating effect of perceived ubiquity (additional analysis).

The bootstrapping method is one of several resampling strategies for estimation and hypothesis testing. "In bootstrapping, the sample is conceptualized as a pseudo-population that represents the broader population from which the sample was derived, and the sampling distribution of any statistic can be generated by calculating the statistic of interest in multiple resamples of the data set" (Preacher et al., 2007, p. 190).

Table 5 presents the results of testing the model that shows the mediating effect of perceived ubiquity. It is a significant regression model because R^2=0.3146, F=154.2202, df1=1.0000, df2=377.0000, p=0.0000. The coefficient value of effect of perceived usefulness on perceived ubiquity is 0.6167, and the t-value is 12.4185 (p=0.0000) which means that the model's overall fit is satisfactory. Meanwhile, the estimated value of the bootstrap is 0.5191 (LLCI) to 0.7144 (ULCI), which means the path coefficient is outside the value of 0.

Table 4. Results of Hypothesis Testing

Hypothesis	Path	Path Coefficient	T-value	Accepted/Rejected
H1	PUS→BI	0.45***	10.27	Accepted
H2	PE→BI	0.18***	3.58	Accepted
H3	HB→BI	0.29***	7.14	Accepted
H4	HB→UB	0.67***	17.59	Accepted
H5	BI→UB	0.68***	18.05	Accepted
X^2/DF=2.08 GFI=0.91 CFI=0.89, NFI=0.89, RMR=0.044, RMSEA=0.054				

*PUS: perceived usefulness, PE: perceived enjoyment, HB: habit, BI: behavioral Intention, UB: use behavior
Note: *p<0.05, **p<0.01, ***p<0.001

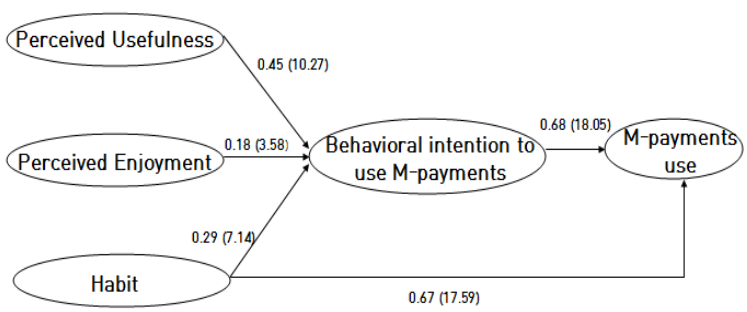

Figure 4. Result of Model Testing

Table 6 presents the results of testing the model that shows the effect of perceived usefulness and perceived ubiquity on behavioral intention. R^2=0.5657 (F=128.2975), df1=2.0000, df2=376.0000, p=0.0000 mean that the model's overall fit is satisfactory. The effect of perceived usefulness on behavioral intention is significant because the path coefficient is 0.5772 (se=0.0770), t=7.4946 (p=0.0000). The effect of perceived ubiquity on behavioral intention is significant because the path coefficient is 0.2605 (se=0.0449), t=5.7998 (p=0.0000).

Table 7 presents the results of testing the model

Table 5. Mediating effect of perceived ubiquity

	R	R-sq	F	df1	df2	p
	.5609	.3146	154.2202	1.0000	377.0000	.0000
Model						
	coefficient	se	t	p	LLCI	ULCI
Constant	1.3243	.3039	4.3581	.0000	.7268	1.9217
Perceived Usefulness	.6167	.0497	12.4185	.0000	.5191	.7144

Table 6. The effect of perceived usefulness and perceived ubiquity on behavioral intention

	R	R-sq	F	df1	df2	p
	.7521	.5657	128.2975	2.0000	376.0000	.0000
Model						
	coefficient	se	t	p	LLCI	ULCI
Constant	.9162	.3791	2.4165	.0161	.1707	1.6617
Perceived Ubiquity	.2605	.0449	5.7998	.0000	.1722	.3488
Perceived Usefulness	.5772	.0770	7.4946	.0000	.4258	.7286

Table 7. The direct effect of perceived usefulness on behavioral intention

	R	R-sq	F	df1	df2	p
	.7160	.5127	114.6412	1.0000	377.0000	.0000
Model						
	coefficient	SE	t	p	LLCI	ULCI
Constant	1.2611	.4358	2.8934	.0040	.4041	2.1181
Perceived Usefulness	.7378	.0689	10.7071	.0000	.6023	.8733

Total effect of perceived usefulness on behavioral intention						
	effect	SE	t	p	LLCI	ULCI
	.7378	.0689	10.7071	.0000	.6023	.8733
Direct effect of perceived usefulness on behavioral intention						
	effect	SE	t	p	LLCI	ULCI
	.5772	.0770	7.4946	.0000	.4258	.7286
Indirect effect of perceived usefulness on behavioral intention						
	effect	Boot SE			Boot LLCI	Boot ULCI
Perceived Ubiquity	.1606	.0292			.1074	.2219

Table 8. The effect of perceived enjoyment on perceived ubiquity

	R	R-sq	F	df1	df2	p
	.6225	.3876	170.9256	1.0000	377.0000	.0000
Model						
	coefficient	se	t	p	LLCI	ULCI
Constant	1.9155	.2491	7.6752	.0000	1.4218	2.4012
Perceived Enjoyment	.5791	.0443	13.0739	.0000	.4920	.6662

Table 9. The effect of perceived enjoyment and perceived ubiquity on behavioral intention

	R	R-sq	F	df1	df2	p
	.7139	.5097	129.6985	2.0000	376.0000	.0000
Model						
	coefficient	se	t	p	LLCI	ULCI
Constant	2.0139	.2523	7.9817	.0000	1.5178	2.5100
Perceived Ubiquity	.2576	.0497	5.1861	.0000	.1599	.3552
Perceived Enjoyment	.4443	.0512	8.6748	.0000	.3436	.5450

that shows the direct effect of perceived usefulness on behavioral intention. R^2=0.5127, t=10.7071 (p=0.0000), and the path coefficient's lower and upper levels are 0.6023 and 0.8733 respectively. Although the coefficient of the direct effect between the perceived usefulness and behavioral intention decreased from 0.7378 (t=10.7071) to 0.5772 (t=7.4946), it's still significant. Meanwhile, the indirect effect of perceived usefulness on behavioral intention, via the mediating effect of perceived ubiquity is 0.1074 (Boot LLCI) to 0.2219 (Boot ULCI). These numbers support our hypothesis that the perceived ubiquity mediates the effect of perceived usefulness on behavioral intention.

Table 8 presents the results of testing the model that shows the effect of perceived enjoyment on perceived ubiquity. The model's overall fit is satisfactory because R^2=0.3876, F=170.9256, df1=1.0000, df2=377.0000, p=0.0000. The coefficient value of effect of perceived enjoyment on perceived ubiquity is .5791 (se=0.0443), and the t-value is 12.4185 (p=.0000) which indicates that the model is significant. Also, the estimated value of the bootstrap is from 0.4920 (LLCI) to 0.6662 (ULCI), which is outside the value of 0.

Table 9 presents the results of testing the model that shows the effect of perceived enjoyment and perceived ubiquity on behavioral intention. The model's overall fit is satisfactory because R^2=0.5097 (F=129.6985), df1=2.0000, df2=376.0000, p=0.0000. The effect of perceived enjoyment on behavioral intention is significant because of the path coefficient is 0.4443 (se=0.0512), t=8.6748 (p=0.0000). The effect of perceived ubiquity on behavioral intention is significant because the path coefficient is 0.2576 (se=.0497), t=5.1861 (p=0.0000). Also, the coefficient value's confidence interval is 0.1599 (LLCI) to 0.3552 (ULCI), which means it's outside the value of 0.

Table 10 presents the results of testing the model that shows the direct effect of perceived enjoyment on behavioral intention. R^2=0.4634, t= 9.4866 (p= .0000), and the path coefficient is from 0.5059 to 0.6811. Although the coefficient of direct effect between the perceived enjoyment and behavioral intention decreased from 0.5395 (t=13.3219) to 0.4443 (t =8.6748), it is still significant. Meanwhile, the indirect effect of perceived enjoyment on behavioral intention through the mediating effect of perceived ubiquity is 0.1492 (se=0.0303). The coefficient value's confidence interval is between 0.0986 (LLCI) and 0.2215 (ULCI). These findings support that perceived

Table 10. The direct effect of perceived enjoyment on behavioral intention

	R	R-sq	F	df1	df2	p
	.6807	.4634	177.4731	1.0000	377.0000	.0000
Model						
	coefficient	se	t	p	LLCI	ULCI
Constant	2.5062	.2642	9.4866	.0000	1.9868	3.0257
Perceived Enjoyment	.5935	.0445	13.3219	.0000	.5059	.6811

Total effect of perceived enjoyment on behavioral intention						
	Effect	SE	t	p	LLCI	ULCI
	.5935	.0445	13.3219	.0000	.5059	.6811
Direct effect of perceived enjoyment on behavioral intention						
	Effect	SE	t	p	LLCI	ULCI
	.4443	.0512	8.6748	.0000	.3436	.5450
Indirect effect of perceived enjoyment on behavioral intention						
	Effect	Boot SE			Boot LLCI	Boot ULCI
Perceived Ubiquity	.1492	.0303			.0986	.2215

Table 11. Moderating effect of self-efficacy: Perceived usefulness

	R	R-sq	F	df1	df2	p
	.7560	.5715	108.0596	3.0000	375.0000	.0000
Model						
	coefficient	se	t	p	LLCI	ULCI
constant	5.7390	.0472	121.5824	.0000	5.6462	5.8319
Self-efficacy	.3144	.0501	6.2746	.0000	.2159	.4130
Perceived Usefulness	.5940	.0879	6.7605	.0000	.4213	.7688
int_1	.0092	.0366	.2513	.8017	-.0627	.0811

ubiquity mediates the effect of perceived enjoyment on behavioral intention.

B. Study Ⅱ: The moderating effect of self-efficacy

In Table 11, R^2=0.5715 (F=108.0596), df1=3.0000, df2=375.0000 (p=0.0000) show good fitness of the measurement model, and the effect of perceived usefulness on behavioral intention is significant because the coefficient is 0.5940, and the t-value is 6.7605. Also, the moderating variable Int_1's coefficient is 0.0092, and its t-value is 0.0366 (p=0.8017), which means that self-efficacy does not moderate the effect of perceived usefulness on behavioral intention. The results of the bootstrap test show that the interval includes the value of 0: LLCI is -0.0627, and ULCI is 0.0811. Therefore, the hypothesis that self-efficacy moderates the relationship between perceived usefulness and behavioral intention must be rejected.

As Table 12 shows, R^2=0.5309 (F=137.8065), df1=3.0000, df2=375.0000 (p=0.0000). It indicates good fit of the measurement model. Furthermore, the effect of perceived enjoyment on behavioral intention is significant because the coefficient is 0.4101 and the t-value is 8.1624 (p=0.0000). Meanwhile,

Table 12. Moderating effect of self-efficacy: Perceived enjoyment

	R	R-sq	F	df1	df2	p
	.7287	.5309	137.8065	3.0000	375.0000	.0000
Model						
	coefficient	se	t	p	LLCI	ULCI
constant	5.8106	.0497	116.9954	.0000	5.7129	5.9082
Self-efficacy	.3239	.0520	6.2333	.0000	.2217	.4261
Perceived Enjoyment	.4101	.0502	8.1624	.0000	.3113	.5089
int_1	-.0777	.0254	-3.0551	.0024	-.1227	-.0277

Table 13. Moderating effect of self-efficacy: Habit

	R	R-sq	F	df1	df2	p
	.7020	.4928	108.5921	3.0000	375.0000	.0000
Model						
	coefficient	se	t	p	LLCI	ULCI
constant	5.8750	.0488	120.3020	.0000	5.7790	5.9711
Self-efficacy	.3737	.0586	6.3731	.0000	.2584	.4890
Habit	.3479	.0445	7.8215	.0000	.2604	.4353
int_1	-.1288	.0230	-5.6027	.0000	-.1740	-.0836

the moderating variable Int_1's coefficient of -0.0777, and its t-value of -3.0551 (p=0.0024) show that self-efficacy moderates the effect of perceived enjoyment on behavioral intention. However, because the coefficient is -0.0777, H9 has been rejected. As for the results of the bootstrap test, LLCI is -0.1277, and ULCI is -0.0277 (i.e., the interval doesn't include the value of 0).

R^2=0.4928 (F=108.5921), df1=3.0000, df2=375.0000 (p=0.0000), presented in Table 13, show good fitness of the measurement model. Furthermore, the effect of habit on behavioral intention is significant because the coefficient is 0.3479 and the t-value is 7.8215 (p=0.0000). Meanwhile, according to the moderating variable Int_1's coefficient of -0.1288 and its t-value of -5.6027 (p=0.0000), self-efficacy moderates the effect of habit on behavioral intention. However, because the coefficient is -0.1288, H10 has been rejected. According to the results of the bootstrap test, the interval doesn't include the value of 0: LLCI is -0.1740, and ULCI is -0.0836.

C. Study Ⅲ: The moderating effect of self-expression

As shown in Table 14, R^2=0.5944 (F=97.2547), df1=3.0000, df2=375.0000 (p=0.0000). This indicates the good fitness of the measurement model. Furthermore, the effect of perceived usefulness on behavioral intention is significant because the coefficient is 0.6018 and the t-value is 7.9226 (p=.0000). Meanwhile, self-expression does not moderate the effect of perceived usefulness on behavioral intention because the moderating variable Int_1's coefficient is -0.0560, and its t-value is -1.4173 (p=0.1572). As for the results of the bootstrap test, LLCI is -0.1337, and ULCI is 0.0217 (i.e., the interval includes the value of 0). Therefore, H11 is rejected.

As shown in Table 15, R^2=0.4822 (F=96.6872), df1=3.0000, df2=375.0000 (p= 0.0000). It indicates the good fitness of the measurement model. In addition, the effect of perceived enjoyment on behavioral intention is significant because the coefficient is 0.4850 and the t-value is 8.7705 (p=0.0000). Also,

Table 14. Moderating effect analysis of self-expression: Perceived usefulness

	R	R-sq	F	df1	df2	p
	.7709	.5944	97.2547	3.0000	375.0000	.0000
Model						
	coefficient	se	t	p	LLCI	ULCI
constant	5.7740	.0458	126.0831	.0000	5.6839	5.8640
Self-expression	.2441	.0342	7.1305	.0000	.1768	.3114
Perceived Usefulness	.6018	.0760	7.9226	.0000	.4524	.7512
int_1	-.0560	.0395	-1.4173	.1572	-.1337	.0217

Table 15. Moderating effect analysis of self-expression: Perceived enjoyment

	R	R-sq	F	df1	df2	p
	.6987	.4882	96.6872	3.0000	375.0000	.0000
Model						
	coefficient	se	t	p	LLCI	ULCI
constant	5.7894	.0565	102.4570	.0000	5.6783	5.9005
Self-expression	.1535	.0457	3.3591	.0009	.0636	.2433
Perceived Enjoyment	.4850	.0553	8.7705	.0000	.3762	.5937
int_1	-.0421	.0329	-1.2791	.2017	-.1068	.0226

Table 16. Moderating effect analysis of self-expression: Habit

	R	R-sq	F	df1	df2	p
	.6395	.4090	90.6974	3.0000	375.0000	.0000
Model						
	coefficient	se	t	p	LLCI	ULCI
constant	5.8475	.0588	99.4864	.0000	5.7319	5.9630
Self-expression	.1188	.0531	2.2399	.0257	.0145	.2232
Habit	.4143	.0508	8.1513	.0000	.3144	.5142
int_1	-.0689	.0240	-2.8757	.4043	-.1160	.0218

the moderating variable Int_1's coefficient is -0.0421, and its t-value is -1.2791 (p=0.2017), which means that self-expression does not moderate the effect of perceived enjoyment on behavioral intention. The results of the bootstrap test as well reject our hypothesis that self-expression moderates the relationship between perceived enjoyment and behavioral intention because LLCI is -0.1068, and ULCI is 0.0226 (i.e., the interval includes the value of 0).

As shown in Table 16, R^2=0.4090 (F=90.6974), df1=3.0000, df2=375.0000 (p=0.0000). It indicates the good fitness of the measurement model. Furthermore, the effect of habit on behavioral intention is significant because the coefficient is 0.4143 and the t-value is 8.1513 (p=0.0000). Meanwhile, the moderating variable Int_1's coefficient is -0.06891, and its t-value is -2.8757 (p=0.4043), which means that self-expression does not moderate the effect of habit on behavioral intention. As for the results of the bootstrap test, they too reject hypothesis 13 because LLCI is -0.1160, and ULCI is 0.0218 (i.e., the interval includes the value of 0).

D. Summary of the hypotheses results

This study explored the key factors influencing consumer adoption of offline m-payments in China; self-efficacy and self-expression were used as moderating variables. Additional analysis was conducted to check if perceived ubiquity has a mediating effect on behavioral intention to use m-payments. Of a total of thirteen hypotheses, seven hypotheses were accepted (H1~H7) and six hypotheses were rejected (H8~H13).

V. Conclusion

A. Discussion

This study researched offline m-payment adoption in the Chinese market based on consumers' point of view. It is important to understand which factors affect consumers' intention to use offline m-payments in China as it is the largest smartphone market in the world. Businesses should consider such factors when they develop and market new mobile technologies. Furthermore, accelerating the diffusion of m-payments usage is expected during the COVID19 pandemic. Due to COVID19, unmanned payment systems (i.e., electronic kiosks) and unmanned (i.e., cashierless) stores are increasing because they help in maintaining social distancing and thus prevents the spread of coronavirus. Therefore, the use of offline m-payment and credit cards that can be used as non-face-to-face payments will increase further. A common feature of offline m-payment is to increase the convenience of using a credit card. This means that a customer can store and use various credit cards on his/her mobile phone. As a result, offline m-payment is more convenient to use than credit cards, so it is replacing credit cards. Therefore, the expansion of the unmanned payment system due to COVID19 is expected to affect the spread and increase of the use of offline m-payments.

This study proposes empirical research on three positive determinants for offline m-payment adoption: perceived usefulness, perceived enjoyment, and habit. All three determinants were used as independent variables. Two important individual traits (self-efficacy and self-expression) were used as moderating variables. Additionally, the perceived ubiquity of consumers, a unique attribute of m-payments, was used as a mediating variable.

In Study I, perceived usefulness, perceived enjoyment, and habit were all found to have a positive effect on behavioral intention. Furthermore, habit and behavioral intention were found to have a positive effect on actual behavior, and perceived usefulness proved to be the strongest factor that affects Chinese consumers' intention to use offline m-payment.

Additional analysis showed that perceived ubiquity is a mediating variable in the relationships between perceived usefulness and behavioral intention and perceived enjoyment and behavioral intention.

Surprisingly, Study II showed that two of the three moderating effects showed significant results. Self-efficacy doesn't moderate the effect consumer's perception of usefulness has on use intention. This implies that regardless of the level of confidence, consumers are willing to conduct a transaction by m-payment because they realize that it is very useful and efficient. However, the findings also showed that self-efficacy has a significant negative moderating effect on the relationship between perceived enjoyment and behavioral intention, as well as between habit and behavioral intention. It seems that people with high self-efficacy tend to believe that offline m-payment use is not simply perceived enjoyment or habit but must have a clear purpose and reason for using it. Therefore, a customer may have negative thoughts about using m-payment due to perceived enjoyment or habit. This can be a very important point in establishing a marketing strategy. For example, for people with high self-efficacy, an effective communication strategy may be to link the use of offline m-payment with rational consumption and emphasize its benefits.

Finally, the current study shows that self-expression has no moderating effect on the process of adoption. This implies that Chinese consumers are not expressing themselves by using offline m-payments while shopping in physical stores. This new technology-based service may have been innovative when it first appeared in the market; however, as time passed and the growing amount of consumers realized how useful and enjoyable it is, offline m-payment has lost its status of value-expressive technology. In other words, in the early days of m-payment, the use of m-payment could be a means of self-expression for groups such as early adopters, for example. However, the recent consumption environment has spread rapidly with the industrial infrastructure related to m-payment, and the result is an indication that the use of m-payment is now commonplace. This once again empathises that the use of m-payment is a convenient payment method for consumers and that the benefits (e.g., earning points) of using m-payment are superior compared to other payment methods. Based on this result, it can be judged that offline m-payment usage has become common among consumers and is changing into a habitual use situation.

B. Implications

First, because perceived usefulness and perceived enjoyment positively affect consumers' behavioral intentions to use offline m-payment, service providers should improve the adoption and retention rate by enhancing those perceptions. Consumers need to see offline m-payment usage as a pleasurable time-and-effort saving process. Banks have successfully created multiple incentives (rewards) to push their clients to use credit cards more frequently to pay for everyday purchases. Similar incentives should be provided to the customers who use offline m-payment systems. Most consumers would repeat using them if discount pricing or coupons are proposed based on their past purchasing behavior. Reward points for the purchase also may be helpful in making the customers see the process of using offline m-payments as pleasant and enjoyable. Furthermore, repeated usage would positively influence usage habit which in its turn will positively affect customer's intention to use offline m-payments in the future. Altogether these should increase retention rate. Similarly, incentives can be applied in the case of non-users to convince them to start using offline m-payments. Consumer interest in rewards is an opportunity for providers to redefine how they build customer loyalty. Offline m-payment systems are appealing for retailers because by giving consumers the opportunity to earn rewards, tracking their earning progress, and seamlessly redeeming rewards, they remove the need for additional "loyalty program" elements like a keychain card or punch card.

Second, since perceived ubiquity was found to mediate influence of consumers' perceived usefulness and perceived enjoyment on behavioral intention to use offline m-payments, service providers and retailers should present ubiquitous payment services to consumers, and make consumers realize that by using offline m-payment they can conduct transactions from anywhere at any time by any mobile device. Eventually, consumers won't adopt offline m-payment unless they can use it to purchase from a vast range of merchants.

Third, it may be useful to integrate promotions and targeted ads from merchants. Consumers almost always carry their mobile phones or PDAs with them. Once they are near or inside the store, they can receive related promotions and ads via offline m-payment applications, which may increase their offline m-payment usage.

C. Limitations and further research

This study has several limitations. First, due to the limited time and budget, the research has targeted only offline m-payment adopters. However, there are differences between adopters and non-adopters' perceptions and beliefs (Aydin and Burnaz, 2016). Therefore, in the future, it would be useful to conduct a comparative study to find which factors differ in their importance for these two categories and if there are additional factors affecting non-adopters' behaviors. These can help to identify which other key factors affect behavioral intention to adopt offline m-payments.

Second, the replies were collected online. Thus, the sample may represent only people who are more or less used to modern technologies, such as computers and the Internet. Furthermore, there were only 4 people older than 50. Thus, the results should be with caution extended to elderly generations and the population in rural areas. In addition, China's population is estimated to be around 1.4 billion. It is difficult to statistically verify that the sample used in the study reflects the entire Chinese market. Thus, it seems that sampling to represent the entire parameter using M-payment is not possible.

Third, this paper explored the determining factors of offline m-payment adoption only in China. Since AliPay is available only in China, Apple Pay and Google Wallet are available only in North America, Samsung Pay is available only in Korea, and so on, further research can be conducted in several countries to compare each market ecosystem and understand the differences in characteristics.

Forth, not all offline m-payments are the same. The process of adoption may vary depending on which technology was applied (Luna et al., 2019).

Finally, the technical capabilities and preferences of businesses while adopting offline m-payment methods are some of the important factors. If businesses are not adopting and providing their customers with this new technology, and modifying it to their customers' needs, it could be a dead end. Thus, future research is necessary to investigate certain important factors which influence adoption of offline m-payments by sellers.

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Appendix A. Measurement Model Assessment

Exploratory factor analysis and Reliability analysis

Exploratory factor analysis (EFA) is "a statistical technique that is used to reduce data to a smaller set of summary variables and to explore the underlining theoretical structure of the phenomena" (Hick et al., 2019, p. 212). It is used to identify the structure of the relationship between the measured variables. According to Hair et al. (2010), factor loading estimates should be higher than 0.50.

In this study, only items that had factor loadings higher than 0.60 were selected. The Kaiser-Meyer-Olkin Measure of Sampling Adequacy value is 0.941. It means that the data are suitable for exploratory factor analysis. To achieve a higher level of reliability, the items with factor loadings lower than 0.60 and cross-loading were removed. The results are as shown in Table 4.

Cronbach's Alpha must be higher than 0.70. As shown in Table A1, all Cronbach's Alpha values are higher than 0.80, which means all the constructs have good reliability and internal consistency.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.941
Bartlett's Test of Sphericity	Approx. Chi-Square	8557.027
	df	253
	Sig.	.000

Table A1. Result of Exploratory Factor Analysis and Reliability Analysis

Items	factor loading	Eigen value	Cronbach's Alpha
Perceived Usefulness1	.869	4.297	0.931
Perceived Usefulness3	.851		
Perceived Usefulness2	.824		
Perceived Usefulness4	.772		
Perceived Enjoyment2	.758	4.078	0.950
Perceived Enjoyment1	.753		
Perceived Enjoyment3	.729		
Perceived Ubiquity1	.831	2.351	0.919
Perceived Ubiquity2	.830		
Habit2	.733	2.069	0.882
Habit3	.687		
Habit1	.636		
Self-efficacy2	.794	1.974	0.839
Self-efficacy1	.685		
Self-expression1	.847	1.911	0.929
Self-expression2	.844		
Self-expression4	.829		
Self-expression3	.828		
Behavioral intention2	.714	1.637	0.912
Behavioral intention3	.699		
Behavioral intention1	.653		
Use behavior1	.752	1.598	0.809
Use behavior2	.689		

Correlation analysis

Table A2 shows the results of the correlation analysis. The Correlation Coefficient (r) turned to be +.495 to 1.00 (relatively strong to strong) for all the relationships. Also, the relationships between the variables are all positive.

Table A2. Results of Correlation Analysis and AVE

	PUS	PE	PUB	HB	SE	EX	BI	UB
PUS	1							
PE	.699**	1						
PUB	.561**	.623**	1					
HB	.469**	.631**	.686**	1				
SE	.526**	.586**	.655**	.641**	1			
EX	.308**	.531**	.580**	.685**	.635**	1		
BI	.716**	.681**	.592**	.617**	.583**	.481**	1	
UB	.495**	.582**	.575**	.671**	.547**	.620**	.681**	1
	SE	HB	UB	BI	PUS	PE	EX	PUB
SE	0.59*							
HB	0.317	0.63*						
UB	0.313	0.223	0.61*					
BI	0.233	0.311	0.222	0.58*				
PUS	0.110	0.245	0.120	0.121	0.62*			
PE	0.216	0.230	0.329	0.221	0.337	0.60*		
EX	0.278	0.121	0.212	0.316	0.325	0.211	0.70*	
PUB	0.124	0.311	0.302	0.117	0.217	0.124	0.346	0.58*

*PUS: perceived usefulness, PE: perceived enjoyment, PUB: perceived ubiquity, HB: habit
SE: self-efficacy, EX: self-expression, BI: behavioral intention, UB: use behavior
**: $p<0.01$
*: Square Root of AVE. AVE = Average Variance Extracted

Confirmatory factor and convergent validity analysis

In this study, the structural equation modeling was used to conduct confirmatory factor analysis and test how well the measured variables represent the number of constructs.

There are six common measures of goodness of fit of the model, such as (1) the ratio of chi-square (X^2) to degrees of freedom (DF), (2) goodness of fit index (GFI), (3) comparative fit index (CFI), (4) normalized fit index (NFI), (5) adjusted goodness of fit index (AGFI), and (6) root mean square residual (RMR). The measures' recommended values are X^2/DF$\leq$3.00, GFI$\geq$0.90, AGFI$\geq$0.80, NFI$\geq$0.90, CFI$\geq$0.90, and RMR$\leq$ 0.10. As shown in Table A3, in the case of our model, the values of measures of goodness of fit are X^2/DF=1.79, GFI=0.91, AGFI=0.891, NFI=0.89, CFI=0.91, RMR=0.054. Therefore, our statistical model fits the set of observations well.

To examine the degree to which the measures of constructs are related, convergent validity was estimated. According to the criterion of Fornell-Larcker (1981), the convergent validity of the measurement model can be assessed by the Average Variance Extracted (AVE) and Composite Reliability (CR).

As shown in Table A3, AVE and CR values for all the constructs are higher than 0.50 and 0.70. It means that for all the constructs, the measures that measure the same construct are related.

Table A3. Results of Confirmatory Factor Analysis and Convergent Validity Analysis

			Unstandardized coefficients	Standardized estimates	S.E.	C.R.	P	Construct reliability	AVE
SE1	←	Self-efficacy	1	0.76				0.69	0.59
SE2	←		0.617	0.597	0.048	14.994	.000		
HB3	←	Habit	1	0.777				0.73	0.63
HB2	←		0.711	0.613	0.059	7.980	.000		
UB1	←	Use behavior	1	0.727				0.74	0.61
UB2	←		0.821	0.775	0.099	9.774	.000		
BI1	←	Behavioral intention	1	0.666				0.67	0.58
BI2	←		0.864	0.624	0.057	9.652	.000		
PUS1	←	Perceived Usefulness	1	0.69				0.68	0.62
PUS2	←		0.884	0.748	0.036	27.151	.000		
PUS3	←		0.893	0.784	0.056	11.756	.000		
PE1	←	Perceived Enjoyment	1	0.874				0.69	0.60
PE2	←		0.982	0.876	0.062	15.981	.000		
PE3	←		0.875	0.732	0.121	4.986	.012		
EX1	←	Self-expression	1	0.952				0.74	0.70
EX2	←		0.923	0.952	0.036	27.523	.000		
EX4	←		0.885	0.768	0.123	5.908	.002		
PUB1	←	Perceived Ubiquity	1	0.881				0.69	0.58
PUB2	←		0.698	0.598	0.137	11.201	.000		
Fit Indices		CMIN	P	CMIN/DF	GFI	AGFI	RMR	NFI	RMSEA
		354.92	.000	1.79	0.91	0.891	0.054	0.89	0.053