Information Systems Frontiers (2022) 24:247–266
https://doi.org/10.1007/s10796-020-10077-6

Influence of Habits on Mobile Payment Acceptance: An Ecosystem Perspective

Lin Jia [1,2] · Xiuwei Song [1] · Dianne Hall [3]

Accepted: 11 October 2020 / Published online: 22 October 2020

Abstract
With the increase in the use of various mobile devices, mobile payments have become a crucial driver for commerce success. However, the percentage of consumers who use or continue using mobile payments in the US is low. This study adopts information technology (IT) ecosystem view and transfer of learning theory and explores the effects of five types of technology use habits on consumers' intention to continue using mobile payments. Results indicate that consumers' online shopping, mobile service use, and cell phone use habits have a positive relationship with their mobile payment use habit, positively affecting their intention to continue using mobile payments. Theoretical and practical implications of the findings are presented.

Keywords Mobile payment · Technology use habit · Transfer of learning · IT ecosystem · Post adoption

1 Introduction

Mobile payments are transactions using mobile devices (e.g., smartphones and tablets) to pay for goods, services, and bills or perform bank transactions using mobile technology (Dahlberg et al. 2008). We are in the era of mobile commerce, and the population of mobile device users is large and growing. Mobile payments have become a crucial facilitator of commerce success. They provide significant benefits, such as fast transactions, great convenience, time saving, and low discount rates, to consumers (Francisco et al. 2015) and result in low marketing cost and high profit for mobile payment service providers (Gupta and Kim 2007). Thus, consumers' use of mobile payments, especially on a continuous basis, will help build a win-win situation and accelerate the prosperity of mobile commerce.

Although many mobile payment services, such as Apple Pay and Google Wallet, are developed in the United States, the percentage of consumers who use mobile payments is low, and many users choose to revert to other payment processes after using mobile payments (Shaikh and Karjaluoto 2015). eMarketer estimated that the transaction volume of mobile payments in the United States in 2018 is approximately \$114.63 billion, and iResearch, a famous e-commerce consulting company in China, reported that the number in China is \$26.9 trillion. The penetration rate of mobile payments in the US is low. Bain's Research Now Retail Banking Net Promoter Score Survey 2018 states that the top three payment methods in the United States are credit card, cash, and debit card, and only 9% and 6% of US citizens adopt Apple Pay and Google Wallet, respectively. Auriemma's 2018 survey reports that 42% of consumers who have used mobile payment services would not recommend them, and the number is only 31% in 2017. These findings are unfavorable for companies who have invested considerable assets in facilitating mobile payments. For example, PayPal bought Paydiant for \$280 million to enter the mobile payment market (Flinders 2015). Companies cannot recover their investments in mobile payments when consumers do not adopt and use them continuously. Thus, facilitating consumers' continuous use of mobile payment services should be explored.

Previous literature well supported the importance of consumers' automatic use of technology in affecting their continued information system (IS) use (Limayem et al. 2007; Polites and Karahanna 2013; Venkatesh et al. 2012). Several studies have focused on the influence of habit of using technologies, such as email, online news service, and Q&A communities, on individuals' future use of the same technology (Kraut et al.

✉ Lin Jia
jialin87@bit.edu.cn

1 School of Management and Economics, Beijing Institute of Technology, Beijing, China

2 Sustainable Development Research Institute for Economy and Society of Beijing, Beijing, China

3 Harbert College of Business, Auburn University, Auburn, AL, USA

1999; Kim et al. 2005; Khansa et al. 2015). However, the establishment of the link between prior and future use of a certain innovation simply reflects the stability in consumers' use behavior across time (Ajzen 1991) and does not contribute to the theoretical understanding of post adoption research. IS academic researchers have explored the role of habit in shifting from legacy systems to new systems with similar functions (Chen et al. 2019; Labrecque et al. 2017; Lee and Joshi 2016; Polites and Karahanna 2012, 2013). They demonstrated that individuals form incumbent system habit during their past experiences of using legacy systems, thereby increasing their switching cost and inertia to use new systems. Thus, enterprises should consider on how to overcome incumbent system habit for facilitating their employees to use new systems. However, this condition is inconsistently true. For example, individuals' habit of scanning Quick Response (QR) code to add friends when using mobile instant messaging services does not facilitate their use of mobile payments. Many studies should explore the influences of connections among different technologies on technology acceptance.

In this study, we examine mobile payment acceptance from the information technology (IT) ecosystem perspective and adopt transfer of learning theories as the theoretical background to address the abovementioned issues. IT ecosystem refers to "a subset of ITs in the IT landscape that are related to each another in a specific context of use" (Adomavicius et al. 2008a, p. 783); the technologies in the ecosystem are interrelated (Adomavicius et al. 2007). Mobile payments are a type of mobile service. In this study, we differentiate mobile payments from other types of mobile services. The term "mobile services" refers to services other than mobile payments (e.g., mobile communication, maps, and news) to avoid confusion. We focus on five types of technologies in the mobile ecosystem, namely, mobile payments, mobile services, online shopping, cell phones, and computers (Basole 2009). The reasons on including the five technologies are explained in the IT Ecosystem View section in the literature review. We investigate the effects of consumers' mobile service use, cell phone use, computer use, and online shopping habits on their mobile payment use habit that affects their intention to continue using mobile payments. Transfer of learning theory states that consumers' habits of shopping online and using mobile services, cell phones, and computers will affect their formation of habits in using similar or new technologies (Haskell 2001).

This research aims to explore the effects of technology use habits on consumers' intention to continue using mobile payments. Whether consumers' technology use habits affect their intention to continue using mobile payments will be investigated. The rest of the paper is organized as follows. Section 2 presents the theoretical background and conceptual model. Section 3 introduces the development of hypotheses. Section 4 discusses the data collection and analysis. Section 5 interprets the results. Section 6 provides the key findings and implications.

This study constructs a brief ecosystem of mobile payments and explores the connections among habits of using technologies included in the ecosystem and their effects on users' continuous use of mobile payments to determine the factors affecting the development of mobile payment habit from the ecosystem perspective. A survey-based data collection is conducted to test the proposed model, and the results indicate that consumers' online shopping, mobile service, and cellphone use habits help develop their mobile payment habit and facilitate their continuous intention to use mobile payments. Consumers' computer use habit does not hinder the development of their mobile payment habit.

This research provides theoretical and practical implications. From the perspective of theoretical implication, this study extends IS habit research by exploring the relationships among different types of habit on the basis of the IT ecosystem view and deepens the understanding of the IT ecosystem view by incorporating transfer of learning theory as an approach to explain the connections among different technologies in mobile payment ecosystem. From the perspective of practical implication, the results can help mobile payment practitioners distinguish loyal consumers that are likely to continuously use their mobile payment services. Knowledge about habit antecedents and consequences is useful in helping firms to design practical guidelines for managing the development of technology habit and increasing profits. The findings provide several suggestions on facilitating the development of consumers' mobile payment use habit.

2 Theoretical Background

2.1 Role of Habit

2.1.1 Habit as a Learning Outcome

More than 45% of human behavior can be driven by habits, and individuals will perform the same behavior when the same contextual cues are found (Wood et al. 2002). This finding reflects the important role of habit in affecting individuals' continuous behavior. Previous literature defined habit on the basis of learning theory and viewed habit as a learning outcome. Hull (1943) viewed habit formation as an associative learning process. Verplanken et al. (1997) defined habits as "learned sequences of acts that become automatic responses to specific situations that may be functional in obtaining certain goals or end states" (p. 540). Habit formation is closely associated with the frequency of past behavior in a stable and recurring context (Shah et al. 2014). A general consensus is that a drive to satisfy a need leads to a response to a particular stimulus, and a particular habit is learned when the response is reinforced and/or repeated (Lankton et al. 2010). With repeated use, individuals learn to use technology and become habituated to the behavior (Lakshmanan and Krishnan 2018). In this study, we define habit as “the extent in which people tend to automatically perform behavior because of learning” (Limayem et al. 2007, p. 709). This definition regards habit as a behavior mode that includes reflexive responses and a complex hierarchical knowledge structure with goals at the top of the structure and repeated behavior at the bottom (Aarts and Dijksterhuis 2000).

2.1.2 Role of Habit and Behavioral Intention in Continuous Behavior

Previous literature discussed the effects of habit on individuals’ continuous behavior. However, different views are found on the mechanisms in which habit affect continuous behavior. Several studies have supported the direct effect of habit on continuous behavior, indicating that habitual users perform a certain behavior automatically triggered by environmental cues without cognitive evaluations (Cheung and Limayen 2005; Kim et al. 2005; Limayem et al. 2003; Limayem et al. 2007)). This view believes that habit will reduce the effects of behavioral intention on continuous behavior. Other studies have confirmed the indirect effect of habit, indicating that habit will affect cognitive factors as perceived by consumers, thereby influencing their continuous behavior. Bem (1972), Eagly and Chaiken (1983), and Kim and Malhotra (2005) defined the habit effect on the basis of self-perception theory and indicated that habit will guide the formation of individuals’ attitudes toward their behavior, thereby affecting their behavior in the future. Gefen (2003) stated that habit will influence individuals’ future intention to use IT and affect their future behavior.

The two views are consistent. Ajzen (2002) believed that behavioral intention influences automatic behavior. In particular, the formation of intention would be stabilized and stored in memory through repeated behavior, and individuals’ intention will be activated under certain environmental cues to guide their behavior (Ajzen 2002). Considering the importance of habit in continuous behavior, Venkatesh et al. (2012) added a habit variable in their UTAUT2 model, including the direct and indirect effects of habit. With the focus on the relationship among different types of habits in mobile payment ecosystem, this study ignores which view is better and uses behavioral intention as a proxy for actual behavior, as indicated by Trafimow (2000) and Verplanken and Orbell (2003).

2.1.3 Different Aspects of Habit Research

IS research has primarily focused on the effects of technology habit on the future use of the same technology. IS research has discussed the positive relationship between past use of e-mail, online news service, and Q&A website on individuals’ future use of the same technology (Kraut et al. 1999; Kim et al. 2005; Khansa et al. 2015). Researchers have contributed this positive relationship to easy processing, learning, and self-perception that help individuals to justify their behavior (Eisend 2019). These findings only indicate that past behavior is a good predictor of future behavior and does not contribute to the theoretical understanding of post adoption research (Ajzen 1991).

IS researchers have explored the effects of individuals’ habit of using legacy systems on their use of new systems (Chen et al. 2019). They demonstrated that habitual use of legacy systems increases individuals’ switching cost and inertia to use new systems, which is called incumbent system habit. This condition is because the implementation of new systems typically indicates the replacement of legacy systems, and individuals will evaluate new systems on the basis of their past experience of old systems. Individuals usually prefer to keep using old systems (Polites and Karahanna 2012). On this basis, previous literature regarded incumbent system habit as a key driver of resistance to the use of new systems (Labrecque et al. 2015). Thus, these studies believe that conflicts are found between legacy and new systems, and enterprises should consider on overcoming their employees’ incumbent system habit (Polites and Karahanna 2012). Several studies have investigated interventions to disrupt incumbent system habits for successfully implementing new systems (Polites et al. 2013).

The review of habit literature shows that the previous literature shifts from focusing on the effects of habit on the future use of the same technology to exploring the effects of habit of using legacy systems on their use of new systems. This finding is a good start point because IS researchers have realized the interrelation among different innovations and explored the effects of habit of old systems on relevant new systems. However, these studies have only focused on the resistance of old system habit on new system use. Whether all old systems will resist the use of new systems need to be investigated. Taking WeChat Pay as an example, which is one of the largest mobile payment services in China, Tencent first develop WeChat users’ habit of scanning QR code to add friends and read information in their mobile instant messaging service, WeChat. Then, Tencent incorporates the QR code feature into its mobile payment service and makes it easy for consumers to accept this payment approach. Thus, many studies are needed to determine the role of habits in affecting the relationship among different technologies.

2.2 IT Ecosystem View

Extensive research are conducted on adoption of innovations, and many theories are used to guide IS adoption research (e.g., theory of planned behavior and united theory of acceptance and use of technology). Previous research and theories individually consider innovation (Adomavicius et al. 2008b) and ignore the effect of other innovations on the adoption of object innovation. The IT ecosystem view suggests that similar or related technologies are interdependent and interact with each other (Adomavicius et al. 2007; Swanson 1994). Innovation ecosystem and the factors that shape innovation success in the ecosystem are increasingly emphasized (Nambisan 2013). The IT ecosystem view is used in this research to explore the correlations between different types of technology use habits.

A technology ecosystem is "a system of interrelated technologies that influence each other's evolution and development" (Adomavicius et al. 2007, p. 201). Technologies in the ecosystem play different roles, such as component, product and application, and support and infrastructure. The component role describes the basic technologies that are necessary to perform the functions of focal technology in the given context of use, the product and application role includes the focal technology and other competing technologies in a certain use context, and the support and infrastructure role describes the technologies that "enable or work in conjunction with product and application role technologies in an IT ecosystem" to add value to the focal technology (Adomavicius et al. 2008a, p. 784). The three technology roles interact with each other and form a triadic causal framework (Adomavicius et al. 2012). Adomavicius et al. (2007, 2008a, b) explored the mutual influence of different technologies from the perspective of technology roles. They defined paths of influence to represent "the effects of innovation across technology roles within an IT ecosystem" (Adomavicius et al. 2008a, p. 784) and summarized nine paths of influence.

This study aims to introduce IT ecosystem view for exploring the factors affecting users' acceptance of mobile payments rather than the development of mobile payment industry. Thus, this study constructs a small mobile payment ecosystem composed of technologies that are closely related to mobile payments on the basis of the three roles of technologies in an IT ecosystem. Three different roles, namely, component, product and application, and support and infrastructure, are found in the ecosystem, as suggested by Adomavicius et al. (2007, 2008a, b, 2012). On the basis of the directions of Basole (2009), this study constructs a brief mobile payment ecosystem composed of five categories of technologies, namely, focal technology mobile payments, mobile services excluding mobile payments, online shopping, cell phones, and computers (Fig. 1).

Mobile payments are the focal technology and represent the "product and application" role in the ecosystem. In this study, mobile payments are a broad concept that applies to any type of purchases using mobile phones. *Cell phones* or smart phones are necessary to perform mobile payments and are included in the mobile payment ecosystem in this study. Cell phones serve as the component role in the ecosystem because the definition of component role demonstrates that basic technologies that are necessary to use focal technology serve as component roles in an IT ecosystem (Adomavicius et al. 2007, 2012). Mobile payments are a type of mobile services. Other types of mobile services may affect users' acceptance of mobile payments. For example, users of WeChat, the top one communication tool in China provided by Tencent Company, may likely use the mobile payment service of Tencent Company. Thus, this study includes mobile services in the mobile payment ecosystem. Considering that we focus on mobile payments in this study, we use the term "mobile services" to represent services other than mobile payments (e.g., mobile Internet, communication, maps, and news) to avoid confusion. *Mobile services* can play the component and the support and infrastructure roles in the ecosystem. For example, consumers access mobile Internet perform mobile payments; therefore, mobile Internet serves as the component role. Mobile payments should be performed using mobile applications, such as Google Wallet. In this scenario, mobile applications serve as the support and infrastructure role.

The support and infrastructure role in the IT ecosystem reflects the importance of consumer financial services, as suggested by Jia et al. (2018). Mobile payments can be used in different scenarios, including offline and online. With the rapid development of e-commerce worldwide, online shopping has become an important channel for consumers to make purchases. As defined by Wikipedia, online shopping is a form of electronic commerce that allows consumers to make a purchase from a seller over the Internet using different devices, such as computer, laptop, tablet, and cell phones. In online shopping, the seller and the buyer are in different locations, and online payment is a necessary process to close the loop of e-commerce. Thus, the scene of *online shopping* increases the importance of mobile payments with the rapid development of mobile commerce and serves as the support and infrastructure role in mobile payment ecosystem (Adomavicius et al. 2012).

This study includes *computer* as an element of mobile payment ecosystem because Adomavicius et al. (2008a) and Pousttchi et al. (2009) suggested that inhibitors of mobile payment adoption should be considered in a mobile payment ecosystem. Computer is parallel to cell phone because they are IT devices. However, different technologies play different roles in the IT ecosystem in accordance with their different effects on the focal technology. Computer users who prefer to use computers in performing transactions are less likely to use smartphones. This condition is because computers have larger screens and more convenient input compared with smartphones (Zhou and Lu 2011), which may make consumers who prefer to use computers to feel uncomfortable, thereby hindering consumers' adoption and limiting the use of mobile financial services, such as mobile payments

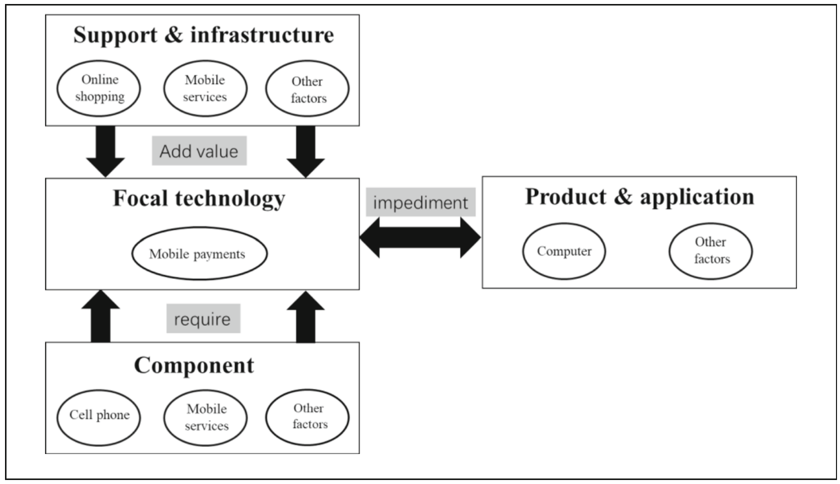

Fig. 1 Mobile Payment Ecosystem in this Study

(Chandra et al. 2010; Sripalawat et al. 2011). Industrial statistics also support this negative influence of computer habit on payments using cell phones. Wolfgang Digital's Key Performance Indicator (KPI) Report 2019 states that 53% of traffic to online stores comes via mobile devices, although this translates to only 32% revenue. Many people browse on mobile devices but purchase through desktops (Carter 2019). Considering that cell phones are necessary devices to perform mobile payments rather than computers, computers serve as the product and application role but not the component role in the ecosystem on the basis of the definitions of different roles in the IT ecosystem view.

The IT ecosystem view emphasizes the mutual influence of technologies in the ecosystem. Adomavicius et al. (2007, 2008a, b) explored the mutual influence of different technologies from the perspective of technology roles. They defined paths of influence to represent "the effects of innovation across technology roles within an IT ecosystem" (Adomavicius et al. 2008a, p. 784) and summarized nine paths of influence. The component role may take the product/application role in the future. Adomavicius et al. (2008b) built an IT ecosystem of digital music and mapped its evolution by considering the paths of influences among three technology roles. The three technology roles interact with each other in a triadic causal framework that contains within-level and cross-level interactions (Adomavicius et al. 2012). Within-level interaction refers to the effect of a technology role on its future development (Adomavicius et al. 2012). For example, infrastructure technologies will drive subsequent development of future infrastructure technologies. Cross-level interaction refers to the effect of a technology role on the future development of other technology roles (Adomavicius et al. 2012). For example, infrastructure technologies will drive subsequent development of future product technologies. However, these interactions are mainly summarized from industrial development on the basis of induction while lacking of solid theoretical support and validation using empirical data.

2.3 Transfer of Learning Theories

As previously mentioned, this study focuses on the influence of habit on technology acceptance and emphasizes their correlations on the basis of IT ecosystem view. Considering that habit is a type of learning outcome, this study reviews the research on transfer of learning to clarify the mechanisms of connections among different technologies. Desse (1958) suggested that transfer of learning is the important topic in the psychology of learning because a central goal of education is to teach students to transfer previously learned knowledge to similar or new situations (Lobato 2006). Previous literature on transfer of learning primarily focuses on two topics, namely, what transfer of learning is and factors affecting it, and how to measure factors that affect transfer of learning (Holton et al. 2000).

2.3.1 Definitions and Types of Transfer of Learning

Different definitions are found for transfer of learning. Perkins and Salomon (1992) suggested that transfer of learning refers to the process where learning occurring in one context enhances or undermines a related performance in another area. Byrnes (1996) and Bransford et al. (2000) defined transfer of learning as the application of knowledge learned in one context to a new context. A popular definition may be the one proposed by Haskell (2001), who defined transfer of learning as the use of past learning when learning something new and its application to similar and new situations. Under this definition, transfer of learning is the ability to apply previously learned skills, processes, and contents to new or different situations (Haskell 2001). Although transfer of learning have multiple definitions, it involves the application, generalizability, and maintenance of previously learned knowledge and skills (Ford and Weissbein 1997). In this research, transfer of learning is defined as the process where consumers' habits of using various technologies enhance or undermine their formation of habits of using similar or new technologies.

Haskell (2001) summarized six levels of transfer, namely, nonspecific, application, context, near, far, and creative transfer. Nonspecific transfer refers to learning that “depends on some connections to past learning” (Haskell 2001, p. 29); application transfer refers to the application of past learning to a specific situation (Haskell 2001); context transfer refers to “applying what one has learned in a slightly different situation” (p. 29); near transfer refers to “when previous knowledge is transferred to new situations that are closely similar but not identical to previous situations” (p. 29); far transfer refers to “applying learning to situations that are relatively dissimilar to the original learning” (p. 29); and creative transfer refers to transferring past learning to a new situation in a creative approach (Haskell 2001). Haskell (2001) suggested that “nonspecific and application transfer are essentially simple learning rather than transfer proper; context transfer is simply the application of learning, thereby making level four as near transfer, and far and creative transfer as far transfer” (p. 30). One example of the first three levels of learning transfer is when an individual applies what he or she has learned in a course to forward questions on a final exam. The effects of online shopping, mobile service (other than mobile payments) use, cell phone use, and computer use habits on mobile payment use habit pertain to the latter three levels of learning transfer. For example, consumers transfer the knowledge learned in using mobile services to new situations, such as learning how to use mobile payments. Consumers who frequently use mobile instant messaging applications are more likely to know how to use mobile payment applications than those who use instant messaging applications less frequently.

2.3.2 Mechanisms of Transfer of Learning

To better support the development of the research model, this study summarizes the mechanisms of transfer of learning on the basis of learning transfer models. The first mechanism is the effect of similarity and compatibility with existing habits. This mechanism is supported by the classic stream of learning transfer models, such as identical element model (Lobato 2006). This model emphasizes the importance of identical elements between the learning and transfer situations in affecting transfer of learning (Thorndike 1924; Thorndike and Woodworth 1901). Butterfield and Nelson (1989) suggested that similarities or connections between past experience and the current situation support transfer of learning. The more similarity between the learning and transfer situations is, the greater the transfer of learning will be (Yorks et al. 1998). Another analogous term of similarity is compatibility. Previous literature supported the importance of compatibility between new technologies with consumers’ existing habit. Existing habits will promote resistance or inertia when new innovation conflicts with existing habits, whereas they will reduce learning cost and facilitate acceptance of new innovation when new innovation is compatible with existing habit (Labrecque et al. 2017).

The second mechanism is the effect of knowledge structure and skills built in past experiences. Prior studies on learning transfer emphasized the importance of similarity while not providing solid explanation. Since 1985, transfer of learning theorists have focused on exploring transfer of learning mechanisms from the field of cognitive psychology and other areas that are related to information processing (Haskell 2001). This stream of learning transfer theories, called the cognitive perspective, emphasizes the effect of individuals’ intrinsic factors on transfer of learning. This stream is built on information processing theory and places the active learner at the center of the learning process (Macaulay and Cree 1999). It suggests that individuals should retrieve a relevant skill or knowledge to transfer what they have previously learned to new situations (Royer 1979). Information processing theory states that learners transfer their past experience and previously obtained information into knowledge or a skill that will affect their current performance or behavior (Newell and Simon 1972). Knowledge is stored in memory as schemata, which is a hypothetical structure where information and knowledge are thought to be organized and processed (Haskell 2001; Macaulay and Cree 1999). A learner will interpret new information in terms of relevant existing schemata when he or she is faced with new tasks to perform or new concepts to learn (Haskell 2001). Previously learned knowledge will be accessed and retrieved to solve problems in transfer situations and develop new habits and routines (Aldrich and Yang 2014). Thus, knowledge structure built in past experience will affect individuals’ cognitive factors, such as attitude, thereby affecting their behavior in the future (Holton, 1996; Holton et al. 2000).

The third mechanism is the effect of environmental factors, such as support and opportunity to use new innovations. The classic perspective emphasizes the similarities between learning and transfer situations, and the cognitive perspective emphasizes the vital role of learners’ prior knowledge or skills in affecting transfer of learning. Each of the two perspectives only focuses on one set of factors that affect transfer of learning. Some researchers have combined previous findings and proposed a holistic view of learning transfer. Apart from similarity and knowledge structure, these researchers have proposed several other factors, where environmental factors, such as external rewards, support from supervisor, and opportunities to use, are well accepted. Baldwin and Ford (1988) are the first researchers to introduce a holistic view for explaining knowledge transfer. They proposed three sets of factors that affect transfer of training, namely, trainee characteristics, training design factors, and work environment. Trainee characteristics include skill or ability, personality factors, and motivation. Training design includes strong transfer design and appropriate content, and working environment includes support and opportunity to use the target innovation (Baldwin and Ford 1988). Holton and his colleagues considered these factors to be a generalized transfer climate and developed a learning transfer system inventory scale to measure it (Holton 1996; Holton et al. 2000; Holton and Baldwin 2003). Four sets of factors, namely, motivational factors (e.g., extrinsic reward), environmental factors (e.g., supervisor support for transfer), trainee characteristics (e.g., learner readiness), and ability factors (e.g., perceived knowledge), are used in the instrument (Holton et al. 2007). Thus, environmental factors will facilitate consumers' learning transfer.

2.4 Summary

In this research, we explore the effects of five technology use habits on consumers' intention to continue using mobile payments. Previous literature on habit usually views technology as independent while overlooking the connection among different innovations. The IT ecosystem view bridges this gap because it supports the connection among different technologies and categorizes those technologies into three different roles. Thus, we introduce the IT ecosystem view as the framework to guide the construction of mobile payment ecosystem. However, the research on the IT ecosystem view is lacking to provide theoretical support for the connections among different innovations in the ecosystem. Considering that the focal variable "habit" is a type of learning outcomes as explained in the prior section, this study introduces transfer of learning theory to provide theoretical support. Combining the IT ecosystem view and transfer of learning theories should enhance the understanding of consumers' mobile payment adoption. The IT ecosystem view emphasizes the positive interrelations among technologies in the ecosystem (Adomavicius et al. 2008a, b), and transfer of learning theories provide some supports to the interrelations among different technologies. Transfer of learning theories demonstrate that an individual transfers his/her learning outcomes, such as knowledge and habit, obtained in the past to new situations. Mobile payments, which is the focal technology in this study, are relatively new compared with mobile service, cell phone, online shopping, and computer technologies. Thus, consumers' habits of shopping online and using mobile services, cell phones, and computers will likely affect their formation of habit of using mobile payments.

3 Development of Hypotheses and Research Model

3.1 Effect of Online Shopping Habit

Online shopping, regardless of using computers or cell phones to make purchases, has become an important part of our daily lives because of its convenience (Beauchamp and Ponder 2010). Consumers who have formed an online shopping habit prefer to shop online anytime and anywhere (Jiang et al. 2013). Only mobile payments can help consumers realize this condition because payment is a necessary stage for consumers to complete transactions, and mobile payments are notable for their mobility, reachability, compatibility, and convenience (Kim et al. 2010). Mobile payments provide consumers with ubiquitous payment services (Lu et al. 2011), allowing consumers to shop online and make payments anytime and anywhere using their cell phones. Thus, mobile payments become attractive and important for consumers who have online shopping habits. This condition facilitates consumers to increase the frequency of mobile payment usage and increases the mobile payment use habit (Hoffman and Novak 1996; Lankton et al. 2010; Novak et al. 2000).

When using online shopping information system, whether it is paid by cash on delivery or payment on the computer end, it will inevitably involve money transaction, which is similar to the transaction attribute of mobile payment information system. When people have the online shopping habit, their familiarity with the online shopping system and the similarity between the online shopping information system and the mobile payment information system will make the transfer of learning work, then, positively affecting the mobile payment habit. Consumers with a high level of online shopping habit are exposed to environmental factors that could facilitate transfer of learning. As explained in the mechanisms of learning transfer, opportunity to use and external rewards are two environmental factors. People with a strong online shopping habit will make online purchases more frequently than those with a weak one. Most e-commerce companies provide different payment options, such as mobile payment, in the payment stage for their consumers. Thus, consumers who frequently shop online have more chances to use mobile payments than those who shop online less frequently. Consumers who pay using computers will become exposed to mobile choice. Lim and Johnson (2002) posited that opportunity to use a target technology is an important reason for high transfer and lack of opportunity to use leads to low transfer. The extent of transfer is reflected as the strength of the relationship between online shopping and mobile payment use habits. Mobile payment service providers usually cooperate with e-commerce platforms to offer price discount when consumers choose to use the mobile choice when they make payments during online shopping. Price discount, the price reduction that consumers obtain when they choose to make a purchase using mobile payments, is an example of an extrinsic reward to transfer for learning new innovation (Holton et al. 2007). First, prior IT use positively influences IT habits (Lankton 2010). Working environment includes support and opportunity to use the target innovation to positively influence transfer of learning (Baldwin and Ford 1988). Adoption behavior, such as using mobile payment in advance is a prior IT use that positively influences the formation of mobile payment usage habit. Some discounts will stimulate users to have many opportunities to use IS, thereby stimulating them to produce prior IT use behavior and forming the habit of using IS. Satisfaction and importance significantly influence IT habits (Lankton 2010). Secondly, consumers may feel the satisfaction and importance of mobile payment when some factors (e.g., discount) allow them the opportunity to use IS, thereby enhancing consumers' continuous use intention and positively affecting the generation of independent use habits. Last, Frequency of past behavior is a predictor of habit (Limayem et al. 2007; Vitak et al. 2011; Wilson et al. 2010). Different from the first point, several stimuli (e.g., discount) for a short time period cannot form the habit of users. These stimuli are only a trigger of mobile payment adoption rather than an enabler to develop users' mobile payment habit. Lankton et al. (2010) stated a general consensus that a drive to satisfy a need leads to a response to a particular stimulus, and a particular habit is learned when the response is reinforced and/or presented. Therefore, the satisfaction and importance of users brought by a particular stimulus will be enhanced when operators continue to provide it. Users will develop the habit of mobile payment. The founding of DIDI and the entry of Uber in the Chinese market repeatedly strengthened the habit of using online car hailing through massive discounts, and the user scale growth rate reached 559.4% in 2014 (China Business Industry Research Institute 2018). After the discount period, the online car market in China reached 290 and 212 million yuan in 2013 and 2017, indicating that a large number of online car-hailing habits are formed although the stimulus has disappeared (Insight and Info Consulting Ltd. 2019).

Considering that consumers can benefit from the discount when they pay using mobile payments regardless of purchasing online or paying bills in brick-and-mortar stores, this condition increases consumers' exposure to mobile payment availability and serves as the cue or trigger that starts mobile payment use habit development, especially for those with a high level of online shopping habit. Thus, we propose that

Hypothesis 1. Consumers' online shopping habit will have a positive relationship with their mobile payment use habit

3.2 Effect of Mobile Service Use Habit

Mobile service use habit refers to the extent where consumers tend to automatically use different types of mobile services (Limayem et al. 2007). In this study, mobile service refers to mobile services, such as location navigation and instant messaging, other than mobile payments (Zhao et al. 2012). Mobile payments are a type of mobile service. Similarity and compatibility between mobile services and mobile payments may encourage consumers to adopt mobile payments on the basis of transfer of learning theory (Butterfield and Nelson 1989; Rogers 2003; Yorks et al. 1998). This condition is because similarity or compatibility with existing mobile service use habit can reflect the specific product features of familiar mobile services. For example, the QR code element is well incorporated in mobile instant messaging and mobile payments, such as WeChat Pay. This incorporation of familiar product features will build strong connection between mobile services and mobile payments and promote the use of mobile payments (Labrecque et al. 2017).

The knowledge structure developed in past experience of using mobile services will affect consumers' cognitive factors, such as self-efficacy of using mobile payments (Giovanis et al. 2012). Consumers that have a high level of self-efficacy are likely to use mobile payments repeatedly (Ajzen 1991). Consumers with a high level of technology self-efficacy are engaged in using technology-based services (Dabholkar and Bagozzi 2002). They have a more positive attitude and intent to use technology-based services than consumers with a low level of technology self-efficacy (Yang 2010). Thus, people with a strong mobile service use habit are likely to have a high level of self-efficacy and feel familiar with mobile payment services, encouraging the formation of a mobile payment use habit (Chiu et al. 2010). The knowledge structure and skills obtained in past experiences of using mobile services also affect consumers' perceived uncertainty and trust. For example, consumers may feel worried of using mobile payments because it involves a high level of uncertainty and different types of risks (Zhou 2014). Frequent use of mobile services without incident will encourage consumers to decrease their perceived uncertainty toward mobile technologies, which is positively related to their institution-based trust in mobile technology. Consumers that have a low level of perceived uncertainty and a high level of institution-based trust in mobile technology are likely to trust mobile payments and use them repeatedly (McKnight et al. 1998, 2002). Transfer of learning is the ability to apply previously learned skills, processes, and contents to new or different situations (Haskell 2001). In this study, mobile service refers to mobile services, such as location navigation and instant messaging, other than mobile payments (Zhao et al. 2012). Before the contact with mobile payment, users exist in the context of mobile services without mobile payments. After the contact with mobile payment, users can apply to mobile payment on the basis of transfer of learning theory in accordance with the previously learned skills, processes, and contents in other mobile services. Thus, we propose that

Hypothesis 2. Consumers' mobile service use habit will have a positive relationship with their mobile payment use habit.

3.3 Effect of Cell Phone Use Habit

Mobile payments are closely related to cell phones because payments are frequently initiated and performed on them. With the increase in cell phone use, the possibility that consumers can rely on their cell phones as primary payment devices increases (Au and Kauffman 2008). This condition can be explained from several aspects. People would prefer to use a tool they use to perform other financial behavior (Wu and Yen 2014). People use their phones for surfing the Internet, checking social networking sites, playing games, using apps, sending texts, and making phone calls. Consumers have formed the habit of consistently carrying their phones, and these phones are ready to use (Jarvenpaa and Lang 2005). Thus, cell phones are a potential tool for consumers to perform financial behavior, and consumers' use of cell phones may positively affect their habit of using mobile financial service, such as mobile payments. Consumers with a strong cell phone use habit tend to explore the potential use of their cell phones (Au and Kauffman 2008). Mobile payments make cell phones flexible payment devices and enable a potential commercial value for them (Andreev et al. 2011). Consumers will consider mobile payments useful because they help them to surpass the limitation of using computers to surf on the Internet, pay bills, and purchase items at the place where the computers are located. Thus, consumers who have formed the habit of using cell phones are likely to be interested in mobile payments.

Cell phone use habit allows consumers to be familiar with mobile technology. This condition reflects the second mechanism of learning transfer, as summarized in the review of learning transfer literature. On the one hand, people build knowledge structure and skills about using cell phone in their past experiences and prefer to apply skills they already have to new situations, such as when they begin to use a new technology (Murray et al. 2010). Consumers who frequently use cell phones can easily learn to use mobile payments, and this process reduces their cost of learning how to use mobile payments. Behavior are prone to be repeated when individuals can perform them quickly and naturally (Lindbladh and Lyttkens 2002). On the other hand, knowledge structure and skills obtained through cell phone usage will affect consumers' attitude toward new technologies (Holton 1996; Holton et al. 2000, 2007). For example, consumers who frequently use cell phones will know how to avoid risk issues, such as fraud, while performing mobile payments. This condition will help reduce their perception for insecurity of mobile payments, thereby enhancing their repeated use of mobile payments. Thus, we propose that

Hypothesis 3. Consumers' cell phone use habit will have a positive relationship with their mobile payment use habit.

3.4 Effect of Computer Use Habit

Online banking and online payments are used as alternatives to mobile payments. Mobile payments are performed using mobile devices, such as smartphones and tablets, whereas online payments are performed using desktops and laptops. Wolfgang Digital's KPI Report 2019 states that 53% of traffic to online stores comes via mobile devices, although this translates to only 32% payments using mobile phones. This finding reflects that many people browse on mobile devices but purchase through desktops (Carter 2019). A possible explanation is the power of computer use habit. Consumers who have a high level of computer use habit may feel that it is more convenient to perform activities using computers, are likely to make online purchases by browsing computer webpages. This condition is because the computer-based interface is considered clear and convenient to consumers with a strong computer use habit (Chandra et al. 2010). Consumers who prefer to use computers may feel challenged when using cell phones to perform tasks because of poor usability caused by lacking adaptation (Venkatesh et al. 2003) and mobile technology limitations (Kalakota and Robinson 2001). For example, consumers who have a high level of computer use habit prefer the computer interface because the screen size of computers is larger and the interface is easier to use compared with mobile devices (Lee and Benbasat 2004). However, consumers occasionally perform mobile payments using mobile devices that have small screens and inconvenient input (Zhou and Lu 2011). These constraints limit the function and usage of mobile financial services, including mobile payments (Sripalawat et al. 2011). The modalities of computer-based payment systems may be relatively different from that of mobile payment systems (Chandra et al. 2010). Many mobile payments do not have similar/comparable computer uses (e.g., in-app purchases, scanning QR code in an offline store to purchase groceries, etc.). This condition reduces consumers' perception of similarity and comparability between traditional and new situations, which is a mechanism of learning transfer as explained in the literature review section. Although consumers with a strong computer use habit are likely to be familiar with computer-based payment systems, they may need to exert extra effort for learning how to use mobile payments. This learning cost creates inertia toward using mobile payments, thereby reducing their tendency to repeatedly use them (Lindbladh and Lyttkens 2002). Thus, we propose that

Hypothesis 4. Consumers' computer use habit will have a negative relationship with their mobile payment use habit.

3.5 Effect of Mobile Payment Use Habit

After the formation of a mobile payment use habit, consumers tend to continue using mobile payments as an automated action (Ouellette and Wood 1998) because habit encourages resistance to change (Polites and Karahanna 2012). Habitual behavior are natural and cognitively easier to perform than other behavior (Lankton et al. 2010). Consumers are likely to repeat behavior that can be performed with minimal effort (Lindbladh and Lyttkens 2002). Thus, mobile payment use habit will encourage consumers to continue using mobile payments. The positive relationship between habit and behavioral intention is supported by IS theories and empirical research. The extended unified theory of acceptance and use of technology integrate habit into the model and posit that habit will positively affect users' behavioral intention toward using an IT innovation (Venkatesh et al. 2012). Empirical research supports the positive relationship between habit and behavioral intention. Gefen (2003) posited that consumers' habit explains a large proportion of the variance of their intention to continue using IT. Hong et al. (2011) demonstrated that IT users' habit has a positive relationship with their intention to continue using agile ISs. Thus, we propose that

Hypothesis 5. Consumers' mobile payment use habit will have a positive relationship with their intention to continue using mobile payments.

3.6 Research Model

A theoretical model based on the logic of IT ecosystem view and transfer of learning theories was proposed to explore the effects of consumers' technology use habits on their future behavior intention (Fig. 2). The proposed model states that online shopping habit, mobile service use habit, and cell phone use habit are positively related to consumers' mobile payment use habit, and computer use habit is negatively related to consumers' mobile payment use habit. Consumers' mobile payment use habit will positively affect their intention to continue using mobile payments.

4 Methodology

4.1 Data Collection

An online survey was conducted to develop an understanding of the effects of technology use habits on consumers' intention to continue using mobile payments. The data were collected using the platform of qualtrics.com, a high-reputation survey distribution platform in the US. A total of 220 questionnaires were collected from the general public of the US. Eighteen questionnaires were excluded during the data screening because of a high rate of similar answers and extremely short completion time, thereby obtaining a final sample size of 202. Table 1 summarizes the demographic information of the participants. More than 85% of the respondents have used mobile payments more than half a year prior to the survey, indicating that they are familiar with mobile payments and are appropriate respondents for this study.

4.2 Measures

The items were obtained from existing scales. Some minor modifications were made to the adopted measures. This research includes five types of technology use habits, namely, online shopping, mobile service use, mobile payment use, cell phone use, and computer use habits. Each type of technology use habit was assessed with the three items adopted from Setterstrom et al. (2013). Users' intention to continue using mobile payments was assessed with the three items adopted from Venkatesh et al. (2012).

The technology acceptance and technology readiness models support the effects of perceived ease of use, perceived usefulness, innovativeness, optimism, discomfort, and insecurity on behavioral intention (Lin et al. 2007). The six variables were used as control variables in this study. Perceived usefulness was measured with the three items adopted from Kim et al. (2010). Perceived ease of use was measured with the three items adopted from Lin et al. (2011). Technology readiness includes four dimensions, namely, discomfort, insecurity, optimism, and innovativeness. Discomfort was assessed with the four items adopted from Jin (2013). Insecurity was assessed with the three items adopted from Lu et al. (2012). Optimism and innovativeness were assessed with the three items adopted from Liljander et al. (2006).

All variables are well-accepted reflective variables on the basis of previous literature. All items were measured on a seven-point Likert scale, ranging from strongly disagree (1) to strongly agree (7). A pilot test was conducted using some convenient samples in the U.S. to test the wording and reliability of the instruments. Subsequently, some minor changes were made to the questionnaires that can be found in the Appendix.

5 Data Analysis and Results

SmartPLS (Ringle et al. 2005) was used to analyze the data. PLS was chosen because of the following reasons. First, PLS is more reliable than covariance-based structural equation modeling (CB-SEM) because PLS has fewer statistical identification problems (Hair et al. 2011). Second, PLS can simultaneously assess the measurement and structural models and can maximize the explained variance of dependent variables

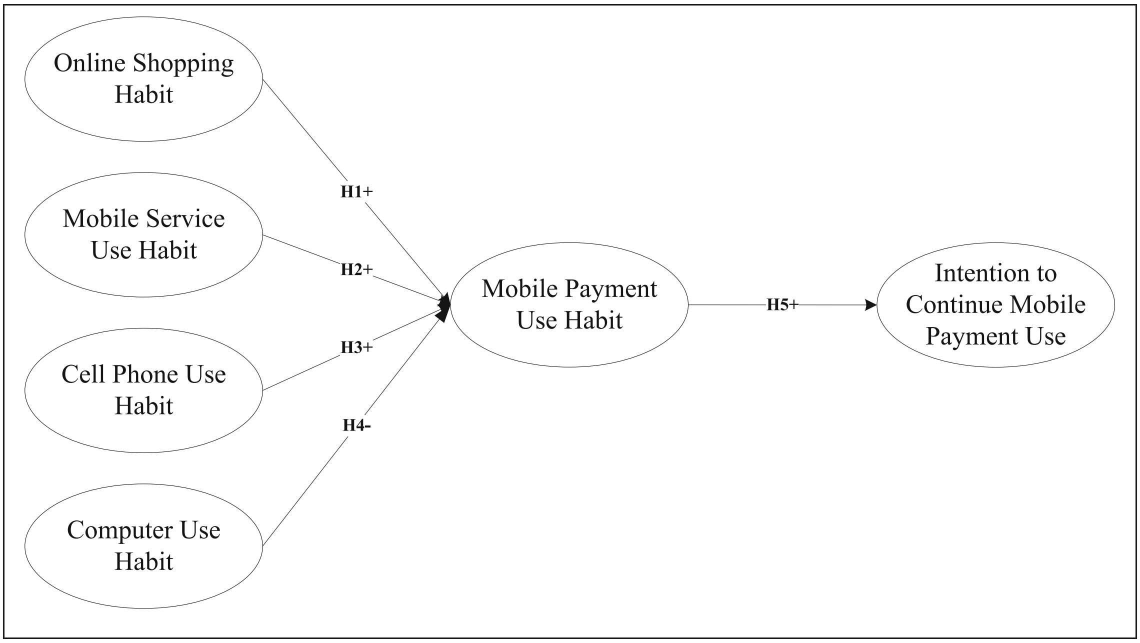

Fig. 2 Research Model

(Xu et al. 2014). The target is to explain the variance in consumers' intention to continue using mobile payments, and we believe that PLS is appropriate for data analysis in this study. Previous literature found that parameter estimations in PLS and CB-SEM are extremely similar (Hair et al. 2011).

5.1 Common Method Bias

All data were collected through a self-report survey. Thus, a potential of common method bias was found (Podsakoff et al. 2003). First, Harman's single-factor test was performed to examine common method bias. Common method bias may exist when a single factor emerges from the unrotated factor solution or one general factor accounts for the majority of the covariance in the variables (Podsakoff et al. 2003). All the construct items were cast into principal components and factor analysis. The result yielded eight factors with eigenvalues greater than 1.0, accounting for 72% of the total variance. No single factor accounts for the majority of variance. Researchers compared the correlations among constructs

Table 1 Demographic Information

Measure	Item	U.S. ($n = 202$)	
		#	%
Age	<21	3	1.5
	21–25	49	24.3
	26–30	35	17.3
	31–35	51	25.2
	>35	64	31.7
Gender	Male	78	38.6
	Female	124	61.4
Education background	Some college or less	115	56.9
	Bachelor	63	31.2
	Master	22	10.9
	PhD or professional	2	1.0
Time to use mobile payments (month)	0–6	28	13.9
	7–12	48	23.8
	13–18	32	15.8
	More than 18	94	46.6

following the procedure established by Pavlou et al. (2007). The results revealed no constructs with correlations greater than 0.9. Malhotra et al. (2006) found that common method variance does not significantly affect IS research although the survey data are collected from a single source. All results indicate that common method bias is unlikely to be a serious concern in this research.

5.2 Measurement Model

This research adopted a two-stage analytical procedure. Confirmative factor analysis was first conducted to assess the measurement model, and the structural relationships were examined. As shown in Table 2, Cronbach's alpha ranges from 0.82 to 0.95, providing evidence of measure reliability (Cronbach 1971). Composite reliability (CR) ranges from 0.88 to 0.97, indicating the validity of internal consistency reliability (Chin 1998). All average variance extracted (AVEs) are larger than 0.5, indicating that convergent validity is met (Fornell and Larcker 1981). We tested the discriminant validity using three tests. First, all squared roots of AVEs are greater than the correlation shared between the construct and other constructs in the model, as shown in Table 3. Second, all items load appropriately on their intended construct, as shown in Table 4. Gefen and Straub (2005) posited that cross loadings derived from PLS procedure will be inevitably higher than from typical exploratory factor analysis; however, differences between item factor and associated cross-loadings are higher than the suggested threshold of 0.1 (Gefen and Straub 2005). Third, all correlations among the constructs are all less than the 0.85 threshold (Kline 1998). These findings suggest adequate convergent and discriminant validity. We checked the variance inflation factors (VIFs) of all independent variables. VIF ranges from 1.54 to 3.28. None of the VIFs exceed 3.3, suggesting that multicollinearity is not a concern.

5.3 Structural Model

The path coefficients and explained variances of the structural model are shown in Fig. 3. The PLS model uses R^2 to assess the explanatory power of a structural model. The model explains 75% of the variance in users' intention to continue using mobile payments. This study controls some variables, as suggested by technology acceptance and initial trust building models. We calculated R^2 excluding the control variables, which is 54.7%. These numbers of R^2 for the two models with and without control variables indicate that the model explains a majority of the variances of consumers' intention to continue using mobile payments. Therefore, the predictive power of the model is good.

The results indicate that online shopping ($b = 0.33$, $p < 0.001$), mobile service use ($b = 0.31$, $p < 0.001$), and cell phone use habits ($b = 0.28$, $p < 0.001$) have a positive relationship with users' mobile payment use habit, thereby supporting H1, H2, and H3. Consumers' computer use habit does not have a significant relationship with mobile payment use habit, indicating that H4 is invalid. Consumers' mobile payment use habit has a positive relationship with their intention to continue using mobile payments ($b = 0.28$, $p < 0.001$), thereby confirming H5.

6 Discussion

6.1 Key Findings

Four out of five hypotheses are supported. This study constructs a brief ecosystem of mobile payment that includes online shopping, mobile services, mobile payments, and cell phones. They are mutually dependent and form an ecology (Adomavicius et al. 2007; Swanson 1994). The IT ecosystem perspective view and transfer of learning theory posit that

Table 2 Latent Variable Reliability and Validity Statistics

Measures	R^2	CR	Cronbach's α	AVE	Mean	Std.
Online shopping habit (OSH)	N/A	0.91	0.86	0.78	5.97	1.11
Mobile service use habit (MSH)	N/A	0.97	0.95	0.91	5.89	1.15
Cell phone use habit (CEH)	N/A	0.94	0.91	0.85	6.44	0.79
Computer use habit (COH)	N/A	0.93	0.88	0.81	6.48	0.73
Mobile payment use habit (MPH)	0.44	0.97	0.95	0.9	5.55	1.31
Behavioral intention (BI)	0.75	0.96	0.93	0.88	5.76	1.19
Perceived ease of use (PEOU)	N/A	0.96	0.94	0.9	6.03	0.96
Perceived usefulness (PU)	N/A	0.93	0.89	0.82	6.05	0.96
Optimism (OPT)	N/A	0.9	0.83	0.75	5.58	1.02
Innovativeness (INN)	N/A	0.9	0.84	0.76	5.30	1.26
Discomfort (DIS)	N/A	0.88	0.82	0.65	3.26	1.35
Insecurity (INS)	N/A	0.91	0.85	0.77	3.84	1.52

Table 3 Square Root of AVE and Correlation Matrix

	OSH	MSH	CEH	COH	MPH	BI	PEOU	PU	OPT	INN	DIS	INS
OSH	**0.88**											
MSH	0.39	**0.96**										
CEH	0.4	0.37	**0.92**									
COH	0.62	0.44	0.5	**0.9**								
MPH	0.52	0.51	0.49	0.41	**0.95**							
BI	0.43	0.43	0.36	0.34	0.74	**0.94**						
PEOU	0.52	0.45	0.51	0.53	0.61	0.64	**0.95**					
PU	0.43	0.45	0.46	0.36	0.68	0.78	0.67	**0.91**				
OPT	0.43	0.45	0.42	0.35	0.67	0.74	0.59	0.77	**0.87**			
INN	0.54	0.35	0.35	0.52	0.53	0.49	0.52	0.42	0.45	**0.87**		
DIS	−0.12	−0.17	−0.22	−0.16	−0.13	−0.31	−0.28	−0.3	−0.23	−0.1	**0.81**	
INS	−0.19	−0.23	−0.3	−0.27	−0.33	−0.52	−0.43	−0.4	−0.37	−0.21	0.63	**0.88**

Bold values are the square roots of AVE

OSH, online shopping habit; *MSH*, mobile service use habit; *CEH*, cell phone use habit; *COH*, computer use habit; *MPH*, mobile payment use habit; *BI*, behavioral intention; *PEOU*, perceived ease of use; *PU*, perceived usefulness; *OPT*, optimism; *INN*, innovativeness; *DIS*, discomfort; *INS*, insecurity

consumers' past usage of different technologies will enhance or undermine their potential usage of similar or new technologies (Haskell 2001). The results show that users' online shopping, mobile service use, and cellphone use habits are positively related to their mobile payment use habit. Those who frequently shop online, use mobile services, and use cellphones are more likely to use mobile payments habitually than those who perform these behavior less frequently.

The results indicate that users' mobile payment use habit has a positive relationship with their intention to continue using mobile payments. Those users who have formed the habit of using mobile payments will likely continue using mobile payments in the future. This finding is consistent with the UATUT2 model, suggesting that consumers' habit will directly affect their behavioral intention toward using mobile payments (Venkatesh et al. 2012).

6.2 Limitations and Future Research

Similar to all research, this study has limitations that should be considered when interpreting the results. For example, a mobile ecosystem is a complex system with many segments (Basole 2009). Cell phones, mobile payments, mobile services, online shopping, and computers are some of the technologies in the mobile ecosystem. Future research is needed to examine the interrelationships among other technologies in the mobile ecosystem. This study adopts a general approach to measure the habits of different technologies, and all the items related to different technology use habits are similar. However, this general approach to measure the habits of different technologies is well-accepted and has been used in many top journal publications, such as Venkatesh et al. (2012). The correlations among different habits are small, reflecting that the respondents can distinguish items for different habits. As mentioned by Limayem et al. (2007), the term "habit" is a combination of repeated use, satisfaction, stable environment, and clear goals. Traditional measurement, such as usage frequency, is unsuitable to reflect the essence of habit. Future study may explore the use of different questions to measure the habits of different technologies. Structural equation modeling can only reveal statistical causality but not factual causality (Chin 1998). Future study can apply research methods, such as experiment, to test the causality among different habits.

6.3 Implication for Theory

Dahlberg et al. (2015) posited that the diffusion mechanisms of mobile payment services in developed economies remain unclear. This study uses a sample of mobile payment users from the United States and explores the role of technology use habits in affecting consumers' intention to continue using mobile payments. This study contributes to academic research in several means.

This study contributes to the research on habit by introducing the IT ecosystem. Prior studies have supported the importance of technology use habits on technology acceptance. They mainly focus on the influence of individuals' habit of using a technology on their future use of the same technology or the effect of habit of using legacy systems on their acceptance of new systems. The connections between different innovations are overlooked. This condition is because popular theories (e.g., theory of planned behavior and united theory of acceptance and use of technology) focus on one focal innovation while overlooking its connection with relevant innovations at least partially. However, IT innovations are dependent

Table 4 Loading and Cross-Loading of Measures

	OSH	MSH	CEH	COH	MPH	BI	PEOU	PU	OPT	INN	DIS	INS
OSH1	**0.91**	0.32	0.35	0.53	0.47	0.39	0.45	0.39	0.41	0.46	−0.12	−0.14
OSH2	**0.90**	0.39	0.39	0.58	0.48	0.42	0.49	0.37	0.39	0.52	−0.15	−0.23
OSH3	**0.84**	0.33	0.32	0.53	0.42	0.33	0.44	0.38	0.35	0.46	−0.04	−0.12
MSH1	0.40	**0.96**	0.34	0.43	0.51	0.42	0.43	0.47	0.45	0.32	−0.15	−0.20
MSH2	0.38	**0.96**	0.36	0.44	0.49	0.42	0.45	0.47	0.46	0.36	−0.19	−0.24
MSH3	0.34	**0.95**	0.34	0.40	0.46	0.37	0.41	0.36	0.38	0.33	−0.16	−0.21
CEH1	0.38	0.30	**0.94**	0.49	0.44	0.31	0.47	0.42	0.35	0.30	−0.21	−0.26
CEH2	0.38	0.33	**0.95**	0.49	0.46	0.33	0.50	0.40	0.38	0.35	−0.21	−0.29
CEH3	0.36	0.38	**0.88**	0.41	0.47	0.35	0.43	0.44	0.42	0.32	−0.18	−0.27
COH1	0.58	0.36	0.45	**0.94**	0.38	0.35	0.52	0.35	0.34	0.49	−0.16	−0.26
COH2	0.58	0.45	0.53	**0.94**	0.41	0.36	0.51	0.34	0.32	0.56	−0.19	−0.26
COH3	0.51	0.39	0.35	**0.81**	0.30	0.20	0.39	0.26	0.28	0.34	−0.06	−0.21
MPH1	0.54	0.47	0.50	0.39	**0.95**	0.73	0.60	0.69	0.66	0.54	−0.14	−0.32
MPH2	0.48	0.50	0.46	0.41	**0.96**	0.70	0.59	0.62	0.62	0.50	−0.13	−0.33
MPH3	0.45	0.50	0.45	0.36	**0.94**	0.68	0.56	0.63	0.64	0.48	−0.10	−0.30
BI1	0.40	0.39	0.35	0.33	0.71	**0.96**	0.62	0.79	0.73	0.46	−0.29	−0.49
BI2	0.43	0.42	0.35	0.33	0.72	**0.96**	0.59	0.75	0.72	0.45	−0.34	−0.52
BI3	0.38	0.39	0.32	0.31	0.65	**0.91**	0.59	0.65	0.62	0.48	−0.23	−0.46
PEOU1	0.45	0.38	0.46	0.47	0.54	0.54	**0.94**	0.58	0.52	0.45	−0.26	−0.38
PEOU2	0.48	0.45	0.53	0.55	0.57	0.59	**0.95**	0.61	0.55	0.52	−0.27	−0.41
PEOU3	0.53	0.44	0.46	0.49	0.62	0.67	**0.95**	0.69	0.60	0.49	−0.26	−0.44
PU1	0.35	0.39	0.45	0.28	0.60	0.64	0.60	**0.90**	0.68	0.35	−0.23	−0.30
PU2	0.43	0.41	0.41	0.34	0.64	0.67	0.62	**0.94**	0.71	0.38	−0.24	−0.34
PU3	0.38	0.42	0.39	0.35	0.61	0.79	0.59	**0.89**	0.71	0.39	−0.32	−0.44
OPT1	0.38	0.37	0.40	0.32	0.62	0.63	0.50	0.63	**0.87**	0.44	−0.19	−0.32
OPT2	0.40	0.47	0.40	0.37	0.60	0.67	0.56	0.73	**0.91**	0.41	−0.25	−0.35
OPT3	0.34	0.33	0.28	0.22	0.53	0.62	0.48	0.65	**0.82**	0.33	−0.17	−0.29
INN1	0.48	0.30	0.30	0.40	0.50	0.44	0.41	0.34	0.42	**0.90**	−0.07	−0.17
INN2	0.44	0.30	0.26	0.36	0.47	0.44	0.42	0.38	0.38	**0.89**	−0.07	−0.18
INN3	0.50	0.31	0.36	0.62	0.43	0.41	0.53	0.37	0.39	**0.82**	−0.13	−0.20
DIS1	−0.13	−0.19	−0.23	−0.23	−0.16	−0.24	−0.30	−0.22	−0.32	−0.10	**0.80**	0.52
DIS2	−0.16	−0.12	−0.19	−0.24	−0.01	−0.17	−0.20	−0.18	−0.15	−0.06	**0.77**	0.47
DIS3	−0.04	−0.10	−0.19	−0.04	−0.11	−0.28	−0.21	−0.30	−0.14	−0.06	**0.83**	0.54
DIS4	−0.08	−0.16	−0.10	−0.06	−0.11	−0.26	−0.19	−0.23	−0.15	−0.09	**0.82**	0.48
INS1	−0.20	−0.25	−0.18	−0.23	−0.28	−0.42	−0.35	−0.33	−0.30	−0.16	0.56	**0.84**
INS2	−0.19	−0.21	−0.37	−0.28	−0.33	−0.50	−0.42	−0.40	−0.37	−0.23	0.58	**0.89**
INS3	−0.11	−0.13	−0.21	−0.21	−0.27	−0.45	−0.37	−0.32	−0.30	−0.16	0.50	**0.89**

Bold values are the square roots of AVE

OSH, online shopping habit; *MSH*, mobile service use habit; *CEH*, Cell phone use habit; *COH*, computer use habit; *MPH*, mobile payment use habit; *BI*, behavioral intention; *PEOU*, perceived ease of use; *PU*, perceived usefulness; *OPT*, optimism; *INN*, innovativeness; *DIS*, discomfort; *INS*, insecurity

and interrelated (Swanson 1994). Online shopping, cell phones, mobile payments, mobile services, and computers are interrelated components of mobile ecosystems. This research adopts the IT ecosystem view, discusses the interrelationships among different types of technology use habits, and finds that consumers' online shopping, mobile service use, and cell phone use habits each have an indirect relationship with intention to continue using mobile payments through mobile payment use habit. This study serves as a response to the criticism of Limayem et al. (2007) that a theoretical basis is lacking to discuss the effects of habit on consumers' behavior.

This study deepens the understanding of Adomavicius et al.'s (2007) IT ecosystem view by incorporating the effects of habit and transfer of learning theory as an approach to explain the connections among different technologies in the mobile payment ecosystem. IT ecosystem view supports the interrelation among IT innovations and categorizes them into three different roles. However, this view does not explain why and how those innovations are connected. This study roots in the habit construct, which is a type of learning outcome as explained in the literature review section, and introduces transfer of learning theory to explain the connections among different types of habits. This study frames the connection between different habits as a knowledge transfer process that affect individuals' positive and negative technology readiness, thereby influencing individuals' formation of habit and acceptance of new technology. This study explains the connection among different innovations in the mobile payment ecosystem by incorporating IT ecosystem view and transfer of learning theory and extends the application of transfer of learning theory from merely education discipline to IS research.

6.4 Implication for Practice

Consumers' repeated behavior is of great importance to the survival of mobile payment service providers because maintaining repeated consumers indicates lower operation cost and higher profits compared with attracting new customers (Chen and Li 2016). Practical implications for the industry can be drawn from this study.

Theoretical underpinnings of the habit construct is of great importance to firms that focus on managing customer relationships (Shah et al. 2014). The findings of this study help distinguish loyal customers that are profitable. The results demonstrate that consumers who frequently shop online, use mobile services, and use cell phones are likely to continue using mobile payments. For example, the fast adoption of Apple Pay reflects the positive effect of cell phone use habit on mobile payment use habit. Apple Pay is a mobile payment service provided by Apple Company. Apple consumers have formed the habit of using Apple products and are likely to form the habit of using Apple Pay. Practitioners can observe consumers' technology use habits by analyzing the information that consumers disclose in social media and other information sources. Practitioners can then distinguish loyal users who are likely to continue using mobile payments. Subsequently, practitioners can send user-specific advertising messages to consumers' wireless devices and encourage them to continuously use mobile payments, thereby fully utilizing limited marketing resources.

Knowledge about habit antecedents and consequences is useful in helping firms design practical guidelines to manage the development of technology habit for increasing profits (Limayem et al. 2007). The findings provide several suggestions on how to facilitate consumers in developing mobile payment use habit. The function mechanisms summarized from transfer of learning models provide some suggestions on how to facilitate the development of mobile payment use habit. For example, the similarity among two innovations can enhance consumers' probability of using the relatively new innovation because similarity between learning and transfer

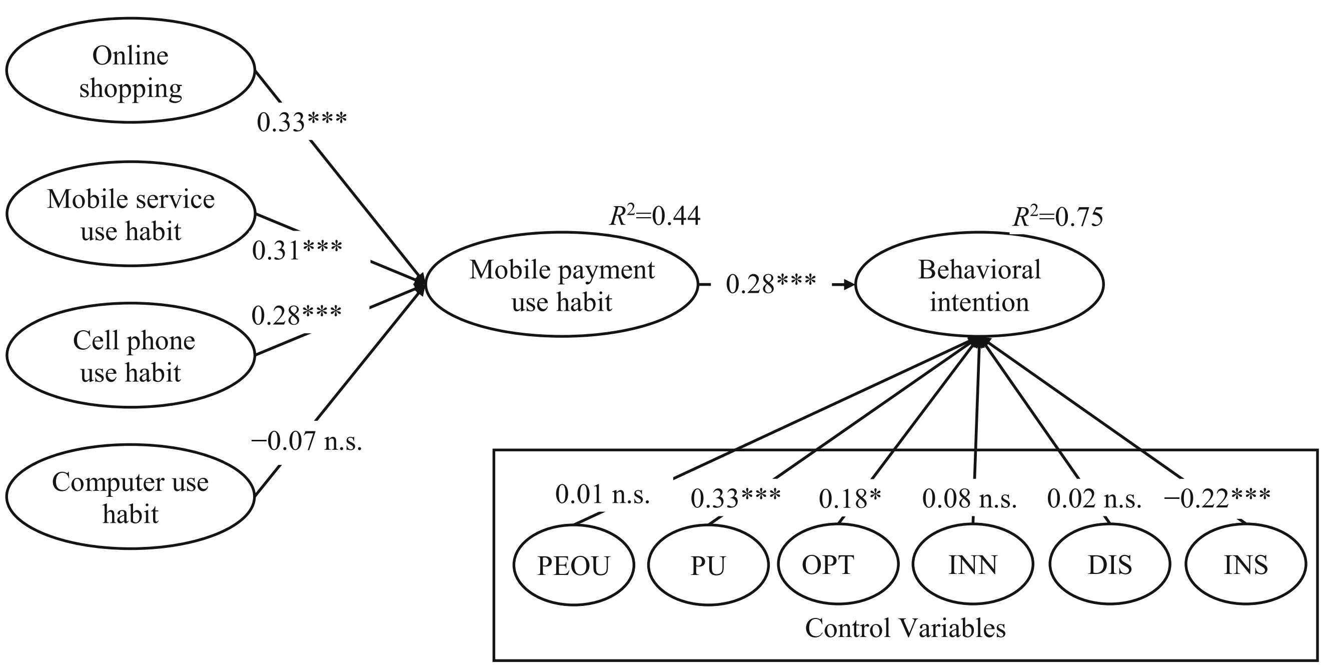

Fig. 3 Structural Model, Note: $*p < 0.05$, $***p < 0.001$, and n.s. = not significant; PEOU = perceived ease of use, PU = perceived usefulness, OPT = optimism, INN = innovativeness, DIS = discomfort, INS = insecurity

situations increases their ability to learn in new situations (Lobato 2006). This condition is implemented by Tencent Company in promoting their mobile payment service at the beginning. In its instant messaging application, WeChat allows individuals to scan QR codes for reading information and adding friends. WeChat Pay incorporates the QR code feature of instant messaging software to read financial information, and this similarity facilitates consumers to use WeChat Pay.

The mobile ecosystem consists of various firms from numerous enabling and supporting segments (Basole 2009). Policy makers can coordinate the management of various components in the IT ecosystem to promote the development of social mobile payment rather than simply increasing the investment in focal technology to make the industry healthy. For example, companies related to online shopping can be encouraged to include the interface with mobile payment in the software implementation when policy makers want to promote the development of mobile payment, in addition to directly encouraging companies related to mobile payment software (e.g., Apple Pay) and hardware (e.g., QR code scanner), thereby enabling consumers to easily use mobile payments. Device manufacturers can be encouraged to provide secure and convenient technological means (e.g., fingerprint payment) for product design.

7 Conclusion

Repeat customers can bring companies five times more profit with low marketing cost (Gupta and Kim 2007). Similarly, mobile payment service providers can gain more profit from their repeat customers compared with other customers. Exploring factors that will encourage consumers to use mobile payments repeatedly is of great importance. Drawing on the IT ecosystem view and transfer of learning theories, we proposed a model suggesting that consumers' online shopping, mobile service use, cell phone use, and computer use habits will affect their mobile payment use habit, thereby positively affecting their intention to continue using mobile payments. This research verifies the vital role of consumers' technology use habits in encouraging them to continue using mobile payments. The results indicate that consumers who frequently shop online and use mobile services and cell phones are likely to use mobile payments regularly. Consumers' mobile payment use habit has a positive relationship with their intention to continue using mobile payments. This study invokes a new research topic in the acceptance of mobile payments, and many studies are needed to explore the adoption and postadoption of mobile payments from the perspective of technology ecosystem.

Acknowledgments This work was supported by the National Natural Science Foundation of China (Grant ID: NSFC 71602009); Beijing Institute of Technology Basic Research Fund Program (Grant ID: 20172142005); Special Fund for Joint Development Program of Beijing Municipal Commission of Education; Beijing Institute of Technology Research Fund Program for Young Scholars.

Appendix

Items

Online Shopping Habit: *Adopted from* Setterstrom et al. (2013)

1. Shopping online has become automatic to me.
2. Shopping online is natural to me.
3. When faced with a particular need, shopping online is an obvious choice to me.

Mobile Service Use habit: *Adopted from* Setterstrom et al. (2013)

1. Using mobile services other than mobile payments has become automatic to me.
2. Using mobile services other than mobile payments is natural to me.
3. When faced with a particular need, using mobile services other than mobile payments is an obvious choice to me.

Cell Phone Use habit: *Adopted from* Setterstrom et al. (2013)

1. Using cellphones has become automatic to me.
2. Using cellphones is natural to me.
3. When faced with a particular need, using a cellphone is an obvious choice to me.

Computer Use habit: *Adopted from* Setterstrom et al. (2013)

1. Using computers has become automatic to me.
2. Using computers is natural to me.
3. When faced with a particular need, using a computer is an obvious choice to me.

Mobile Payment Use habit: *Adopted from* Setterstrom et al. (2013)

1. Using mobile payments has become automatic to me.
2. Using mobile payments is natural to me.
3. When faced with a particular need, using mobile payments is an obvious choice to me.

Intention to continued use: *Adopted from* Venkatesh et al. (2012)

1. I intend to continue using mobile payments in the future.
2. I predict that I will continue to use mobile payments frequently in the future.
3. I will strongly recommend that others use mobile payments.

Perceived Ease of Use: *Adopted from* Lin et al. (2011)

1. Learning to use mobile payments is easy for me.
2. Becoming skillful at using mobile payments is easy for me.
3. Overall, I find mobile payments easy to use.

Perceived Usefulness: *Adopted from* Kim et al. (2010)

1. Using mobile payments enables me to pay quickly.
2. Using mobile payments makes it easy for me to conduct transactions.
3. I find mobile payments a useful possibility for making payments.

Technology Readiness—discomfort: *Adopted from* Jin (2013)

1. I sometimes think that mobile payments are not designed for use by ordinary people.
2. Mobile payments have health risks that are not discovered until after people have used them.
3. Mobile payments have safety risks that are not discovered until after people have used them.
4. Mobile payments consistently appear to fail at the worst possible time.

Technology Readiness—insecurity: *Adopted from* Lu et al. (2012)

1. I can never be sure that the financial information I provided with my cellphone actually reaches the right place.
2. I consider it unsafe to perform any kind of payments with my cellphone.
3. I am concern that financial information I send with my cellphone will be seen by other people.

Technology Readiness—optimism: *Adopted from* Liljander et al. (2006)

1. Using mobile payments allows me to have better control on my daily life.
2. Using mobile payments gives me freedom of mobility.
3. Products and services that use mobile payment technology are more convenient to use than those without mobile payment technology.

Technology Readiness—innovativeness: *Adopted from* Liljander et al. (2006)

1. Other people seek advice from me on new information technologies.
2. In general, I am among the first in my circle of friends to acquire new IT when it is available.
3. I can usually determine new information technologies without help from others.

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Lin Jia is an associate professor of Information Systems at School of Management and Economics, Beijing Institute of Technology. He got the PhD degree from Harbert College of Business, Auburn University. He currently serves as the editorial board member of the Internet Research. His research has appeared in journals such as International Journal of Information Management, Information Technology & People, Journal of Organizational and End User Computing, Journal of Cleaner Production, and others. His current research interests include e-commerce, medical big data analytics, and information technology management.

Xiuwei Song is a graduate student in the Department of Management Engineering at School of Management and Economics, Beijing Institute of Technology. His research interests include Electronic Commerce, Data-driven Decision-Making, and Health Care Management.

Dianne Hall is a Torchmark Professor of Information Systems and Analytics at Auburn University. She holds a doctorate in Information and Operations Management from Texas A&M University. Her work appears in academic and practitioner journals such as the Journal of the Association for Information Systems, Decision Support Systems, Communications of the Association for Information Systems, International Journal of Physical Distribution and Logistics Management, International Journal of Logistics Management, Communications of the Association for Computing Machinery, and others. Her work has also appeared in several books. Her current research interests include applications of information technologies in support of innovation, knowledge management, logistics, healthcare, supply chain resiliency, and contingency planning, as well as enhanced decision-making processes.