The Effect of Consumer Learning on Intention to Use Mobile Payments

by

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Abstract

With the fast development of mobile applications and mobile internet, we arrive at the mobile commerce era. Mobile payments, a promising form of electronic payments, will become an important channel for conducting transactions especially with regard to mobile commerce. As the popularity of mobile devices increases, mobile payments have become one of the critical drivers for mobile commerce success. It is necessary to examine how to encourage mobile payments adoption and continuous usage. The series of essays in this dissertation strive to address these issues.

Essay 1 explores consumers' trust building in the consumer learning process and its effect on consumers' behavioral intention toward mobile payments. Results verify the vital role of consumer learning in building trust and encouraging consumers to engage in mobile payments. This essay also explores which characteristics differentiate users and non-users and differentiate American and Chinese consumers. The research is the foundation of an understanding of the effect of culture on mobile payments acceptance, and deepens our understanding of how consumer learning can be used to help consumers build trust and encourage them to accept mobile payments.

Essay 2 explores how consumers' learning outcomes affect their mobile payments acceptance decision. This essay views self-efficacy, attitude, and perceived knowledge as outcomes of consumer learning. Results indicate that consumer learning has a positive relationship with learning outcomes, which then enhance consumers' behavioral intention toward

mobile payments. When we statistically compared our results across users and non-users and across American and Chinese consumers, the similarities and differences in the cognitive processes involved for adoption and post adoption became apparent.

Essay 3 explores the effect of technology usage habits and price discount on consumers' intention to continue using mobile payments. Results indicate that consumers' online shopping habit, mobile service usage habit, and cell phone usage habit each have a positive relationship with their mobile payment usage habit and thereafter enhance their intention to continue using mobile payments. This essay also found mixed effect of price discount on the relationship between mobile payment usage habit and its three predictors.

Taken together, these three essays systematically explore factors affecting consumers' acceptance of mobile payments and also discuss the effect of culture on their cognitive processes involved for adoption and post adoption of mobile payments. Results extend our understanding of factors affecting consumers' adoption and post-adoption of mobile payments. Implications for research and practice provide suggestions for better understanding of mobile payment acceptance and applying the results to managerial contexts.

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ESSAY 1

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ESSAY 1: TRUST BUILDING IN THE CONSUMER LEARNING PROCESS AND ITS EFFECT ON CONSUMERS' BEHAVIORAL INTENTION TOWARD MOBILE PAYMENTS

Introduction

McKinsey (2013a) emphasizes twelve disruptive technologies with the potential for massive impact on how people live and work and on industries and economies. Mobile internet is at the top of the list. The report also suggests that mobile payments represent a large opportunity made possible by mobile internet technology. An electronic transaction can "save 50 to 70 percent of processing costs over a paper transaction, and the total potential economic impact of moving transactions to an electronic format is estimated to be US$200 billion to US$300 billion per year in 2025" (McKinsey, 2013a, p. 37). Mobile payments, payments made by individuals who use mobile devices to pay for goods, services, and bills or perform bank transactions (Dahlberg, Mallat, Ondrus, & Zmijewska, 2008), are a promising form of electronic payments.

Mobile payments will become an important channel for conducting transactions, especially within mobile commerce (Yang et al., 2012). Many researchers and business analysts believe that mobile payments will flourish in the coming years. It is estimated that worldwide mobile payment revenue will rise to US$998.5 billion by 2016 (Business Wire, 2012). However, the acceptance rate of mobile payments is low although the growth forecast for them is very positive (Duane, O'Reilly, and Andreev, 2014). In the U.S., only 37% of smartphone owners have used their phones to make a mobile payment (Nielsen, 2014). In China, only twenty nine percent of consumers have used mobile payments, among which only six percent of consumers use mobile payments frequently and twenty three percent of consumers use mobile payments occasionally (iResearch, 2013). McKinsey indicates that about 45% of U.S. consumers are open to the idea of using mobile payments, but this number has fallen since 2011 (McKinsey, 2013b). According to the MasterCard mobile payments readiness index, no country has achieved a mainstream consumer acceptance, and we are still in the early days for the adoption of mobile payments globally (MasterCard, 2014). Singapore ranks first with an index of 45.6, and the indexes for the United States and China are 41.5 and 36.5, respectively (MasterCard, 2014). These numbers indicate that consumers are not widely accepting of mobile payments. More research is needed to explore the drivers of mobile payment acceptance.

Trust is an important driver of consumers' acceptance of IT innovations, especially when there is a high level of risk associated with them (Coleman, 1990; Gefen et al., 2003). Pavlou (2003) found that consumers' trust has a positive relationship with their adoption of e-commerce. Trust is also viewed as a driver of consumers' adoption of mobile banking (Kim et al., 2009; Luo et al., 2010). Mobile payments operate based on mobile internet and there is high uncertainty and perceived risk associated with both (Zhou, 2014). Top concern of consumers are money safety, personal information leakage, and mobile device virus infection (iResearch, 2013). Trust in technology decreases the perception of risk. Thus, trust is anticipated to have a positive relationship with consumers' intention to use mobile payments.

Consumers' trust in mobile technology is dynamic (Lin, Wang, Wang, & Lu, 2014). Consumers modify their trust in mobile payments according to new information they obtain during the consumer learning process. In this process, external factors play an important role in affecting consumers' trust in mobile payments (Liebana-Cabanillas et al., 2014). Liebana-Cabanillas et al. (2014) posited that social influences and social norms are two types of external factors that have a positive relationship with consumers' trust in mobile payments. They proposed that future research should explore the influence of other external elements on consumers' trust in mobile payments (Liebana-Cabanillas et al., 2014). For example, word of mouth and media usage are considered external factors that affect consumers' trust in mobile payments (Chandra et al., 2010; Kim et al., 2009).

Apart from trust, culture has been accepted as an important factor that will affect adoption and usage of mobile technologies (Dahlberg et al., 2008; Dai & Palvia, 2009; Zhang, Zhu, & Liu, 2012). As mobile payment services spread globally, the importance of culture should be included in acceptance research regarding mobile payments (Dahlberg et al., 2008). In addition, culture is closely related to trust in online environments and will influence how trust is developed and the effect of trust on behavioral outcomes such as adoption (Gefen, Benbasat, & Pavlou, 2008). Gefen et al. (2008) suggested that "future research could take culture and gender into account more seriously when examining the effects of trust on behavioral outcomes" (Benbasat, & Pavlou, 2008, p. 280). However, little research has performed cross-cultural research on mobile payment acceptance (Arvidsson, 2014; Dahlberg et al., 2008).

In order to analyze the issues mentioned above, we adopt the definition of innovation as an "on-going process involving persuasive communication and learning" (Lee & Xia, 2011, p. 289) and separate consumer learning into passive and active consumer learning, which are represented by exposure to mobile payments and information searching, respectively. Exposure to mobile payments is composed of media usage, positive word of mouth, and explicit and implicit social influence, which are under the umbrella of external factors that will affect the acceptance of mobile payments. We view consumer learning as a source of quality information and explore the effect of consumer learning on consumers' trust building and behavioral intention toward mobile payments. This research explores trust building and its effect on mobile payments acceptance in two countries: China and the United States, which are culturally different and represent the eastern and the western cultures, respectively (Hofstede, 1980, 1991, 2001).

The objective of this research is to explore consumers' trust building in the consumer learning process and its effect on consumers' behavioral intention toward mobile payments. Our research questions are: (1) whether consumer learning can increase consumers' trust in mobile payments and hence affect their behavioral intention toward mobile payments; and (2) what factors differentiate the users and non-users and differentiate American and Chinese consumers. The rest of the paper proceeds as follows. The theoretical background and conceptual model are presented first. Then, the hypotheses are developed. Data collection and analysis are explained next followed by presentation of the results.

Theoretical Background

To investigate the effect of consumer learning on trust building and mobile payment acceptance, we drew on four theories as summarized in Table 1. Social cognitive theory and the stimulus-organism-response (SOR) framework serve as overarching theories in our model conceptualization while the multi-stage decision making model and the initial trust building model are used to support links among model constructs.

Social Cognitive Theory

Social cognitive theory was proposed by Bandura (1977b, 1986). This theory emphasizes dual relationships among three sets of factors: environmental, personal, and behavioral factors. Behavior refers to behavioral intention or actual behavior toward the object. Environmental factors refer to either social or physical factors that are external to the person and affect a person’s behavior (Compeau & Higgins, 1995). Personal factors are “any cognitive, motivational, emotional, personality or demographic aspects characterizing an individual” (Carillo, 2012, p. 22). The relationship among these three sets of factors are characterized as dual direction. For example, Bandura (1977b) indicates that an individual’s behaviors are responses from a combination of his or her own traits and behaviors of other individuals within the environment. Meanwhile, outcome from past behavior may affect an individual’s self-efficacy, which belongs to personal factors.

Table 1.
Theoretical Background

Categories	Theory	Source of theory
Overarching theories	Social cognitive theory	Bandura, 1977b; 1986.
	Stimulus-organism-response framework	Eroglue et al., 2001; Mehrabian and Russell, 1974.
Supporting theories	Initial trust building theory	McKnight et al., 1998; McKnight, Choudhury, and Kacmar, 2002.
	Multi-stage decision making theory	Bruyn and Lilien, 2008; Dewey, 1910.

Social cognitive theory presents self-efficacy as the core term. Bandura (1977a) discussed the relationship between environmental factors and self-efficacy and summarized four sources of self-efficacy: performance accomplishments (e.g., direct experience), vicarious experience (e.g., implicit social influence), verbal persuasion (e.g., media usage, positive word of mouth and explicit social influence), and physiological states (e.g., relaxation). IS researchers started to use social cognitive theory in the early 1990s after they realized the importance of self-efficacy to IS acceptance (Carillo, 2012). Since then, social cognitive theory has been applied to a variety of research disciplines. Carillo (2012) suggested that social cognitive theory is mainly applied to three research areas: computer training and/or use, software training and/or use, and internet-based applications or services (p. 249). The topic of our research, mobile payments, belongs to the third area.

According to social cognitive theory, each of the three sets of factors can serve as a dependent variable. However, behavioral intention or actual behavior are the most represented dependent variables because researchers try to explain and predict human behaviors (Carillo, 2012). In this research, behavioral intention is also used as the dependent variable; the model we propose can be used to explain consumers' behavioral intention toward mobile payments.

Stimulus-Organism-Response (SOR) Framework

Mehrabian and Russell (1974) proposed the M-R model based on the SOR paradigm. Mehrabian and Russell (1974) posited that three basic emotion states, known as PAD (pleasure, arousal, and dominance), mediate the relationship between an environmental stimulus and an approach or avoidance response (Mehrabian & Russell, 1974). There are some critics of the M-R model. Russell & Pratt (1980) found that dominance does not have a significant relationship with the response. Bagozzi (1983) criticized the narrow scope of the stimulus in the M-R model and posited that it should include managerially controllable factors such as "advertising, price, product/package design, and distribution policies" (p. 142), and environmental factors such as "competition, social pressure, legal regulations, and economic conditions" (p. 142). Additionally, Eroglue et al. (2001) criticized the narrow scope of the organism and expanded the M-R model by including cognitive states as a part of the organism. Cognitive states refer to "everything that goes in minds of consumers that concern the acquisition, processing, retention, and retrieval of information" (Eroglue et al., 2001, p. 181). Cognitive states include but are not limited to attitudes, beliefs, comprehension, and knowledge (Eroglue et al., 2001). The SOR framework in this research is adapted from the expanded M-R model.

In the SOR framework, stimulus refers to the impetus within the environment with potential to affect the consumers' cognitive and affective processes (Fiore & Kim, 2007), organism refers to "the mediating processes between the stimulus and consumers' response" (Fiore & Kim, 2007, p. 426), and response refers to "the concluding result of the internal processes of the organism" (Fiore & Kim, 2007, p. 432). Behavioral intention is the mostly used dependent variable in SOR research (Kawaf & Tagg, 2012). The SOR framework suggests that an individual will change his or her affective and cognitive attitudes after he or she is exposed to some type of stimulus, and further, affective and cognitive attitudes will contribute to the response (a behavior such as purchase or adoption).

The SOR framework has been applied to prediction of consumer responses toward a variety of products, services, technologies, traditional brick-n-mortar stores, and online stores (Lee, Ha, & Widdows, 2011). Fiore and Kim (2007) proposed an integrative model to explain consumers' shopping experience within the SOR framework. In their model, stimulus is expressed as environmental input variables, organism is expressed as a set of factors that belong to cognition, consciousness, affect, and value, and response is expressed as behavioral factors such as behavioral intentions. Wang, Minor, and Wei (2011) proposed a research model to examine online consumers' hierarchical response to web aesthetics by combining the tripartite model of attitude and SOR framework. In their research, perceived web aesthetics serve as the stimuli, affective changes and cognitive reactions serve as the organism, and conative inclinations serve as the response. According to their research, perceived web aesthetics encourage consumers to change their affective and cognitive attitude, influencing consumers' purchase behavior. Lee, Ha, and Widdows (2011) adapted the SOR framework to explore consumer responses to high-technology products. They proposed that high-technology product attributes will elicit consumers' cognitive and affective attitudes, contributing to their approach-avoidance behavior.

The scope of stimulus, organism, and response is flexible; a user of the SOR framework should choose variables to represent stimulus, organism, and response based on his or her research questions and context. Many researchers use features of products to represent stimulus. However, stimulus is not limited to tangible and intangible features of a product. Anything that provokes action can be considered stimulus variables (Bagozzi, 1986). Kim and Lennon (2010) used amount of information to represent the stimulus, perceived risk and satisfaction to represent the organism, and intention to revisit and purchase intention to represent the response. Fang (2012) considered sellers' online interactivity strategies as the stimulus and discussed its effect on perceived diagnosticity and deception, affecting consumers' transaction intention. However, greater attention should be paid to social environmental stimuli (Kawaf & Tagg, 2012) such as word of mouth and social influence of friends and relatives.

Initial Trust Building Theory

McKnight et al. (1998) and McKnight, Choudhury, and Kacmar (2002) proposed the initial trust building model, explaining the trust building mechanism and the role of trust in affecting behavioral intention as follows:

Trust building levers→ Trust in vendor→Trust intention

Trust building levers refer to some environmental or personal factors that help build trust. They used disposition to trust and institution-based trust to represent trust building levers. Trust intentions refer to intention to engage in trust related behaviors and are positively related with trust related behaviors such as adoption and purchase (McKnight et al., 2002). According to the model, disposition to trust and institution-based trust each have a positive effect on trust belief and in turn, affects trust intention. McKnight et al. (2002) suggested that trust plays a central role in helping consumers overcome the uncertainty and risk of purchasing from online sellers and encourages consumers to adopt e-commerce. They applied the initial trust building model to e-commerce and tested the items they proposed to measure disposition to trust, institution-based trust, trusting belief, and trust intention. They found that disposition to trust is positively related to both trust belief and institution-based trust. Trust belief then positively affects individuals' trusting intention.

Multi-Stage Decision Making Model

Dewey (1910) first proposed the multi-stage buying decision process that includes problem/need recognition, information searching, alternatives evaluation, purchase decision, and post purchase behavior. Consumers' decision making processes start when they recognize the need to purchase a product or service. They will search for initial information to help reduce the number of products or services from which to choose into a reasonable number of alternatives. More detailed information is then sought about each alternative to facilitate the final selection.

Simon (1960) proposed the Intelligence-Design-Choice (IDC) model that is similar to the Dewey (1910) buying decision process. According to Simon's model, an individual goes through three stages during the decision process: intelligence gathering, design, and choice (Simon, 1960). Simon viewed individuals' decision making as information processing. In order to make a wise decision, individuals should search environment for information to make a decision. Then, they design possible alternatives with information they obtain and consider the consequences of each alternatives. Simon (1960) posited that individuals have limited ability to process knowledge, and thus a satisficing decision is acceptable. Individuals will compare of each alternative and choose one.

A similar model of decision making is proposed by Bruyn and Lilien (2008). The model includes three stages: awareness, interest, and final decision. In the awareness stage, people become aware of the existence of an object because of exposure to the object or having received information about the object from the external environment. After becoming aware of the object, individuals will search for information to see whether the object meets their needs. During this stage, they will distinguish alternatives to the object and search for more detailed information. With the information they obtain, they become more knowledgeable of the object. Their knowledge will then be used to evaluate the object and its alternatives. After the evaluation, they will make a final selection of either the original object or one of its alternatives.

General speaking, there are three stages in the consumer decision making process, which are awareness, information searching, and decision making. However, as Kotler and Keller (2008) said, consumers do not need to move through every stage of the decision making process. For example, a person with higher personal innovativeness or who has received strong positive word of mouth from friends or relatives may decide to adopt the innovation without searching for more information, thus bypassing that stage.

Summary

Adoption of innovation is a process involving persuasive communication and learning (Lee & Xia, 2011), and social cognitive theory focuses on individual learning (Carillo, 2012). Thus, social cognitive theory is used as the overarching theory to explore the relationship between consumer learning and adoption of innovation. Social cognitive theory emphasizes the bidirectional relationships among environmental, personal, and behavioral factors (Carillo, 2012). In this research, we follow the logic of environmental factors→personal factors→behavioral factors, which is also supported by stimulus-organism-response framework.

The stimulus-organism-response framework suggests that an individual will change his/her affective and cognitive status after he/she is exposed to environmental stimulus, and thereafter affect his/her behavioral factors. In addition, initial trust building theory and multi-stage decision making theory support links among model constructs. Initial trust building theory emphasizes the importance of trust in affecting consumers' behavioral intention while multi-stage decision making theory supports the importance of information searching in consumers' decision making process.

Research Model and Hypotheses Development

Research Model

We use social cognitive theory and the SOR framework as the overarching theories for our model that is proposed by combining multi-stage decision making theory and initial trust building theory with social cognitive theory and the SOR framework (Figure 1). In this model, exposure to mobile payments serves as the initiation of consumer learning. If an individual is interested in mobile payments, he or she will search for information to reduce his or her uncertainty about mobile payments and evaluate the pros and cons of them. Based on past literature, we define uncertainty about mobile payments as a consumer's perceived risk because of confusion and lack of knowledge about them (Lin & Nguyen, 2011; Pavlou et al., 2007). Exposure to mobile payments, perceived uncertainty, and information searching will then affect consumers' trust in mobile payments, affecting their behavioral intention. Definitions of variables in this research are summarized in Table 2.

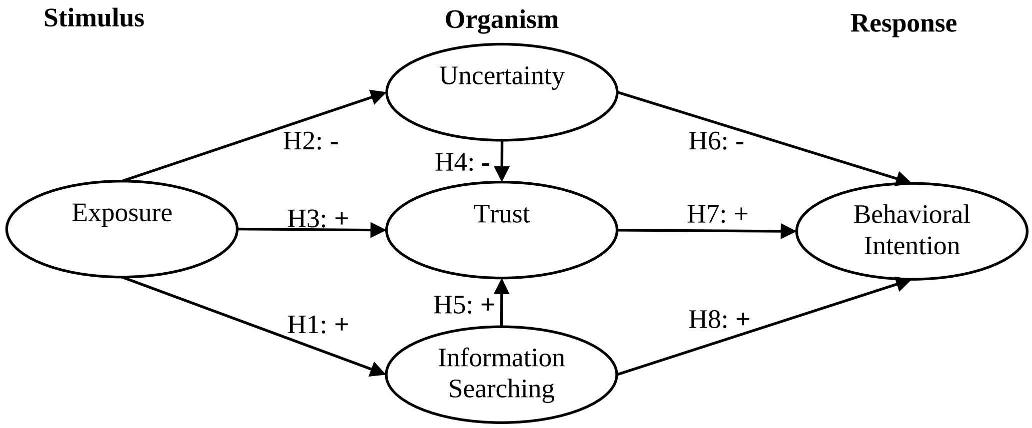


Figure 1. Trust Building in the Consumer Learning Process

Table 2.
Definitions of Variables

Variable	Definition	Source(s)
Word of mouth	Informal communication among consumers about mobile payments.	e.g., Liu, 2006
Social influence	The extent to which consumers perceive that important others (e.g., family and friends) believe they should use a particular technology such as mobile payments.	e.g., Venkatesh et al., 2012
Media usage	The extent to which messages regarding mobile payments are transmitted through mass media such as television, newspapers, magazines, radio, and the Internet.	e.g., Wei et al., 2011
Information searching	The process by which individuals seek information about mobile payments.	e.g., Browne, Pitts, & Wetherbe, 2007
Trust in mobile payments	The belief that mobile payments have characteristics that would benefit the individual.	e.g., McKnight et al.,1998
Uncertainty	A consumer's perceived risk because of confusion and lack of information about mobile payments.	e.g., Antioco and Kleijnen (2010); Lin and Nguyen (2011)
Behavioral intention	Consumers' intention to use or continue using mobile payments.	e.g., Venkatesh et al., 2012

Hypotheses Development

Consequences of exposure to mobile payments.

Exposure refers to "the degree to which an individual has acquired or exchanged information about the technology and its usage" (Khalifa, Cheng, & Shen, 2012, p. 15). Exposure to word of mouth, advertising, promotion or press coverage are methods by which consumer's interest may be elevated (Kulkarni, Kannan, & Moe, 2012). Awareness and interest about new technology may occur after consumers are exposed to information about it (Yoo, 2008). Consumers will benefit from information searching no matter whether they have prior knowledge or not (Kulkarni, Kannan, & Moe, 2012). Individuals do not simply respond to environmental influences, but also actively seek and interpret information (Nevid, 2009). After consumers become aware of and interested in new technology, they are motived to search for more information about it before making an adoption decision (Bruyn & Lilien, 2008). The positive relationship between exposure to information about mobile payments and information searching is supported by multi-stage decision making models, according to which individuals will search for additional information to evaluate alternatives before making a final decision (Bruyn & Lilien, 2008; Dewey, 1910; Simon, 1960).

Hypothesis 1. Exposure to information regarding mobile payments will encourage consumers to search for additional information about mobile payments.

Information asymmetry is an important reason of perceived uncertainty (Datta & Chatterjee, 2008). Uncertainty exists because consumers do not have adequate information and knowledge on which to act (Kim & Han, 2009; Kwon, Choi, & Kim, 2007). For example, they do not know whether mobile payments are operable and whether service providers will behave opportunistically. Exposure to mobile payments, the degree to which an individual has been exposed to information about mobile payments and their usage (Khalifa et al., 2012), reduces the information asymmetry. With repeated exposures to information regarding mobile payments, consumers' perceived uncertainty is reduced (Lee, 2001).

In this research, exposure to mobile payments is composed of positive word of mouth, implicit and explicit social influence, and mass media. Exposure to mobile payments is one of the most commonly employed mechanisms for reducing uncertainty (Bradac, 2001; Weick, 1995). The positive relationship between exposure to information regarding mobile payments and perceived uncertainty can be explained in several reasons. First, Allsop (2007) posited that mass media, social influence, and word of mouth serve as antecedents of firm reputation. Firm reputation is a valuable asset and is important for companies to achieve success (Chandra et al., 2010). It takes time for firms to build reputation, but reputation is easy to lose (Kartalia, 2000). Mobile payment service providers will strive to avoid behaving opportunistically to the detriment of consumers and to perform actions as expected by consumers in order to retain or improve firm reputation necessary for business success. Thus, consumers may believe that mobile payment service providers that have a better reputation will be less likely to behave opportunistically, making their future behaviors more predictable. Datta and Chatterjee (2008) posited that perceived uncertainty reflects the extent to which mobile payment service providers' future behaviors are unpredictable. Hence, exposure to mobile payments will increase consumers' perceived reputation of mobile payments service providers and thereafter reduces consumers' uncertainty about them.

In addition, through repeated exposure to mobile payments, consumers build a framework and understanding of mobile payments and the related ecosystem (Gefen, 2000). This helps consumers explicate their expectation of operability of mobile payments and future behavior of mobile payment service providers. Thus, exposure to mobile payments increases consumers' familiarity with mobile payments (Gursoy, 2001). Familiarity will reduce consumers' perceived uncertainty toward an object, and this negative relationship is well supported by past literature. Gulati (1995) concluded that familiarity helps consumers reduce uncertainty by telling them what to expect. Gefen (2000) posited that familiarity can reduce perceived uncertainty by allowing consumers to generate a knowledge structure. Lee (2001) and Zhou and Nakamoto (2007) also posited that familiarity is negatively related to perceived uncertainty. Thus, it is anticipated that exposure to information regarding mobile payments will increase consumers' familiarity with them and thereafter reduce consumers' perceived uncertainty about them.

Hypothesis 2. Exposure to information regarding mobile payments will reduce consumers' uncertainty about mobile payments.

Wang (2012) posited that mobile marketers should manage positive assessments of mobile payments by increasing consumers' media exposure to them, and consumers will perceive mobile payments as available alternative if they are exposed to various advertising and publicity messages. Repeated exposure to mobile payments will remind consumers of mobile payment service providers and mobile payments services, increasing consumers' familiarity with mobile payments. People tend to trust an object with which they are familiar (Siau & Shen, 2003). Thus, repeated exposure to information regarding mobile payments will increase familiarity with mobile payments and encourage them to trust mobile payments (Gefen, 2000; Moorthy & Hawkins, 2005).

Zuckers (1986) suggested that characteristics-based trust is an important mode for building trust. Chandra et al. (2010) posited that perceived reputation of mobile payment service providers will encourage consumers to trust in mobile payments. Exposure to mobile payments helps consumers build an image of mobile payment service provider reputation. For example, word of mouth is closely related to consumers' perception of firm reputation. Positive word of mouth will increase consumers' perceived firm reputation, and negative word of mouth will reduce consumers' perceived firm reputation (Allsop, 2007). However, for the purpose of this study, we are looking at positive outcomes. In this research, positive word of mouth but not negative word of mouth is included as a component of exposure to mobile payments. Positive word of mouth is a socially generated signal of product or service (Amblee & Bui, 2011). Mobile payment users convey their positive feelings about mobile payments to their friends and relatives, increasing people's perceived reputation of mobile payments. Reputation serves as a trust signal and will have a positive relationship with consumers' trust in mobile financial service (Chandra et al., 2010; Flavia'n et al., 2006; Kim, Shin, & Lee, 2009).

With exposure to mobile payments, consumers are passively informed of the characteristics of mobile payments (Valck, van Bruggen, & Wierenga, 2009; Wang, 2012). For example, mobile marketers use mass media to attract consumers by providing them with information on advantages of products or services (Wei et al., 2011). Consumers become aware of the advantages and the disadvantages involved with mobile payments and know more about how to protect themselves when they use mobile payments. This reduces consumers' perceived risk of using mobile payments. Reduction of perceived risk has a positive relationship with consumers' trust in mobile payments (Chandra et al., 2010). In view of these, we posit that:

Hypothesis 3. Exposure to information regarding mobile payments will help encourage consumers to trust mobile payments.

Predictors of trust in mobile payments.

Uncertainty about mobile payments is exacerbated by mobile technology. Mobile payments are built on wireless networks that are vulnerable for attack, increasing the level of uncertainty for consumers (Zhou, 2013). Trust is the expectation that a party will not behave opportunistically to the detriment of another (Bunduchi, 2005). Trust has generally been defined in terms of perception of certainty, and uncertainty reduction is required to build trust (Koljatic & Silva, 2008). Thus, reduction of perceived uncertainty should improve consumers' trust of mobile payments. Past literature supports the negative relationship between perceived uncertainty and trust (Dainton & Aylor, 2001; Datta & Chatterjee, 2008; Holmes & Rempel, 1987; Planalp et al., 1988). Kwon and Suh (2004) posited that perceived uncertainty in trading relationships will decrease trust. Wang and Benbasat (2008) suggested that reduction of uncertainty applies to the early stages of trust formation. Datta and Chatterjee (2008) posited that consumers tend to reduce their trust in an object if they are not sure of what to expect from it. Sales literature also describes uncertainty as a factor that directly affects trust development (Mallin, O'Donnell, & Hu, 2010). This negative link between perceived uncertainty and trust is also supported by theories such as knowledge-based affect theory (Demerath, 1993) and the theory of motivation (Turner, 1988), according to which perceived uncertainty has a negative relationship with trust.

The negative relationship between perceived uncertainty and trust can be explained in several approaches. First, perceived uncertainty will increase consumers' doubt regarding mobile payment service providers' ability to help consumers complete a transaction (Nicolaou, Ibrahim, & Heck, 2013), which is an important factor affecting consumers' trusting in mobile payments (McKnight et al., 1998, 2002). Thus, perceived uncertainty will decreasing consumers' trust in mobile payments. In addition, perceived uncertainty will cause anxiety of using mobile payments (Asveld & Roeser, 2009). For example, consumers may be concerned regarding possible money loss if they make mistakes that they cannot correct. With anxiety in mind, consumers are less likely to trust in innovations such as mobile payments (Hwang & Kim, 2007). Moreover, perceived uncertainty reflects consumers' perceived risk of mobile payments (Lin & Nguyen, 2011). Perceived risk is an antecedent of trust as concluded by Mitchell (1999). Thus, perceived uncertainty will negatively affect consumers' trust in mobile payments.

Hypothesis 4. Consumers' uncertainty about mobile payments will decrease their trust in mobile payments.

Information searching is the process by which individuals seek information about using mobile payments (Browne, Pitts, & Wetherbe, 2007). It is possible that consumers will get exposed to both positive and negative information regarding mobile payments during their information searching process. However, we focus on positive outcomes of information searching because consumers prefer to attribute other individuals' failure to internal factors while attributing their success to external factors (Zuckerman, 1979). Consumers may believe that bad things that happen to other individuals will not happen to themselves. Thus, negative information regarding mobile payments may not significantly affect consumers' cognitive and affective status.

Individuals rely on information searching to reduce uncertainty and increase trust (Flanagin, 2007). Consumers trust in mobile payments because they know about them (Lin & Nguyen, 2011). On the contrary, they do not tend to trust mobile payments if they lack information regarding them. Through information searching, consumers obtain needed information, which is an important prerequisite to trust (Flavia'n et al., 2006). For example, they can search for information about characteristics of mobile technology that include perceived environmental risk and structural assurance and characteristics of service providers such as the reputation of service providers. Chandra et al. (2010) posited that these characteristics of mobile payments and service providers have a positive relationship with consumers' trust in mobile payments. Thus, information searching is anticipated to increase consumers' trust in mobile payments.

Trust reflects an individual's positive expectation toward another party's future behavior (Mayer et al., 1995). Knowledge about another party is required to predict the behavior of other party (Doney et al., 1998). Consumers accumulate trust-relevant knowledge about mobile payment through information searching (Komiak & Benbasat, 2006). Consumers will use the information and knowledge they obtain through information searching to predict performance of mobile payments in the future and evaluate whether mobile payments will operate stably (Doney & Cannon, 1997). Additionally, during information searching, consumers can determine the nature of mobile payments, how to use them, when to use them, and what the expected benefits and potential risks are. This is referred as familiarity, which is "experience with the what, who, how, and when of what is happening" (Gefen et al. 2003, p.63). Thus, information searching will increase consumers' familiarity with mobile payments (Gefen et al., 2003). Familiarity has a positive relationship with consumers' trust in mobile payments. This is well supported by past literature (Bhattacherjee, 2002; Gefen, 2000; Komiak & Benbasat, 2006). Komiak and Benbasat (2006) separated trust to cognitive trust and emotional trust and concluded that familiarity has a positive relationship with both. Hence, information searching increases consumers' familiarity with mobile payments and thereafter encourages consumers to trust in mobile payments.

Hypothesis 5. Consumers' information searching will increase their trust in mobile payments.

Predictors of consumers' behavioral intention.

There is a high level of uncertainty associated with mobile payments (Zhou, 2014). Users may be exposed to risk related to mobile payments if they decide to adopt mobile payments (Yang et al., 2012). People tend to avoid uncertainty (Baldwin, 1992; Hofstede, 1980, 1991, 2001). An increase in uncertainty will lead to a decrease in consumers' acceptance of mobile payments (Berger & Calabrese, 1975). People are less likely to adopt and use an innovation if they do not like it. Thus, perceived uncertainty is anticipated to have a negative relationship with consumers' intention to use mobile payments. This relationship is supported by past literature. Mallat (2007) suggested that perceived uncertainty has a negative relationship with adoption of innovations. Au and Kauffman (2008) also posited that consumers tend to have a higher level of perceived uncertainty if there are too many competing plans and providers of mobile payments, and that uncertainty will slow down technology adoption among consumers.

Uncertainty reflects consumers' concern about their exposure to risk and potential loss. This may include concerns that the service providers will misuse their personal information or that the system may be unstable or inoperable, preventing successful completion of the transaction (Nicolaou et al., 2013). Thus, uncertainty is likely to be accompanied by negative emotions such as anxiety (Asveld & Roeser, 2009; Karahanna et al., 1999), worry (Alaszewski, & Coxon, 2009), and fear (Demerath, 1993). Anxiety, worry, and fear will reduce consumers' self-efficacy of using an innovation such as mobile payments (Bandura, 1986; Kwang & Kim, 2007), which in turn, decrease consumers' intention to use (Ajzen, 1991). Adding to the negative effect of these concerns on behavioral intention is consumers' own subjective probability of suffering loss (Chiles & McMackin, 1996). Thus, the perceived risk is amplified, negatively affecting consumers' intention to use mobile payments (Yang, et al., 2012). In addition, because people try to avoid behavior that invokes anxious feelings (Compeau & Higgins, 1995), concerns are negatively associated with consumers' behavioral intention.

Hypothesis 6. Consumers who perceive more uncertainty about mobile payments will be less likely to use mobile payments.

Past research has identified many factors affecting technology acceptance, one of which is trust in IT innovations. Consumers are more willing to conduct payments with trustworthy channels (Mallat, 2007). The relationship between trust and behavioral intention is supported by both the initial trust building theory and empirical research. According to the initial trust building theory, trust belief toward a behavior will have a positive relationship with trust behavior such as adoption of mobile payments in this research (McKnight et al., 1998, 2002). Past research posited that consumers' trust in mobile payments affects their behavioral intention directly and indirectly through mediators. Chandra et al. (2010) suggested that consumers' trust in mobile payment affects their behavioral intention directly and indirectly through perceived usefulness and ease of use. In addition, Lu et al. (2011) posited that trust affects consumers' behavioral intention directly and indirectly through perceived risk and relative advantage.

Trust in mobile payments reflects consumers' expectation that mobile payment service providers will provide services that securely and successfully meet their needs (Shin, 2009). People will not use mobile payments if they think that service providers are not customer service oriented. Trust is particularly important when it comes to financial services because consumers worry about money loss (Coleman, 1990). In addition to financial concerns, the infrastructure that facilitates mobile payments is itself often a concern for consumers (Zhou, 2014). People tend to avoid risk and use trustworthy innovations. Trust helps reduce consumers' fears and worries about potential loss that may happen because of their usage of mobile payments (Gefen et al., 2003; McKnight et al., 2002), thus reducing the perceived risks of mobile payments. Perceived risk has a negative relationship with consumers' intention to use mobile payments (Shin, 2009). Thus, trust reduces consumers' perceived risk about mobile payments and encourage them to use mobile payments.

Hypothesis 7. Consumers' trust in mobile payments will increase their intent to use mobile payments.

Information searching is an important stage of the consumer decision making process, and consumers search for information before they make a decision (Bruyn & Lilien, 2008; Dewey, 1910; Simon, 1960). There are several barriers to consumers' adoption and use of mobile financial services such as value, risk, and image barriers (Laukkanen & Kiviniemi, 2010). These barriers reflect consumers' concern as to whether the innovation is easy to use, useful, and secure. Information regarding an innovation such as mobile payments will help consumers overcome these acceptance barriers (Laukkanen & Kiviniemi, 2010). Through information searching, consumers become more knowledgeable about mobile payments, improving consumers' perception of their ability to use mobile payments. This ability, or self-efficacy, is positively associated to consumers' intention to use mobile payments (Bandura, 1986). Thus, information about a product or service serves as a factor affecting its adoption (Pikkarainen et al., 2004) while lack of information will impede the adoption of an innovation (Kuisma et al., 2007).

Consumers may obtain both positive and negative information through information searching. Positive information may encourage consumers to trust mobile payments, but negative information may allow them to learn about problems of mobile payment and thus impede them to trust mobile payments. However, for the purpose of this study, we are looking at positive outcomes of information searching as past literature. As a result of information searching, consumers learn more about the benefits of using mobile payments and form an overall assessment of the utility of mobile payments based on the information they obtain. This overall assessment, referred to as perceived value (Zeithaml, 1988), increases the possibility that a consumer will indicate an intention to use mobile payments (Setterstrom et al., 2013). Meanwhile, information searching not only increases the quantity of information but improves the quality of information because consumers can actively target information that fills a knowledge gap. Information quality has a positive relationship with individuals' intention to use mobile payments (DeLone & McLean, 1992, 2003). In addition, information searching refers to time and energy consumers spend on learning how to use mobile payments in this research, which is a type of sunk cost (Park et al., 2012). Sunk cost is one component of switching cost, which will increase consumers' inertia to make a change and thus encourage them to use or continue use mobile payments (Polites & Karahanna, 2012). Past research has reached similar conclusions. For example, Hahn and Kim (2009) posited that consumers' information search behavior has a positive relationship with their purchase intention. Thus,

> ***Hypothesis 8. Consumers' information searching will increase their intent to use mobile payments.***

Methodology

Data Collection

A survey based research was used to develop an understanding of consumers' trust building in their consumer learning process and its effect on their behavioral intention toward mobile payments. Two sets of data were collected. The first dataset was collected from general public in China. Three hundred and forty questionnaires were collected from China. Eighteen questionnaires were excluded from the dataset as unsuitable for analysis, making the final sample size 322. In the China dataset, there are 216 respondents who have used mobile payments and 106 respondents who have not used mobile payments. The second dataset was collected from general public in the U.S. Three hundred and twenty questionnaires were collected from the U.S. Thirty three questionnaires were excluded during the data screening, making the final sample size 287. In the U.S. dataset, there are 165 respondents who have used mobile payments and 122 respondents who have not used mobile payments.

In order to make a comparison of the user and the non-user groups and the China and the U.S. datasets, we randomly selected 106 questionnaires from each group. Hence, we have four groups: the user group from China, the user group from the U.S., the non-user group from China, and the non-user group from the U.S. Each group has 106 respondents. Table 3 summarizes the demographic information of the participants.

Measures

Wherever possible, items were drawn from existing scales. Some minor modifications were made to the adopted measures. All items are measured on a seven-point Likert scale, ranging from strongly disagree (1) to strongly agree (7). Because data was collected from both users and non-users, two versions of the questionnaire were used, targeting users and non-users. The English instruments were translated into Chinese by following the back translation approach. In order to test the wording and reliability of the items, a pilot test was conducted using a group of volunteer respondents in China and one English speaking group. Subsequently, some minor changes were made to the questionnaires that can be found in the Appendix 1 (English version only).

Table 3.
Demographic Information

Measure	Item	China				The U.S.			
		User group (n=106)		Non-user group (n=106)		User group (n=106)		Non-user group (n=106)	
		#	%	#	%	#	%	#	%
Age	<21	6	5.7	11	10.4	0	0	2	1.9
	21-25	58	54.7	54	50.9	20	18.9	24	22.6
	26-30	31	29.2	23	21.7	49	46.2	17	16
	31-35	9	8.5	11	10.4	35	33	29	27.4
	>35	2	1.9	7	6.6	2	1.9	34	21.1
Gender	Male	65	61.3	57	53.8	49	46.2	69	65.1
	Female	41	38.7	49	46.2	57	53.8	37	34.9
Education background	Some college or less	20	18.9	20	18.9	45	42.5	62	58.5
	Bachelor	60	56.6	63	59.4	42	39.6	29	27.4
	Master	23	21.7	19	17.9	18	17	12	11.3
	PhD or Professional	3	2.8	4	3.8	1	0.9	3	2.8
Time of using mobile payments (Months)	None	N/A	N/A	106	100	N/A	N/A	106	100
	0-6	24	22.6	N/A	N/A	17	16	N/A	N/A
	7-12	18	17.0	N/A	N/A	27	25.5	N/A	N/A
	13-18	20	18.9	N/A	N/A	18	17	N/A	N/A
	>18	44	41.5	N/A	N/A	44	41.5	N/A	N/A

Positive word of mouth was assessed with three items adapted from Alexandrov and Babakus (2013). Media usage was assessed with seven items adapted from Loibl et al. (2009) and Wei et al. (2011). Explicit social influence was assessed with three items adapted from Venkatesh et al. (2012), and implicit social influence was assessed with three items adapted from Kim et al. (2007). Uncertainty was assessed with four items adapted from Pavlou et al. (2007).

Information searching was assessed with five items adapted from Barki et al. (2007). Trust in mobile payments was assessed with eight items adapted from Chandra et al. (2010) and Lu et al. (2011). Intention to use was assessed with three items adapted from Gu et al. (2009), and intention to continue using was assessed with three items adapted from Venkatesh et al. (2012). Disposition to trust was assessed with three items adapted from Zhou (2011). Institution-based trust was assessed with six items adapted from Setterstrom et al. (2013). Perceived ease of use was assessed with three items adapted from Lin et al. (2011). Perceived usefulness was assessed with three items adapted from Kim et al. (2010).

According to the initial trust building model (McKnight et al., 1998), disposition to trust and institution-based trust will affect consumers' behavioral intention. The technology acceptance model supports the effect of perceived ease of use and perceived usefulness on behavioral intention (Lin et al., 2007). Thus, disposition to trust, institution-based trust, perceived ease of use, and perceived usefulness were used as control variables in this research.

Data Analysis and Results

SmartPLS (Ringle, Wende, & Will, 2005) was used to analyze the data. PLS was chosen for its ability to handle non-normality in the data, and because the goal of this research is to explain variance in the outcome variable (Gefen & Straub, 2000). Exposure to mobile payments was measured using multiple subscales, which are media usage, positive word of mouth, explicit social influence, and implicit social influence. We condensed exposure to mobile payments using latent variable scores of the subscales as items of the higher order construct. We first calculated the latent variable scores of each subscale using SmartPLS, and four latent variable scores were generated. Then we took these four factor scores as the reflective items for exposure to mobile payments. Latent variable scores have been widely used in prior studies to simplify a research model (Sun et al., 2012; Williams & Hazer, 1986)

Common Method Bias

All data was collected through a self-report survey. Thus, there is a potential of common method bias (Podsakoff et al. 2003). This research examined common method bias using three tests. First, the Harmon’s single factor test was performed. Common method bias may exist if: a single factor emerges from the unrotated factor soluation, 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 factor analysis. For the user group from China, the result yielded 7 factors with eigenvalues greater than 1.0, which accounted for 77.8 percent of the total variance. The first factor captured only 31.5 percent of the variance in the data. For the non-user group from China, the result yielded 6 factors with eigenvalues greater than 1.0, which accounted for 78 percent of the total variance. The first factor captured only 37.5 percent of the variance in the data. For the user group from the U.S., the result yielded 5 factors with eigenvalues greater than 1.0, which accounted for 77.6 percent of the total variance. The first factor captured only 46 percent of the variance in the data. For the non-user group from the U.S., the result yielded 5 factors with eigenvalues greater than 1.0, which accounted for 81 percent of the total variance. The first factor captured only 46 percent of the variance in the data. The results indicate that no single-factor accounts for the majority of variance.

Second, researchers compared correlations among constructs by following the procedure established by Pavlou, Liang, and Xue (2007). The results revealed no constructs with correlations over 0.8.

Third, the unmeasured latent method construct (ULMC) technique (Liang et al. 2007) was performed. For the user group from China, the results demonstrate that the average substantively explained variance of the indicators is 0.698, while the average method-based variance is 0.015. The ratio of substantive variance to method variance is about 46.5:1. In addition, the results revealed that 22 method factor loadings (out of 27) were not significant at a 95 percent confidence level. For the non-user group from China, the results demonstrate that the average substantively explained variance of the indicators is 0.755, while the average method-based variance is 0.0103. The ratio of substantive variance to method variance is about 73.3:1. In addition, the results revealed that 24 method factor loadings (out of 27) were not significant at a 95 percent confidence level. For the user group from the U.S., the results demonstrate that the average substantively explained variance of the indicators is 0.804, while the average method-based variance is 0.0307. The ratio of substantive variance to method variance is about 26.2:1. In addition, the results revealed that 23 method factor loadings (out of 27) were not significant at a 95 percent confidence level. For the non-user group, the results demonstrate that the average substantively explained variance of the indicators is 0.832, while the average method-based variance is 0.0136. The ratio of substantive variance to method variance is about 61.3:1. In addition, the results revealed that 22 method factor loadings (out of 27) were not significant at a 95 percent confidence level. Taken together the above results indicate that common method bias is unlikely to influence the analysis below.

Measurement Model

The control variables do not have significant impact on intention to (continue) use for any groups, excluding perceived usefulness. Thus, results with perceived usefulness are reported below. This research adopted the two-stage analytical procedure (Anderson & Gerbing, 1988;

Hair et al., 1998). Confirmative factor analysis was first conducted to assess the measurement model; then, the structural relationships were examined. As shown in Tables 4, 5, 6, and 7, Cronbach's alpha ranged from 0.712 to 0.926 for the user group from China, 0.798 to 0.952 for the non-user group from China, 0.821 to 0.957 for the user group from the U.S., 0.886 to 0.962 for the non-user group from the U.S., providing evidence of measure reliability (Cronbach, 1971). Meanwhile, composite reliability (CR) ranged from 0.825 to 0.947 for the user group from China, from 0.868 to 0.960 for the non-user group from China, from 0.882 to 0.967 for the user group from the U.S., and from 0.922 to 0.975 for the non-user group from the U.S., indicating valid internal consistency reliability (Chin, 1998). All AVEs are larger than 0.5, indicating that convergent validity is met (Fornell & Larcker, 1981). Additionally, as shown in Tables 4, 5, 6, and 7, all squared roots of the AVEs are greater than the correlation shared between the construct and other constructs in the model. As shown in Tables 8, 9, 10, and 11, all items load appropriately on their intended construct. All these results indicate discriminant validity. Jointly, these findings suggest adequate convergent and discriminant validity. We also investigated the variance inflation factors (VIFs) of all the independent variables. VIF for the user group from China ranged from 1.361 to 2.627, and VIF for the non-user group from China ranged from 1.337 to 2.428. VIF for the user group from the U.S. ranged from 1.471 to 3.327, and VIF for the non-user group from the U.S. ranged from 1.673 to 3.243. None of the VIFs exceed 10, suggesting that multicollinearity is not a concern (Petter et al. 2007).

Structural Model

The path coefficients and explained variances of the structural model for both groups are shown in Figure 2 and Figure 3. PLS model does not generate the model fit statistics but uses R^2 to assess the explanatory power of a structural model. For the China dataset, the model explained

59.7% of the variance in users' intention to continue using, and 58.5% of the variance in non-users' intention to use. For the U.S. dataset, the model explained 69.3% of the variance in users' intention to continue using, and 67.8% of the variance in non-users' intention to use. These statistics validate the predictive power of the model.

Table 4.
Measurement Validity for the User Group from China

User Group										
	R2	**CR**	**Cronbach's α**	**AVE**	**EXP**	**INS**	**TR**	**UNC**	**INT**	**PU**
EXP	N/A	0.825	0.712	0.547	**0.739**					
INS	0.187	0.890	0.847	0.618	0.432	**0.786**				
TR	0.331	0.933	0.917	0.637	0.295	0.194	**0.798**			
UNC	0.001	0.947	0.926	0.818	0.025	0.121	-0.468	**0.904**		
INT	0.597	0.932	0.890	0.820	0.357	0.239	0.496	-0.445	**0.906**	
PU	N/A	0.940	0.904	0.840	0.173	0.022	0.339	-0.261	0.658	**0.916**

Note: Bold diagonal values are the square root of average variance extracted; EXP=exposure, INS=information searching, TR=trust, UNC=uncertainty, INT=intention to continue using, and PU=perceived usefulness.

Table 5.
Measurement Validity for the Non-User Group from China

Non-User Group										
	R2	**CR**	**Cronbach's α**	**AVE**	**EXP**	**INS**	**TR**	**UNC**	**INT**	**PU**
EXP	N/A	0.868	0.798	0.624	**0.790**					
INS	0.182	0.921	0.892	0.701	0.427	**0.837**				
TR	0.585	0.922	0.873	0.798	0.368	0.381	**0.893**			
UNC	0.374	0.960	0.952	0.752	0.451	0.427	0.577	**0.867**		
INT	0.066	0.943	0.920	0.806	-0.256	-0.182	-0.424	-0.447	**0.898**	
PU	N/A	0.941	0.909	0.842	0.128	0.055	0.583	0.229	-0.286	**0.918**

Note: Bold diagonal values are the square root of average variance extracted; EXP=exposure, INS=information searching, TR=trust, UNC=uncertainty, INT=intention to use, and PU=perceived usefulness.

Table 6.
Measurement Validity for the User Group from the U.S.

User Group										
	R2	**CR**	**Cronbach's α**	**AVE**	**EXP**	**INS**	**TR**	**UNC**	**INT**	**PU**
EXP	N/A	0.882	0.821	0.658	**0.811**					
INS	0.16	0.944	0.927	0.773	0.4	**0.879**				
TR	0.607	0.964	0.957	0.771	0.710	0.470	**0.878**			
UNC	0.115	0.952	0.932	0.832	-0.34	-0.123	-0.472	**0.912**		
INT	0.693	0.967	0.948	0.906	0.595	0.420	0.727	-0.527	**0.952**	
PU	N/A	0.900	0.835	0.750	0.369	0.484	0.489	-0.344	0.683	**0.866**

Note: Bold diagonal values are the square root of average variance extracted; EXP=exposure, INS=information searching, TR=trust, UNC=uncertainty, INT=intention to continue using, and PU=perceived usefulness.

Table 7.
Measurement Validity for the Non-User Group from the U.S.

Non-User Group										
	R2	**CR**	**Cronbach's α**	**AVE**	**EXP**	**INS**	**TR**	**UNC**	**INT**	**PU**
EXP	N/A	0.922	0.886	0.748	**0.865**					
INS	0.418	0.960	0.948	0.827	0.647	**0.909**				
TR	0.485	0.965	0.958	0.775	0.608	0.350	**0.880**			
UNC	0.045	0.962	0.947	0.863	-0.213	0.081	-0.458	**0.929**		
INT	0.678	0.975	0.962	0.929	0.624	0.436	0.775	-0.268	**0.964**	
PU	N/A	0.949	0.920	0.861	0.459	0.359	0.531	-0.160	0.621	**0.928**

Note: Bold diagonal values are the square root of average variance extracted; EXP=exposure, INS=information searching, TR=trust, UNC=uncertainty, INT=intention to use, and PU=perceived usefulness.

For the user group from China, the results indicate that exposure to mobile payments has a positive impact on information searching (b=0.432, p<0.001) and trust (b=0.243, p<0.01) but does not affect perceived uncertainty, supporting H1 and H3 while not supporting H2. Uncertainty has a negative relationship with both consumers' trust in mobile payments (b=-0.492, p<0.001) and intention to use them (b=-0.265, p<0.001). Thus, H4 and H6 are supported. Information searching does not affect consumers' trust but has a positive relationship with their intention to continue using mobile payments (b=0.231, p<0.01), supporting H8 while not supporting H5. Trust has a positive relationship with consumers' intention to continue using mobile payments (b=0.147, $p<0.05$), supporting H7.

Table 8.
Cross Loading for the User Group from China

	EXP	UNC	INS	TRU	INT	PU
EXP1	**0.740**	-0.155	0.278	0.337	0.481	0.308
EXP2	**0.842**	-0.054	0.370	0.295	0.302	0.120
EXP3	**0.793**	0.022	0.296	0.288	0.302	0.163
EXP4	**0.549**	0.254	0.323	-0.064	-0.022	-0.068
UNC1	0.030	**0.883**	0.068	-0.382	-0.411	-0.187
UNC2	0.040	**0.895**	0.121	-0.375	-0.288	-0.150
UNC3	0.028	**0.907**	0.143	-0.435	-0.448	-0.304
UNC4	-0.003	**0.932**	0.104	-0.485	-0.439	-0.281
INS1	0.253	0.025	**0.804**	0.116	0.244	0.151
INS2	0.285	0.058	**0.825**	0.100	0.261	0.134
INS3	0.386	0.106	**0.813**	0.204	0.274	0.04
INS4	0.328	0.123	**0.755**	0.143	0.015	-0.118
INS5	0.422	0.159	**0.728**	0.180	0.087	-0.145
TRU1	0.237	-0.468	0.163	**0.884**	0.520	0.345
TRU2	0.231	-0.465	0.136	**0.864**	0.486	0.335
TRU3	0.261	-0.463	0.028	**0.880**	0.381	0.309
TRU4	0.295	-0.510	0.091	**0.890**	0.542	0.378
TRU5	0.154	-0.235	0.155	**0.630**	0.324	0.191
TRU6	0.182	-0.235	0.202	**0.700**	0.301	0.211
TRU7	0.240	-0.261	0.325	**0.745**	0.251	0.140
TRU8	0.267	-0.227	0.198	**0.750**	0.255	0.172
INT1	0.253	-0.416	0.124	0.401	**0.901**	0.768
INT2	0.295	-0.447	0.210	0.491	**0.951**	0.591
INT3	0.435	-0.340	0.329	0.458	**0.862**	0.412
PU1	0.155	-0.196	0.013	0.304	0.559	**0.92**
PU2	0.165	-0.252	0.024	0.334	0.643	**0.944**
PU3	0.154	-0.266	0.023	0.291	0.602	**0.884**

Note: EXP=exposure, INS=information searching, TR=trust, UNC=uncertainty, INT=intention to continue use, and PU=perceived usefulness.

Table 9.
Cross Loading for the Non-User Group from China

	EXP	UNC	INS	TRU	INT	PU
EXP1	**0.830**	-0.286	0.324	0.437	0.357	0.164
EXP2	**0.876**	-0.244	0.377	0.443	0.354	0.06
EXP3	**0.767**	-0.128	0.257	0.250	0.278	0.230
EXP4	**0.671**	-0.094	0.388	0.226	0.126	-0.040
UNC1	-0.263	**0.930**	-0.174	-0.441	-0.382	-0.259
UNC2	-0.274	**0.907**	-0.186	-0.430	-0.422	-0.240
UNC3	-0.190	**0.863**	-0.148	-0.367	-0.349	-0.271
UNC4	-0.176	**0.890**	-0.141	-0.353	-0.364	-0.261
INS1	0.347	-0.173	**0.875**	0.378	0.326	0.076
INS2	0.353	-0.196	**0.879**	0.401	0.381	0.137
INS3	0.390	-0.196	**0.800**	0.248	0.316	0.173
INS4	0.355	-0.108	**0.846**	0.390	0.304	-0.057
INS5	0.346	-0.086	**0.781**	0.359	0.260	-0.107
TRU1	0.438	-0.429	0.355	**0.897**	0.604	0.333
TRU2	0.409	-0.489	0.342	**0.926**	0.567	0.218
TRU3	0.365	-0.448	0.324	**0.913**	0.599	0.300
TRU4	0.407	-0.472	0.334	**0.910**	0.590	0.296
TRU5	0.326	-0.247	0.367	**0.757**	0.399	0.037
TRU6	0.366	-0.300	0.428	**0.806**	0.373	0.130
TRU7	0.423	-0.349	0.430	**0.884**	0.413	0.138
TRU8	0.387	-0.310	0.412	**0.828**	0.404	0.061
INT1	0.276	-0.361	0.258	0.437	**0.893**	0.631
INT2	0.387	-0.390	0.329	0.512	**0.920**	0.556
INT3	0.319	-0.385	0.428	0.595	**0.865**	0.380
PU1	0.050	-0.214	-0.020	0.151	0.460	**0.927**
PU2	0.068	-0.156	0.033	0.185	0.440	**0.912**
PU3	0.199	-0.367	0.113	0.269	0.651	**0.914**

Note: EXP=exposure, INS=information searching, TR=trust, UNC=uncertainty, INT=intention to use. PU=perceived usefulness.

Table 10.
Cross Loading for the User Group from the U.S.

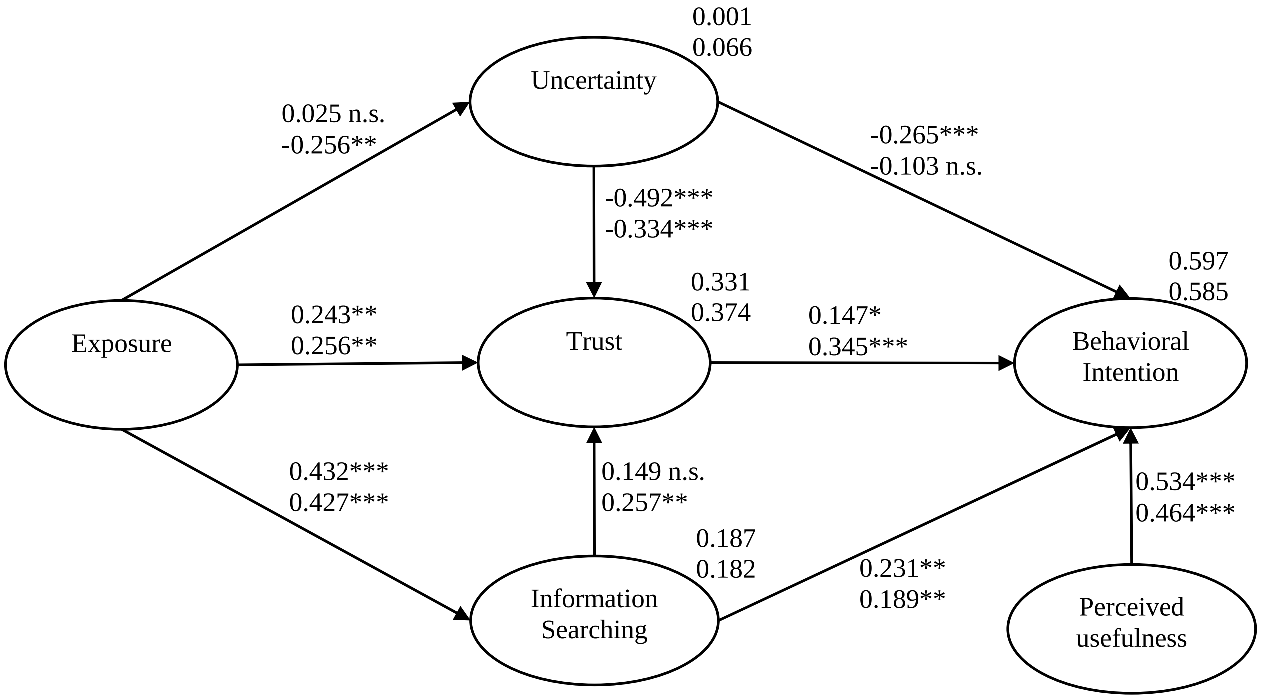
	EXP	UNC	INS	TRU	INT	PU
EXP1	**0.835**	-0.321	0.229	0.575	0.507	0.229
EXP2	**0.910**	-0.336	0.362	0.674	0.582	0.386
EXP3	**0.885**	-0.362	0.369	0.640	0.559	0.368
EXP4	**0.570**	0.048	0.376	0.353	0.178	0.155
UNC1	-0.274	**0.889**	-0.071	-0.388	-0.457	-0.267
UNC2	-0.351	**0.917**	-0.165	-0.442	-0.465	-0.374
UNC3	-0.272	**0.897**	-0.079	-0.421	-0.509	-0.282
UNC4	-0.336	**0.944**	-0.126	-0.468	-0.492	-0.327
INS1	0.255	-0.132	**0.870**	0.343	0.342	0.497
INS2	0.362	-0.147	**0.896**	0.443	0.388	0.520
INS3	0.326	-0.114	**0.863**	0.388	0.333	0.427
INS4	0.447	-0.121	**0.894**	0.481	0.431	0.358
INS5	0.332	-0.020	**0.872**	0.382	0.330	0.341
TRU1	0.657	-0.549	0.423	**0.905**	0.706	0.478
TRU2	0.647	-0.516	0.455	**0.932**	0.694	0.489
TRU3	0.604	-0.472	0.426	**0.915**	0.683	0.481
TRU4	0.623	-0.459	0.452	**0.892**	0.713	0.473
TRU5	0.445	-0.155	0.301	**0.681**	0.320	0.184
TRU6	0.645	-0.322	0.380	**0.880**	0.607	0.391
TRU7	0.643	-0.374	0.448	**0.909**	0.663	0.447
TRU8	0.691	-0.357	0.388	**0.885**	0.608	0.400
INT1	0.556	-0.483	0.384	0.695	**0.953**	0.696
INT2	0.536	-0.503	0.389	0.661	**0.965**	0.675
INT3	0.608	-0.520	0.425	0.718	**0.937**	0.578
PU1	0.176	-0.185	0.314	0.307	0.412	**0.762**
PU2	0.342	-0.318	0.455	0.379	0.628	**0.918**
PU3	0.395	-0.358	0.463	0.548	0.685	**0.909**

Note: EXP=exposure, INS=information searching, TR=trust, UNC=uncertainty, INT=intention to continue use, and PU=perceived usefulness.

Table 11.
Cross Loading for the Non-User Group from the U.S.

	EXP	UNC	INS	TRU	INT	PU
EXP1	**0.877**	-0.256	0.524	0.539	0.486	0.329
EXP2	**0.945**	-0.191	0.573	0.609	0.632	0.450
EXP3	**0.832**	-0.229	0.473	0.500	0.562	0.440
EXP4	**0.797**	-0.051	0.675	0.444	0.471	0.37
UNC1	-0.220	**0.938**	0.043	-0.433	-0.246	-0.184
UNC2	-0.199	**0.944**	0.047	-0.469	-0.259	-0.173
UNC3	-0.188	**0.928**	0.132	-0.398	-0.277	-0.157
UNC4	-0.183	**0.906**	0.083	-0.399	-0.210	-0.071
INS1	0.590	0.130	**0.913**	0.262	0.347	0.369
INS2	0.617	0.019	**0.906**	0.331	0.437	0.379
INS3	0.520	0.160	**0.902**	0.225	0.325	0.352
INS4	0.603	0.077	**0.930**	0.342	0.390	0.265
INS5	0.594	0.011	**0.894**	0.401	0.456	0.280
TRU1	0.617	-0.397	0.340	**0.907**	0.662	0.456
TRU2	0.562	-0.479	0.304	**0.918**	0.682	0.486
TRU3	0.531	-0.462	0.259	**0.924**	0.641	0.476
TRU4	0.556	-0.411	0.292	**0.926**	0.704	0.472
TRU5	0.339	-0.354	0.285	**0.749**	0.522	0.339
TRU6	0.554	-0.276	0.396	**0.854**	0.765	0.531
TRU7	0.547	-0.369	0.317	**0.863**	0.742	0.501
TRU8	0.537	-0.476	0.271	**0.888**	0.711	0.458
INT1	0.597	-0.257	0.438	0.726	**0.969**	0.602
INT2	0.555	-0.208	0.414	0.711	**0.971**	0.597
INT3	0.646	-0.304	0.407	0.798	**0.951**	0.595
PU1	0.375	0.003	0.350	0.397	0.481	**0.927**
PU2	0.383	-0.129	0.345	0.453	0.550	**0.948**
PU3	0.497	-0.273	0.311	0.594	0.664	**0.908**

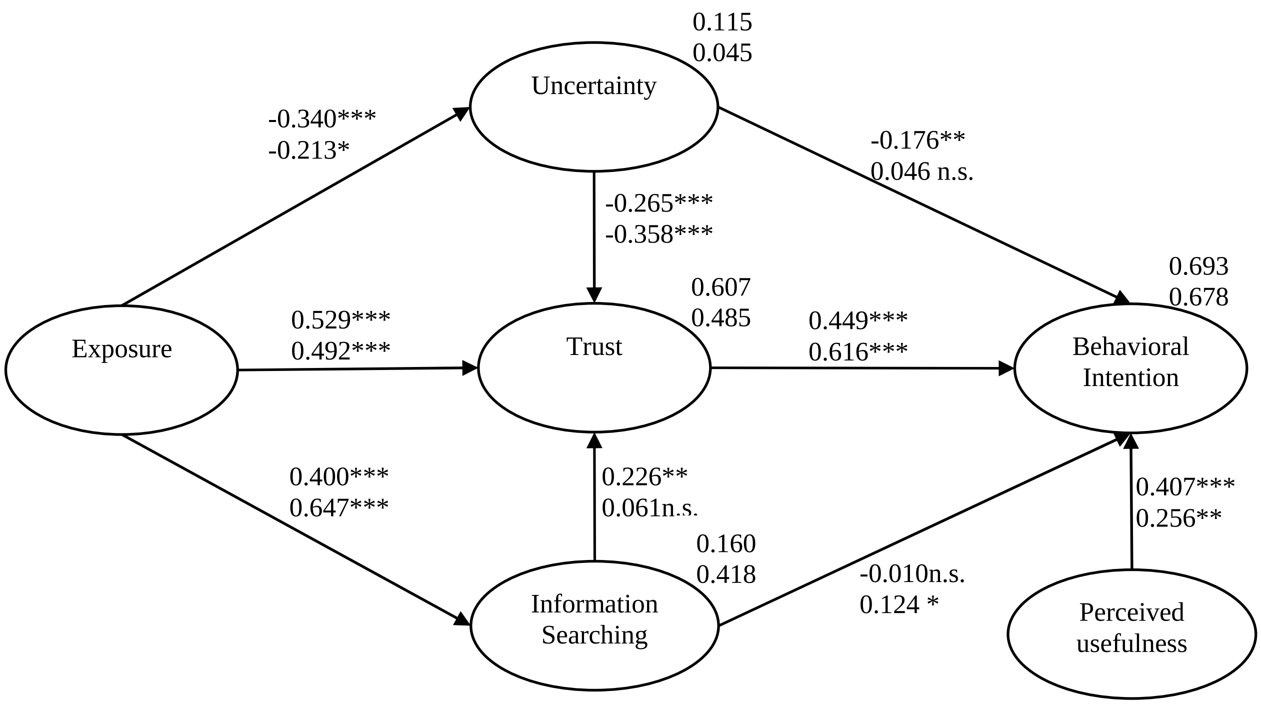
Note: EXP=exposure, INS=information searching, TR=trust, UNC=uncertainty, INT=intention to use. PU=perceived usefulness.



Note: the coefficients above variables are the R square; the upper path coefficients are for the user group, and the lower path coefficients are for the non-user group; *p<0.05, **p<0.01, ***p<0.001, and n.s.=not significant.

Figure 2. Structural Model (China)

For the non-user group from China, the results indicate that exposure to mobile payments has a negative impact on uncertainty (b=-0.256, p<0.01), supporting H2. Exposure to mobile payments has a positive relationship with information searching (b=0.427, p<0.001) and trust (b=0.256, p<0.01), supporting H1 and H3. Uncertainty has a negative relationship with consumers' trust in mobile payments (b=-0.334, p<0.001) but does not affect their intention to use mobile payments. Thus, H4 is supported while H6 is not. Information searching helps consumers build trust (b=0.257, p<0.01) and has a positive relationship with their intention to use mobile payments (b=0.189, p<0.01), supporting H5 and H8. Trust has a positive relationship with consumers' intention to use mobile payments (b=0.345, p<0.001), supporting H7.



Note: the coefficients above variables are the R square; the upper coefficients are for the user group, and the lower coefficients are for the non-user group; *p<0.05, **p<0.01, ***p<0.001, and n.s.=not significant.

Figure 3. Structural Model (the U.S.)

For the user group from the U.S., the results indicate that exposure to mobile payments has a negative impact on uncertainty (b=-0.34, p<0.001), supporting H1. Exposure to mobile payments has a positive relationship with information searching (b=0.400, p<0.001) and trust (b=0.529, p<0.001), supporting H2 and H3. Uncertainty has a negative relationship with consumers' trust in mobile payments (b=-0.265, p<0.001), and information searching has a positive relationship with consumers' trust in mobile payments (b=0.226, p<0.01). Thus, H4 and H5 are supported. In addition, uncertainty (b=-0.176, p<0.01) and trust (b=0.449, p<0.001) has a significant relationship with consumers' intention to continue using mobile payments, but information searching does not affect consumers' intention to continue using mobile payments. Thus, H6 and H7 are supported but H8 is not.

For the non-user group from the U.S., the results indicate that exposure to mobile payments has a negative impact on uncertainty (b=-0.213, p<0.05), supporting H1. Exposure to mobile payments has a positive relationship with trust (b=0.492, p<0.001) and information searching (b=0.647, p<0.001), supporting H2 and H3. Uncertainty has a negative relationship with non-users' trust in mobile payments (b=-0.358, p<0.001) but does not affect non-users' intention to use mobile payments. Thus, H4 is supported but H6 is not. Information searching has a positive relationship with non-users' intention to use mobile payment (b=0.124, p<0.05) but does not affect non-users' trust in mobile payments, supporting H8 but not H5. In addition, non-users' trust in mobile payments is positively related to their intention to use mobile payments (b=0.616, p<0.001). Thus, H7 is supported. The results of the hypotheses testing are summarized in Table 12.

Multi Group Analysis

In the structural model, the path coefficients vary across the user and the non-user groups and across China and the U.S. A multi group analysis was performed with PLS to test whether these differences are significant (Chin, 2000; Keil et al., 2000).

Table 12.
Summary of Hypotheses Tests

Hypotheses	**China**		**The U.S.**	
	Users	**Non-Users**	**Users**	**Non-users**
H1. Exposure → Information Searching	Supported	Supported	Supported	Supported
H2. Exposure → Uncertainty	Not Supported	Supported	Supported	Supported
H3. Exposure → Trust	Supported	Supported	Supported	Supported
H4. Uncertainty → Trust	Supported	Supported	Supported	Supported
H5. Information Searching →Trust	Not supported	Supported	Supported	Not supported
H6. Uncertainty →Behavioral Intention	Supported	Not supported	Supported	Not supported
H7. Trust →Behavioral Intention	Supported	Supported	Supported	Supported
H8. Information Searching →Behavioral Intention	Supported	Supported	Not supported	Supported

First, we compared the user and the non-user groups from China. The results are summarized in Table 13 that shows that three path coefficients are significantly different between the user group and the non-user group. Additionally, information searching does not have a significant relationship with users' trust in mobile payments but has a positive relationship with non-users' trust in mobile payments, an additional difference between the two groups. According to the results, four path coefficients are different between the two groups: exposure to uncertainty, information searching to trust, uncertainty to intention, and trust to intention.

Table 13.
Result of Parametric Multi-Group Analysis with PLS for the Two Groups of China

Path	b:users	b:non-users	Equal variance P (one tail)	Different variance P (one tail)
H1: Exposure -> Information Searching	0.432*	0.427*	0.480	0.480
H2: Exposure -> Uncertainty	**0.025**	**-0.256***	**0.012**	**0.013**
H3: Exposure -> Trust	0.243*	0.256*	0.457	0.457
H4: Uncertainty -> Trust	-0.492*	-0.334*	0.095	0.096
H5: Information Searching->Trust	*0.149*	*0.257**	*0.189*	*0.191*
H6: Uncertainty -> Intention	**-0.265***	**-0.103**	**0.048**	**0.048**
H7: Trust -> Intention	**0.147***	**0.345***	**0.033**	**0.034**
H8: Information Searching -> Intention	0.231*	0.189*	0.333	0.334
Control: Usefulness -> Intention	0.534*	0.464*	0.211	0.212

Note: Bolded indicates statistically differences between groups; italic indicates differences because one is significant and the other is not; *are significant path coefficients.

Second, we compared the user and the non-user groups from the U.S. The results are summarized in Table 14 that shows that three path coefficients are significantly different between the user group and the non-user group. Additionally, information searching does not have a significant relationship with non-users' trust in mobile payments but has a positive relationship with users' trust in mobile payments, an additional difference between the two groups. According to the results, four path coefficients are different between the two groups: exposure to information searching, information searching to trust, uncertainty to intention, and information searching to intention.

Table 14.
Result of Parametric Multi-Group Analysis with PLS for the Two Groups of the U.S.

Path	b:users	b:non-users	Equal variance P (one tail)	Different variance P (one tail)
H1: Exposure -> Information Searching	**0.4***	**0.647***	**0.014**	**0.014**
H2: Exposure -> Uncertainty	-0.340*	-0.213*	0.166	0.167
H3: Exposure -> Trust	0.529*	0.492*	0.383	0.383
H4: Uncertainty -> Trust	-0.265*	-0.358*	0.187	0.188
H5: Information Searching->Trust	*0.226**	*0.061*	*0.063*	*0.064*
H6: Uncertainty -> Intention	**-0.176***	**0.046**	**0.002**	**0.002**
H7: Trust -> Intention	0.449*	0.616*	0.107	0.108
H8: Information Searching -> Intention	**-0.010**	**0.124***	**0.042**	**0.043**
Control: Usefulness -> Intention	0.407*	0.256*	0.085	0.086

Note: Bolded indicates statistically differences between groups; italic indicates differences because one is significant and the other is not; *are significant path coefficients.

Third, we compared the user groups from China and the U.S. The results are summarized in Table 15 that shows that five path coefficients are significantly different across the user groups from China and the U.S. Additionally, information searching does not have a significant relationship with users’ trust in mobile payments but has a positive relationship with non-users’ trust in mobile payments, an additional difference across the two groups. According to the results, six path coefficients are different between the two groups: exposure to uncertainty, exposure to trust, uncertainty to trust, information searching to trust, information searching to intention, and trust to intention.

Table 15.
Result of Parametric Multi-Group Analysis with PLS for Users of China and the U.S.

Path	b:Users from China	b:Users from the U.S.	Equal variance P (one tail)	Different variance P (one tail)
H1: Exposure -> Information Searching	0.432*	0.400*	0.395	0.395
H2: Exposure -> Uncertainty	**0.025**	**-0.340***	**0.002**	**0.002**
H3: Exposure -> Trust	**0.243***	**0.529***	**0.004**	**0.005**
H4: Uncertainty -> Trust	**-0.492***	**-0.265***	**0.007**	**0.008**
H5: Information Searching->Trust	*0.149*	*0.226**	*0.242*	*0.243*
H6: Uncertainty -> Intention	-0.265*	-0.176*	0.173	0.174
H7: Trust -> Intention	**0.147***	**0.449***	**0.007**	**0.007**
H8: Information Searching -> intention	**0.231***	**-0.010**	**0.004**	**0.004**
Control: Usefulness -> Intention	0.534*	0.407*	0.097	0.098

Note: Bolded indicates statistically differences between groups; italic indicates differences because one is significant and the other is not; *are significant path coefficients.

Finally, we compared the non-user groups from China and the U.S. The results are summarized in Table 16 that shows that five path coefficients are significantly different between the user group and the non-user group. Additionally, information searching does not have a significant relationship with trust of non-users' from the U.S. but has a positive relationship with trust of non-users' from China, an additional difference between the two groups. According to the results, six path coefficients are different between the two groups: exposure to information searching, exposure to trust, information searching to trust, uncertainty to intention, trust to intention, and perceived usefulness to intention.

Table 16.
Result of Parametric Multi-Group Analysis with PLS for Non-Users of China and the U.S.

Path	b:Non-users from China	b:Non-users from the U.S.	Equal variance P (one tail)	Different variance P (one tail)
H1: Exposure -> Information Searching	**0.427***	**0.647***	**0.018**	**0.019**
H2: Exposure -> Uncertainty	-0.256*	-0.213*	0.370	0.371
H3: Exposure -> Trust	**0.256***	**0.492***	**0.045**	**0.045**
H4: Uncertainty -> Trust	-0.334*	-0.358*	0.426	0.426
H5: Information Searching->Trust	*0.257**	*0.061*	*0.052*	*0.053*
H6: Uncertainty -> Intention	**-0.103**	**0.046**	**0.031**	**0.032**
H7: Trust -> Intention	**0.345***	**0.616***	**0.013**	**0.014**
H8: Information Searching -> Intention	0.189*	0.124*	0.227	0.228
Control: Usefulness -> Intention	**0.464***	**0.256***	**0.020**	**0.021**

Note: Bolded indicates statistically differences between groups; italic indicates differences because one is significant and the other is not; *are significant path coefficients.

Discussion

Key Findings

Overall, all eight hypotheses are fully or partially supported. The results of our study provide insight into the importance of exposure to mobile payments and its relationship with consumers' trust in mobile payments and behavioral intention toward mobile payments. Considering the complexity of the hypotheses testing and multi-group comparisons, we summarized the results of hypotheses testing and multi-group analysis in Tables 17, 18, 19, and 20. In these tables, differential impact across groups refers to one of the two conditions: one coefficient is significant while the other is not, no matter whether the difference is statistically significant; or the difference across the two groups is statistically different. Meanwhile, same impact across groups means that both coefficients are significant or insignificant and there is no statistically difference across the two groups. In addition, the significant column for "differential impact across groups" refers to the difference across the two groups is statistically significant and the not significant column refers to the difference is insignificant. The significant column for "same impact across groups" refers to both path coefficients are significant while the not significant column refers to both are insignificant. Stronger influence for the user group means the absolute path coefficient of the user group is larger than that of the non-user group while stronger influence for the non-user group means the absolute path coefficient of the non-user group is larger than that of the user group.

Table 17.
Summary of Testing Results for the Two Groups from China

Type of Hypothesis	**Significant**	**Not Significant**
Different path coefficients across groups	**Stronger Influence for the User Group**	
	H6: Uncertainty -> Behavioral Intention	N/A
	Stronger Influence for the Non-User Group	
	H2: Exposure -> Uncertainty H7: Trust -> Behavioral Intention	H5: Information searching->Trust
Path coefficients that have no difference	H1: Exposure -> Information searching H3: Exposure -> Trust H4: Uncertainty -> Trust H8: Information searching -> Behavioral Intention Control: Usefulness->Behavioral Intention	N/A

Influence of Exposure to Mobile Payments

Our results reveal two consequences of exposure to mobile payments: increased information searching and trust in mobile payments. This finding is supported by the multi-stage decision making models. Consumers will search for information after they become aware of the need to make a final decision or solve a problem such as whether to adopt mobile payments

(Bruyn & Lilien, 2008; Dewey, 1910; Simon, 1960). The findings suggest that consumers who have more exposure to mobile payments are more likely to search for information about mobile payments than those who have less exposure to mobile payments.

Table 18.
Summary of Testing Results for the Two Groups from the U.S.

Type of Hypothesis	Significant	Not Significant
Different path coefficients across groups	**Stronger Influence for the User Group**	
	N/A	H5: Information searching->Trust H6: Uncertainty -> Behavioral Intention
	Stronger Influence for the Non-User Group	
	H1: Exposure -> Information searching	H8: Information searching -> Behavioral Intention
Path coefficients that have no difference	H2: Exposure -> Uncertainty H3: Exposure -> Trust H4: Uncertainty -> Trust H7: Trust -> Behavioral Intention Control: Usefulness->Behavioral Intention	N/A

Table 19.
Summary of Testing Results for the Two User Groups

Type of Hypothesis	Significant	Not Significant
Different path coefficients across groups	**Stronger Influence for the Users Group from China**	
	H4: Uncertainty -> Trust H8: Information searching -> Behavioral Intention	N/A
	Stronger Influence for the User Group from the U.S.	
	H2: Exposure -> Uncertainty H3: Exposure -> Trust H7: Trust -> Behavioral Intention	H5: Information searching->Trust
Path coefficients that have no difference	H1: Exposure -> Information Searching H6: Uncertainty -> Behavioral Intention Control: Usefulness->Behavioral Intention	N/A

Table 20.
Summary of Testing Results for the Two Non-User Groups

Type of Hypothesis	Significant	Not Significant
Different path coefficients across groups	**Stronger Influence for the Non-User Group from China**	
	Control: Usefulness->Behavioral Intention	H5: Information Searching->Trust H6: Uncertainty -> Behavioral Intention
	Stronger Influence for the Non-User Group from the U.S.	
	H1: Exposure -> Information Searching H3: Exposure -> Trust H7: Trust -> Behavioral Intention	N/A
Path coefficients that have no difference	H2: Exposure -> Uncertainty H4: Uncertainty -> Trust H8: Information searching -> Behavioral Intention	N/A

Results show that exposure to mobile payments will encourage consumers to trust in them. This finding is consistent with social cognitive theory (Bandura, 1977b, 1986). Exposure to mobile payments pertains to environmental factors while trust pertains to personal factors. According to social cognitive theory, environmental factors will directly affect consumers' personal factors (Bandura, 1977b, 1986). Siau and Shen (2003) emphasized the importance of convincing consumers to use mobile payment by demonstrating features such as convenience and cost efficiency and thereafter affecting consumers' trust. Exposure to mobile payments serves as mechanisms to convey relevant information to consumers, encouraging them to trust in mobile payments.

There are some differences between users and non-users. Path comparisons indicate that the path between exposure to mobile payments and perceived uncertainty is negatively significant for Chinese non-users, but not for Chinese users. One possible explanation is that users have already formed an opinion that is not variable. External influences such as exposure to mobile payments no longer affect them (or, are ignored) and thus cannot affect their perceived uncertainty. However, non-users lack of information about mobile payments and use exposure to mobile payments as a source of information, helping them decrease their uncertainty.

The results suggest that American non-users' exposure to mobile payments has a stronger influence than American users' exposure to mobile payments on their information searching. Users have past experience of using mobile payments, and generally speaking, they know more about mobile payments than non-users (Venkatesh, 2012), reducing their dependence on searching for information to make final decisions than non-users.

When we statistically compared our results across the Chinese and American respondents, the differences became apparent. The results indicate that the path between exposure to mobile payments and perceived uncertainty is negatively significant for American users, but not for Chinese users. In addition, American users' exposure to mobile payments has a stronger influence than Chinese users' exposure to mobile payments on their trust in mobile payments. These two findings can be explained from the perspective of one dimension of nation cultures: high and low context cultures. Exposure in high-context cultures such as China is implicit and indirect while exposure in low-context cultures such as the U.S. is more direct, less implicit, and more informative (Singh, Zhao, & Hu, 2005). Thus, we can expect that the U.S. exposure has a stronger influence than that of China on consequences of exposure to mobile payments.

Antecedents of Trust in Mobile Payments

Exposure to mobile payments serves as a predictor of consumers' trust in mobile payments, which has been discussed above. Our results pertaining to the relationship between perceived uncertainty and trust also warrant some discussions. Non-users who have a higher level of uncertainty are less likely to trust mobile payments but exposure reduces uncertainty for this group. This finding is consistent with the findings of Wang and Benbasat (2008), who suggested that reduction of uncertainty applies to the early stage of trust formation. Meanwhile, results indicate that users' perceived uncertainty also reduces their trust in mobile payments. Thus, reduction of uncertainty also applies to trust formation in the post adoption stage.

Path comparisons indicate that the path between information searching and trust is positively significant for Chinese non-users, but not for Chinese users. However, oppositely, the path between information searching and trust is positively significant for American users, but not for American non-users. One possible reason is the different level of information searching for Chinese users, Chinese non-users, American users, and American non-users. A t-test was performed to test whether the mean of information searching is different between American users and Chinese users and between American non-users and Chinese non-users. Results indicate that the American user group (mean=4.75, Std=1.284) has a higher level of information searching than Chinese user group (mean=4.23, Std=1.314). Thus, this could explain the finding that the path between information searching and trust is significant for American users, but not for Chinese users. In addition, consumers rely on trust-relevant knowledge about the trustee to build their expectation toward the trustee's future behavior (Komiak & Benbasat, 2006). Chinese non-users are more familiar with mobile payments than American non-users (MasterCard, 2014). Compared with Chinese non-users, American non-users may have less knowledge to organize the information they find to evaluate operability of mobile payments. Thus, American non-users' information searching may not affect their trust in mobile payments.

The results also find that Chinese users' perceived uncertainty has a stronger negative influence than American users' perceived uncertainty on their trust in mobile payments. This is related to the impact of uncertainty avoidance. Individuals from China have a higher level of uncertainty avoidance than individuals from the U.S. (Singh et al., 2005). This means that Chinese users will perceive a higher level of perceived risk than that of American users under a given level of uncertainty. Therefore, Chinese users are less likely to trust mobile payments than American users under the certain level of perceived uncertainty.

Antecedents of Behavioral Intention

Our results show that consumers' trust in mobile payments increases their intention to (continue to) use mobile payments. Our finding of the positive relationship between trust and behavioral intention is supported by the initial trust building theory, according to which consumers' trust in an object will increase the likelihood of engaging with that object (McKnight et al., 1998, 2002). Similar results can be found in Lu et al. (2011) and Zhou (2014), who posited that consumers' trust in mobile payments positively affects their intention to use mobile payments.

Path comparisons suggest that the path between perceived uncertainty and behavioral intention is negatively significant for Chinese and American users, but not for Chinese and American non-users. This reflects that non-users are willing to try mobile payments even though they feel uncertain about them. We tested whether trust serves as a mediator between uncertainty and non-users' intention to use mobile payments. According to the results of the Sobel tests, trust fully mediates the relationship between uncertainty and non-users' intention to use mobile payments (China: Sobel statistics= -2.738, P-value<0.01; the U.S.: Sobel statistics= -3.44, P-value<0.001).

The results also indicate that Chinese non-users' trust in mobile payments has a stronger influence than Chinese users' trust in mobile payments on their behavioral intention. The importance of trust depends on the degree of perceived risk (Coleman, 1990), and thus, the less the perceived risk, the less the effect of trust on behavioral intention. Mobile payment users learned how to protect their properties during the prior usage of mobile payments, reducing their perceived risk of using mobile payments. Thus, the relationship between users' trust on behavioral intention is weaker than that of non-users.

In addition, the path between information searching and behavioral intention is positively significant for American non-users, but not for American users. We tested whether trust serves as a mediator between American users' information searching and their behavioral intention. According to the results of the Sobel tests, trust fully mediates the relationship between American users' information searching and their intention to continue using mobile payments (Sobel statistics=2.584, P-value<0.01).

There are also some differences across Chinese and American consumers. The results show that American users' and non-users' trust in mobile payments has a stronger positive influence than Chinese users' and non-users' trust on their behavioral intention. Yoon (2009) posited that the degree of uncertainty avoidance negatively moderates the relationship between trust and behavioral intention. The higher the level of uncertainty avoidance, the lower the effect of trust on behavioral intention. Chinese consumers have a higher level of uncertainty avoidance than American consumers (Singh et al., 2005). Thus, the relationship between trust and behavioral intention of American consumers is stronger than that of Chinese consumers.

Limitations

As with all research, there are some limitations that should be considered when interpreting the results. First, the data was collected by using a self-report survey. Hence there is potential for common method biases (Podsakoff et al., 2003). However, common method bias is not a significant problem as shown by testing. Second, exposure to mobile payments explains only a small amount of the variance of consumers' uncertainty. Future research is needed to explore the sources of consumers' perceived uncertainty and ways to reduce it. Third, the limited source and special characteristics of the sample restrict the generalization of the findings in this research. However, most of our respondents are in their 20s or 30s, two age groups who are more willing to adopt mobile payments than other age groups (Scevak, 2010).

Implications for Theory

This research explores the similarities and differences across adoption and post adoption. Past research has suggested that predictors of adoption and post adoption are different (Limayem, at al., 2007; Setterstrom et al., 2013). However, there are variables that can be used to predict both. Anderson (1991) argues that affective states, attitudes, and belief are not replaced by new information; rather, new attitudes and beliefs are formed by integrating old attitudes and beliefs with new information. Thus, consumers update their trust in mobile payments during their learning process. This research finds that exposure to mobile payments, perceived uncertainty, information searching, and trust in mobile payments can be used to predict both adoption and post adoption behavior. Moreover, past research focuses on changes in significance of path coefficient between adoption and post adoption while ignoring the differences in the strength of relationships (Setterstrom et al., 2013). Our research explores the difference in the strength of relationships across the user and the non-user groups thus extending the body of knowledge of technology acceptance.

Few past literature performs cross-culture research of mobile payments acceptance. This research chose China and the U.S. to represent the eastern and western cultures, respectively. This research explores the similarities and differences across Chinese and American consumers.

The results suggest that consumers’ exposure to mobile payments will attract their attentions and encourage them to search for information of mobile payments. Exposure to mobile payments and perceived uncertainty about mobile payments each have a significant relationship with consumers’ trust in mobile payments, which, in turn, increases Chinese and American consumers’ intention to use mobile payments. We also found several differences across the Chinese and American consumers as shown in Tables 19 and 20. This research serves as foundation of cross-culture research on mobile payments acceptance.

This research also contributes to trust building research. We explore the trust building during the consumer learning process. Consumer learning is separated into active and passive learning, which are represented by exposure to mobile payments and information searching, respectively. We then use exposure to mobile payments and information searching to predict consumers’ trust in mobile payments. Past literature views trust as a reducer of uncertainty (Pavlou et al., 2007). However, Bandura (1977b, 1986) suggested that there is a dual relationship between environmental factors and personal factors. This research explores the effect of uncertainty on trust because our focus is trust building. Results indicate that exposure to mobile payments and perceived uncertainty serve as antecedents to consumers’ trust in mobile payments.

Additionally, our results indicate that consumers’ information searching will have a positive relationship with their trust and behavioral intention. In this research, we discussed the importance of information searching before consumers make adoption or post adoption decisions and found that information searching is needed to encourage consumers to accept mobile payments. Information searching refers to time and energy consumers spent on learning how to use mobile payments in this research, which is a type of sunk cost (Park et al., 2012). Sunk cost is one component of switching cost, which will increase consumers' inertia to make a change and thus encourage them to use or continue use mobile payments (Polites & Karahanna, 2012).

Implications for Practice

This research provides mobile payments vendors with some suggestions on how to attract non-users and retain users. Vendors should increase consumers' exposure to mobile payments because it will encourage consumers to search for information and to trust mobile payments. For example, mobile payment service providers can give users an incentive to encourage them to recommend mobile payments to their friends. Wechat mobile payments, remote mobile payments based on the instant messaging app called Wechat, launched a marketing initiative called "Qiang hongbao" to attract non-users during the 2014 Chinese Spring Festival. Users of Wechat mobile payments can send out digital money parcels to their friends who also use Wechat. The amount of money in those digital parcels are randomly decided by the Wechat system. The more digital parcels people grab, the more money they receive. However, they must create a Wechat mobile payment account and link credit or debit cards to it before they may receive the money. Wechat mobile payments increased their market share with this initiative (Liao & Li, 2014).

Importantly, uncertainty will reduce consumers' trust in mobile payments. Thus, vendors need to investigate sources of consumers' uncertainty, and take steps to reduce it. Mallat (2007) posited that perceived risk is the most important barrier to adopting mobile payment services. About 75% of consumers worry about security and transaction risks of mobile payments (Lu et al., 2011). Some mobile payment service providers cooperate with insurance companies and purchase insurance for their users to protect their transactions.

Meanwhile, vendors should realize the differences between users and non-users in their decision making process and develop different marketing tactics. There are two common differences between users and non-users for both China and the U.S. consumers. First, perceived uncertainty does not affect non-users' adoption but has a negative relationship with users' post adoption. Thus, vendors need to explore the sources of users' uncertainty, and design marketing messages that can help reduce users' uncertainty. Second, non-users' trust in mobile payments has a stronger influence than users' trust in mobile payments on consumers' behavioral intention toward mobile payments. Vendors should show non-users how they protect consumers' property and rights to encourage non-users to trust mobile payments. Some examples of trust building mechanisms are company reputation, structural assurance, information quality, and system quality (Chandra, et al., 2010; Zhou, 2011). There are also some differences across users and non-users which can be found in Tables 13 and 14. For example, for Chinese consumers, exposure to mobile payments is effective in reducing non-users' perceived uncertainty. However, they are usually less interested in messages about mobile payments than users. Thus, vendors need to consider how to attract the attention of non-users.

Vendors, especially international mobile payment service providers such as PayPal, should realize the cultural differences across Chinese and American consumers in their decision making process. First, American consumers' exposure to mobile payments has a stronger influence than that of Chinese consumers on their trust in mobile payments. Thus, vendors should explore the most effective structure of exposure mechanisms and adapt their marketing tactics to the relevant market to help consumers build trust in mobile payments. Second, trust and perceived usefulness play an important role in affecting consumers' adoption and usage decisions. However, American consumers' trust in mobile payments has a stronger influence than that of Chinese consumers on their intention to use mobile payments while Chinese consumers' perceived usefulness has a stronger influence than that of American consumers on their intention to use them. Thus, in order to achieve success in markets such as China and the U.S., vendors should address trust building and transmission of information about usefulness of mobile payments. However, vendors should emphasize the importance of trust building mechanisms when they enter a market such as the U.S., and they should emphasize the importance of perceived usefulness when they enter a market such as China.

Conclusion

Trust is a powerful factor influencing consumers' willingness to use mobile payments (Duane et al., 2014). This research explores consumers' trust building in the consumer learning process and its effect on their behavioral intention toward mobile payments. We developed a model suggesting that exposure to mobile payments encourages consumers to search for information and build trust in mobile payments, which in turn affects their behavioral intention. This research verifies the vital role of consumer learning in building trust and encouraging consumers to engage in mobile payments.

We also explore what characteristics differentiate users and non-users and differentiate American and Chinese consumers. When we compared our results across the user and non-user groups and across American and Chinese consumers, the similarities and differences in the cognitive processes involved for adoption and post adoption became apparent. The results provide vendors with suggestions on how to attract non-users and retain users and how to adapt their marketing tactics to achieve success in the U.S. and China. The research is the foundation of an understanding of the effect of culture on mobile payments acceptance, and deepens our understanding of how consumer learning, represented as exposure to mobile payments and information searching, can be used to help consumers build trust and encourage them to accept mobile payments.

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APPENDIX 1: Instrument

Table A. Measurement Items for Users
Exposure to Mobile Payments: Media Usage 1. I often obtain information about mobile payments from online newspapers. 2. I often obtain information about mobile payments from printed newspapers. 3. I often obtain information about mobile payments from online magazines. 4. I often obtain information about mobile payments from printed magazines. 5. I often obtain information about mobile payments from TV. 6. I often obtain information about mobile payments from radio. 7. I often obtain information about mobile payments from the Internet (excluding online newspapers and magazines). *Adapted from Loibl et al. (2009) and Wei et al. (2011)* Positive Word of Mouth 1. People say positive things about mobile payments. 2. People recommend using mobile payments to me. 3. Someone else from whom I seek advice recommends mobile payments for me. *Adapted from Alexandrov and Babakus (2013)* Explicit Social Influence 1. People who are important to me think that I should use mobile payments. 2. People who influence my behavior think that I should use mobile payments. 3. People whose opinions that I value prefer that I use mobile payments. *Adapted from Venkatesh et al. (2012)* Implicit Social Influence 1. People who are important to me use mobile payments. 2. People who influence my behavior use mobile payments. 3. People whose opinions that I value use mobile payments. *Adapted from Kim et al. (2007)*
Information Searching: 1. I have researched, on my own initiative, in order to increase my knowledge of using mobile payments. 2. I have researched, on my own initiative, in order to increase my mastery of using mobile payments. 3. I have explored several information sources, on my own initiative, concerning using mobile payments. 4. I have spent much time and energy learning about using mobile payments. 5. I have invested much time and energy in order to better use mobile payments. *Adapted from Barki et al. (2007)*
Trust: 1. I trust mobile payment systems to be reliable.

2. I trust mobile payment systems to be secure. 3. I believe mobile payment systems are trustworthy. 4. I trust mobile payment systems. 5. Even if the mobile payment systems are not monitored, I'd trust them to do the job correctly. 6. Mobile payments always provide accurate financial services. 7. Mobile payments always provide reliable financial services. 8. Mobile payments always provide safe financial services. *Adapted from Chandra et al. (2010) and Lu et al. (2011)*
Uncertainty 1. I feel that using mobile payments involves a high degree of uncertainty. 2. I feel the uncertainty associated with using mobile payments is high. 3. I am exposed to many transaction uncertainties if I use mobile payments. 4. There is a high degree of uncertainty when using mobile payments. *Adapted from Pavlou et al. (2007)*
Intention to continue using 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. *Adapted from Venkatesh et al. (2012)*
Perceived Usefulness 1. Using mobile payments enables me to pay more quickly. 2. Using mobile payments makes it easier for me to conduct transactions. 3. I find mobile payments a useful possibility for making payments. *Adopted from Kim et al. (2010)*

Table B. Measurement Items for Non-Users
Exposure to Mobile Payments: Media Usage 1. I often obtain information about mobile payments from online newspapers. 2. I often obtain information about mobile payments from printed newspapers. 3. I often obtain information about mobile payments from online magazines. 4. I often obtain information about mobile payments from printed magazines. 5. I often obtain information about mobile payments from TV. 6. I often obtain information about mobile payments from radio. 7. I often obtain information about mobile payments from the Internet (excluding online newspapers and magazines). *Adapted from Loibl et al. (2009) and Wei et al. (2011)* Positive Word of Mouth 1. People say positive things about mobile payments. 2. People recommend using mobile payments to me. 3. Someone else from whom I seek advice recommends mobile payments for me. *Adapted from Alexandrov and Babakus (2013)* Explicit Social Influence 1. People who are important to me think that I should use mobile payments. 2. People who influence my behavior think that I should use mobile payments. 3. People whose opinions that I value prefer that I use mobile payments. *Adapted from Venkatesh et al. (2012)* Implicit Social Influence 1. People who are important to me use mobile payments. 2. People who influence my behavior use mobile payments. 3. People whose opinions that I value use mobile payments. *Adapted from Kim et al. (2007)*
Information Searching: 1. I have researched, on my own initiative, in order to increase my knowledge of using mobile payments. 2. I have researched, on my own initiative, in order to increase my mastery of using mobile payments. 3. I have explored several information sources, on my own initiative, concerning using mobile payments. 4. I have spent much time and energy learning about using mobile payments. 5. I have invested much time and energy in order to better use mobile payments. *Adapted from Barki et al. (2007)*
Trust: 1. I trust mobile payment systems to be reliable. 2. I trust mobile payment systems to be secure. 3. I believe mobile payment systems are trustworthy.

4. I trust mobile payment systems. 5. Even if the mobile payment systems are not monitored, I'd trust them to do the job correctly. 6. Mobile payments always provide accurate financial services. 7. Mobile payments always provide reliable financial services. 8. Mobile payments always provide safe financial services. *Adapted from Chandra et al. (2010) and Lu et al. (2011)*
Uncertainty 1. I feel that using mobile payments involves a high degree of uncertainty. 2. I feel the uncertainty associated with using mobile payments is high. 3. I am exposed to many transaction uncertainties if I use mobile payments. 4. There is a high degree of uncertainty when using mobile payments. *Adapted from Pavlou et al. (2007)*
Intention to use: 1. I intend to use mobile payments in the future. 2. I predict that I will frequently use mobile payments in the future. 3. In the future, I will strongly recommend that others use mobile payments. *Adapted from Gu et al. (2009)*
Perceived Usefulness 1. Using mobile payments would enable me to pay more quickly. 2. Using mobile payments would make it easier for me to conduct transactions. 3. I would find mobile payments a useful possibility for making payments. *Adopted from Kim et al. (2010)*

ESSAY 2: EXAMINING CONSUMER LEARNING AS A WAY TO PROMOTE BEHAVIORAL INTENTION TOWARD MOBILE PAYMENTS

Introduction

Adoption of innovation is an on-going process involving persuasive communication and learning (Lee & Xia, 2011, P. 289). This process is affected by different stakeholders such as governments, companies that develop innovations, the media, and end users. User acceptance is of the greatest importance because users cannot benefit from their implementation of an innovation if they do not use it (Setterstrom, Pearson, & Orwig, 2013) and companies that develop innovations cannot recover investments in new technology if consumers do not buy it. Continuous usage is a factor in a long term relationship and often encourages consumers to develop loyalty toward the object that is being used (Deng, Lu, Wei, & Zhang, 2010). Adoption of IT innovations is analogous to the purchase of products/services in the consumer context (Deng, Turner, Gehling, & Prince, 2010), and consumer loyalty is important to vendor success. For example, online sellers can earn five times more profit from repeat consumers than from new consumers because repeat consumers are less sensitive to price and spend more at online stores (Gupta & Kim, 2007; Reichheld & Schefter, 2000). Adoption and post adoption of innovation have attracted much attention from information systems (IS) academics and have become important IS research topics.

Adoption and post adoption behaviors are continuous processes although continuous usage is not simply an extension of the adoption decision. The difference between technology adoption and continuous usage has attracted the attention of IS researchers (Setterstrom et al., 2013). Past research has suggested that predictors of technology adoption and continuous usage are different (Limayem, Hirt, & Cheung, 2007), but there should be some concepts that can be used to predict both. Learning outcomes can serve as these predictors because learning is continuous, and learning outcomes such as affective states, attitudes, and belief can evolve as environmental factors change (Bandura, 1977b, 1988). Anderson (1991) argues that affective states, attitudes, and belief are not replaced by new information; rather, new attitudes and beliefs are formed by integrating old attitudes and beliefs with information as it is received. Consumers update their trust, knowledge, and attitude about a technology during the learning process. A model can be used to predict, at least to some extent, both behavior and post adoption behaviors by integrating consumer learning and learning outcomes.

In this research, we use mobile payments as the artifact and explore consumers' acceptance of them. Mobile payments refer to any transaction that is initiated, activated, and confirmed using mobile devices (Au & Kauffman, 2008). During mobile payment processes, money is transferred from payer to receiver via an intermediary or directly (Mallat, 2007). Many researchers and business analysts believe that mobile payments will flourish in coming years. It is estimated that worldwide mobile payment revenue will rise to US$998.5 billion in 2016 (Business Wire, 2012). Mobile payments, a promising form of electronic payments, will become an important channel for conducting transactions especially with regard to mobile commerce (Yang, Lu, Gupta, Cao, & Zhang, 2012). It is necessary to examine how to encourage mobile payments adoption and continuous usage.

Adoption of innovations cannot happen spontaneously. Awareness of the existence of IT innovations is always the first step of the diffusion process (Dinev & Hu, 2007). Perceived awareness is viewed as a subjective self-assessment of consumers' knowledge that measures how much consumers know about products or innovations (Mihaela-Roxana, 2010). Because there are many types of IT innovations, prospective consumers rely on external information sources to learn more about an innovation before making adoption decisions (Doh & Hwang, 2009). Communication serves as an important information source and plays a vital role in encouraging diffusion of innovations (Jiang & Benbasat, 2007; Rogers, 2003). There are two categories of communication channels: interpersonal and mass media (Rogers, 2003). Mass media channels include radio, television, newspapers, magazines, and new media such as the Internet, while interpersonal channels involve an information exchange between two or more individuals (Rogers, 2003) such as social influence and word of mouth. The positive effect of social influence on innovation adoption is supported by adoption theories such as the theory of planned behavior (TPB) (Ajzen, 1991). Meanwhile, word of mouth has long been accepted as the most important communication format between individual consumers (Derbaix & Vanhamme, 2003) and is proposed to initiate the consumer learning process (Bruyn & Lilien, 2008).

There are many theories to guide IS acceptance research such as the innovation diffusion theory, the theory of reasoned action (TRA), the theory of planned behavior (TPB), the technology acceptance model (TAM), the unified theory of acceptance and use of technology (UTAUT), and the extended unified theory of acceptance and use of technology (UTUAT 2). In this study, adoption is viewed as a consumer learning process, during which attitude is formed. TPB is the most widely used theory in attitude-behavior research. According to TPB, behavioral intention is predicted by attitude, subjective norm, and perceived behavioral control, which are determined by behavioral beliefs, normative beliefs, and control beliefs, respectively (Ajzen, 1991). Social cognitive theory focuses on individual learning and indicates that environmental factors, personal factors, and behavior affect each other interactively (Bandura, 1977b; Bandura, 1986). In this research, the importance of consumer learning is explored by integrating social cognitive theory and TPB.

However, TPB has some shortcomings. For example, there is doubt that the theory adequately captures all theoretical determinants of intention (Rise, Sheeran, & Hukkelberg, 2010). TPB does not address some potentially important concepts such as learning and perceived knowledge. Benbasat and Barki (2007) posited that researchers should explore learning behavior in TPB research. Ajzen (1991) also encouraged others to extend TPB by including additional concepts if they help increase the prediction power of TPB. In addition, belief structures in TPB are not easy to measure (Taylor & Todd, 1995). The theory begins after the belief about social norm, perceived behavioral control, and attitude are formed while neglecting the formation of these beliefs (Bagozzi, 2007). Taylor and Todd (1995) decomposed the belief structures and proposed the decomposed theory of planned behavior in which behavioral beliefs include perceived usefulness, ease of use, and compatibility, normative beliefs include peer influence and superior influence, and control beliefs include self-efficacy, resource facilitating conditions, and technology facilitating conditions (Taylor & Todd, 1995). However, it emphasized the measurement of these beliefs while not exploring the formation of these beliefs. Moreover, TPB does not consider the interrelationships among predictors of behavioral intention in the model. Wu (2006) suggested that attitudes, subjective norms, and perceived behavioral control not only have direct effects on behavioral intention but also interact with each other.

We extend the research discussed above by viewing IT acceptance as a consumer learning process and viewing the belief structures in TPB as learning outcomes. This serves as a response to the suggestion of Benbasat and Barki (2007) that researchers should explore learning behavior in TPB research. Social cognitive theory and the theory of planned behavior serve as background theories to explore the effect of consumer learning on consumers' acceptance of mobile payments. We also explore the interaction among predictors of behavioral intention in TPB by adopting the tripartite model of attitude. Meanwhile, the potential to include perceived knowledge in TPB research is also discussed by exploring the role of consumer learning and perceived knowledge in adoption and post adoption of mobile payments. The main goal of this study is to discuss how consumer learning can affect people's mobile payments acceptance decisions. Our research questions are:

RQ1: How do consumers' learning outcomes affect their mobile payments acceptance decisions?

RQ2: What characteristics differentiate users and non-users?

The rest of the paper proceeds as follows. The theoretical background and conceptual model are presented first. Then, the hypotheses are developed. Data collection and analysis are explained next, followed by presentation of the results. Key findings and implications are then discussed.

Literature Review

Mobile Payments

Definition of mobile payments.

Mobile payments are payments that use mobile devices to pay for goods, services, and bills or perform banking transactions by using mobile technology (Dahlberg et al., 2008; Gerpott & Kornmeier, 2009; Mallat, 2007). Two important components of the definition are mobile devices and mobile technology. Mobile devices are handheld devices such as cell phones, smartphones, PDAs, pocket PCs, tablet PCs or multimedia readers with wireless capability (or any other way of connecting to online banking services) (Cruz & Laukkanen, 2010). Gartner

Group (2009) proposed that mobile payments are performed by using mobile technologies including near field communication (NFC), short message service (SMS), wireless application protocol (WAP) or direct mobile billing.

Categories of mobile payments.

There are two popular mobile payment systems: remote and proximity mobile payments (Chandra, Srivastava, & Theng, 2010). Different types of mobile payments are supported by different technologies. Remote mobile payments are based on mobile technologies such as short message services (SMS), which is leveraged by PayPal (Au & Kauffman, 2008). Proximity mobile payments are often based on technologies such as near field contact (NFC) (Zhou, 2013). Vivotech uses NFC technology to provide mobile payment services for consumers (Au & Kauffman, 2008). There are three types of mobile payment business modes: mobile network operator (MNO) led such as mobile payments provided by China Mobile, bank and financial institution led such as mobile banking provided by Citibank, and third party led such as mobile payments provided by PayPal (Turner, 2009).

Actual behavior control.

Consumers need to use smart devices such as smartphones or tablets and access the internet to perform mobile payments. Business Wire (2013a) indicated that smartphone ownership in developed markets (U.S., U.K., France, and Germany) jumped to 64% in 2013 from 49% in 2012, while the rate in developing markets (Brazil, Russia, India, and China) jumped to 37% in 2013 from 24% in 2012. The smartphone ownership rate of China is especially high among developing markets. According to Nielsen (2013), 66% of phone users in China use smartphones. Additionally, mobile internet users are growing fast as well. Close-Up Media (2013) reported that the global mobile internet market will have a robust growth in the next five years and should reach to estimated US$402.8 billion in 2018. It is estimated that the worldwide penetration rate of mobile internet will reach 37% in 2015 (Business Wire, 2013b). Increasing smartphone ownership and a fast growing mobile internet market provide a foundation for the growth of mobile payments.

Importance of mobile payments research.

Research on mobile payments is of great importance. Payment is necessary to complete transactions in mobile commerce. As the popularity of mobile devices increases, mobile payments become one of the critical drivers for mobile commerce success (Yang et al., 2012). Mobile payments also make smartphones flexible payment devices and thus realize a potential commercial value of smartphones (Andreev, Duane, & O'Reilly, 2011). Companies have invested considerable assets in mobile payments. For example, China Mobile invested US$7 billion in the Shanghai Pudong Development Bank to prepare for their mobile payments business (Yang et al., 2012); three U.S wireless carriers, Verizon, AT&T, and T-Mobile, invested US$100 million in the Isis mobile wallet in order to compete with Google wallet (Kharif, 2011). However, companies can recover their investment and profit only if consumers adopt the mobile payment service and use it continuously. Many industry stakeholders can benefit from mobile payment service. Organizations may achieve organizational value via the provision of mobile payments to consumers. The value may result from, for example, extension of their market to less developed regions by providing mobile payment services for those who have no access to the Internet other than through mobile devices. The acceptance rate of mobile payments is low although the growth forecast for mobile payments is very positive (Duane, O'Reilly, & Andreev, 2014). However, several researchers have concluded that consumers do not have positive attitudes toward mobile shopping, and in particular making mobile payments using smartphones (Duane et al., 2014).

Theoretical Background

We drew on several frameworks to explore the effect of consumer learning on mobile payment acceptance as listed in Table 1. Social cognitive theory serves as the overarching theory. TPB is used to explore the effect of social influence, self-efficacy, attitude, and perceived knowledge on behavioral intention. The multi-stage decision making model, the model of learning outcomes, and the tripartite model of attitude are used to support links among concepts in the model.

Table 1.
Theoretical Background

Framework	**Source(s)**
Social cognitive theory	Bandura, 1977b; 1986.
Theory of planned behavior	Ajzen, 1991.
Multi-stage decision making theory	Bruyn and Lilien, 2008; Dewey, 1910; Simon, 1960.
Model of learning outcomes	Kraiger, Ford, and Salas, 1993
Tripartite model of attitude	Lavidge and Steiner, 1961; Rosenberg and Hovland, 1960.

Social cognitive theory.

Social cognitive theory was proposed by Bandura (1977b, 1986); it presents behavior as one set of factors in a triadic causal framework (Figure 1). Behavior refers to behavioral intention or actual behavior toward the object. The other two sets of factors are personal factors and environmental factors. Environmental factors refer to either social or physical factors that are external to an individual and affect his or her behavior (e.g., positive word of mouth, social influence, and media usage) (Compeau & Higgins, 1995). Personal factors are “any cognitive, motivational, emotional, personality or demographic aspects characterizing an individual" (Carillo, 2012, p. 22) (e.g., attitude, self-efficacy, and perceived knowledge).

Social cognitive theory presents self-efficacy as the core term. Bandura (1977b) indicates that an individual's behaviors are responses from a combination of his or her own traits and behaviors of other individuals within the environment. Meanwhile, outcome from past behavior may affect an individual's self-efficacy, which belongs to personal factors. Bandura (1977a) discussed the relationship between environmental factors and self-efficacy and summarized four sources of self-efficacy: performance accomplishments (e.g., direct experience), vicarious experience (e.g., implicit social influence), verbal persuasion (e.g., positive word of mouth, explicit social influence, and media usage), and physiological states (e.g., relaxation).

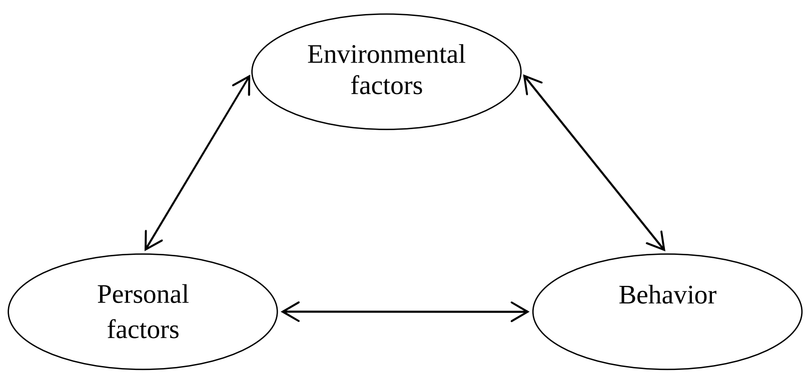


Figure 1. Triadic causal nature of human functioning

IS researchers started to use social cognitive theory in the early 1990s after they realized the importance of self-efficacy to IS acceptance (Carillo, 2012). Since then, social cognitive theory has been applied to a variety of research disciplines. Carillo (2012) suggested that "social cognitive theory is mainly applied to three research areas: computer training and/or use, software training and/or use, and internet-based applications or services" (p. 249). According to social cognitive theory, each of the three sets of factors can serve as a dependent variable. However, behavioral intention or actual behavior are the most represented dependent variables because researchers try to explain and predict human behaviors (Carillo, 2012). In this research, behavioral intention is used as the dependent variable because we attempt to explain factors that affect consumers' acceptance of mobile payments. We explore this topic by positing that environmental factors lead to personal factors that lead to behavioral factors.

Theory of planned behavior (TPB).

One area of IT acceptance research is the attitude-behavior approach. The TPB, proposed by Ajzen (1991), is one of the most widely used models in this approach. The TPB is considered a comprehensive foundation that can be used to explain most adoption behaviors (Taylor & Todd, 1995). According to the theory, behavioral intention is predicted by attitude toward the behavior, subjective norms, and perceived behavioral control. Behavior is then predicted by perceived behavioral control, actual behavior control, and behavioral intention.

Attitude is an individual's positive or negative feelings about performing a behavior (Ajzen & Fishbein, 1980). Subjective norms refer to "perceived social pressure to perform or not to perform a behavior" (Ajzen, 1991, p. 188). Social influence closely resembles subjective norm (Johnston & Warkentin, 2010). Venkatesh, Morris, Davis, and Davis (2003) posited that "social influence is represented as subjective norm in TPB" (p. 451), suggesting that social influence and social norm are interchangeable. Perceived behavioral control is composed of two correlated sub-constructs: self-efficacy and controllability (Ajzen, 2002). Self-efficacy is a consumer's belief about his or her ability to do something (Bandura, 1986) while controllability refers to the belief about the extent to which performing the behavior is voluntary (Ajzen, 2002). Ajzen (2002) suggested that self-efficacy accounts for significant portions of variance in intention while controllability does not significantly improve the prediction of intention. Thus, we use self-efficacy to represent perceived behavioral control in this research.

Multi-stage decision making model.

Dewey (1910) first proposed the multi-stage buying decision process, which includes problem/need recognition, information searching, alternatives evaluation, purchase decision, and post purchase behavior. Consumers' decision making processes start when they recognize the need to purchase a product or service. They will search for initial information to help reduce the number of products or services from which to choose into a reasonable number of alternatives. More detailed information is then sought about each alternative to facilitate the final selection.

Simon (1960) proposed the Intelligence-Design-Choice (IDC) model that is similar to the Dewey (1910) buying decision process. According to the Simon model, an individual goes through three stages during the decision process: intelligence gathering, design, and choice (Simon, 1960). Simon viewed individuals' decision making as information processing. In order to make a decision, individuals search environment for information to make a decision. Then, they design possible alternatives with information they obtain and conceive consequences of each alternative. Simon (1960) posited that individuals have limited capability to process knowledge, and thus less than an ideal decision is acceptable. Individuals will compare the efficacy of each alternative and choose one that, while not perfect, is acceptable.

A similar model of decision making is proposed by Bruyn and Lilien (2008). The model includes three stages: awareness, interest, and final decision. In the awareness stage, people become aware of the existence of an object because of exposure to the object or having received information about the object from the external environment. After becoming aware of the object, individuals will search for information to see whether the object meets their needs. During this stage, they will distinguish alternatives to the object and search for more detailed information. With the information they obtain, they become more knowledgeable of the object. Their knowledge will then be used to evaluate the object and its alternatives. After the evaluation, they will make a final selection of either the original object or one of its alternatives.

General speaking, there are three stages in the consumer decision making process, which are awareness, information searching, and decision making. However, as Kotler and Keller (2008) said, consumers do not need to move through every stage of the decision making process. For example, a person with higher personal innovativeness or who has received strong positive word of mouth from friends or relatives may decide to adopt the innovation without searching for more information, thus bypassing that stage.

Model of learning outcomes.

Any process that changes consumers' memory and behavior is considered consumer learning (Arnould, Price, & Zinkhan, 2001). Through communication and learning, individuals obtain knowledge and experience, increasing their capacity to utilize technology (Saga & Zmud, 1994). There are two main categories of consumer learning: direct consumer learning and indirect consumer learning. In direct consumer learning, consumers learn from their product usage experiences. In indirect consumer learning, consumers learn from outside sources such as word of mouth, advertisements, and information searching (Li, Daugherty, & Biocca, 2003).

Learning is a form of intangible, cognitive activity that is goal directed. Learning outcomes reflect the efficacy of learning processes. Kraiger et al. (1993) proposed that learning has three categories of outcomes, which are cognitive outcomes, skill-based outcomes, and affective outcomes. According to Kraiger et al. (1993), cognitive outcomes refer to "a class of variables related to the quantity and type of knowledge and the relationships among knowledge elements" (p. 313). They summarized three types of knowledge: declarative knowledge (know-what knowledge), procedural knowledge (know-how knowledge), and tacit knowledge (information about which, when, and why). This category reflects the knowledge that users have, for example, about what a technology is and how to use it (Marcolin, Compeau, Munro, & Huff, 2000).

Affective outcomes refer to "a class of variables encompassing issues such as attitudes, motivation, and goals that are relevant to the objectives of the training program" (Kraiger et al., 1993, p. 319). This category represents users' change in their attitude and motivation toward an object as a result of the learning experience (Ng, Dyne, & Ang, 2009). Affective learning outcomes have two dimensions, attitudinal outcomes and motivation. Attitudinal outcomes include self-efficacy and attitude toward using an object; motivation includes engaging intentionally, goal difficulty, exerting effort, persisting on a task, and mastery orientation (Kraiger, 2002).

Skill-based outcomes or behavioral learning outcomes concern the development of technical or motor skills (Kraiger et al., 1993). This category includes compilation and automaticity. Roberson, Kulik, and Pepper (2001) and Kalinoski, et al. (2012) used behavioral intentions and behavior to represent behavioral learning outcomes. With knowledge obtained as cognitive learning outcomes, people build competency to perform tasks faster and more fluidly. Through continual practice, people will reach the automaticity stage, in which they develop the habit of performing tasks without much conscious thought.

Tripartite model of attitude.

Attitude captures individuals' positive or negative evaluations of performing a certain behavior and thus can be used to predict consumers' behavioral intention (Ajzen, 1991).

Rosenberg and Hovland (1960) proposed the tripartite model of attitude, in which attitude is composed of the affective component, the behavioral component, and the cognitive component. The affective component refers to individuals' emotions toward the object, the behavioral component refers to how individuals tend to act toward the object, and the cognitive component refers to individuals' thoughts and beliefs about the object (Breckler, 1984). Li et al. (2003) posited that consumers' behavioral intention is the most widely used behavior measure.

Lavidge and Steiner (1961) used the tripartite model of attitude to explore consumer learning in advertising. They summarized three functions of advertisement: the cognitive function, the affective function, and the conative function. The cognitive function refers to intellectual, mental, or relational states, the affective function refers to emotional or feeling states, and the conative function refers to the states relating to the tendency to treat objects as positive or negative (Lavidge & Steiner, 1961, p. 60). They also explored how advertisements move potential consumers from being aware of the existence of the product toward the final purchase. According to Lavidge and Steiner (1961), consumers first sense the stimuli and obtain relevant information from the surrounding environment, and then they develop attitudes and feelings about the product, which in turn affect their purchase decisions.

The tripartite model of attitude has been used in research areas such as customer loyalty, advertising, consumer learning, and IS acceptance. Dick and Basu (1994) utilized the three dimensions of attitude structure and presented the attitude-based framework of customer loyalty with three phases: belief, affect, and intention. Oliver (1999) applied the model to loyalty development and extended the framework by adding the action phase. Oliver (1999) proposed that customer can become loyal at each phase of the attitude development process: cognitive loyalty → affective loyalty →conative loyalty → action loyalty.

Li et al. (2003) evaluated the impact of 3-D advertising by adopting the tripartite model of attitude. They also explored the role of virtual experience in facilitating consumer learning (Li et al., 2003). In Li et al. (2003), knowledge, attitude, and purchase intentions were chosen to represent the cognitive, affective, and conative components of attitude, respectively. The tripartite attitude model has also been applied to IS acceptance research. Hong, Thong, Chasalow, and Dhillon (2011) applied the tripartite model of attitude to consumer acceptance of agile information systems. They used perceived usefulness, perceived ease of use, social influence, and facilitating conditions to represent the cognitive dimension of attitude, satisfaction and comfort with change to represent the affective dimension of attitude, and habit as the behavioral dimension of attitude.

Research Model and Hypotheses Development

Research Model

In order to explore the impact of consumer learning on consumers' behavioral intention toward mobile payments, a conceptual model as shown in Figure 2 is proposed by combining background theories listed in Table 1. According to the model, exposure to mobile payments will increase consumers' information searching. Both exposure to mobile payments and information searching will increase consumers' self-efficacy and perceived knowledge, which have a positive relationship with their attitude toward using mobile payments. Consumers' self-efficacy, perceived knowledge, and attitude toward using mobile payments will then positively influence their behavioral intention toward mobile payments. Definitions of the variables used in this study are listed in Table 2.

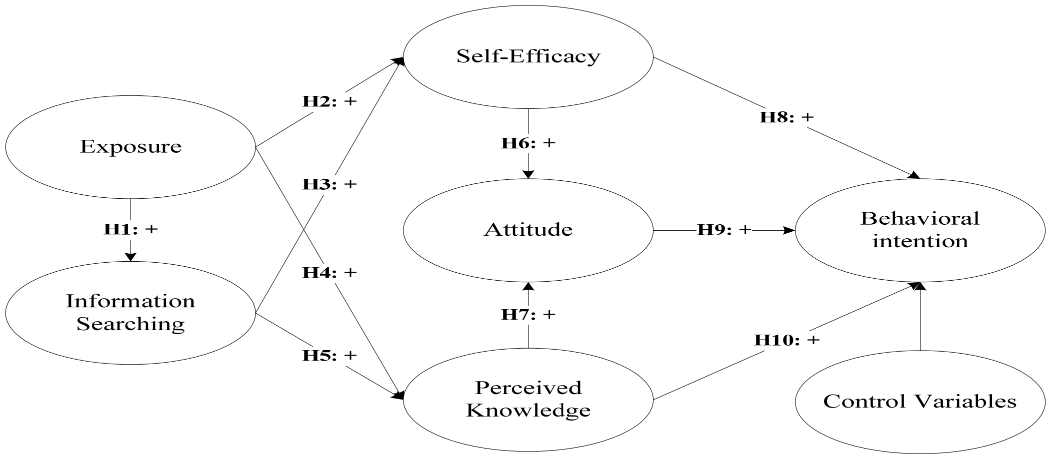


Figure 2. Research Model

Table 2.
Definitions of variables

Variable	Definition	Source(s)
Positive word of mouth	Positive informal communication among consumers about mobile payments.	e.g., Liu, 2006
Explicit social influence	The extent to which consumers perceive that important others (e.g., family and friends) believe they should use a particular technology such as mobile payments.	e.g., Venkatesh, Thong, and Xu, 2012
Implicit social influence	The extent to which consumers perceive that important others (e.g., family and friends) use a particular technology themselves.	e.g., Kim, Jahng, Lee, 2007
Media usage	The extent to which messages regarding mobile payments are transmitted through mass media such as television, newspapers, magazines, radio, and the Internet.	e.g., Wei, Frankwick, Gao, and Zhou, 2011
Information searching	The process by which individuals seek information about mobile payments.	e.g., Browne, Pitts, & Wetherbe, 2007
Attitude toward using mobile payments	Individuals' positive or negative evaluations of using mobile payments.	e.g., Ajzen, 1991
Self-efficacy	Consumers' belief about their ability to use mobile payments.	e.g., Bandura, 1986
Perceived knowledge	A subjective self-assessment of how much consumers know about mobile payments.	e.g., Mihaela-Roxana, 2010
Behavioral intention	Consumers' intention to use or continue to use mobile payments.	e.g., Venkatesh et al., 2012

Hypotheses Development

The importance of information in consumers' decision making process is well accepted. Gefen and Straub (2000) posited that online consumers obtain product information before purchasing products. Similarly, consumers should search for information before deciding whether to adopt and use mobile payments (Bruyn & Lilien, 2008; Dewey, 1910; Simon, 1960). Exposure refers to "the degree to which an individual has acquired or exchanged information about the technology and its usage" (Khalifa, Cheng, & Shen, 2012, p.15). Individuals do not simply respond to environmental influences, but also actively seek and interpret information to which they are exposed (Nevid, 2009). After they are exposed to information regarding mobile payments, they may seek additional information on specific attributes of mobile payments or how mobile payments compare relative to other payments methods (Kulkarni et al., 2012). They may also search for information to distinguish the correctness of information they receive and thereafter make a final decision. Exposure to information regarding mobile payments is viewed as the start point of the consumer learning process in this research.

Exposure to information regarding mobile payments will increase consumers' awareness and interest about them and thereafter encourage consumers to search for additional information regarding them. In this research, exposure to information regarding mobile payments is composed of positive word of mouth, implicit and explicit social influence, and mass media usage. Exposure to word of mouth, advertising, promotion, and mass media coverage are methods by which consumer's interest may be elevated (Kulkarni, Kannan, & Moe, 2012). With repeated exposure to information regarding mobile payments, consumers are attracted to them (Zajonc, 1968). Yoo (2008) also found that repeated exposure to information about or use of an innovation can lead to attractiveness and awareness of the innovation which is mobile payments in this research. After people become aware and attracted of an innovation, they will search for additional information to make further decision on whether to adopt and use it (Bruyn & Lilien, 2008; Rogers, 2003).

Searching for additional information is contingent upon exposure to information regarding mobile payments. This notion is captured in the multi-stage decision making models, which assume a sequential relationship between exposure to information regarding an innovation and searching for additional information (Bruyn & Lilien, 2008; Dewey, 1910; Simon, 1960). According to the multi-stage decision making models, consumers realize the need to make a decision on whether to adopt and use mobile payments when they are exposed to information regarding them, and then, they will search for information to obtain knowledge that will be used to evaluate possible alternative and make a selection (Bruyn & Lilien, 2008; Dewey, 1910; Simon, 1960). In view of this, exposure to information regarding mobile payments serves as the starting point of the acceptance process because it informs consumers about the existence of mobile payments and encourages consumers to search for information before they make decisions.

> ***Hypothesis 1. Exposure to information regarding mobile payments will encourage consumers to search for additional information about mobile payments.***

Bandura (1977a) proposed four sources of consumers' self-efficacy: performance accomplishments, vicarious experience, verbal persuasion, and physiological states. In this research, vicarious experience and social persuasion attract our attention. Vicarious experience refers to individuals' experience to observe other people's behavior and its consequences (Bandura, 1977a, 1986) while implicit social influence reflects consumers' perception that important others use mobile payments (Kim et al., 2007). Thus, vicarious experience is represented by implicit social influence in this study. Meanwhile, past literature distinguishes different types of social persuasion such as positive word of mouth (Mazzarol, Sweeney, & Soutar, 2007), explicit social influence (Lu & Hsiao, 2007), and media usage (Pecujlija, & Culibrk, 2012). These types of social persuasion are used to represent social persuasion in this study. The positive relationship between exposure to mobile payments and self-efficacy is supported by the social cognitive theory (Bandura, 1977a, 1977b, & 1986), and empirical research also reports a positive correlation between vicarious experience and self-efficacy and between social persuasion and self-efficacy (Warkentin, Johnston, & Shropshire, 2011).

Exposure to mobile payments facilitates consumers' self-efficacy through affecting their physiological states. On one hand, exposure to mobile payments will reduce consumers' negative judgment of their physiological states. For example, exposure to mobile payments will reduce consumers' anxiety toward using them (Beckers, Wicherts, & Schmidt, 2007). With repeated exposure to mobile payments, consumers become familiar with them. Familiarity with mobile payments has a negative relationship with consumers' anxiety about mobile payments (Arndt, Feltes, & Hanak, 1983; Fuller, Chelley, & Brown, 2006), which belongs to the judgment of their own physiological states (Bandura, 1977a). On the other hand, exposure to mobile payments will increase consumers' positive judgment of their physiological states. Zajonc (1968) proposed the mere-exposure effect, which means that with repeated exposure to mobile payments, individuals will more likely appreciate them. Salanova and Schaufeli (2000) also posited that exposure to an innovation will increase an individual's appraisal of it. Judgment of one's own physiological states is a source of self-efficacy as suggested by Bandura (1977a). Thus, exposure to mobile payments will reduce consumers' negative judgment of their physiological states and increase consumers' positive judgment, increasing their self-efficacy.

The IS literature has also invested some effort to explain the impact of exposure on consumers' self-efficacy toward the objective innovation. Compeau and Higgins (1995) tested the positive relationship between system exposure and end-user self-efficacy. Warkentin et al. (2011) viewed exposure as an external cue and tested its impact on consumers' behavioral intention through self-efficacy. Khalifa et al. (2012) also explored the effect of exposure to mobile commerce on its adoption and found that exposure positively affects individuals' self-efficacy. In view of the supports mentioned above, we posit that:

Hypothesis 2. Consumers' exposure to mobile payments will increase their self-efficacy about using mobile payments.

Information searching is usually goal-directed (David, Song, Hayes, & Fredin, 2007). At the beginning of the information searching, consumers have vague goals. In this study, consumers search for information to learn how to use mobile payments. Information searching, the process by which individuals seek information about mobile payments (Browne, Pitts, & Wetherbe, 2007), serves as an active mechanism of learning. Through information searching, consumers learn to use mobile payments. Thus, self-efficacy, consumers' belief about their ability to use mobile payments (Bandura, 1986), is anticipated to be affected by information searching.

Through information searching, consumers obtain related knowledge, resources, and supports about mobile payments. For example, they can obtain introduction of what is and how to use mobile payments from websites of mobile payment service providers. They can also search for information about other people's mobile payment usage experiences which will positively affect their self-efficacy judgment (Bandura, 1977a). Huang, Liu, and Chang (2012) posited that availability of related knowledge, resources, and supports directly affects consumers' perception of their capability of using IT innovations such as mobile payments. With support and resources obtained through information searching, individuals become more confident of using mobile payments (Compeau & Higgins, 1995; Huang, et al., 2012).

Information searching also reduces consumers' uncertainty about mobile payments and thereafter increases their self-efficacy of using them. Uncertainty exists because consumers do not have adequate information on which and how to act (Kim & Han, 2009; Kwon, Choi, & Kim, 2007). Through information searching, consumers obtain quality and quantity of information (Ramirez, Walther, Burgoon, & Sunnafrank, 2002). This helps consumers reduce their perceived uncertainty (Brashers, 2001), boosting their self-efficacy. Past literature also supports the positive relationship between information searching and consumers' self-efficacy of using mobile payments (Bauer, Bodner, Erdogan, & Truxillo, 2007; van Beuningen, de Ruyter, & Wetzels, 2009). Thus, we posit that

Hypothesis 3. Consumers' information searching will increase their self-efficacy of using mobile payments.

Perceived knowledge refers to what consumers think they know about mobile payments (Brucks, 1985). Consumers often feel that they learn a great deal from exposure to new technologies because exposure itself is information exchange (Gravill, Compeau, & Marcolin, 2006; Khalifa et al., 2012). One possible explanation is that, with repeated exposure to mobile payments, consumers may become more familiar with mobile payments without necessarily gaining more actual knowledge of mobile payments than those who are less exposed to them (Park, 2001). Familiarity is one important aspect of perceived knowledge, and consumers will perceive themselves knowledgeable of mobile payments if they are familiar with mobile payments (O'Cass, 2004). Thus, exposure to information regarding mobile payments is anticipated to increase consumers' perceived knowledge.

Exposure to information regarding mobile payments will initiate consumers' implicit learning and thereafter increase consumers' perception of their knowledge of them. Individuals will learn when they process information to which they are exposed (Mayer, 2003). Reber (1967) posited that individuals will naturally learn when they are exposed to stimulus without requiring consciousness. This learning mechanism is known as "implicit learning" (Reber, 1967). Perceived knowledge is one type of learning outcome (Kraiger, 1993). Thus, consumers will feel more knowledgeable of using mobile payments as of result of their implicit learning initiated by exposure to information regarding mobile payments.

In this research, exposure to information regarding mobile payments is represented as consumers' exposure to positive word of mouth, social influence, and mass media. Consumers' interaction with friends and exposure to mass media such as advertisement are two sources of their product knowledge (O'Cass, 2004). For example, Sohail and Al-Jabri (2014) posited that consumers gain information and thereafter knowledge about products or innovations through exposure to mass media such as newspapers, television, and the Internet. The positive effect of exposure to information regarding mobile payments on perceived knowledge is also supported by some past research. Broussard (2000) and Tewksbury, Weaver, and Maddex (2001) found that consumers' frequency of exposure to online advertising and information on the Internet about an innovation will have a positive relationship with their perceived knowledge of the object. Thus, we posit that:

Hypothesis 4. Consumers' exposure to mobile payments will increase their perceived knowledge about mobile payments.

Information searching is a process by which individuals seek information about a problem, situation, or artifact independently (Browne et al., 2007). It is a process during which consumers purposely change their state of knowledge (Marchionini, 1995; Pelsmacker & Janssens, 2007). Thus, information searching is anticipated to increase consumers' perceived knowledge of mobile payments (Brucks, 1985). In this research, we emphasize the positive effects of increasing information searching because consumers search for information before they make final decisions and people who do more information searching will have more understanding of the innovation, and thus are more likely to adopt it (Pelsmacker & Janssens, 2007).

The positive relationship between information searching and perceived knowledge is easily explained. Information searching will boost consumers' self-confidence, and thereafter allow them to feel more knowledgeable about mobile payments. Past research has viewed information searching as an important factor that increases consumers' confidence (Gershoff, 2001; Kaid, 2001; O'Cass & Pecotich, 2005). Consumers feel more confident because they will have more understanding of the innovation through searching for information regarding mobile payments. Consumers' self-confidence is an important antecedent to their perceived knowledge (Mattila & Wirtz, 2002; Park, Mothersbaugh, & Feick, 1994; Wirtz & Mattila, 2003).

In addition, consumers obtain information, a source of knowledge, through their information searching behavior. Independent exploration behavior is an important type of information searching behavior (Barki, Titah, & Boffo, 2007). By searching for information independently, consumers obtain information in which they are interested. Knowledge is an appropriate collection of information, and information is transferred to knowledge when consumers add insight and better understanding to information (Spiegler, 2003). By searching for information, consumers also become more informed and confident about mobile payments (Smith et al., 2011). Feeling informed means "believing that you have some understanding of the product (e.g., quality), how it meets personal needs, and potential time-related post-purchase issues" (Smith, Johnston, & Howard, 2011, p. 643). Feeling informed is the belief of consumers about their state of knowledge, which is anticipated to improve consumers' knowledge about IT innovations (Barki, et al., 2007). In view of the support discussed above, we suggest that the more effort consumers spend on information searching, the more information they get, and thus the more knowledgeable they feel.

Hypothesis 5. Consumers' information searching will increase their perceived knowledge about mobile payments.

Self-efficacy reflects the extent to which mobile payments consumers think they are able to use mobile payments (Bandura, 1986). The positive relationship between self-efficacy and attitude is captured in tripartite model of attitude. Tripartite model of attitude categorizes general attitude to cognitive, affective, and conative attitudes and supports the effect of the cognitive components on the affective components (Lavidge & Steiner, 1961). According to the tripartite model of attitude, self-efficacy, an element of the cognitive dimension, is anticipated to positively affect attitude, a factor of the affective dimension (Ajzen & Sexton, 1999). This logic is reasonable because individuals prefer and enjoy behaviors that they are able to perform while they dislike those that they do not think they can successfully perform (Compeau & Higgins, 1995). Bandura (1993) even posited that perceived self-efficacy can predict positive attitudes better than actual ability.

Self-efficacy will encourage consumers to form a positive attitude toward mobile payments by reducing their perceived risk and anxiety toward using mobile payments. Consumers with high self-efficacy tend to think that they can handle uncertainty appropriately and make accurate decisions with limited information (Cho & Lee, 2006), reducing their perceived risk toward a desired behavior (Kim & Kim, 2005). In addition, self-efficacy reflects consumers' efficacy to cope with potential emergency events that will make them feel anxious. Thus, a high level of self-efficacy will allow consumers to reduce their anxiety of using technologies (Bandura, 1977a, 1986). Reduction of perceived risk and anxiety will encourage consumers to form a positive attitude toward using technologies (Dash & Saji, 2008; Okazaki, Molina, & Hirose, 2012; Venkatesh, 2000).

Some research also supports the effect of self-efficacy on attitude toward a desired behavior. For example, Oliver and Shapiro (1993) posited that people's self-efficacy positively influences their willingness to achieve the desired outcomes that reflects their attitude toward the behavior. Hsu and Chiu (2004) found that consumers' self-efficacy affects their attitude toward using e-service, and Gangadharbatla (2007) discussed the effect of self-efficacy on consumers' attitude of using social networking sites. Thus, we posit that

Hypothesis 6. Consumers with a higher level of self-efficacy will be more likely to form a positive attitude toward using mobile payments than those with a lower level of self-efficacy.

Both knowledge and attitude are closely related to information one has. Knowledge about mobile payments is used by consumers to evaluate them and form opinions and beliefs about them (Martin & Lueg, 2013). Without such knowledge, attitude formation will not happen (Little & John, 2002). The impact of knowledge on attitude is supported by the traditional knowledge-attitude-behavior logic (Severin & Tankard, 2000). This logic assumes that "before people consume most goods and services, they have some information about these goods and services and form some attitude, no matter how weak that attitude or how quickly the attitude was formed" (Barry, 2002, p. 46). Given that mobile payments has advantages such as mobility, reachability, compatibility, and convenience compared to other payment approaches (Kim, Mirusmonov, & Lee, 2010), we anticipate that consumers who perceive themselves knowledgeable of mobile payments are more likely to form a more positive attitude than those who have a lower level of perceived knowledge.

Perceived knowledge reflects how consumers think they are familiar with mobile payments (Mihaela-Roxana, 2010). Perceived knowledge allows consumers to become familiar with characteristics of mobile payments and then encourages them to form a positive attitude toward mobile payments. With knowledge about mobile payments, individuals form an initial attitude about the innovation based on their perceptions of technological characteristics such as perceived usefulness and ease of use (Kang, Lim, Kim, & Yang, 2012). People prefer what is familiar and feel discomfort when they are faced with unfamiliar objects (Venkatesan, 1973). Moreover, perceived knowledge will encourage consumers to form positive attitude through reducing their anxiety of using mobile payments. Lack of knowledge and confidence of handling emergency events during using mobile payments is an important source of consumers' anxiety (Bandura, 1977a, 1986). Consumers who perceive themselves knowledgeable of mobile payments will be more confident in handling emergency events during their usage of mobile payments, decreasing their anxiety of using mobile payments. Anxiety has a negative impact on consumers' attitudes about IT innovations such as mobile payments (Venkatesh, 2000).

The positive relationship between perceived knowledge and attitude is also supported by some past literature. Mathieson and Chin (2001) posited that perceived knowledge has a positive relationship with individuals' attitude toward using information systems. Eastman, Eastman, and Eastman (2002) proposed that individuals with a high level of perceived knowledge about an innovation may be more likely to have a positive attitude toward it. Pelsmacker and Janssens (2007) and Lin and Hwang (2014) suggested that perceived knowledge will encourage consumers to generate positive feelings toward IT innovations such as mobile payments. In view of the support mentioned above, we anticipate that people with a higher level of perceived knowledge will form a more positive attitude toward mobile payments than those with a lower level of perceived knowledge.

Hypothesis 7. Consumers' perceived knowledge will have a positive relationship with their attitude toward using mobile payments.

Past research has identified many predictors of behavioral intention such as self-efficacy and attitude. Their ability to predict behavioral intention is supported by theories such as theory of planned behavior. According to that theory, self-efficacy and attitude positively influence consumers' behavioral intention toward mobile payments (Ajzen, 1991). The effects of self-efficacy and attitude on behavioral intention have been verified by past research. Past literature has applied the theory of planned behavior to predict many different types of behaviors such as the adoption of electronic commerce (Pavlou & Fygenson, 2006), advanced mobile services acceptance (Nicola´s et al., 2008; Nysveen, Pedersen, & Thorbjornsen, 2005), continued use of social network sites (AI-Debei et al., 2013), and acceptance of mobile wallet (Shin, 2009). Thus, it is anticipated that

Hypothesis 8. Consumers' self-efficacy regarding the use of mobile payments will have a positive relationship with their behavioral intention toward using mobile payments.

Hypothesis 9. Consumers' attitude toward using mobile payments will have a positive relationship with their behavioral intention toward using mobile payments.

Perceived knowledge influences consumers' decision behavior (Smith et al., 2011). Berger, Ratchford, & Haines Jr. (1994) suggested that perceived knowledge serves as a direct antecedent of consumers' behavioral intention. It is reasonable because perceived knowledge encourages consumers to adopt innovations through reducing their perceived risk and uncertainty. Consumers are not familiar with a new IT innovation or new features of the innovation, increasing their perceive risk and uncertainty regarding it. Perceived risk and uncertainty are two barriers that will impede consumers' intention to use mobile payments (Dahlberg et al., 2008; Lu et al., 2011; Mallat, 2007). Knowledge about IT innovations reduces individuals' perceived risk and uncertainty (Conrath, 1967). Thus, consumers' perceived knowledge reduces their perceived risk and uncertainty about mobile payments and thereafter encourages them to use mobile payments.

Perceived knowledge encourages consumers to accept IT innovations while lack of knowledge impedes their acceptance of innovations. This logic is well supported by past literature. Mathieson and Chin (2001) posited that perceived knowledge has a positive relationship with individuals' intention to use information systems. Lin and Chen (2006) and Zhu (2004) also emphasized the importance of the amount of product knowledge and found that consumers' knowledge affects their purchase intention through shaping their decision making process. Bhattacherjee and Hikmet (2007) mentioned that related knowledge will help physicians transition into using HIT systems. Meanwhile, lack of knowledge is also considered a barrier to the adoption of innovations. Venkatesh and Brown (2001) found that consumers did not adopt personal computers because of their lack of knowledge about them. Meanwhile, small firms did not adopt EDI at first because they lacked knowledge about it (Chau, 2001). In view of all support mentioned above, we posit that:

Hypothesis 10. Consumers' perceived knowledge about mobile payments will have a positive relationship with their behavioral intention toward using mobile payments.

Methodology

Data Collection

A survey based research was used to develop an understanding of the relationship between consumer learning and consumers' behavioral intention toward mobile payments. Two sets of data were collected. The first dataset was collected from general public in China. Four hundred and twenty four respondents were collected from China. Ninety eight respondents from the China dataset were excluded from the dataset during data screening, making the final sample size 326. In this dataset, there are 210 respondents who have used mobile payments and 116 respondents who have not used mobile payments. The second dataset was collected from general public in the U.S. Two hundred and sixty two responses were collected from the U.S. Fifteen respondents were excluded during the data screening, making the final sample 247. In this dataset, 116 respondents have used mobile payments and 131 respondents have not used mobile payments. In order to make a comparison of the user and the non-user groups and the China and the U.S. datasets, we randomized selected 116 questionnaires from each group. Hence, we have four groups: the user group from China, the non-user group from China, the user group from the U.S., and the non-user group from the U.S., each of which has 116 respondents. Table 3 summarizes the demographic information of the participants.

Table 3.
Demographic Information

		China				The U.S.			
Measure	Item	User group (n=116)		Non-user group (n=116)		User group (n=116)		Non-user group (n=116)	
		#	%	#	%	#	%	#	%
Age	<21	2	2	3	2.6	3	2.6	7	6.0
	21-25	59	59.6	45	38.8	20	17.2	17	14.7
	26-30	22	22.2	26	22.4	36	31.0	23	19.8
	31-35	8	8.1	21	18.1	38	32.8	30	25.9
	>35	8	8.1	21	18.1	19	16.4	39	33.6
Gender	Male	67	67.7	71	61.2	40	34.5	36	31.0
	Female	32	32.3	45	38.8	76	65.5	80	69.0
Education background	Some college or less	8	8.1	15	12.9	71	61.2	80	69.0
	Bachelor	59	59.6	51	44	37	31.9	26	22.4
	Master	22	22.2	34	29.3	7	6.0	10	8.6
	PhD or Professional	10	10.1	16	13.8	1	0.9	0	0
Time of using mobile payment (Months)	None	N/A	N/A	116	100	N/A	N/A	116	100
	0-6	16	16.2	N/A	N/A	22	19.0	N/A	N/A
	7-12	29	29.2	N/A	N/A	32	27.6	N/A	N/A
	13-18	21	21.2	N/A	N/A	28	24.1	N/A	N/A
	19-36	18	18.2	N/A	N/A	20	17.2	N/A	N/A
	More than 36	15	15.2	N/A	N/A	14	12.1	N/A	N/A

Measures

Wherever possible, items were drawn from existing scales. Some minor modifications were made to the adopted measures. All items are measured on a seven-point Likert scale, ranging from strongly disagree (1) to strongly agree (7). Because data were collected from both current and potential users, two versions of the questionnaire were used targeting users and non-users. The English instruments was translated into Chinese by following the back translation approach. In order to test the wording and reliability of the items, a pilot test was conducted using a group of volunteer respondents in China and one English speaking group. Subsequently, some minor changes were made to the questionnaires that can be found in Appendix 2 (English version only).

Positive word of mouth was assessed with three items adapted from Alexandrov, Lilly, and Babakus (2013). Media usage was assessed with five items adapted from Loibl et al. (2009) and Wei et al. (2011). Explicit social influence was assessed with three items adapted from Venkatesh et al. (2012), and implicit social influence was assessed with three items adapted from Kim et al. (2007). Information searching was assessed with five items adapted from Barki et al. (2007). Attitude toward using was assessed with four items adapted from Schierz et al. (2010). Self-efficacy was assessed with three items adapted from Hsieh, Rai, and Keil (2011). Perceived knowledge was assessed with four items adapted from Suh and Lee (2005). Potential users' intention to use was assessed with three items adapted from Gu, Lee, and Suh (2009), and current users' intention to continue using was assessed with three items adapted from Venkatesh et al. (2012). Perceived usefulness was assessed with three items adapted from Kim et al., (2010). Disposition to trust was assessed with three items adapted from Zhou (2011). Institution-based trust was assessed with six items adapted from Setterstrom et al. (2013).

The technology acceptance model and the initial trust building model support the effect of perceived ease of use, perceived usefulness, disposition to trust, and institution-based trust on behavioral intention (Lin, Shih, & Sher, 2007; McKnight et al., 1998, 2002). Thus, perceived ease of use, perceived usefulness, disposition to trust, and institution-based trust were used as control variables in this research.

Data Analysis and Results

SmartPLS 2.0 (Ringle, Wende, & Will, 2005) was used to analyze the data. PLS was chosen for its ability to handle non-normality in the data, and because the goal of this research is to explain variance in the outcome variable (Gefen & Straub, 2000). Exposure to mobile payments was measured using multiple subscales, which are media usage, positive word of mouth, explicit social influence, and implicit social influence. We condensed exposure to mobile payments by using latent variable scores of the subscales as items of the higher order construct. We first calculated the latent variable scores of each subscale of exposure to mobile payments using SmartPLS, and four latent variable scores were generated. Then we took these four factor scores as the reflective items for exposure to mobile payments. Latent variable scores have been widely used in prior studies to simplify a research model (Sun et al., 2012).

Common Method Bias

All data was collected through a self-report survey. Thus, there is a potential of common method bias (Podsakoff et al. 2003). This research examined common method bias using three tests. First, the Harmon's single factor test was performed. Common method bias may exist if: 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 factor analysis. For the user group from China, the result yielded

8 factors with eigenvalues greater than 1.0, which accounted for 75 percent of the total variance. The first factor captured only 30 percent of the variance in the data. For the non-user group from China, the result yielded 7 factors with eigenvalues greater than 1.0, which accounted for 77 percent of the total variance. The first factor captured only 40 percent of the variance in the data. For the user group from the U.S., the results yielded 6 factors with eigenvalues greater than 1.0, which accounted for 75 percent of the total variance. The first factor captured only 42 percent of the variance in the data. For the non-user group from the U.S., the results yielded 6 factors with eigenvalues greater than 1.0, which accounted for 77 percent of the total variance. The first factor captured only 46 percent of the variance in the data. The results indicate that no single-factor accounts for the majority of variance.

Second, researchers compared correlations among constructs by following the procedure established by Pavlou, Liang, and Xue (2007). The results revealed no constructs with correlations over 0.8.

Third, the unmeasured latent method construct (ULMC) technique (Liang, Saraf, Hu, & Xue, 2007) was performed. For the user group from China, the results demonstrate that the average substantively explained variance of the indicators is 0.720, while the average method-based variance is 0.0087. The ratio of substantive variance to method variance is about 82.8:1. In addition, the results revealed that 30 method factor loadings (out of 35) were not significant at a 95 percent confidence level. For the non-user group from China, the results demonstrate that the average substantively explained variance of the indicators is 0.738, while the average method-based variance is 0.006. The ratio of substantive variance to method variance is about 123.8:1. In addition, the results revealed that 30 method factor loadings (out of 35) were not significant at a 95 percent confidence level. For the user group from the U.S, the results demonstrate that the average substantively explained variance of the indicators is 0.768, while the average method-based variance is 0.012. The ratio of substantive variance to method variance is about 62.5:1. In addition, the results revealed that 29 method factor loadings (out of 35) were not significant at a 95 percent confidence level. For the non-user group from the U.S, the results demonstrate that the average substantively explained variance of the indicators is 0.803, while the average method-based variance is 0.006. The ratio of substantive variance to method variance is about 139:1. In addition, the results revealed that 31 method factor loadings (out of 35) were not significant at a 95 percent confidence level. Taken together the above results indicate that common method bias is unlikely to influence the analysis below.

Measurement Model

Perceived ease of use has no significant relationship with consumers' behavioral intention toward mobile payments for neither group. Thus, results with perceived usefulness, disposition to trust and institution based trust were reported below. This research adopted the two-stage analytical procedure (Anderson & Gerbing, 1988; Hair, Anderson, Tatham, & Black, 1998). Confirmative factor analysis was first conducted to assess the measurement model; then, the structural relationships were examined. As shown in Tables 4, 5, 6, and 7, Cronbach's alpha ranged from 0.718 to 0.911 for the user group from China, from 0.823 to 0.91 for the non-user group from China, from 0.818 to 0.940 for the user group from the U.S., and from 0.828 to 0.953 for the non-user group from the U.S., providing evidence of measure reliability (Cronbach, 1971). Meanwhile, composite reliability (CR) ranged from 0.828 to 0.944 for the user group from China, from 0.885 to 0.937 for the non-user group from China, from 0.880 to 0.952 for the user group from the U.S., and from 0.886 to 0.969 for the non-user group from the U.S., indicating valid internal consistency reliability (Chin, 1998). All AVEs are larger than 0.5, indicating that convergent validity is met (Fornell & Larcker, 1981). Additionally, as shown in Tables 4, 5, 6, and 7, all squared roots of AVEs are greater than the correlation shared between the construct and other constructs in the model. As shown in Tables 8, 9, 10, and 11, all items load appropriately on their intended construct. All these results indicate discriminant validity. Jointly, these findings suggest adequate convergent and discriminant validity. We also checked the variance inflation factors (VIFs) of all the independent variables. VIF for the user group from China ranged from 1.205 to 2.114, VIF for the non-user group from China ranged from 1.797 to 3.005, VIF for the user group from the U.S. ranged from 1.859 to 4.658, and VIF for the non-user group from the U.S. ranged from 2.441 to 3.366. None of the VIFs exceed 10, suggesting that multicollinearity is not a concern (Petter et al. 2007).

Table 4.
Measurement Validity for the User Group from China

					User group								
	R2	**CR**	**Cronbach's α**	**AVE**	**EXP**	**ATT**	**BI**	**DISP**	**INS**	**IBT**	**PK**	**SEL**	**PU**
EXP	N/A	0.828	0.718	0.553	**0.743**								
ATT	0.260	0.907	0.862	0.709	0.354	**0.842**							
BI	0.427	0.879	0.792	0.709	0.485	0.517	**0.842**						
DISP	N/A	0.930	0.889	0.816	0.072	0.321	0.241	**0.903**					
INS	0.102	0.924	0.897	0.708	0.319	0.198	0.360	0.0904	**0.842**				
IBT	N/A	0.925	0.901	0.674	0.435	0.499	0.490	0.276	0.229	**0.821**			
PK	0.317	0.907	0.863	0.709	0.303	0.399	0.331	0.239	0.546	0.435	**0.842**		
SEL	0.182	0.862	0.758	0.676	0.403	0.452	0.546	0.220	0.260	0.426	0.408	**0.822**	
PU	N/A	0.944	0.911	0.848	0.262	0.595	0.353	0.105	0.0839	0.352	0.377	0.504	**0.921**

Note: EXP=exposure, ATT=attitude, BI=behavioral intention, DISP=disposition to trust, INS=information searching, IBT=institution-based trust, PK=perceived knowledge, SEL=self-efficacy, and PU=perceived usefulness.

Table 5.
Measurement Validity for the Non-User Group from China

					Non-User group								
	R2	**CR**	**Cronbach's α**	**AVE**	**EXP**	**ATT**	**BI**	**DISP**	**INS**	**IBT**	**PK**	**SEL**	**PU**
EXP	N/A	0.885	0.823	0.661	**0.813**								
ATT	0.3253	0.909	0.866	0.716	0.557	**0.846**							
BI	0.6596	0.937	0.898	0.831	0.564	0.691	**0.912**						
DISP	N/A	0.918	0.867	0.790	0.436	0.447	0.558	**0.889**					
INS	0.2342	0.933	0.910	0.735	0.484	0.335	0.404	0.48	**0.858**				
IBT	N/A	0.925	0.904	0.674	0.463	0.467	0.572	0.562	0.4	**0.821**			
PK	0.3429	0.887	0.832	0.665	0.414	0.433	0.364	0.434	0.563	0.403	**0.815**		
SEL	0.3806	0.919	0.869	0.791	0.383	0.553	0.483	0.535	0.609	0.412	0.574	**0.889**	
PU	N/A	0.934	0.894	0.825	0.455	0.692	0.640	0.221	0.372	0.318	0.394	0.510	**0.909**

Note: EXP=exposure, ATT=attitude, BI=behavioral intention, DISP=disposition to trust, INS=information searching, IBT=institution-based trust, PK=perceived knowledge, SEL=self-efficacy, and PU=perceived usefulness.

Table 6.
Measurement Validity for the User Group from the U.S.

					User group								
	R2	**CR**	**Cronbach's α**	**AVE**	**EXP**	**ATT**	**BI**	**DISP**	**INS**	**IBT**	**PK**	**SEL**	**PU**
EXP	N/A	0.907	0.863	0.710	**0.843**								
ATT	0.427	0.880	0.818	0.650	0.546	**0.806**							
BI	0.775	0.933	0.891	0.822	0.476	0.766	**0.906**						
DISP	N/A	0.915	0.861	0.783	0.344	0.460	0.535	**0.885**					
INS	0.231	0.947	0.930	0.781	0.480	0.408	0.347	0.247	**0.884**				
IBT	N/A	0.952	0.940	0.770	0.435	0.643	0.689	0.663	0.316	**0.877**			
PK	0.507	0.911	0.868	0.721	0.514	0.483	0.554	0.377	0.679	0.390	**0.849**		
SEL	0.109	0.937	0.899	0.831	0.230	0.629	0.695	0.361	0.318	0.479	0.525	**0.912**	
PU	N/A	0.923	0.875	0.801	0.464	0.745	0.798	0.435	0.386	0.521	0.491	0.711	**0.895**

Note: EXP=exposure, ATT=attitude, BI=behavioral intention, DISP=disposition to trust, INS=information searching, IBT=institution-based trust, PK=perceived knowledge, SEL=self-efficacy, and PU=perceived usefulness.

Structural Model

The path coefficients and explained variances of the structural model for both groups from China and the U.S. are shown in Figure 3 and Figure 4, respectively. The PLS model does not generate the model fit statistics but uses R^2 to assess the explanatory power of a structural model. In the

China dataset, the model explained 42.7% of the variance in users' intention to continue using, and 66% of the variance in non-users' intention to use. In the American dataset, the model explained 77.5% of the variance in users' intention to continue using, and 63.9% of the variance in non-users' intention to use. These statistics validate the predictive power of the model.

Table 7.
Measurement Validity for the Non-User Group from the U.S.

					Non-User group								
	R2	**CR**	**Cronbach's α**	**AVE**	**EXP**	**ATT**	**BI**	**DISP**	**INS**	**IBT**	**PK**	**SEL**	**PU**
EXP	N/A	0.886	0.828	0.662	0.814								
ATT	0.332	0.927	0.894	0.760	0.497	0.871							
BI	0.639	0.969	0.951	0.911	0.594	0.710	0.955						
DISP	N/A	0.927	0.881	0.809	0.351	0.543	0.533	0.899					
INS	0.549	0.962	0.951	0.835	0.741	0.402	0.489	0.308	0.914				
IBT	N/A	0.963	0.953	0.812	0.421	0.527	0.568	0.725	0.406	0.901			
PK	0.594	0.893	0.832	0.684	0.653	0.466	0.498	0.471	0.758	0.511	0.827		
SEL	0.188	0.967	0.949	0.907	0.383	0.544	0.536	0.596	0.420	0.535	0.572	0.952	
PU	N/A	0.951	0.923	0.866	0.523	0.698	0.725	0.496	0.404	0.509	0.478	0.660	0.931

Note: EXP=exposure, ATT=attitude, BI=behavioral intention, DISP=disposition to trust, INS=information searching, IBT=institution-based trust, PK=perceived knowledge, SEL=self-efficacy, and PU=perceived usefulness.

For the user group from China, the results indicate that exposure to mobile payments has a positive impact on information searching (b=0.319, p<0.001) and self-efficacy (b=0.357, p<0.001) but does not affect perceived knowledge, supporting H1 and H2 while not supporting H4. Information searching has a positive relationship with perceived knowledge (b=0.500, p<0.001) but does not affect self-efficacy. Thus, H5 is supported while H3 is not. Self-efficacy (b=0.347, p<0.01) and perceived knowledge (b=0.258, p<0.05) each have a positive relationship with consumers' attitude, supporting both H6 and H7. Self-efficacy (b=0.358, p<0.05) and attitude (b=0.287, p<0.05) both have a positive relationship with users' intention toward mobile payments, but perceived knowledge does not affect users' behavioral intention. Thus, H8 and H9 are supported while H10 is not.

Table 8.
Cross Loading for the User Group from China

	EXP	ATT	BI	DISP	INS	IBT	PK	SEL	PU
EXP1	**0.835**	0.348	0.445	0.052	0.187	0.414	0.242	0.240	0.212
EXP2	**0.768**	0.206	0.301	0.0597	0.194	0.290	0.219	0.252	0.216
EXP3	**0.539**	0.095	0.210	0.076	0.328	0.124	0.203	0.187	0.071
EXP4	**0.795**	0.367	0.448	0.032	0.228	0.428	0.229	0.458	0.257
ATT1	0.309	**0.891**	0.496	0.261	0.193	0.546	0.337	0.355	0.523
ATT2	0.365	**0.825**	0.446	0.326	0.147	0.438	0.298	0.416	0.542
ATT3	0.237	**0.869**	0.362	0.213	0.137	0.419	0.354	0.333	0.573
ATT4	0.274	**0.778**	0.427	0.275	0.185	0.275	0.354	0.409	0.369
BI1	0.280	0.415	**0.756**	-0.011	0.285	0.308	0.266	0.529	0.393
BI2	0.441	0.481	**0.886**	0.289	0.281	0.425	0.303	0.432	0.259
BI3	0.490	0.410	**0.878**	0.305	0.343	0.495	0.267	0.429	0.252
DISP1	0.081	0.259	0.167	**0.839**	0.081	0.180	0.171	0.218	0.102
DISP2	0.094	0.368	0.264	**0.924**	0.100	0.355	0.286	0.226	0.127
DISP3	0.016	0.219	0.201	**0.943**	0.060	0.171	0.165	0.149	0.047
INS1	0.125	0.150	0.282	0.023	**0.827**	0.211	0.477	0.254	0.099
INS2	0.235	0.202	0.317	0.045	**0.859**	0.248	0.474	0.228	0.116
INS3	0.264	0.209	0.244	0.058	**0.848**	0.172	0.413	0.232	0.095
INS4	0.328	0.138	0.299	0.107	**0.874**	0.179	0.482	0.183	0.014
INS5	0.367	0.139	0.361	0.135	**0.799**	0.157	0.450	0.205	0.039
IBT1	0.393	0.572	0.460	0.205	0.245	**0.733**	0.460	0.392	0.401
IBT2	0.267	0.177	0.307	0.354	0.083	**0.68**	0.269	0.247	0.153
IBT3	0.448	0.429	0.333	0.253	0.222	**0.850**	0.379	0.283	0.316
IBT4	0.350	0.367	0.443	0.252	0.199	**0.903**	0.354	0.292	0.253
IBT5	0.287	0.439	0.388	0.272	0.137	**0.873**	0.281	0.406	0.325
IBT6	0.384	0.406	0.435	0.0729	0.210	**0.861**	0.365	0.437	0.251
PK1	0.257	0.368	0.333	0.220	0.533	0.419	**0.882**	0.383	0.325
PK2	0.286	0.402	0.288	0.319	0.301	0.318	**0.777**	0.388	0.324
PK3	0.219	0.231	0.197	0.133	0.550	0.294	**0.860**	0.249	0.321
PK4	0.259	0.333	0.283	0.130	0.450	0.420	**0.846**	0.344	0.298
SEL1	0.384	0.438	0.483	0.248	0.172	0.329	0.329	**0.877**	0.379
SEL2	0.270	0.329	0.470	-0.029	0.254	0.309	0.335	**0.739**	0.531
SEL3	0.335	0.339	0.387	0.319	0.221	0.417	0.344	**0.845**	0.333
PU1	0.284	0.541	0.395	0.056	0.097	0.344	0.394	0.478	**0.958**
PU2	0.241	0.563	0.300	0.096	0.084	0.284	0.350	0.459	**0.929**
PU3	0.179	0.551	0.251	0.163	0.040	0.348	0.277	0.457	**0.874**

Note: EXP=exposure, ATT=attitude, BI=behavioral intention, DISP=disposition to trust, INS=information searching, IBT=institution-based trust, PK=perceived knowledge, SEL=self-efficacy, and PU=perceived usefulness.

Table 9.
Cross Loading for the Non-User Group from China

	EXP	ATT	BI	DISP	INS	IBT	PK	SEL	PU
EXP1	**0.909**	0.465	0.515	0.404	0.493	0.425	0.405	0.291	0.356
EXP2	**0.880**	0.468	0.448	0.387	0.401	0.429	0.331	0.319	0.322
EXP3	**0.641**	0.453	0.362	0.158	0.264	0.225	0.302	0.265	0.418
EXP4	**0.796**	0.438	0.494	0.430	0.386	0.400	0.302	0.373	0.405
ATT1	0.442	**0.884**	0.645	0.431	0.233	0.456	0.337	0.433	0.586
ATT2	0.559	**0.893**	0.658	0.420	0.252	0.509	0.377	0.379	0.584
ATT3	0.446	**0.839**	0.499	0.246	0.257	0.301	0.293	0.450	0.67
ATT4	0.433	**0.762**	0.521	0.391	0.377	0.307	0.438	0.588	0.511
BI1	0.476	0.670	**0.905**	0.439	0.362	0.547	0.294	0.472	0.666
BI2	0.475	0.632	**0.94**	0.509	0.333	0.499	0.360	0.477	0.569
BI3	0.595	0.584	**0.889**	0.583	0.412	0.518	0.343	0.368	0.510
DISP1	0.326	0.378	0.443	**0.850**	0.454	0.509	0.398	0.510	0.233
DISP2	0.432	0.429	0.544	**0.918**	0.413	0.533	0.376	0.442	0.187
DISP3	0.396	0.382	0.494	**0.897**	0.419	0.457	0.388	0.483	0.175
INS1	0.400	0.320	0.326	0.333	**0.877**	0.341	0.486	0.569	0.393
INS2	0.399	0.327	0.336	0.318	**0.888**	0.318	0.477	0.560	0.387
INS3	0.446	0.354	0.363	0.375	**0.877**	0.318	0.485	0.542	0.398
INS4	0.432	0.231	0.380	0.514	**0.856**	0.385	0.476	0.460	0.234
INS5	0.399	0.196	0.329	0.531	**0.787**	0.358	0.490	0.472	0.169
IBT1	0.242	0.348	0.486	0.522	0.244	**0.774**	0.317	0.359	0.240
IBT2	0.370	0.290	0.410	0.477	0.341	**0.773**	0.353	0.279	0.209
IBT3	0.337	0.249	0.345	0.458	0.377	**0.817**	0.349	0.407	0.199
IBT4	0.41	0.382	0.506	0.503	0.338	**0.859**	0.420	0.400	0.248
IBT5	0.408	0.468	0.501	0.411	0.361	**0.840**	0.254	0.313	0.358
IBT6	0.495	0.504	0.526	0.409	0.328	**0.859**	0.305	0.288	0.287
PK1	0.330	0.402	0.281	0.323	0.469	0.230	**0.855**	0.523	0.350
PK2	0.409	0.448	0.314	0.408	0.366	0.425	**0.786**	0.461	0.239
PK3	0.391	0.303	0.354	0.408	0.606	0.370	**0.892**	0.531	0.381
PK4	0.168	0.235	0.212	0.245	0.366	0.276	**0.717**	0.317	0.322
SEL1	0.396	0.563	0.479	0.557	0.603	0.388	0.531	**0.943**	0.484
SEL2	0.171	0.344	0.314	0.330	0.454	0.244	0.460	**0.798**	0.402
SEL3	0.406	0.528	0.467	0.500	0.550	0.435	0.538	**0.92**	0.470
PU1	0.397	0.616	0.586	0.175	0.302	0.283	0.326	0.387	**0.906**
PU2	0.408	0.570	0.567	0.174	0.326	0.232	0.325	0.448	**0.911**
PU3	0.434	0.698	0.589	0.253	0.386	0.350	0.420	0.555	**0.909**

Note: EXP=exposure, ATT=attitude, BI=behavioral intention, DISP=disposition to trust, INS=information searching, IBT=institution-based trust, PK=perceived knowledge, SEL=self-efficacy, and PU=perceived usefulness.

Table 10.
Cross Loading for the User Group from the U.S.

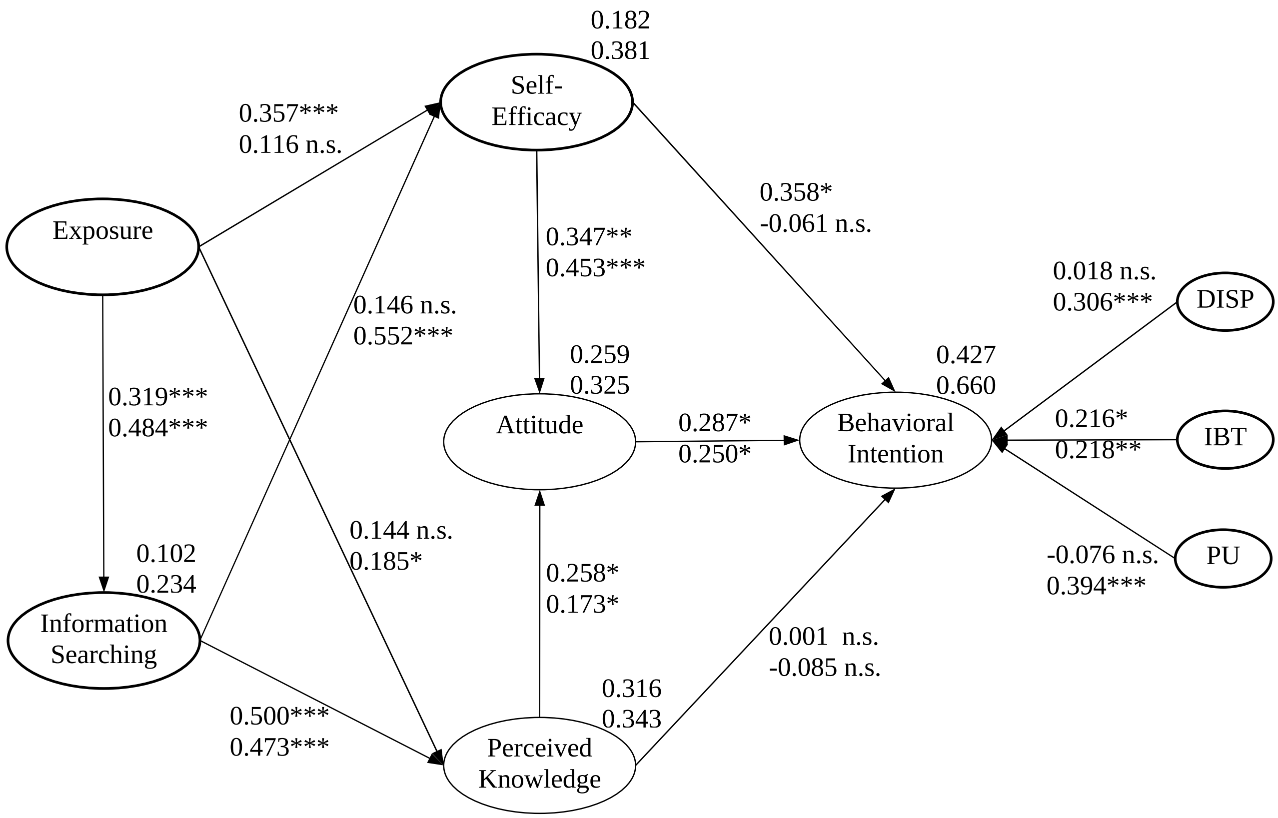
	EXP	ATT	BI	DISP	INS	IBT	PK	SEL	PU
EXP1	**0.940**	0.470	0.417	0.271	0.536	0.351	0.530	0.203	0.445
EXP2	**0.865**	0.536	0.490	0.298	0.355	0.397	0.439	0.282	0.479
EXP3	**0.690**	0.210	0.178	0.210	0.303	0.239	0.333	-0.041	0.072
EXP4	**0.857**	0.551	0.451	0.374	0.387	0.457	0.400	0.241	0.450
ATT1	0.493	**0.916**	0.735	0.451	0.316	0.643	0.438	0.610	0.652
ATT2	0.522	**0.845**	0.652	0.390	0.317	0.541	0.413	0.473	0.606
ATT3	0.361	**0.760**	0.588	0.232	0.304	0.407	0.393	0.590	0.657
ATT4	0.379	**0.685**	0.454	0.443	0.432	0.474	0.290	0.288	0.461
BI1	0.354	0.719	**0.930**	0.468	0.323	0.615	0.503	0.734	0.761
BI2	0.430	0.662	**0.900**	0.466	0.312	0.571	0.469	0.602	0.684
BI3	0.513	0.701	**0.889**	0.521	0.309	0.683	0.532	0.550	0.721
DISP1	0.324	0.450	0.556	**0.921**	0.316	0.662	0.431	0.432	0.428
DISP2	0.313	0.322	0.374	**0.795**	0.084	0.463	0.202	0.186	0.354
DISP3	0.279	0.434	0.465	**0.931**	0.215	0.608	0.330	0.299	0.368
INS1	0.334	0.386	0.347	0.251	**0.896**	0.304	0.612	0.341	0.349
INS2	0.376	0.383	0.319	0.251	**0.916**	0.314	0.633	0.272	0.365
INS3	0.380	0.377	0.355	0.243	**0.893**	0.335	0.647	0.386	0.414
INS4	0.454	0.297	0.239	0.142	**0.856**	0.174	0.551	0.224	0.262
INS5	0.581	0.356	0.266	0.200	**0.856**	0.258	0.552	0.168	0.308
IBT1	0.305	0.506	0.544	0.641	0.258	**0.893**	0.273	0.373	0.405
IBT2	0.411	0.600	0.547	0.553	0.318	**0.885**	0.305	0.387	0.412
IBT3	0.419	0.578	0.627	0.649	0.276	**0.915**	0.332	0.408	0.447
IBT4	0.374	0.545	0.612	0.559	0.280	**0.859**	0.394	0.440	0.424
IBT5	0.403	0.575	0.601	0.490	0.245	**0.791**	0.339	0.419	0.545
IBT6	0.369	0.574	0.672	0.595	0.287	**0.915**	0.391	0.481	0.498
PK1	0.452	0.485	0.560	0.424	0.551	0.454	**0.862**	0.608	0.508
PK2	0.384	0.223	0.234	0.190	0.405	0.103	**0.672**	0.165	0.188
PK3	0.456	0.411	0.482	0.305	0.677	0.336	**0.935**	0.476	0.421
PK4	0.457	0.468	0.537	0.327	0.637	0.358	**0.904**	0.448	0.482
SEL1	0.236	0.616	0.673	0.459	0.351	0.505	0.515	**0.922**	0.666
SEL2	0.161	0.580	0.587	0.302	0.251	0.358	0.459	**0.907**	0.642
SEL3	0.226	0.518	0.633	0.208	0.257	0.436	0.457	**0.905**	0.636
PU1	0.399	0.556	0.646	0.388	0.303	0.398	0.448	0.559	**0.872**
PU2	0.441	0.707	0.764	0.400	0.368	0.498	0.471	0.638	**0.932**
PU3	0.405	0.726	0.724	0.382	0.362	0.496	0.399	0.707	**0.880**

Note: EXP=exposure, ATT=attitude, BI=behavioral intention, DISP=disposition to trust, INS=information searching, IBT=institution-based trust, PK=perceived knowledge, SEL=self-efficacy, and PU=perceived usefulness.

Table 11.
Cross Loading for the Non-User Group from the U.S.

	EXP	ATT	BI	DISP	INS	IBT	PK	SEL	PU
EXP1	**0.898**	0.416	0.541	0.344	0.639	0.388	0.599	0.377	0.441
EXP2	**0.73**	0.458	0.506	0.245	0.456	0.317	0.463	0.268	0.471
EXP3	**0.756**	0.291	0.377	0.207	0.703	0.287	0.554	0.266	0.330
EXP4	**0.859**	0.475	0.517	0.341	0.585	0.376	0.495	0.328	0.477
ATT1	0.482	**0.889**	0.610	0.501	0.386	0.518	0.424	0.432	0.555
ATT2	0.417	**0.878**	0.595	0.568	0.331	0.553	0.448	0.452	0.559
ATT3	0.424	**0.909**	0.647	0.456	0.347	0.376	0.427	0.549	0.724
ATT4	0.412	**0.806**	0.622	0.366	0.339	0.396	0.320	0.459	0.584
BI1	0.575	0.669	**0.962**	0.510	0.470	0.525	0.488	0.529	0.710
BI2	0.565	0.682	**0.961**	0.462	0.481	0.497	0.471	0.486	0.701
BI3	0.559	0.681	**0.940**	0.552	0.449	0.602	0.468	0.517	0.666
DISP1	0.347	0.548	0.493	**0.926**	0.327	0.690	0.535	0.588	0.464
DISP2	0.242	0.409	0.426	**0.851**	0.136	0.558	0.294	0.483	0.408
DISP3	0.349	0.500	0.514	**0.918**	0.349	0.696	0.426	0.532	0.462
INS1	0.654	0.375	0.383	0.241	**0.923**	0.326	0.680	0.377	0.354
INS2	0.701	0.428	0.510	0.285	**0.926**	0.368	0.697	0.371	0.401
INS3	0.657	0.321	0.428	0.273	**0.904**	0.383	0.703	0.357	0.363
INS4	0.683	0.330	0.420	0.321	**0.925**	0.407	0.718	0.410	0.378
INS5	0.688	0.382	0.489	0.287	**0.892**	0.368	0.665	0.404	0.351
IBT1	0.386	0.488	0.514	0.659	0.346	**0.938**	0.460	0.471	0.424
IBT2	0.410	0.391	0.472	0.626	0.354	**0.894**	0.396	0.411	0.409
IBT3	0.396	0.463	0.553	0.682	0.392	**0.942**	0.488	0.457	0.440
IBT4	0.395	0.512	0.528	0.630	0.399	**0.928**	0.507	0.516	0.468
IBT5	0.307	0.461	0.408	0.596	0.307	**0.758**	0.364	0.495	0.474
IBT6	0.378	0.528	0.575	0.718	0.386	**0.932**	0.520	0.547	0.539
PK1	0.629	0.404	0.401	0.410	0.737	0.461	**0.876**	0.454	0.357
PK2	0.300	0.350	0.287	0.183	0.224	0.173	**0.522**	0.235	0.268
PK3	0.606	0.429	0.476	0.416	0.777	0.464	**0.942**	0.572	0.465
PK4	0.560	0.374	0.464	0.493	0.633	0.517	**0.899**	0.562	0.468
SEL1	0.414	0.584	0.585	0.593	0.430	0.577	0.543	**0.935**	0.659
SEL2	0.358	0.503	0.481	0.564	0.401	0.482	0.563	**0.963**	0.615
SEL3	0.308	0.448	0.444	0.536	0.359	0.453	0.522	**0.959**	0.600
PU1	0.536	0.573	0.648	0.396	0.374	0.419	0.440	0.562	**0.923**
PU2	0.478	0.631	0.670	0.448	0.367	0.467	0.461	0.640	**0.960**
PU3	0.448	0.738	0.703	0.533	0.387	0.531	0.433	0.637	**0.909**

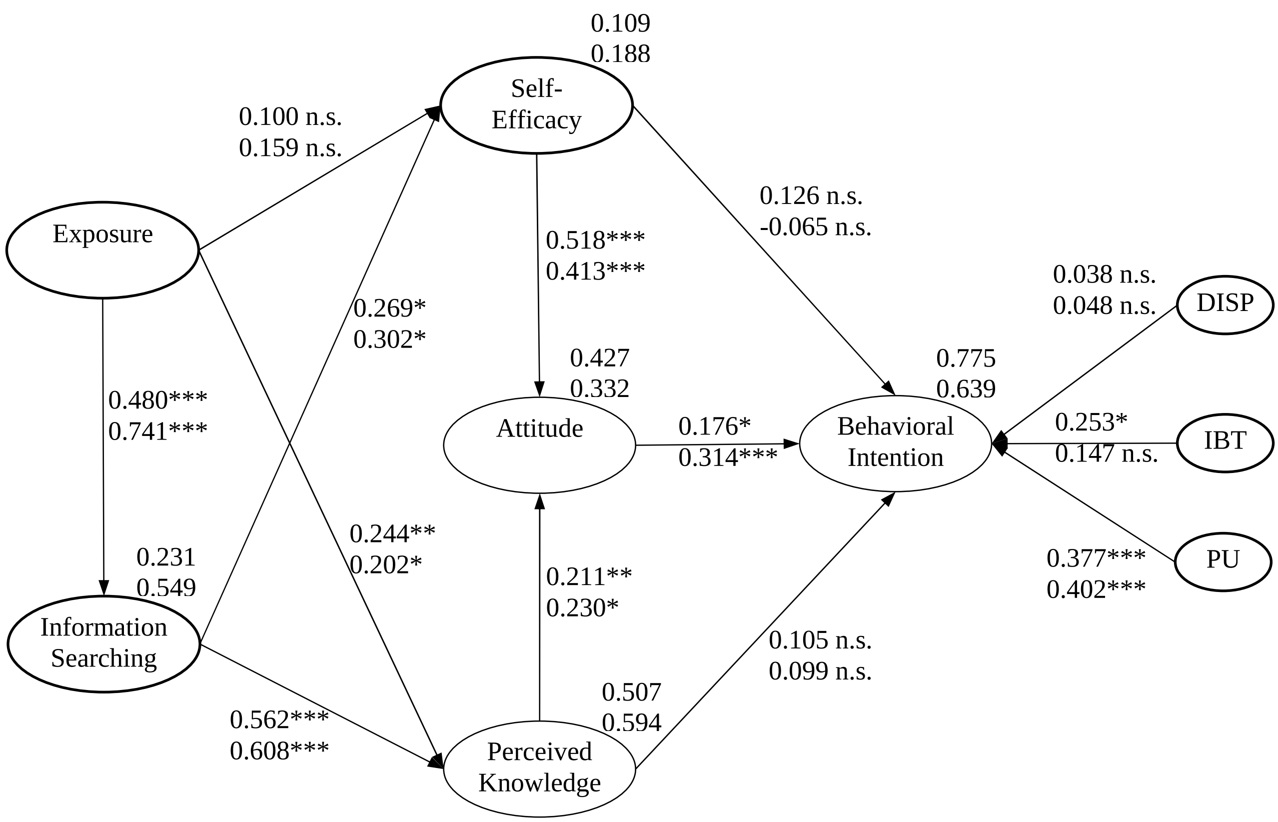
Note: EXP=exposure, ATT=attitude, BI=behavioral intention, DISP=disposition to trust, INS=information searching, IBT=institution-based trust, PK=perceived knowledge, SEL=self-efficacy, and PU=perceived usefulness.



Note: the upper coefficients are for the user group, and the lower coefficients are for the non-user group; *p<0.05, **p<0.01, ***p<0.001, and n.s.=not significant; control variables: DISP= disposition to trust, IBT=institution-based trust, and PU=perceived usefulness.

Figure 3. Structural Model for China

For the non-user group from China, the results indicate that exposure to mobile payments has a positive impact on information searching (b=0.484, p<0.001) and perceived knowledge (b=0.185, p<0.05) but does not affect self-efficacy, supporting H1 and H4 while not supporting H2. Information searching has a positive relationship with perceived knowledge (b=0.473, p<0.001) and self-efficacy (b=0.552, p<0.001). Thus, H3 and H5 are supported. Self-efficacy (b=0.453, p<0.001) and perceived knowledge (b=0.173, p<0.05) each have a positive relationship with consumers’ attitude, supporting both H6 and H7. Attitude (b=0.250, p<0.05) has a positive relationship with users’ intention toward mobile payments, but self-efficacy and perceived knowledge do not affect users' behavioral intention. Thus, H9 is supported while H8 and H10 are not.



Note: the upper coefficients are for the user group, and the lower coefficients are for the non-user group; *p<0.05, **p<0.01, ***p<0.001, and n.s.=not significant; control variables: DISP=disposition to trust, IBT=institution-based trust, and PU=perceived usefulness.

Figure 4. Structural Model for the U.S.

For the user group from the U.S., the results indicate that exposure to mobile payments has a positive impact on information searching ($b=0.480$, $p<0.001$) and perceived knowledge ($b=0.244$, $p<0.01$) but does not affect self-efficacy, supporting H1 and H4 while not supporting H2. Information searching has a positive relationship with self-efficacy ($b=0.269$, $p<0.05$) and perceived knowledge ($b=0.562$, $p<0.001$). Thus, H3 and H5 is supported. Self-efficacy ($b=0.518$, $p<0.001$) and perceived knowledge ($b=0.211$, $p<0.01$) each have a positive relationship with consumers' attitude, supporting both H6 and H7. Attitude ($b=0.176$, $p<0.05$) has a positive relationship with users' intention to continue using mobile payments, but self-efficacy and perceived knowledge do not affect users' behavioral intention. Thus, H9 is supported while H8 and H10 are not.

For the non-user group from the U.S., the results indicate that exposure to mobile payments has a positive impact on information searching ($b=0.741$, $p<0.001$) and perceived knowledge ($b=0.202$, $p<0.05$) but does not affect self-efficacy, supporting H1 and H4 while not supporting H2. Information searching has a positive relationship with self-efficacy ($b=0.302$, $p<0.05$) and perceived knowledge ($b=0.608$, $p<0.001$). Thus, H3 and H5 are supported. Self-efficacy ($b=0.413$, $p<0.001$) and perceived knowledge ($b=0.230$, $p<0.05$) each have a positive relationship with consumers' attitude, supporting H6 and H7. Attitude ($b=0.314$, $p<0.001$) has a positive relationship with users' intention to continue using mobile payments, but self-efficacy and perceived knowledge do not affect users' behavioral intention. Thus, H9 is supported while H8 and H10 are not. Results of the hypotheses testing are summarized in Table 12.

Table 12.
Summary of Hypotheses Testing

Hypotheses	**China**		**U.S.A**	
	Users	**Non-Users**	**Users**	**Non-Users**
H1. Exposure → Information Searching	Supported	Supported	Supported	Supported
H2. Exposure → Self-Efficacy	Supported	Not Supported	Not Supported	Not Supported
H3. Information Searching → Self-Efficacy	Not Supported	Supported	Supported	Supported
H4. Exposure → Perceived Knowledge	Not Supported	Supported	Supported	Supported
H5. Information Searching →Perceived Knowledge	Supported	Supported	Supported	Supported
H6. Self-Efficacy → Attitude	Supported	Supported	Supported	Supported
H7. Perceived Knowledge → Attitude	Supported	Supported	Supported	Supported
H8. Self-Efficacy → Behavioral Intention	Supported	Not Supported	Not Supported	Not Supported
H9. Attitude → Behavioral Intention	Supported	Supported	Supported	Supported
H10. Perceived Knowledge → Behavioral Intention	Not supported	Not Supported	Not Supported	Not Supported

Multi Group Analysis

In the structural model, the path coefficients vary across the user and the non-user groups and across China and the U.S. datasets. A multi group analysis with PLS was conducted in order to test whether these differences are significant (Chin, 2000).

Frist, we compared the user and the non-user groups from China. The results are summarized in Table 13 that shows that five path coefficients are significantly different between the user group and the non-user group. Additionally, exposure to mobile payments has a significant relationship with users' perceived knowledge but does not have a positive relationship with non-users' perceived knowledge, an additional difference between the two groups. According to the results, six path coefficients are different between the two groups: exposure to self-efficacy, information searching to self-efficacy, self-efficacy to behavioral intention, and disposition to trust to behavioral intention, perceived usefulness to behavioral intention, and exposure to perceived knowledge.

Second, we compared the user and the non-user groups from the U.S. The results are summarized in Table 14 that shows that two path coefficients are significantly different across the user and the non-user groups. Additionally, institution based trust has a significant relationship with users' intention to continue using mobile payments but does not affect non-users' intention to use, an additional difference across the two groups. According to the results, three path coefficients are different across the two groups: exposure to information searching, self-efficacy to behavioral intention, and institution-based trust to behavioral intention.

Third, we compared the user groups from China and the U.S. The results are summarized in Table 15 that shows that two path coefficients are significantly different across the user groups from China and the U.S. Additionally, information searching has a positive relationship with self-efficacy of users from the U.S. but does not affect self-efficacy of users from China, exposure to mobile payments positively affect American users' perceived knowledge but does not affect Chinese users' perceived knowledge, and Chinese users' self-efficacy positively affects their behavioral intention but American users' self-efficacy does not. According to the results, five path coefficients are different between the two groups: exposure to self-efficacy, information searching to self-efficacy, exposure to perceived knowledge, self-efficacy to behavioral intention, and perceived usefulness to behavioral intention,

Table 13.
Result of Parametric Multi-Group Analysis with PLS for the Two Groups of China

Path	b:users	b:non-users	Equal variance P (one tail)	Different variance P (one tail)
H1: Exposure -> Information Search	0.319*	0.484*	0.077	0.077
H2: Exposure -> Self-Efficacy	**0.357***	**0.116**	**0.030**	**0.030**
H3: Information Searching -> Self-Efficacy	**0.146**	**0.552***	**0.0003**	**0.0003**
H4: Exposure -> Perceived Knowledge	*0.144*	*0.185**	*0.363*	*0.363*
H5: Information Searching -> Perceived Knowledge	0.500*	0.473*	0.412	0.412
H6: Self-Efficacy -> Attitude	0.347*	0.453*	0.262	0.262
H7: Perceived Knowledge -> Attitude	0.258*	0.173*	0.265	0.265
H8: Self-Efficacy -> Behavioral Intention	**0.358***	**-0.061**	**0.004**	**0.004**
H9: Attitude -> Behavioral Intention	0.287*	0.250*	0.405	0.405
H10: Perceived Knowledge -> Behavioral Intention	0.001	-0.085	0.179	0.179
Control: Disposition to Trust -> Behavioral Intention	**0.018**	**0.306***	**0.001**	**0.001**
Control: Institution Based Trust -> Behavioral Intention	0.216*	0.218*	0.495	0.495
Control: Usefulness -> Behavioral Intention	**-0.076**	**0.394***	**0.0002**	**0.0002**

Note: Bolded indicates statistically differences between groups; italic indicates differences because one is significant and the other is not; *are significant path coefficients.

Finally, we compared the non-user groups from China and the U.S. The results are summarized in Table 16 that shows that three path coefficients are significantly different between the user group and the non-user group. Additionally, Chinese non-users' institution-based trust positively affect their behavioral intention but American non-users' institution-based trust does not affect their behavioral intention. According to the results, four path coefficients are different between the two groups: exposure to information searching, perceived knowledge to behavioral intention, disposition to trust to behavioral intention, and institution-based trust to behavioral intention.

Table 14.
Result of Parametric Multi-Group Analysis with PLS for the Two Groups of the U.S.

Path	b:users	b:non-users	Equal variance P (one tail)	Different variance P (one tail)
H1: Exposure -> Information Search	**0.480***	**0.741***	**0.0003**	**0.0004**
H2: Exposure -> Self-Efficacy	0.100	0.159	0.330	0.331
H3: Information Searching -> Self-Efficacy	0.269*	0.302*	0.423	0.423
H4: Exposure -> Perceived Knowledge	0.244*	0.202*	0.380	0.380
H5: Information Searching -> Perceived Knowledge	0.562*	0.608*	0.356	0.357
H6: Self-Efficacy -> Attitude	0.518*	0.413*	0.208	0.209
H7: Perceived Knowledge -> Attitude	0.211*	0.230*	0.441	0.442
H8: Self-Efficacy -> Behavioral Intention	**0.126**	**-0.065**	**0.030**	**0.030**
H9: Attitude -> Behavioral Intention	0.176*	0.314*	0.087	0.088
H10: Perceived Knowledge -> Behavioral Intention	0.105	0.098	0.470	0.470
Control: Disposition to Trust -> Behavioral Intention	0.038	0.048	0.448	0.448
Control: Institution Based Trust -> Behavioral Intention	*0.253**	*0.147*	*0.240*	*0.241*
Control: Usefulness -> Behavioral Intention	0.377*	0.402*	0.422	0.422

Note: Bolded indicates statistically differences between groups; italic indicates differences because one is significant and the other is not; *are significant path coefficients.

Discussion

Key Findings

Overall, nine of ten hypotheses are fully or partially supported. Results of hypotheses testing and multi group analysis are summarized in Tables 17, 18, 19, and 20. In these tables, differential impact across groups means one of two conditions: first, one coefficient is significant while the other is not, no matter whether the difference is statistically significant; and second, the difference across the two groups is statistically different. Meanwhile, same impact across groups means that both coefficients are significant or insignificant and there is no statistically difference across the two groups. In addition, the significant column for “differential impact across groups” refers to the difference across the two groups is significant and the not significant column refers to the difference is insignificant. The significant column for “same impact across groups” refers to both path coefficients are significant while the not significant column refers to both are insignificant. Stronger influence for the user group means the absolute path coefficient of the user group is larger than that of the non-user group while stronger influence for the non-user group means the absolute path coefficient of the non-user group is larger than that of the user group.

Table 15.
Result of Parametric Multi-Group Analysis with PLS for Users of China and the U.S.

Path	b:users from China	b:users from the U.S.	Equal variance P (one tail)	Different variance P (one tail)
H1: Exposure -> Information Search	0.319*	0.480*	0.062	0.062
H2: Exposure -> Self-Efficacy	**0.357***	**0.100**	**0.014**	**0.014**
H3: Information Searching -> Self-Efficacy	*0.146*	*0.269**	*0.189*	*0.190*
H4: Exposure -> Perceived Knowledge	*0.144*	*0.244**	*0.201*	*0.202*
H5: Information Searching -> Perceived Knowledge	0.500*	0.562*	0.278	0.278
H6: Self-Efficacy -> Attitude	0.347*	0.518*	0.109	0.110
H7: Perceived Knowledge -> Attitude	0.258*	0.211*	0.360	0.361
H8: Self-Efficacy -> Behavioral Intention	*0.358**	*0.126*	*0.077*	*0.078*
H9: Attitude -> Behavioral Intention	0.287*	0.176*	0.223	0.225
H10: Perceived Knowledge -> Behavioral Intention	0.001	0.105	0.086	0.087
Control: Disposition to Trust -> Behavioral Intention	0.018	0.038	0.387	0.388
Control: Institution Based Trust -> Behavioral Intention	0.216*	0.253*	0.405	0.406
Control: Usefulness -> Behavioral Intention	**-0.076**	**0.377***	**0.0003**	**0.0004**

Note: Bolded indicates statistically differences between groups; italic indicates differences because one is significant and the other is not; *are significant path coefficients.

Table 16.
Result of Parametric Multi-Group Analysis with PLS for Non-Users of China and the U.S.

Path	b:non-users from China	b:non-users from the U.S.	Equal variance P (one tail)	Different variance P (one tail)
H1: Exposure -> Information Search	**0.484***	**0.741***	**0.003**	**0.003**
H2: Exposure -> Self-Efficacy	0.116	0.159	0.383	0.384
H3: Information Searching -> Self-Efficacy	0.552*	0.302*	0.050	0.051
H4: Exposure -> Perceived Knowledge	0.185*	0.202*	0.449	0.449
H5: Information Searching -> Perceived Knowledge	0.473*	0.608*	0.165	0.166
H6: Self-Efficacy -> Attitude	0.453*	0.413*	0.400	0.401
H7: Perceived Knowledge -> Attitude	0.173*	0.230*	0.334	0.335
H8: Self-Efficacy -> Behavioral Intention	-0.061	-0.065	0.480	0.480
H9: Attitude -> Behavioral Intention	0.250*	0.314*	0.287	0.288
H10: Perceived Knowledge -> Behavioral Intention	**-0.085**	**0.099**	**0.034**	**0.035**
Control: Disposition to Trust -> Behavioral Intention	**0.306***	**0.048**	**0.007**	**0.007**
Control: Institution Based Trust -> Behavioral Intention	*0.218**	*0.147*	*0.292*	*0.292*
Control: Usefulness -> Behavioral Intention	0.394*	0.402*	0.474	0.474

Note: Bolded indicates statistically differences between groups; italic indicates differences because one is significant and the other is not; *are significant path coefficients.

Table 17.
Summary of Testing Results for the Two Groups from China

<table>
<tr><th>Type of Hypothesis</th><th>Significant</th><th>Not Significant</th></tr>
<tr><td rowspan="4">Differential Impact Across Groups</td><td colspan="2">Stronger Influence for the User Group</td></tr>
<tr><td>H2: EXP -> SEL
H8: SEL -> BI</td><td>N/A</td></tr>
<tr><td colspan="2">Stronger Influence for the Non-User Group</td></tr>
<tr><td>H3: INS -> SEL
Control: PU -> BI
Control: DISP -> BI</td><td>H4: EXP -> PK</td></tr>
<tr><td>Same Impact Across Groups</td><td>H1: EXP -> INS
H5: INS -> PK
H6: SEL -> ATT
H7: PK -> ATT
H9: ATT -> BI
Control: IBT -> BI</td><td>H10: PK -> BI</td></tr>
</table>

Note: EXP=exposure, ATT=attitude, BI=behavioral intention, DISP=disposition to trust, INS=information searching, IBT=institution-based trust, PK=perceived knowledge, SEL=self-efficacy, and PU=perceived usefulness.

Influence of exposure to mobile payments.

The results show that exposure to mobile payments will encourage consumers to search for information about mobile payments. Thus, consumers with a higher level of exposure to mobile payments will be more likely to search for information about mobile payments, allowing them to be more knowledgeable about mobile payments. This finding is supported by the multi stage decision making theories, according to which an individual will search for information and then make decisions with information they obtain during the information searching process (Bruyn & Lilien, 2008; Dewey, 1910; Simon, 1960).

Table 18.
Summary of Testing Results for the Two Groups from the U.S.

Type of Hypothesis	Significant	Not Significant
Differential Impact Across Groups	**Stronger Influence for the User Group**	
	N/A	Control: IBT -> BI
	Stronger Influence for the Non-User Group	
	H1: EXP -> INS	N/A
Same Impact Across Groups	H3: INS -> SEL H4: EXP -> PK H5: INS -> PK H6: SEL -> ATT H7: PK -> ATT H9: ATT -> BI Control: PU -> BI	H2: EXP -> SEL H8: SEL -> BI H10: PK -> BI Control: DISP -> BI

Note: EXP=exposure, ATT=attitude, BI=behavioral intention, DISP=disposition to trust, INS=information searching, IBT=institution-based trust, PK=perceived knowledge, SEL=self-efficacy, and PU=perceived usefulness.

Table 19.
Summary of Testing Results for the Two User Groups

Type of Hypothesis	Significant	Not Significant
Differential Impact Across Groups	**Stronger Influence for the User Group**	
	H2: EXP -> SEL	H8: SEL -> BI
	Stronger Influence for the Non-User Group	
	Control: PU -> BI	H3: INS -> SEL H4: EXP -> PK
Same Impact Across Groups	H1: EXP -> INS	H10: PK -> BI Control: DISP -> BI
	H5: INS -> PK	
	H6: SEL -> ATT	
	H7: PK -> ATT	
	H9: ATT -> BI	
	Control: IBT -> BI	

Note: EXP=exposure, ATT=attitude, BI=behavioral intention, DISP=disposition to trust, INS=information searching, IBT=institution-based trust, PK=perceived knowledge, SEL=self-efficacy, and PU=perceived usefulness.

There are some differences between users and non-users. Path comparisons indicate that the path between exposure to mobile payments and self-efficacy is positively significant for Chinese users, but not for Chinese non-users. According to the results of Sobel test, information searching fully mediates the relationship between Chinese non-users' exposure and self-efficacy (Sobel statistic=4.352, $p<0.001$). Information searching fully mediates the relationship between American non-users' exposure and self-efficacy (Sobel statistic=5.596, $p<0.001$). This suggests that exposure to mobile payments does not directly affect non-users' self-efficacy but has an indirectly relationship with self-efficacy through information searching.

Table 20.
Summary of Testing Results for the Two Non-User Groups

Type of Hypothesis	Significant	Not Significant
Differential Impact Across Groups	**Stronger Influence for the User Group**	
	Control: DISP -> BI	Control: IBT -> BI
	Stronger Influence for the Non-User Group	
	H1: EXP -> INS	N/A
Same Impact Across Groups	H3: INS -> SEL H4: EXP -> PK H5: INS -> PK H6: SEL -> ATT H7: PK -> ATT H9: ATT -> BI Control: PU -> BI	H2: EXP -> SEL H8: SEL -> BI H10: PK -> BI

Note: EXP=exposure, ATT=attitude, BI=behavioral intention, DISP=disposition to trust, INS=information searching, IBT=institution-based trust, PK=perceived knowledge, SEL=self-efficacy, and PU=perceived usefulness.

Results show that the path between exposure to mobile payments and perceived knowledge is positively significant for Chinese non-users, but not for Chinese users. This is because users have past experience of using mobile payments, and generally speaking, they know more about mobile payments than non-users (Venkatesh, 2012), reducing their dependence on external information sources to make final decisions. However, non-users lack knowledge of mobile payments, increasing their dependence on external information sources. We also performed a Sobel test for Chinese users. According to the results, information searching fully mediates the relationship between exposure and perceived knowledge (Sobel statistics=3.268, $p<0.001$). This suggests that Chinese users' exposure to mobile payments has an indirect effect on their perceived knowledge through information searching.

Meanwhile, American non-users' exposure to mobile payments has a stronger influence than American users' exposure to mobile payments on their information searching. This is reasonable because individuals with little knowledge of mobile payments will do more information searching than those with high prior knowledge (Bettman & Park, 1980). American non-users are less knowledgeable of mobile payments compared with users. Thus, American non-users respond more to exposure to mobile payments.

When we statistically compared our results across Chinese and American consumers, the differences became apparent. Results suggest that the path between exposure to mobile payments and self-efficacy is positively significant for Chinese users, but not for American users. This can be explained by one dimension of nation cultures: individualism or collectivism. Individualists rely more on privately referenced information such as their own experience and self-oriented information searching while collectivists rely more on in-group opinions such as positive word of mouth and social influence (Erez & Earley, 1993). Components of exposure, excluding media usage, reflect in-group opinions, and thus are more likely to affect self-efficacy of collectivists.

Results show that the path between exposure to mobile payments and perceived knowledge is positively significant for American users, but not for Chinese users. In addition, American non-users' exposure to mobile payments has a stronger influence than Chinese non-users' exposure to mobile payments on their information searching. Exposure in high-context cultures such as China is implicit and indirect while exposure in low-context cultures such as the U.S. is more direct, less implicit, and more informative (Singh, Zhao, & Hu, 2005). Exposure to mobile payments in the U.S. should be more information richness than that of China. In addition, explicit knowledge is more sharable than implicit knowledge. American users are more likely to accumulate knowledge based on their exposure to mobile payments. Thus, American consumers respond more to exposure to mobile payments, and the U.S. exposure has a stronger influence than that of China on consequences of exposure to mobile payments.

Influence of information searching.

Consumer knowledge is an important construct in explaining their consumption behavior (Bruyn & Lilien, 2008; Dewey, 1910; Simon, 1960). There are three categories of knowledge: perceived knowledge, objective knowledge, and usage knowledge (Brucks, 1985), of which perceived knowledge has been considered a stronger predictor for behaviors than other types of knowledge (Lee & Koo, 2012). The results indicate that information searching has a positive relationship with consumers' perceived knowledge. Information searching represents active consumer learning, and learning and knowledge are closely related in knowledge management literature (Janz & Prasarnphanich, 2003). With information that they obtain during information searching, consumers become familiar with mobile payments and think that they know more about mobile payments even without gaining objective knowledge (Park, 2001).

Results show that the path between information searching and self-efficacy is positively significant for Chinese non-users, but not for Chinese users. Prior experience is one source of self-efficacy, and users rely on their past experience to build self-efficacy (Bandura, 1977b, 1988). Information searching may no longer affect them (or, are ignored) and thus cannot affect their self-efficacy. However, non-users lack past experience of using mobile payments and use information searching as a source of information, helping them build self-efficacy.

Results also suggest that the path between information searching and self-efficacy is positively significant for American users, but not for Chinese users. Vicarious experience is one source of self-efficacy (Bandura, 1977b, 1986). During consumers' information searching, they should be able to learn other consumers' experience of using mobile payments. China is vulnerable to cyber-attack, and thus Chinese consumers' are more likely to get exposed to other people's failure experiences during their information searching. Success strengthens self-efficacy, and failure decreases self-efficacy (Bandura, 1977b, 1986). Thus, it is reasonable that information searching has a positive relationship with American users' self-efficacy but does not affect Chinese users' self-efficacy.

Antecedents of attitude.

This research distinguishes two antecedents of consumers' attitude toward mobile payments: self-efficacy and perceived knowledge. The results show that consumers are more likely to have a positive attitude if they have a higher level of self-efficacy and perceived knowledge. This is reasonable since people love what is familiar and feel discomfort when they are faced with unfamiliar objects (Venkatesan, 1973). These findings are consistent with tripartite model of attitude. Lavidge and Steiner (1961) and Dick and Basu (1994) posited that consumers' cognition belief will has a positive relationship with their affection, which, in turn, affect consumers' final attitude toward an object. Self-efficacy and perceived knowledge reflect consumers' belief of their ability to use mobile payments and will positively affect their attitude toward using mobile payments.

Antecedents of behavioral intention.

This research explores the importance of attitude in encouraging consumers to use or continue use mobile payments. According to the results, consumers who have a positive attitude toward mobile payments are more likely to use or continue use mobile payments than those who have a negative attitude toward mobile payments, no matter in China or the U.S. The relationship between attitude and behavioral intention is well supported by theory of planned behavior (Ajzen, 1991), which views attitude as an important predictor of consumers' behavioral intention.

Results indicate that the relationship between self-efficacy and behavioral intention is positively significant for Chinese users, but not for Chinese non-users. In addition, American consumers' self-efficacy does not affect their behavioral intention toward mobile payments. We performed Sobel tests and found that Chinese non-users' and American consumers' attitude fully mediates the relationship between their self-efficacy and behavioral intention (Chinese non-users: Sobel statistic=2.12, $p<0.05$; American users: Sobel statistic=2.18, $p<0.05$; American non-users: Sobel statistic=3.24, $p<0.01$). Thus, self-efficacy does not directly affect Chinese non-users' and American consumers' behavioral intention but has an indirect relationship with their behavioral intention through attitude.

The path between self-efficacy and behavioral intention is positively significant for Chinese users, but not for American users. This finding suggests that Chinese users pay greater attention to self-efficacy. This finding is consistent with findings of past literature. Chinese culture is collective and long term orientated while the U.S. culture is individualistic and short-term oriented (Hofstede, 1980). Klassen (2004) posited that "among collectivists, efficacy beliefs are typically lower but equally or even more predictive of performance" (p. 225). Meanwhile, Chan and Lau (2002) and Tan, Yan, and Urquhart (2007) verified that self-efficacy will exert a stronger influence on Chinese users' behavioral intention than on American users' behavioral intention.

The finding that perceived knowledge does not affect consumers' behavioral intention toward mobile payments is unexpected. One possible reason is that perceived knowledge affects consumers' behavioral intention through perceived ease of use (Kim, Mirusmonov, & Lee, 2010). However, mobile payments service are designed to be easy to use. Thus, perceived ease of use no longer is a significant predictor of mobile payments acceptance. In addition, early adopters of mobile payments rely on perceived knowledge whereas late adopters do not (Kim et al., 2010). Perceived knowledge is important in the initial stage of diffusion of innovation, but now, consumers are knowledgeable about mobile payments, and perceived knowledge no longer affects consumers' behavioral intention.

Limitation

As with all research, there are some limitations that should be considered when interpreting the results of this research. First, the data was collected by using a self-report survey. Hence there is potential for common method biases (Podsakoff et al., 2003). However, common method bias is not a significant problem in this research. Second, in some groups, the model explained a small part of variance of information searching and self-efficacy. However, all R-squares exceed the acceptable threshold of 10 percent as suggested by Falk and Miller (1992), indicating substantive explanatory power of the model. Future research is needed to explore antecedents of information searching and self-efficacy. Third, the limited source and special characteristics of the sample restrict the generalization of the findings in this research. However, most of our samples are in their 20s or 30s, who are more willing to adopt mobile payment than other age groups (Scevak, 2010). They worth our attention because our target is to encourage adoption of mobile payments.

Implications for Theory

We view adoption of innovation as an on-going process involving persuasive communication and learning (Lee & Xia, 2011) and construct consumer learning as a combination of positive word of mouth, explicit social influence, implicit social influence, and media usage. Then, we explore the effect of consumer learning on adoption and post adoption of mobile payments. We use perceived knowledge and self-efficacy, attitude, and behavioral intention to represent cognitive outcomes, affective outcome, and behavioral outcome, respectively, by following the tripartite model of attitude. Then, we discuss the effect of consumer learning on consumers' behavior intention toward mobile payments.

Our research contributes to adoption and post-adoption research. This research explores the similarity and difference across adoption and post adoption. Past research has suggested that predictors of technology adoption and continuous usage are different (Limayem et al., 2007; Setterstrom et al., 2013). However, there are some continuous variables that can be used to predict both technology adoption and continuous usage. Learning outcomes can serve as these predictors because learning is continuous, and learning outcomes such as affective states, attitudes, and belief can evolve as environmental factors change (Bandura, 1977b, 1988) or as individuals obtain new information (Anderson, 1991). This research finds that exposure to mobile payments and information searching will have a positive relationship with self-efficacy and perceived knowledge, which affect consumers' attitude toward mobile payments. Then, attitude can be used to predict both adoption and post adoption behavior. Meanwhile, past research focuses on changes in significance of path coefficient while ignoring the differences in the strength of relationships (Setterstrom et al., 2013). Our research also focuses on differences in the strength of relationships and finds some differences across the user and the non-user groups as shown in Tables 13, 14, 15, and 16.

This research also contributes to cross cultural research on mobile payments acceptance. Few prior studies examine cross culture research on mobile payments acceptance. We choose China and the U.S. to represent the eastern and western cultures, respectively, and explore the similarities and differences across Chinese and American consumers. The results reveal that consumers' exposure to mobile payments will attract their attention and encourage them to search for information of mobile payments. Exposure to mobile payments and information searching will affect consumers' self-efficacy and perceived knowledge in different approaches. Self-efficacy and perceived knowledge will then affect consumers' attitude toward mobile payments, which has a positive relationship with their behavioral intention. We also found several differences across the Chinese and American consumers as shown in Tables 15 and 16. This research serves as foundation of cross-culture research on mobile payments acceptance.

Our findings also contribute to research on the theory of planned behavior. Benbasat and Barki (2007) requested that we lack of exploration of learning behavior in TPB research. In this study, we use exposure to mobile payments and information searching to represent consumer learning, and view consumer learning as the source of three types of beliefs in theory of planned behavior. In addition, attitude is viewed as an important predictor of behavioral intention in theory of planned behavior (Ajzen, 1991). McKinsey indicates that about 45% of U.S. consumers have a positive attitude toward using mobile payments, but this number has fallen since 2011 (McKinsey, 2013). We explore the interactions among attitude, social influence, and self-efficacy, three predictors of behavioral intention in the theory of planned behavior, as requested by Wu (2006). Results indicate that self-efficacy and perceived knowledge can serve as predictors of consumers' attitude toward using mobile payments. Moreover, we found that the effect of consumers' attitude on their behavioral intention is stable while the effect of self-efficacy is not. Perceived knowledge does not have a direct relationship with behavioral intention, but has an indirect relationship with behavioral intention through attitude.

Implications for Practice

This research deepens our understanding of similarities and differences between users and non-users of mobile payments. This research provides mobile payments practitioners with some suggestions on how to attract non-users to adopt mobile payments and retain current users of mobile payments. First, exposure to mobile payments plays an important role in affecting consumers' adoption and use of mobile payments. This research suggests four ways of increasing users' exposure to mobile payments, which are positive word of mouth, media usage, explicit social influence, and implicit social influence. For example, practitioners can provide monetary bonus to encourage satisfied users to generate more positive word of mouth and social influence. Second, practitioners should utilize consumers' curiosity to encourage their information searching because information searching will increase consumers' perceived knowledge and thereafter encourage consumers to form a positive attitude toward mobile payments. For example, practitioners can initiate exploration in mobile games and encourage consumers to search for information about mobile payments by providing decent monetary or non-monetary bonus. Third, consumers should think of how to improve consumers' self-efficacy because it is positive related to consumers' attitude toward mobile payments. Bandura (1977) summarized four sources of self-efficacy: performance accomplishments (e.g., direct experience), vicarious experience (e.g., implicit social influence), verbal persuasion (e.g., positive word of mouth, explicit social influence, and media usage), and physiological states (e.g., relaxation). Fourth, marketers should efficiently utilize marketing communication to bolster consumers' perceived knowledge through well-developed marketing messages. Influencing consumers’ perceived knowledge will lead to positive attitude toward using mobile payments.

Meanwhile, practitioners should aware of the differences between users and non-users in relevant countries and develop different marketing tactics. In the China mobile payment market, practitioners should emphasize mechanisms of building self-efficacy to retain current users because their self-efficacy affects consumers’ behavioral intention directly and indirectly through attitude toward mobile payments. Practitioners should realize the importance of exposure to mobile payments in building current users’ self-efficacy. Meanwhile, they should encourage non-users to search for information about mobile payments because information searching has a positive relationship with their self-efficacy and thereafter encourages consumers to form a positive attitude toward mobile payments. Practitioners should consider how to attract non-users’ to search for information about mobile payments. However, this is challenging because non-users are less interested in mobile payments messages than users. In addition, practitioners should convey message about usefulness of mobile payments to non-users to attract non-users.

In the U.S. mobile payment market, in order to attract non-users, practitioners should increase consumers’ exposure to mobile payments, which will encourage consumers to search for information about mobile payments. In the U.S., users worry about the security of mobile payments, and institution-based trust plays an important role in affecting their intention to continue using mobile payments. Thus, practitioners and governments should consider how to convince current users of the security of mobile payments. There are mainly two ways to build confidence regarding security: regulation and infrastructure. Governments should facilitate a legal structure such as enacting well-developed laws relating to mobile payments that can efficiently settle disputes and strongly protect consumers’ property rights and financial assets.

Meanwhile, an industrial standard is needed to operate the industry efficiently. Additionally, governments should encourage investment in telecommunication sectors and build a secure and efficient telecommunication system to increase the coverage of mobile internet and penetration rate of smartphones. At the same time, governments should support the development of mobile technology to increase the safety of mobile payments technology.

Conclusion

This research serves as an exploration of the relationship between consumer learning and consumers' behavioral intention toward mobile payments. We developed a model suggesting that exposure to mobile payments and information searching affect consumers' self-efficacy and perceived knowledge. These two factors have a positive relationship with consumers' attitude toward using mobile payments, which positively affects their behavioral intention toward mobile payments. This research verifies the vital role of consumer learning in encouraging consumers' to adopt and use mobile payments. We also explore the differences across the user and the non-user groups and across Chinese and American consumers. When we compared our results across groups, the similarities and differences in the cognitive processes involved for adoption and post adoption became apparent. This research deepens our understanding of how consumer learning can affect consumers' attitude toward mobile payments and thereafter encourage them to accept mobile payments.

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APPENDIX 2: Instrument

Table A. Measurement Items for Users
Exposure to Mobile Payments
Media Usage
1. I often obtain information about mobile payments from online newspapers.
2. I often obtain information about mobile payments from printed newspapers.
3. I often obtain information about mobile payments from online magazines.
4. I often obtain information about mobile payments from printed magazines.
5. I often obtain information about mobile payments from TV.
6. I often obtain information about mobile payments from radio.
7. I often obtain information about mobile payments from the Internet (excluding online newspapers and magazines).
Adapted from Loibl et al. (2009) and Wei et al. (2011)
Positive Word of Mouth
1. People say positive things about mobile payments.
2. People recommend using mobile payments to me.
3. Someone else from whom I seek advice recommends mobile payments for me.
Adapted from Alexandrov and Babakus (2013)
Explicit Social Influence
1. People who are important to me think that I should use mobile payments.
2. People who influence my behavior think that I should use mobile payments.
3. People whose opinions that I value prefer that I use mobile payments.
Adapted from Venkatesh et al. (2012)
Implicit Social Influence
1. People who are important to me use mobile payments.
2. People who influence my behavior use mobile payments.
3. People whose opinions that I value use mobile payments.
Adapted from Kim et al. (2007)
Information Searching
1. I have researched, on my own initiative, in order to increase my knowledge of using mobile payments.
2. I have researched, on my own initiative, in order to increase my mastery of using mobile payments.
3. I have explored several information sources, on my own initiative, concerning using mobile payments.
4. I have spent much time and energy learning about using mobile payments.

5. I have invested much time and energy in order to better use mobile payments. *Adapted from Barki et al. (2007)*
Self-Efficacy 1. I feel comfortable using mobile payments on my own. 2. I can easily use mobile payments on my own. 3. I feel comfortable using mobile payments even if there is no one around me to tell me how to use it. *Adapted from Hsieh et al. (2011)*
Attitude 1. Using mobile payments is a good idea. 2. Using mobile payments is wise. 3. Using mobile payments is useful. 4. Using mobile payments is interesting. *Adapted from Schierz et al. (2010)*
Perceived Knowledge 1. I feel very knowledgeable about mobile payments. 2. If I continue using mobile payments, I would need to gather very little information in order to make a wise decision. 3. If a friend asked me about mobile payments, I could give them advice about different kinds of mobile payments. 4. I feel very confident about my ability to tell the difference in quality among different kinds of mobile payments. *Adapted from Suh and Lee (2005)*
Intention to continue using 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. *Adapted from Venkatesh et al. (2012)*
Disposition to Trust 1. It is easy for me to trust an information technology. 2. I tend to trust an information technology, even though I have little knowledge of it. 3. My tendency to trust information technology is high. *Adapted from Zhou (2011)*
Institution-based Trust 1. I believe mobile technology has enough safeguards to make me feel comfortable using it to make mobile payments.

2. I feel assured that legal structures adequately protect me from payment problems with mobile technology.
3. I feel assured that technological structures adequately protect me from payment problems with mobile technology.
4. I feel confident that encryption and other technological advances with mobile technology make it safe for me to use mobile payments.
5. In general, the mobile technology provides a robust environment to perform mobile payments.
6. In general, the mobile technology provides a safe environment to perform mobile payments.
Adapted from Setterstrom et al. (2013)
Perceived Usefulness
1. Using mobile payments enables me to pay more quickly.
2. Using mobile payments makes it easier for me to conduct transactions.
3. I find mobile payments a useful possibility for making payments.
Adopted from Kim et al. (2010)

Table B. Measurement Items for Non-Users
Exposure to Mobile Payments: Media Usage 1. I often obtain information about mobile payments from online newspapers. 2. I often obtain information about mobile payments from printed newspapers. 3. I often obtain information about mobile payments from online magazines. 4. I often obtain information about mobile payments from printed magazines. 5. I often obtain information about mobile payments from TV. 6. I often obtain information about mobile payments from radio. 7. I often obtain information about mobile payments from the Internet (excluding online newspapers and magazines). *Adapted from Loibl et al. (2009) and Wei et al. (2011)* Positive Word of Mouth 1. People say positive things about mobile payments. 2. People recommend using mobile payments to me. 3. Someone else from whom I seek advice recommends mobile payments for me. *Adapted from Alexandrov and Babakus (2013)* Explicit Social Influence 1. People who are important to me think that I should use mobile payments. 2. People who influence my behavior think that I should use mobile payments. 3. People whose opinions that I value prefer that I use mobile payments. *Adapted from Venkatesh et al. (2012)* Implicit Social Influence 1. People who are important to me use mobile payments. 2. People who influence my behavior use mobile payments. 3. People whose opinions that I value use mobile payments. *Adapted from Kim et al. (2007)*
Information Searching: 1. I have researched, on my own initiative, in order to increase my knowledge of using mobile payments. 2. I have researched, on my own initiative, in order to increase my mastery of using mobile payments. 3. I have explored several information sources, on my own initiative, concerning using mobile payments. 4. I have spent much time and energy learning about using mobile payments. 5. I have invested much time and energy in order to better use mobile payments.

Adapted from Barki et al. (2007)
Self-Efficacy: 1. I feel comfortable using mobile payments on my own. 2. I can easily use mobile payments on my own. 3. I feel comfortable using mobile payments even if there is no one around me to tell me how to use it. *Adapted from Hsieh et al. (2011)*
Attitude: 1. Using mobile payments is a good idea. 2. Using mobile payments is wise. 3. Using mobile payments is useful. 4. Using mobile payments is interesting. *Adapted from Schierz et al. (2010)*
Perceived Knowledge: 1. I feel very knowledgeable about mobile payments. 2. If I adopt mobile payments, I would need to gather very little information in order to make a wise decision. 3. If a friend asked me about mobile payments, I could give them advice about different kinds of mobile payments. 4. I feel very confident about my ability to tell the difference in quality among different kinds of mobile payments. *Adapted from Suh and Lee (2005)*
Intention to Use: 1. I intend to use mobile payments in the future. 2. I predict that I will frequently use mobile payments in the future. 3. In the future, I will strongly recommend that others use mobile payments. *Adapted from Gu et al. (2009)*
Disposition to Trust: 1. It is easy for me to trust an information technology. 2. I tend to trust an information technology, even though I have little knowledge of it. 3. My tendency to trust information technology is high. *Adapted from Zhou (2011)*
Institution-based Trust: 1. I believe mobile technology has enough safeguards to make me feel comfortable using it to make mobile payments. 2. I feel assured that legal structures adequately protect me from payment problems with

mobile technology. 3. I feel assured that technological structures adequately protect me from payment problems with mobile technology. 4. I feel confident that encryption and other technological advances with mobile technology make it safe for me to use mobile payments. 5. In general, the mobile technology provides a robust environment to perform mobile payments. 6. In general, the mobile technology provides a safe environment to perform mobile payments. *Adapted from Setterstrom et al. (2013)*
Perceived Usefulness 1. Using mobile payments would enable me to pay more quickly. 2. Using mobile payments would make it easier for me to conduct transactions. 3. I would find mobile payments a useful possibility for making payments. *Adopted from Kim et al. (2010)*

ESSAY 3: THE EFFECT OF TECHNOLOGY USAGE HABITS AND PRICE DISCOUNT ON CONSUMERS' INTENTION TO CONTINUE USING MOBILE PAYMENTS

Introduction

Mobile payments are transactions that use mobile devices to pay for goods, services, and bills or perform bank transactions by using mobile technology (Dahlberg, Mallat, Ondrus, & Zmijewska, 2008; Gerpott & Kornmeier, 2009; Mallat, 2007). Today, we are in the era of mobile commerce. As the popularity of mobile devices increases, mobile payments have become one of the critical drivers for mobile commerce success (Yang, Lu, Gupta, Cao, & Zhang, 2012). Mobile payment service providers can achieve success by encouraging consumers to continuously use mobile payments. This is because continuous usage of mobile payments encourages consumers to develop loyalty toward mobile payments (Deng et al., 2010) and results in lower marketing cost and more profit (Gupta & Kim, 2007; Reichheld & Schefter, 2000).

However, the percentage of consumers who frequently use mobile payments is low. According to a 2012 McKinsey report, in the United States, 3% of mobile payment users perform mobile payments once to several times a day, and 13% of users perform mobile payments once a week; in China, 13% of users perform mobile payments once to several times a day, and 15% of users perform mobile payments once a week (Ewing, Leberman, Mendelsohn, & Milner, 2012). This is not ideal for the companies who have invested considerable assets in mobile payments. For example, China Mobile invested US$7 billion in the Shanghai Pudong Development Bank to prepare for its mobile payments business (Yang et al., 2012); three

American wireless carriers, Verizon, AT&T, and T-Mobile, invested US$100 million in Softcard mobile wallet in order to compete with Google wallet (Kharif, 2011). Companies cannot recover their investments in mobile payments if consumers do not adopt and use it continuously. Low continuous usage rate is also not ideal for consumers. They cannot benefit from the implementation of mobile payments if they do not use it (Setterstrom, Pearson, & Orwig, 2013). Thus, it is important to explore factors that affect consumers' intention to continue using mobile payments.

Some IS acceptance research has focused on the importance of habit, which reflects consumers' automatic usage of technology (Limayem, Hirt, & Cheung, 2007; Polites & Karahanna, 2013; Venkatesh, Thong, & Xu, 2012; Yang et al., 2012). However, Limayem et al. (2007) noted that there is no convincing argument or a sound theoretical base for the relationship between habit and behavioral intention. As a response to the criticism of Limayem et al. (2007), Venkatesh et al. (2012) explored the effect of habit on an individual's technology usage behavior. Venkatesh et al. (2012) posited that habit not only has a direct effect on consumers' technology usage but has an impact on their intention to use technology, which in turn affects their technology usage. However, Venkatesh et al. (2012) did not explicate the mechanisms through which habit affects consumers' behavioral intention. Further research is needed to investigate the effect of habit on consumers' mobile payment adoption behavior (Yang et al., 2012).

Past literature focuses on the effect of consumers' prior usage of a certain IT innovation on their future usage of it. The effect of a similar innovation on their future usage of the initial innovation has been largely neglected. Ajzen (1991) posited that the establishment of the link between prior and future usage of a certain innovation does not contribute to theoretical understanding of post adoption research. The link simply reflects the stability in consumers' usage behavior across time (Ajzen, 1991). In this study, technology acceptance is viewed from the IT ecosystem perspective, and transfer of learning theories serve as the theoretical background.

IT ecosystem refers to “a subset of information technologies in the IT landscape that are related to one another in a specific context of use” (Adomavicius, Bockstedt, Gupta, & Kauffman, 2008a, p. 783). Mobile payments are a type of mobile service. Mobile payments, mobile services (other than mobile payments), online shopping, and cell phones belong to the mobile ecosystem (Basole, 2009). This study focuses on four types of technology usage habits, which are mobile payment usage habit, mobile service usage habit (other than mobile payments), cell phone usage habit, and online shopping habit. We investigate how different types of technology usage habits affect consumers' intention to continue using mobile payments. This study also explores the moderation effect of price discount on the transference of online shopping habit, mobile service usage habit, and cell phone usage habit to mobile payment usage habit. This serves as a response to the request of Shin (2007, 2008) to explore the importance of moderators that affect technology adoption.

The objective of this research is to explore the effect of technology usage habits and price discount on consumers' intention to continue using mobile payments. Our research questions are: first, do consumers' technology usage habits affect their intention to continue using mobile payments; and whether price discount moderates consumers' transference of three types of technology usage habits to mobile payment usage habit. The rest of the paper proceeds as follows. The theoretical background and conceptual model are presented first. Then, the hypotheses are developed. Data collection and analysis are explained next, followed by presentation of the results. Key findings and implications are then discussed.

Theoretical Background and Research Model

IT Ecosystem View

There has been extensive research on adoption of innovations, and there are many theories to guide IS adoption research such as theory of planned behavior and the united theory of acceptance and use of technology. A critique of past research and theories is that they consider the innovation individually (Adomavicius, Bockstedt, Gupta, & Kauffman, 2008b), and thus the effect of other innovations on the adoption of the object innovation is neglected. The IT ecosystem view suggests that similar or related technologies interact with each other (Swanson, 1994). In addition, it highlights dynamic and interdependent relationships among interrelated technologies in the IT ecosystem (Adomavicius et al., 2007). Thus, the IT ecosystem view is adopted to explore the effect of technology usage habits on the adoption of mobile payments.

Adomavicius, Bockstedt, Gupta, and Kauffman (2007) defined a technology ecosystem as “a system of interrelated technologies that influence each other’s evolution and development” (p. 201). They distinguished three roles of technologies in the ecosystem: component, product and application, and support and infrastructure roles. The component role describes basic technologies that are necessary to perform functions of focal technology in the given context of use; the product and application role that includes the focal technology and other competing technologies in a certain usage context; and the support and infrastructure role that describes technologies that “enable or work in conjunction with product and application role technologies in an IT ecosystem” (Adomavicius et al., 2008a, p. 784). These three technology roles interact with each other in a triadic causal framework that contains both within-level and cross-level interactions (Adomavicius, Bockstedt, & Gupta, 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 future development of other technology roles (Adomavicius et al., 2012). For example, infrastructure technologies will drive subsequent development of future product technologies.

The IT ecosystem view emphasizes the mutual influence of technologies in the ecosystem. Adomavicius et al. (2007, 2008) explored the mutual influence of different technologies from the perspective of technology roles. They defined paths of influence to represent “the impacts of innovation across technology roles within an IT ecosystem” (Adomavicius et al., 2008a, p. 784) and summarized nine paths of influence. For example, the component role may take on the product/application role in the future. Adomavicius et al. (2008) built an IT ecosystem of digital music and mapped its evolution by considering paths of influences among three technology roles.

Basole (2009) developed the mobile ecosystem by converging different firms in the ecosystem. There are fourteen segments in the ecosystem such as device manufacturers, application & software providers, and mobile network operators (Basole, 2009). Mobile payments are a component of the mobile ecosystem. In this research, we focus on four relevant technologies: online shopping, mobile service excluding mobile payment, cell phone, and mobile payment. Mobile payment infrastructure serves as the focal technology in the ecosystem. Mobile services other than mobile payments can play two different roles: the component role and the product & application role. For example, remote mobile payments are based on mobile apps while mobile banking is similar to mobile payments. Online shopping and cell phones play the support and infrastructure role in the ecosystem.

Transfer of Learning Theories

Desse (1958) suggested that transfer of learning is the most important topic in the psychology of learning because a central goal of education is to teach students to transfer previously learned knowledge from their initial learning to similar or new situations (Lobato, 2006). Past literature on transfer of learning focuses primarily on two topics: first, what is transfer of learning and which factors affect it; second, how can factors that affect transfer of learning be measured (Holton, Bates, & Ruona, 2000).

Definitions and types of transfer of learning.

There are different definitions of transfer of learning. Perkins and Salomon (1992) suggested that transfer of learning refers to the process whereby 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. The most 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 the application of that learning to both similar and new situations; thus transfer of learning is the ability to apply previously learned skills, processes, or content to new or different situations. Although there are multiple definitions of transfer of learning, it is generally agreed that transfer of learning involves the application, generalizability, and maintenance of previously learned knowledge and skills (Ford & Weissbein, 1997). In this research, transfer of learning is defined as the process during which consumers' habits of using various technologies enhances or undermines their formation of habits of using similar or new technologies.

Haskell (2001) summarized six levels of transfer, which are nonspecific transfer, application transfer, context transfer, near transfer, far transfer, and creative transfer. Nonspecific transfer refers to learning that “depends on some connection 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 quite dissimilar to the original learning” (p. 29), and creative transfer refers to transferring past learning to new situation in a creative approach (Haskell, 2001). Haskell (2001) further suggested that “nonspecific transfer and application transfer are essentially simple learning, not transfer proper at all; context transfer is simply the application of learning, reserving level four as near transfer, and far transfer and creative transfer as far transfer” (p. 30). The effect of consumers’ mobile payment usage habit on their future usage of mobile payments pertains to the first three levels of learning transfer, and the effect of their online shopping habit, mobile service usage habit, and cell phone usage habit on behavioral intention pertains to the latter three levels of learning transfer.

Models of transfer of learning.

There are three streams of learning transfer models. The first one is the classic stream. This stream emphasizes the importance of environmental factors such as similarity between the learning situation and the transfer situation. The identical element model is one representative model of this stream (Lobato, 2006). This model emphasizes the importance of identical elements between the learning situation and the transfer situation in affecting transfer of learning (Thorndike, 1924; Thorndike & 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 situation and transfer situation, the greater the transfer of learning (Yorks et al., 1998). There are two types of similarity, surface similarity and deep similarity (Day & Goldstone, 2012; Juvina et al., 2013). Deep similarity facilitates transfer of learning while surface similarity can either facilitate or hinder transfer of learning depending on whether the similarity leads individuals toward an optimal or sub-optimal solution in the target situation (Juvina et al., 2013). However, the classic stream does not address the intrinsic factors of people.

Since 1985, transfer of learning theorists have become interested in 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 refers to the cognitive perspective and emphasizes the impact of individuals' intrinsic factors on transfer of learning. This stream is built on information processing theory and puts the active learner at the center of the learning process (Macaulay & 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). According to information processing theory, learners transfer their experience and previously obtained information into knowledge or a skill that will affect their performance or behavior (Newell & Simon, 1972). Knowledge is stored in memory as schemata, which is a hypothetical structure by which information and knowledge is thought to be organized and processed (Haskell, 2001; Macaulay & Cree, 1999). When a learner is faced with new tasks to perform or new concepts to learn, he or she will interpret new information in terms of relevant existing schemata (Haskell, 2001). Thus, previously learned knowledge will be accessed and retrieved to solve problems in transfer situations.

The classic perspective emphasizes 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 these two perspectives focuses only on one set of factors that affect transfer of learning. Baldwin and Ford (1988) were among the first researchers to introduce a holistic model to explain transfer of learning. They proposed three sets of factors that will affect transfer of training: trainee characteristics, training design factors, and work environment. Trainee characteristics include skill or ability, personality factors, and motivation; training design includes a strong transfer design and appropriate content; and working environment includes support and opportunity to use (Baldwin & Ford, 1988). Some researchers consider these factors a generalized transfer climate (Holton & Baldwin, 2000). Holton (1996) and Holton et al. (2000) developed the learning transfer system inventory scale, which can be used to measure transfer climate. There are four sets of factors in the instrument: motivational factors, such as extrinsic reward, trainee characteristics, such as learner readiness and self-efficacy, environmental factors, such as supervisor support for transfer and supervisor sanctions, and ability factors, such as perceived knowledge (Holton et al., 2007). Price discount, the price reduction that consumers obtain if they choose to make a purchase using mobile payments, is an example of extrinsic motivation to transfer (Yeung, Yee, & Morris, 2010). In this research, we explore the moderation effect of price discount on consumers' transfer of learning.

Summary

The combination of the IT ecosystem view and transfer of learning theories may enhance our understanding of consumers' mobile payment adoption. The IT ecosystem view coincides with transfer of learning theories, which suggest that consumers' past usage of different technologies will enhance or undermine their potential usage of similar or new technologies

(Haskell, 2001). The IT ecosystem view has some shortcomings. For example, the IT ecosystem view emphasizes the positive relationship between technologies in the ecosystem (Adomavicius et al., 2008), but does not explore factors that affect the strength of those paths of influence.

Transfer of learning theories make up for the shortcomings of the IT ecosystems view. For example, the classic stream of learning transfer models emphasizes the importance of similarity between learning and transfer situations (Lobato, 2006). Deep similarity will boost transfer of learning while surface similarity can either facilitate or hinder transfer of learning (Juvina et al., 2013). In addition, the holistic stream of learning transfer models addresses factors that affect transfer of learning. Holton (1996) and Holton et al. (2000) proposed four sets of factors that affect transfer of learning, one of which is motivation factors such as monetary reward. In this research, we explore the effects of four relevant technologies and discuss the moderation effect of price discount on transfer of learning. Combining the IT ecosystem view and transfer of learning theories may enhance our understanding of the relationships among these factors.

Research Model

Dowrick (2012) posited that an individual’s future behavior is affected by his or her past specific and relevant behaviors. A theoretical model was developed based on the IT ecosystem view and transfer of learning theories to explore the impact of price discount and consumers’ technology usage habits on their future behavior intention (Figure 1). According to the model, online shopping habit, mobile service usage habit, and cell phone usage habit will have a positive relationship with consumers’ mobile payment usage habit, which will positively impact their intention to continue using mobile payments. In addition, price discount will positively moderate consumers’ transference from online shopping, mobile service usage, and cell phone usage habits to mobile payment usage habit.

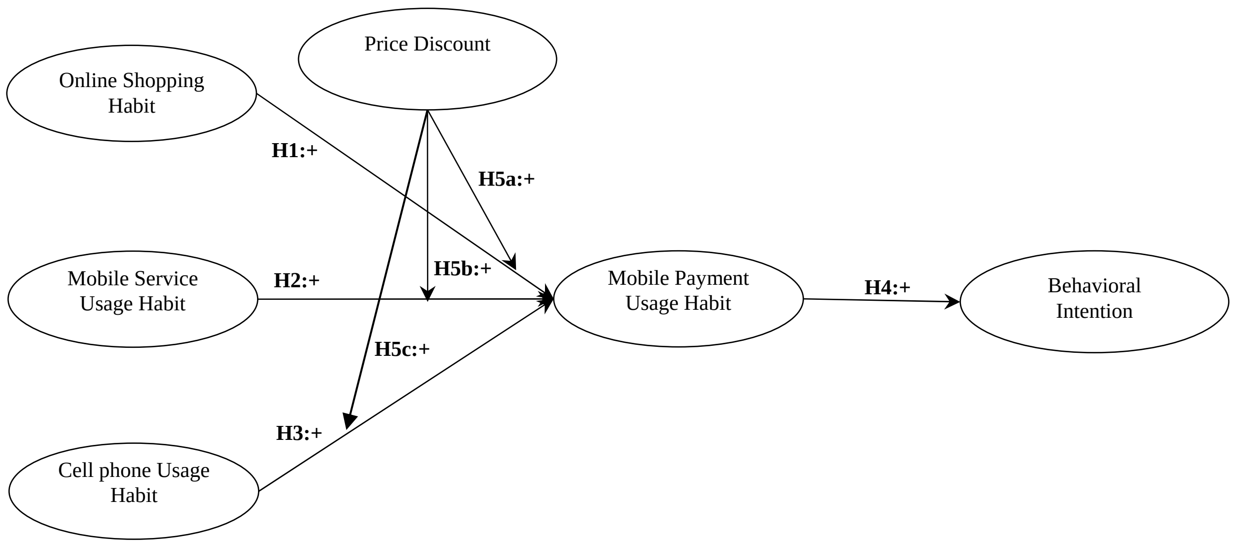


Figure 1. Research Model

Hypotheses Development

Effect of Online Shopping Habit

Online shopping has become an important part of our daily lives. Online shopping habit reflects the extent to which consumers tend to automatically shop online (Limayem et al., 2007). Consumers shop online because, at least to some extent, it is convenient (Beauchamp & Ponder, 2010). Consumers who have formed online shopping habits prefer to shop online anytime and anywhere (Jiang et al., 2013). This requires availability of flexible payment approaches because payment is a necessary stage for consumers to complete transactions (Jiang et al., 2013). Mobile payments are an effective payment option (Yang et al., 2012) because they 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 if they have access to mobile internet.

Thus, mobile payments become attractive and important for consumers who have an online shopping habit. Consumers who consider mobile payments attractive and important are more likely to develop a mobile payment usage habit (Lankton, Wilson, & Mao, 2010). Thus, consumers who shop online frequently may consider mobile payments important, encouraging them to form a mobile payment usage habit. A similar conclusion can be found in Hoffman and Novak (1996) and Novak et al. (2000), who posited that importance has a positive relationship with consumers' increased use of information technologies.

Additionally, people with a strong online shopping habit will make online purchase more frequently than those with a weak one. Most e-commerce companies provide different payment options in the payment stage for their consumers, one of which is mobile payments. Thus, consumers who shop online frequently have more chances to use mobile payments than those who shop online less frequently. An individual's frequency of mobile payment use is a good predictor of his/her mobile payment usage habit (Jolley, Mizerski, Olaru, 2006). In addition, Lim and Johnson (2002) posited that opportunity to use is an important reason for high transfer and lack of opportunity to use is an important reason for low transfer. The extent of transfer is reflected as the strength of relationship between online shopping habit and mobile payment usage habit. Thus, the more frequently consumers shop online, the more frequently they have the opportunity to use mobile payments, and the more likely they will develop a mobile payment usage habit.

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

Effect of Mobile Service Usage Habit

Mobile service usage habit refers to the extent to which consumers tend to automatically use different types of mobile services (Limayem et al., 2007). There are many types of mobile services such as downloading ring tones and pictures, location navigation, instant messaging, and mobile banking (Zhao, Lu, Zhang, & Chau, 2012). Mobile payments are a type of mobile service. However, we focus on the adoption of mobile payments and explore the effect of mobile service usage habit (other than mobile payments) on consumers' mobile payment acceptance. Mobile services refer to services other than mobile payments in this study. Mobile payments are similar to other types of mobile services because all of them are based on mobile technology. For example, remote mobile payments may be based on mobile applications such as mobile instant messaging. Similarity and compatibility between mobile services and mobile payments may encourage consumers to adopt mobile payments (Roger, 2003). Transfer of learning theories also support that similarity between mobile services and mobile payments encourages consumers to form or strengthen their mobile payment usage habit (Butterfield & Nelson, 1989; York et al., 1998).

Past experience of using mobile services has a positive relationship with accepting mobile payments (Giovanis, Binioris, & Polychronopoulos, 2012). Experience with using mobile services will boost consumers' self-efficacy of using mobile payments (Giovanis et al., 2012). Consumers that have a high level of self-efficacy are more likely to use mobile payments repeatedly (Ajzen, 1991). Thus, people with a stronger mobile service usage habit are more likely to have a higher level of self-efficacy and feel more familiar with mobile payment services, encouraging the formation of a mobile payment usage habit (Chiu, et al., 2010). Moreover, mobile payments involve a high level of uncertainty and different types of risks (Zhou, 2014). Frequent usage of mobile services will encourage consumers to decrease their perceived uncertainty toward mobile technologies, which is positively related with their institution-based trust in mobile technology. Institution-based trust refers to an individual's perceived trust in the institutional environment such as mobile technology in this study (McKnight et al., 2002). Mobile payments are operated on mobile technology. Consumers that have a lower level of perceived uncertainty and a higher level of institution-based trust in mobile technology are more likely to trust mobile payments and thereafter use them repeatedly according to the initial trust building theory (McKnight et al., 1998, 2002). This logic is supported by past literature such as Kim and Han (2009), who posited that consumers' trust in an innovation is positively related to their intention to use the innovation habitually. In view of the above, we posit that

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

Effect of Cell Phone Usage Habit

People use their smartphones for surfing the Internet, checking social networking sites, playing games, using apps, sending texts, and making phone calls. This leads to the formation of a high-level cell phone usage habit, which refers to the extent to which consumers tend to automatically use cell phones (Limayem et al., 2007). Mobile payments are closely related to cell phones because payments are initiated and performed on mobile devices such as cell phones. As cell phone usage expands, the possibility that consumers can rely on their cell phones as primary payment devices increases (Au & Kauffman, 2008). This can be explained from several aspects. First, consumers with a stronger cell phone usage habit tend to explore potential usage of their cell phones (Au & Kauffman, 2008). Mobile payments make smartphones flexible payment devices and thus realize a potential commercial value of smartphones (Andreev, Duane, & O'Reilly, 2011). Consumers will consider mobile payments useful because it helps them move beyond the limitation of using computers to surf on the internet, pay bills, and purchase items. Thus, consumers who have formed the habit of using cell phones are more likely to be interested in mobile payments.

Additionally, cell phone usage habit allows consumers to be more familiar with mobile technology. Consumers who use cell phones frequently can learn to use mobile payments easily and know how to avoid risk issues such as fraud while performing mobile payments. Thus, frequent use of cell phones makes it easier for consumers to use mobile payments. Behaviors are prone to be repeated if individuals can perform them quickly and relatively effortlessly (Lindbladh & Lyttkens, 2002). Thus, cell phone usage habit will reduce consumers' effort to learn how to habitually use mobile payments and thus encourage consumers to use mobile payments. In view of the reasons mentioned above, it is anticipate that

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

Effect of Mobile Payment Usage Habit

The majority of people's actions are executed on a routine basis (Aarts & Dijksterhuis, 2000). We cannot often explain why we are willing to perform a certain kind of behavior; rather, the behavior is a habit. Habit in our context refers to the extent to which people tend to use mobile payments automatically (Limayem et al., 2007). After the formation of a mobile payment usage habit, consumers tend to continue using mobile payments as a matter of automated action. This relationship is reasonable because consumers' habit encourages resistance to change

(Polites & Karahanna, 2012), which has a positive relationship with their intention to continue using a certain innovation. In addition, habitual behaviors are effortless and cognitively easier to perform than other behaviors (Lankton et al., 2010). Consumers are more likely to repeat behaviors that can be performed with less effort (Lindbladh & Lyttkens, 2002). Thus, mobile payment usage habit will encourage consumers to continue using mobile payments. The positive relationship between habit and behavioral intention is also supported by the extended unified theory of acceptance and use of technology (Venkatesh et al., 2012). Hence, we posit that

Hypothesis 4. Consumers' mobile payment usage habit will have a positive relationship with their intention to continue using mobile payments.

Moderation Effect of Price Discount

Mobile payments can be used to make payments in different areas such as shopping online, purchasing mobile tickets, transferring money, paying credit bills, buying lottery, paying power bills, and paying taxi bills. Comprehensiveness of usage refers to "the extent to which an individual makes use of the various applications offered under the umbrella of a single IS system" (Limayem et al., 2007, p. 715). In order to encourage users to use mobile payments and increase their comprehensiveness of usage, service providers may offer their consumers with different types of price discount. For example, Tecent Company, one of the largest mobile payment service providers and IT companies, offers a seven to nine percent discount for consumers who use their mobile payment services to purchase their virtual products (Tenpay, 2014). Price discount may motivate consumers to use mobile payments because they can save money. Thus, a price discount should encourage consumers to use mobile payments (Haaker, de Vos, & Bouwman, 2006).

Past literature of learning transfer summarizes four sets of factors that will affect transfer of learning: motivational factors (e.g., extrinsic reward), trainee characteristics (e.g., self-efficacy), environmental factors (e.g., supervisor support), and ability factors (e.g., perceived knowledge) (Holton et al., 2007). Extrinsic motivation refers to behaviors that are performed for externally reward such as pay and promotion (Deci et al., 1991). Price discount is an extrinsic motivation to transfer (Burke & Hutchins, 2007; Yeung, Yee, & Morris, 2010). In this research, we explore learning transfer from three types of technology usage habits, online shopping habit, mobile service usage habit, and cell phone usage habit, to mobile payment usage habit. As a component of extrinsic motivation to transfer, price discount is anticipated to encourage consumers to learn to use mobile payments (Haskell, 2001; Haskell et al., 2007). Thus, price discount will encourage the transfer from three technology usage habits to mobile payment usage habit, which means that price discount positively moderates the relationship between online shopping usage habit and mobile payment usage habit, between mobile service usage habit and mobile payment usage habit, and between cell phone usage habit and mobile payment usage habit.

For consumers who have an online shopping habit, price discount means saving for them if they use mobile payments to complete online transactions. Meanwhile, consumers with a high level of mobile service and cell phone usage habits can enjoy the price discount with little learning cost (Chiu et al., 2012; Lankton et al., 2010). This is because they know how to use mobile phones and mobile services and do not need to spend much time learning how to use mobile payments. Price discount boosts consumers' perceived usefulness of mobile payments (Warr & Bunce, 1995), which motivates consumers to transfer their online shopping, cell phone, and mobile service habits to use mobile payment regularly (Joo, Joung, & Son, 2014). Thus, we anticipate that:

Hypothesis 5a. Price discount will positively moderate the relationship between online shopping habit and mobile payment usage habit.

Hypothesis 5b. Price discount will positively moderate the relationship between mobile service usage habit and mobile payment usage habit.

Hypothesis 5c. Price discount will positively moderate the relationship between cell phone usage habit and mobile payment usage habit.

Methodology

Data Collection

A survey based research was used to develop an understanding of the effects of technology usage habits and price discount on consumers' intention to continue using mobile payments. Two sets of data were collected. The first dataset was collected from the general public in China. Two hundred and thirty one questionnaires were collected. Eleven questionnaires were excluded from the dataset during data screening, making the final sample size 220. The second dataset was collected from the general public in the United States. Two hundred and twenty questionnaires were collected from the U.S. Eighteen questionnaires were excluded during the data screening, making the final sample size 202. We randomly selected 202 questionnaires from the China dataset in order to compare Chinese and American respondents. Table 1 summarizes the demographic information of the participants.

Table 1.
Demographic Information

Measure	Item	China (n=202)		The U.S. (n=202)	
		#	%	#	%
Age	<21	13	6.4	3	1.5
	21-25	98	48.5	49	24.3
	26-30	55	27.2	35	17.3
	31-35	23	11.4	51	25.2
	>35	13	6.4	64	31.7
Gender	Male	132	65.3	78	38.6
	Female	70	34.7	124	61.4
Education background	Some college or less	36	17.8	115	56.9
	Bachelor	119	58.9	63	31.2
	Master	39	19.3	22	10.9
	PhD or more	8	4.0	2	1.0
Time to use mobile payments (Month)	0-6	47	23.3	28	13.9
	7-12	39	19.3	48	23.8
	13-18	35	17.3	32	15.8
	More than 18	81	40.1	94	46.6

Measures

Wherever possible, items were drawn from existing scales. Some minor modifications were made to the adopted measures. All items are measured on a seven-point Likert scale, ranging from strongly disagree (1) to strongly agree (7). The English instruments were translated into Chinese by following the back translation approach. Pilot tests were conducted using some volunteer respondents in China as well as in the U.S. to test the wording and reliability of the Chinese and English instruments, respectively. Subsequently, some minor changes were made to the questionnaires that can be found in the Appendix 3 (English version only).

This research involves four types of technology usage habits: online shopping habit, mobile service usage habit, mobile payments usage habit, and cell phone usage habit. Each type of technology usage habit was assessed with three items adapted from Setterstrom et al. (2013). Price discount was assessed with three items adapted from Yeung et al. (2010) and Pavlou and Fygenson (2006). Users' intention to continue using mobile payments was assessed with three items adapted from Venkatesh et al. (2012). Perceived usefulness was measured with three items adapted from Kim, Mirusmonov, and Lee (2010). Perceived ease of use was measured with three items adapted from Lin et al. (2011). Disposition to trust was measured with three items adapted from Zhou (2011). Institution-based trust was assessed with six items adapted from Setterstrom et al. (2013).

The technology acceptance model and the initial trust building model support the effect of perceived ease of use, perceived usefulness, disposition to trust, and institution-based trust on behavioral intention (Lin, Shih, & Sher, 2007; McKnight et al., 1998, 2002). Therefore, perceived ease of use, perceived usefulness, disposition to trust, and institution-based trust were used as control variables in this study.

Data Analysis and Results

SmartPLS (Ringle, Wende, & Will, 2005) was used to analyze the data. PLS was chosen for its ability to handle non-normality in the data and because the goal of this research is to explain variance in the outcome variable (Gefen & Straub, 2000).

Common Method Bias

All data was collected through a self-report survey. Thus, there is a potential of common method bias (Podsakoff et al. 2003). This research examined common method bias using three tests. First, the Harmon's single factor test was performed. Common method bias may exist if 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 factor analysis. For the China group, the result yielded six factors with eigenvalues greater than 1.0, which accounted for 75 percent of the total variance. The first factor captured only 37 percent of the variance in the data. For the U.S. group, the result yielded six factors with eigenvalues greater than 1.0, which accounted for 81 percent of the total variance. The first factor captured only 48 percent of the variance in the data. The results indicate that no factor accounts for the majority of variance.

Second, researchers compared correlations among constructs by following the procedure established by Pavlou, Liang, and Xue (2007). The results revealed no constructs with correlations over 0.8.

Third, the unmeasured latent method construct (ULMC) technique (Liang et al. 2007) was performed. For the China group, the results demonstrate that the average substantively explained variance of the indicators is 0.785, while the average method-based variance is 0.005. The ratio of substantive variance to method variance is about 150:1. In addition, the results revealed that 22 method factor loadings (out of 24) were not significant at a 95 percent confidence level. For the U.S. group, the results demonstrate that the average substantively explained variance of the indicators is 0.856, while the average method-based variance is 0.008. The ratio of substantive variance to method variance is about 110:1. In addition, the results revealed that 19 method factor loadings (out of 24) were not significant at a 95 percent confidence level. All results indicate that common method bias is unlikely to be a serious concern for this research.

Measurement Model

Perceived ease of use and disposition to trust did not have a significant relationship with consumers' intention to continue using mobile payments, and are not represented in the results reported below. This research adopted the two-stage analytical procedure (Anderson & Gerbing, 1988; Hair et al., 1998). Confirmative factor analysis was first conducted to assess the measurement model; then, the structural relationships were examined. As shown in Tables 2 and 3, Cronbach's alpha ranged from 0.827 to 0.942 for the China group and from 0.860 to 0.955 for the U.S. group, providing evidence of measure reliability (Cronbach, 1971). Meanwhile, composite reliability (CR) ranged from 0.897 to 0.963 for the China group and from 0.915 to 0.970 for the U.S. group, indicating valid internal consistency reliability (Chin, 1998). All AVEs are larger than 0.5, indicating that convergent validity is met (Fornell & Larcker, 1981). Additionally, as shown in Tables 2 and 3, all squared roots of AVEs are greater than the correlation shared between the construct and other constructs in the model. As shown in Tables 4 and 5, all items load appropriately on their intended construct. All these results indicate discriminant validity. Jointly, these findings suggest adequate convergent and discriminant validity. We also checked the variance inflation factors (VIFs) of all the independent variables. VIF ranged from 1.455 to 2.330 for the China group and from 1.445 to 4.034 for the U.S. group. None of the VIFs exceed 5, suggesting that multicollinearity is not a concern (Petter et al. 2007).

Table 2.
Measurement Validity for the China Group

	R^2	CR	Cronbach's α	AVE	OSH	MSH	MPH	CH	BI	IBT	PU
OSH	N/A	0.897	0.827	0.745	**0.863**						
MSH	N/A	0.963	0.942	0.896	0.453	**0.946**					
MPH	0.309	0.938	0.901	0.836	0.452	0.458	**0.914**				
CH	N/A	0.909	0.847	0.770	0.467	0.609	0.456	**0.877**			
BI	0.554	0.904	0.840	0.760	0.434	0.430	0.555	0.411	**0.871**		
IBT	N/A	0.937	0.919	0.712	0.277	0.202	0.449	0.185	0.493	**0.844**	
PU	N/A	0.931	0.889	0.819	0.404	0.340	0.399	0.472	0.655	0.405	**0.905**

Note: bold values are the square roots of average variance extracted; OSH=online shopping habit, MSH=mobile service usage habit, MPH=mobile payment usage habit, CH=Cell phone usage habit, BI=behavioral intention, IBT=institution-based trust, and PU=perceived usefulness.

Table 3.
Measurement Validity for the U.S. Group

	R^2	CR	Cronbach's α	AVE	OSH	MSH	MPH	CH	BI	IBT	PU
OSH	N/A	0.915	0.860	0.782	**0.884**						
MSH	N/A	0.970	0.953	0.914	0.391	**0.956**					
MPH	0.438	0.966	0.946	0.903	0.517	0.513	**0.950**				
CH	N/A	0.944	0.910	0.849	0.401	0.366	0.494	**0.921**			
BI	0.749	0.958	0.935	0.885	0.433	0.427	0.740	0.360	**0.941**		
IBT	N/A	0.964	0.955	0.817	0.371	0.361	0.656	0.317	0.773	**0.904**	
PU	N/A	0.933	0.893	0.822	0.427	0.453	0.680	0.455	0.778	0.680	**0.907**

Note: bold values are the square roots of average variance extracted; OSH=online shopping habit, MSH=mobile service usage habit, MPH=mobile payment usage habit, CH=Cell phone usage habit, BI=behavioral intention, IBT=institution-based trust, and PU=perceived usefulness.

Structural Model

We first tested the main effect without considering the moderation effects and then tested the differences between the China and the U.S. datasets. Then, moderation effects were tested separately for the China and the U.S. datasets.

Main effect.

The path coefficients and explained variances of the structural model are shown in Figure 2. The PLS model use R^2 to assess the explanatory power of a structural model. The model explained 55.4% of the variance in users' intention to continue using mobile payments for the China group (adjusted R^2=0.540) and explained 74.9% of the variance in users' intention to continue using mobile payments for the U.S. group (adjusted R^2=0.741). Therefore, the predictive power of the model is validated.

The results indicate that online shopping habit (China: b=0.258, $p<0.01$; the U.S.: b=0.293, $p<0.001$), mobile service usage habit (China: b=0.217, $p<0.05$; the U.S.: b=0.301, $p<0.001$), and cell phone usage habit (China: b=0.203, $p<0.05$; the U.S.: b=0.266, $p<0.001$) each have a positive relationship with users' mobile payment usage habit, supporting H1, H2, and H3.

In addition, consumers' mobile payment usage habit has a positive relationship with their intention to continue using mobile payments (China: b=0.290, p<0.001; the U.S.: b=0.262, p<0.001). Hence, H4 is supported. Two control variables, institution-based trust (China: b=0.172, p<0.01; the U.S.: b=0.360, p<0.001) and perceived usefulness (China: b=0.470, p<0.001; the U.S.: b=0.355, p<0.001) each have a positive relationship with users' intention to continue using mobile payments.

Table 4.
Cross Loading for the China Group

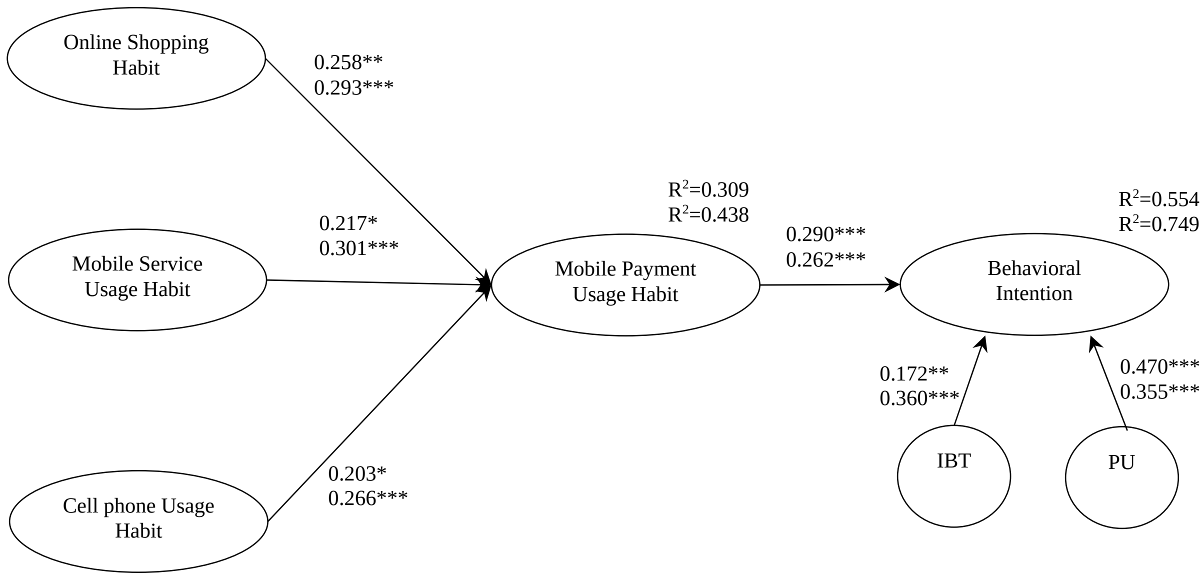
	OSH	MSH	MPH	CH	BI	IBT	PU
OSH1	**0.883**	0.351	0.394	0.389	0.343	0.254	0.326
OSH2	**0.919**	0.405	0.423	0.414	0.384	0.217	0.328
OSH3	**0.782**	0.423	0.349	0.410	0.402	0.250	0.402
MSH1	0.450	**0.946**	0.447	0.585	0.424	0.201	0.337
MSH2	0.426	**0.970**	0.450	0.554	0.414	0.163	0.329
MSH3	0.409	**0.923**	0.402	0.593	0.380	0.212	0.297
MPH1	0.455	0.385	**0.917**	0.408	0.501	0.396	0.378
MPH2	0.443	0.410	**0.944**	0.383	0.539	0.414	0.386
MPH3	0.340	0.462	**0.879**	0.462	0.481	0.420	0.330
CH1	0.438	0.551	0.460	**0.920**	0.395	0.232	0.445
CH2	0.441	0.564	0.383	**0.936**	0.363	0.161	0.457
CH3	0.343	0.484	0.346	**0.767**	0.315	0.073	0.330
BI1	0.391	0.485	0.503	0.465	**0.875**	0.420	0.578
BI2	0.428	0.386	0.521	0.371	**0.922**	0.419	0.612
BI3	0.310	0.243	0.422	0.229	**0.815**	0.453	0.520
IBT1	0.259	0.154	0.428	0.168	0.458	**0.828**	0.328
IBT2	0.121	0.091	0.318	0.053	0.423	**0.835**	0.303
IBT3	0.201	0.133	0.377	0.156	0.371	**0.836**	0.365
IBT4	0.220	0.162	0.297	0.079	0.397	**0.859**	0.341
IBT5	0.268	0.224	0.405	0.209	0.411	**0.858**	0.372
IBT6	0.324	0.257	0.438	0.268	0.424	**0.848**	0.344
PU1	0.357	0.360	0.412	0.495	0.616	0.388	**0.914**
PU2	0.304	0.258	0.302	0.370	0.548	0.338	**0.920**
PU3	0.428	0.298	0.362	0.409	0.609	0.369	**0.881**

Note: OSH=online shopping habit, MSH=mobile service usage habit, MPH=mobile payment usage habit, CH=Cell phone usage habit, BI=behavioral intention, IBT=institution-based trust, and PU=perceived usefulness.

Table 5.
Cross Loading for the U.S. Group

	OSH	MSH	MPH	CH	BI	IBT	PU
OSH1	**0.910**	0.318	0.468	0.351	0.386	0.318	0.389
OSH2	**0.897**	0.391	0.485	0.386	0.422	0.370	0.366
OSH3	**0.844**	0.326	0.416	0.323	0.335	0.292	0.381
MSH1	0.400	**0.959**	0.514	0.342	0.424	0.360	0.467
MSH2	0.384	**0.963**	0.494	0.365	0.425	0.360	0.467
MSH3	0.335	**0.946**	0.462	0.341	0.374	0.311	0.359
MPH1	0.537	0.469	**0.947**	0.501	0.731	0.655	0.685
MPH2	0.483	0.498	**0.963**	0.458	0.698	0.615	0.622
MPH3	0.452	0.498	**0.941**	0.446	0.678	0.599	0.629
CH1	0.377	0.299	0.435	**0.938**	0.313	0.283	0.421
CH2	0.375	0.330	0.457	**0.947**	0.333	0.286	0.399
CH3	0.355	0.377	0.470	**0.877**	0.345	0.305	0.437
BI1	0.405	0.389	0.714	0.347	**0.956**	0.745	0.792
BI2	0.433	0.425	0.717	0.347	**0.957**	0.742	0.747
BI3	0.382	0.393	0.655	0.320	**0.909**	0.693	0.650
IBT1	0.340	0.333	0.566	0.332	0.706	**0.882**	0.632
IBT2	0.327	0.305	0.592	0.281	0.660	**0.924**	0.575
IBT3	0.340	0.303	0.607	0.250	0.696	**0.942**	0.606
IBT4	0.371	0.324	0.587	0.228	0.705	**0.911**	0.600
IBT5	0.313	0.323	0.585	0.258	0.679	**0.835**	0.639
IBT6	0.320	0.361	0.619	0.362	0.740	**0.924**	0.629
PU1	0.347	0.394	0.597	0.447	0.636	0.553	**0.898**
PU2	0.432	0.409	0.636	0.411	0.673	0.596	**0.937**
PU3	0.380	0.424	0.614	0.386	0.788	0.683	**0.885**

Note: OSH=online shopping habit, MSH=mobile service usage habit, MPH=mobile payment usage habit, CH=Cell phone usage habit, BI=behavioral intention, IBT=institution-based trust, and PU=perceived usefulness.



Note: upper coefficients are for the China group, and lower coefficients are for the U.S. group; *p<0.05, **p<0.01, ***p<0.001; IBT=institution-based trust, and PU=perceived usefulness.

Figure 2. Structural Model (Main Effect)

Cross-culture comparison.

In the structural model, the path coefficients vary across the China and the U.S. groups, promoting a multi-group analysis with PLS to test whether these differences are significant (Chin, 2000; Keil et al., 2000). As shown in Table 6, only the link between institution-based trust and intention to continue using mobile payments is different across the two groups.

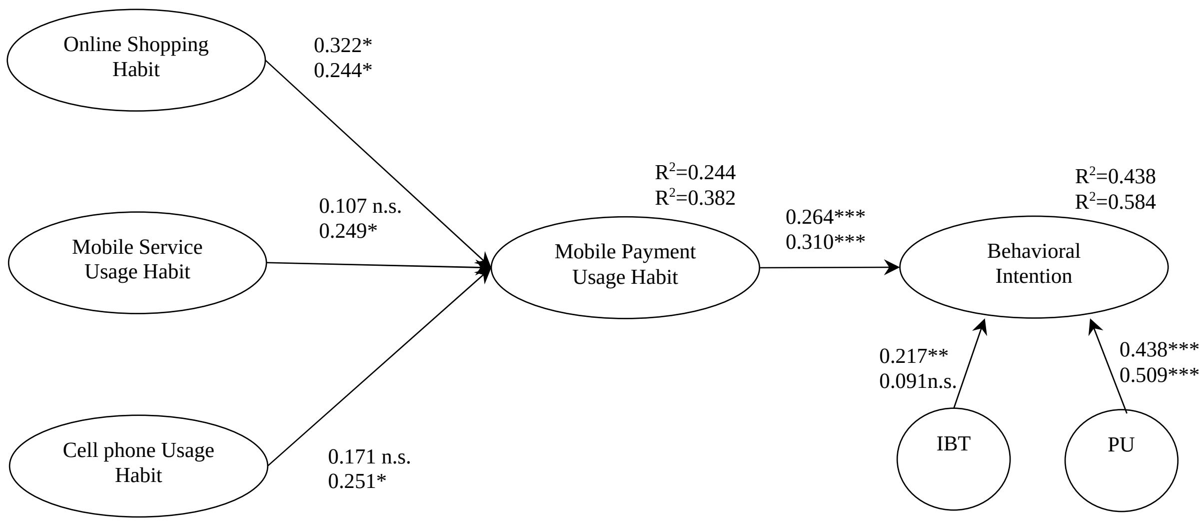
Table 6.
Result of Parametric Multi-Group Analysis for Users of China and the U.S.

Path	b:China	b:the U.S.	Equal variance P (one tail)	Different variance P (one tail)
H1: OSH -> MPH	0.258*	0.293*	0.386	0.386
H2: MSH -> MPH	0.217*	0.301*	0.221	0.222
H3: CH -> MPH	0.203*	0.266*	0.277	0.278
H4: MPH -> BI	0.290*	0.262*	0.368	0.368
Control: PU -> BI	0.470*	0.355*	0.074	0.075
Control: IBT -> BI	**0.172***	**0.360***	**0.010**	**0.010**

Note: Bolded indicates differences between groups; *are significant path coefficients; OSH=online shopping habit, MSH=mobile service usage habit, MPH=mobile payment usage habit, CH=Cell phone usage habit, BI=behavioral intention, IBT=institution-based trust, and PU=perceived usefulness.

Moderation of price discount for the China group.

To test our hypotheses pertaining to the moderating effects, we conducted a multi-group analysis with a median split to separate each dataset according to price discount (Tsai & Bagozzi, 2014). We built separate structural models for the high and the low price discount groups (Figure 3) and performed a multi group analysis to identify any difference in the coefficients of the hypothesized paths as shown in Table 7. Three path coefficients are different across the two groups: mobile service usage habit to mobile payment usage habit, cell phone usage habit to mobile payment usage habit, and institution-based trust to behavioral intention.



Note: upper coefficients are for high price discount, and lower coefficients are for low price discount; *p<0.05, **p<0.01, ***p<0.001, n.s.=not significant; IBT=institution-based trust, and PU=perceived usefulness.

Figure 3. Structural Model (China)

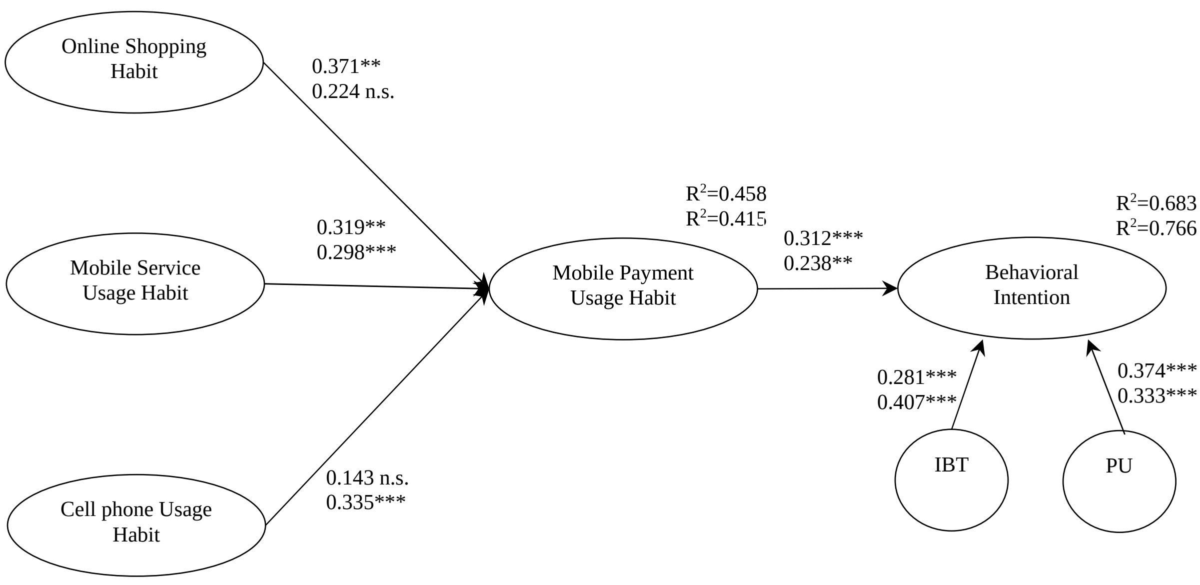
Moderation of price discount for the U.S. group.

To test our hypotheses pertaining to the moderating effects, we conducted multi-group analyses with a median split to separate the groups according to price discount (Tsai & Bagozzi, 2014). We built separate structural models for the high and the low price discount groups (Figure 4) and performed a multi group analysis to identify any difference in the coefficients of the hypothesized paths as shown in Table 8. Two path coefficients are different across the two groups: online shopping habit to mobile payment usage habit and cell phone usage habit to mobile payment usage habit.

Table 7.
Comparison of the Low and the High Price Discount Groups for China

Path	b: High	b: Low	Equal variance P (one tail)	Different variance P (one tail)
H1: OSH -> MPH	0.322*	0.244*	0.330	0.330
H2: MSH -> MPH	*0.107*	*0.249**	*0.194*	*0.195*
H3: CH -> MPH	*0.171*	*0.251**	*0.312*	*0.313*
H4: MPH -> BI	0.264*	0.310*	0.350	0.350
Control: PU -> BI	0.438*	0.509*	0.258	0.259
Control: IBT -> BI	**0.217***	**0.091**	**0.128**	**0.129**

Note: Note: Bolded indicates statistically differences between groups; italic indicates differences because one is significant and the other is not; *are significant path coefficients; OSH=online shopping habit, MSH=mobile service usage habit, MPH=mobile payment usage habit, CH=Cell phone usage habit, BI=behavioral intention, IBT=institution-based trust, and PU=perceived usefulness.



Note: upper coefficients are for high price discount, and lower coefficients are for low price discount; *p<0.05, **p<0.01, ***p<0.001, n.s.=not significant; IBT=institution-based trust, and PU=perceived usefulness.

Figure 4. Structural Model (the U.S.)

Table 8.
Comparison of the Low and the High Price Discount Groups for the U.S.

Path	b: High	b: Low	Equal variance P (one tail)	Different variance P (one tail)
H1: OSH -> MPH	**0.371***	**0.224**	**0.188**	**0.189**
H2: MSH -> MPH	0.319*	0.298*	0.442	0.442
H3: CH -> MPH	**0.143**	**0.335***	**0.066**	**0.067**
H4: MPH -> BI	0.312*	0.238*	0.278	0.279
Control: PU -> BI	0.374*	0.333*	0.361	0.362
Control: IBT -> BI	0.281*	0.407*	0.133	0.134

Note: Bolded indicates differences between groups; *are significant path coefficients; OSH=online shopping habit, MSH=mobile service usage habit, MPH=mobile payment usage habit, CH=Cell phone usage habit, BI=behavioral intention, IBT=institution-based trust, and PU=perceived usefulness.

Discussion

Key Findings

Overall, four out of five hypotheses are fully supported, and the moderation hypothesis is mixed and partially supported (see Table 9). The results of our research provide insight into the effect of consumers' technology usage habits and price discount on their intention to continue using mobile payments.

Table 9.
Summary of Hypotheses Tests

Hypotheses	China	The U.S.
H1. Online Shopping Habit→ Mobile Payment Usage Habit	Supported	Supported
H2. Mobile Service Usage Habit→ Mobile Payment Usage Habit	Supported	Supported
H3. Cell phone Usage Habit→ Mobile Payment Usage Habit	Supported	Supported
H4: Mobile Payment Usage Habit→ Behavioral Intention	Supported	Supported
H5a. Price discount moderates Online Shopping Habit→ Mobile Payment Usage Habit	Not Supported	Supported
H5b. Price discount moderates Mobile Service Usage Habit→ Mobile Payment Usage Habit	Support the Reverse Hypothesis	Not Supported
H5c. Price discount moderates Cell phone Usage Habit→ Mobile Payment Usage Habit	Support the Reverse Hypothesis	Support the Reverse Hypothesis
Control: Perceived Usefulness→ Behavioral Intention	Supported	Supported
Control: Institution-Based Trust→ Behavioral Intention	Supported	Supported

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

This research distinguishes three predictors of mobile payment usage habit: online shopping habit, mobile service usage habit, and cell phone usage habit. Online shopping, mobile services, mobile payments, and cell phone belong to the mobile ecosystem (Adomavicius et al., 2008a). These innovations are mutually dependent, forming an ecology (Adomavicius et al., 2007; Swanson, 1994). The IT ecosystem perspective posits that consumers' past usage of different technologies will enhance or undermine their potential usage of similar or new technologies (Haskell, 2001). According to the results, users' online shopping habit, mobile service usage habit, and cellphone usage habit are positively related to their mobile payment usage 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 behaviors less frequently.

We also find a difference between American and Chinese users. The results indicate that American users' institution-based trust, one of the control variables, has a stronger positive influence than Chinese users' institution-based trust on their intention to continue using mobile payments. One possible reason is that Chinese consumers have a higher level of uncertainty avoidance than American consumers (Singh et al., 2005). The higher the level of uncertainty avoidance, the lower the effect of trust on behavioral intention (Yoon, 2009). Thus, the relationship between trust and behavioral intention of Chinese consumers is weaker than that of American consumers.

Our findings regarding the effect of price discount on consumers' transference from online shopping habit, mobile service usage habit, and cell phone usage habit to mobile payment usage habit is interesting. For the U.S. group, price discount positively moderates the relationship between online shopping habit and mobile payment usage habit, supporting H5a. This means that price discount will strengthen the effect of online shopping habit on mobile payment usage habit. One possible reason is that consumers perform learning transference to pursue price equity in their transactions (Noe & Schmitt, 1986). The payment stage is necessary to finish online shopping, and consumers may enjoy the price discount that is available just because mobile payments are used. Thus, price discount will motivate consumers to transfer their online shopping habit to mobile payment usage habit to enjoy the price discount and achieve price equity. Although H5a is not supported in the China group, the coefficient of the path between online shopping habit and mobile payment usage habit for the high price discount group is larger than that of low price discount group as shown in Table 7.

Moreover, for the China group, price discount negatively moderates the relationship between mobile service usage habit and mobile payment usage habit and price discount negatively moderates the relationship between cell phone usage habit and mobile payment usage habit in both the China and the U.S. groups, both of which are opposite to what was expected. Apparently, price discount may not always entice consumers, especially those in China, to engage with mobile payments. A similar conclusion was found by Deci et al. (1999) and Lepper and Greene (1978), who posited that extrinsic motivators such as price discount may be temporarily effective, but will undermine future motivation and performance. Kontoghiorghes (2001) also found that extrinsic motivation such as pay has a negative or weak association with transfer of learning. Thus, practitioners do not need to provide consumers with a high level of price discount to attract consumers to continue using mobile payments if they have formed a strong habit of using cell phone and mobile services (other than mobile payments).

Limitations and Future Research

As with all research, there are some limitations that should be considered when interpreting the results of this research. First, data was collected by using a self-report survey. Hence, there is a potential for common method biases (Podsakoff et al., 2003). However, common method bias is not a significant problem in this research. Second, a mobile ecosystem is a complex system with many segments (Basole, 2009). Cell phones, mobile payments, mobile services (other than mobile payments), and online shopping are just some of technologies in the mobile ecosystem. Future research is needed to examine the interrelationships among technologies in the mobile ecosystem. Third, non-monetary promotions such as free gifts are becoming more important (Palazon & Delgado-Ballester, 2009). However, we explore only the effect of price discount on users' intention to continue using mobile payments. Future research is needed to explore the effects of non-monetary promotions on behavioral intention toward mobile payments.

Implication for Theory

This research highlights the role of technology usage habits and price discount in affecting consumers' intention to continue using mobile payments, contributing to IT acceptance research.

This research explores the post adoption of mobile payments from the perspective of an IT ecosystem and transfer of learning theories. IT innovations are not independent but are interrelated (Swanson, 1994). Online shopping, cell phones, mobile payments, and mobile services are interrelated components of mobile ecosystems. In this research, we discuss the interrelationships among different types of technology usage habits, and found that consumers' online shopping habit, mobile service usage habit, and cell phone usage habit each have an indirect relationship with intention to continue using mobile payments through mobile payment usage habit. This research also validates the reasonability of using transfer of learning theories and the IT ecosystem perspective as background theories to explain the effect of different types of technology usage habits on consumers' behavioral intention. Thus, this study serves as a response to the criticism of Limayem et al. (2007) that there is a lack of theory bases to discuss the effect of habit on consumers' behavior intention.

The research also contributes to research on technology usage habit. Habit has attracted academics' attention to explain human behaviors (Polites & Karahanna, 2013; Venkatesh et al., 2012). This research distinguishes three predictors of consumers' mobile payment usage habit: online shopping habit, mobile service usage habit, and cell phone usage habit. Results indicate that consumers' online shopping habit, mobile service usage habit, and cell phone usage habit each have a positive relationship with their mobile payment usage habit. These findings are consistent with the IT ecosystem perspective (Swanson, 1994) and transfer of learning theories (Holton et al., 2000, 2007).

This research sheds light on how to find the most loyal mobile payment users and how to retain current users. Results indicate that loyal mobile payment users have a high level of online shopping habit, mobile service usage habit, and cell phone usage habit. Results also indicate that mobile payment usage habit and perceived usefulness each have a direct impact on consumers' intention to continue using mobile payments. Thus, these two factors matter in retaining current mobile payments users.

Our research also contributes to research on the effect of price discount on consumers' transfer of learning and intention to continue using mobile payments. According to the results, price discount positively moderates the relationship between American users' online shopping habit and mobile payment usage habit. In addition, price discount negatively moderates the relationship between Chinese users' mobile service usage habit and mobile payment usage habit. Price discount also negatively moderates the relationship between consumers' cell phone usage habit and mobile payment usage habit. Results indicate that price discount has a mixed effect on the transfer of learning. More research are needed to clarify the effect of price discount on the adoption of individual innovations, especially innovations related to financial services.

Implication for Practice

Practical implications for industry can be drawn from these findings. Based on the conclusions of this study, we can distinguish current users who are more likely to continue using mobile payments. Results demonstrate that consumers' who frequently shop online, use mobile services, and use cell phones are more likely to continue using mobile payments. Practitioners can observe consumers' technology usage habits by analyzing information that consumers disclose in social media. Then, practitioners can distinguish loyal users who are more likely to continue using mobile payments. Thereafter, practitioners can send user-specific advertising messages to consumers' wireless devices.

In addition, perceived usefulness influences consumers' intention to continue using mobile payments. Thus, practitioners should highlight the usefulness of mobile payments in their marketing activities such as advertising. They should also pay attention to the information quality of their user interfaces to encourage consumers to realize the usefulness of their mobile payment services. Meanwhile, as one critical driver for mobile commerce success (Yang et al., 2012), mobile payments will positively affect economic development. Governments should cooperate with mobile payment service providers to boost the safe and robust development of the mobile payment industry, taking advantage of institution-based trust.

Consumers are familiar with online shopping, mobile services, and cell phones. Practitioners should encourage consumers to develop a mobile payment usage habit. The identical element model posits that similarity between learning and transfer situations supports consumers' ability to learn in new situations (Lobato, 2006). Thus, practitioners should cue consumers to the similarities and connections between mobile payment services and other well-accepted technologies such as online shopping, mobile services other than mobile payments, and cell phones.

Price discount is another factor that affects transfer of learning. However, practitioners should use it carefully because its effect on consumers' post adoption of mobile payments is complex. Past literature also supports our conclusions. For example, Dodds et al. (1991) posited that price discount has a negative effect on perceived quality, but a positive effect on perceived value and willingness to buy. In this research, we find that price discount positively moderates the relationship between online shopping habit and mobile payment usage habit, particularly for American users. Thus, marketers should provide a price discount for those who shop online frequently to encourage them to continue using mobile payments. However, marketers do not need to provide a price discount for those who use mobile services and cell phone frequently because it may undermine the effect of mobile service and cell phone habits on use of mobile payments. Correspondingly, marketers should consider providing a price discount for those who use mobile services and cell phones less frequently to encourage their use of mobile payments. Generally speaking, marketers should consider how to frame price discount because it will affect consumers’ perception of it (Darke & Chung, 2005). While our research invokes a new research topic in the post adoption of mobile payments, more research is necessary to explore the optimal balance between technology usage habits and price discount.

Conclusion

Repeat customers can bring companies five times more profit with lower marketing cost (Gupta & Kim, 2007). It is of great importance to explore factors that will encourage consumers to use mobile payments repeatedly. This research serves as an exploration of the impact of price discount and consumers’ technology usage habits on their intention to continue using mobile payments. Drawing on the IT ecosystem view and transfer of learning theories, we developed a model suggesting that consumers’ online shopping habit, mobile service usage habit, and cell phone usage habit will affect their mobile payment usage habit, which in turn positively impacts their intention to continue using mobile payments. In addition, price discount moderates the transference from these three types of technology usage habits to mobile payment usage habit. This research verifies the vital role of consumers’ technology usage habits in encouraging them to continue using mobile payments. Results indicate that consumers who shop online and use mobile services and cell phones frequently are more likely to use mobile payments regularly, which has a positive relationship with their intention to continue using mobile payments. This research is the foundation of an understanding of the impact of price discount and consumers’ technology usage habits on their intention to continue using mobile payments, and contributes to research on the role of individual differences in affecting consumers’ behavioral intention toward mobile payments.

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APPENDIX 3: Instrument

Table A. Measurement Items
Online Shopping Habit 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. *Adapted from Setterstrom et al. (2013)*
Mobile Service Usage Habit 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. *Adapted from Setterstrom et al. (2013)*
Cell Phone Usage Habit 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. *Adapted from Setterstrom et al. (2013)*
Mobile Payment Usage Habit 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. *Adapted from Setterstrom et al. (2013)*
Price Discount 1. I can save money on purchases if I pay by using mobile payments. 2. I will purchase products at a bargain price if I pay by using mobile payments. 3. I can purchase products with a price reduction if I pay by using mobile payments. *Adapted from Yeung et al. (2010) and Pavlou & Fygenson (2006)*
Intention to continue using 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. *Adapted from Venkatesh et al. (2012)*
Disposition to Trust 1. It is easy for me to trust an information technology. 2. I tend to trust an information technology, even though I have little knowledge of it. 3. My tendency to trust information technology is high. *Adapted from Zhou (2011)*
Institution-based Trust 1. I believe mobile technology has enough safeguards to make me feel comfortable using it to make mobile payments. 2. I feel assured that legal structures adequately protect me from payment problems with mobile technology. 3. I feel assured that technological structures adequately protect me from payment problems with mobile technology.

4. I feel confident that encryption and other technological advances with mobile technology make it safe for me to use mobile payments. 5. In general, the mobile technology provides a robust environment to perform mobile payments. 6. In general, the mobile technology provides a safe environment to perform mobile payments. *Adapted from Setterstrom et al. (2013)*
Perceived Ease of Use 1. Learning to use mobile payments was easy for me. 2. It was easy for me to become skillful at using mobile payments. 3. Overall, I find mobile payments easy to use. *Adapted from Lin et al. (2011)*
Perceived Usefulness 1. Using mobile payments enables me to pay more quickly. 2. Using mobile payments makes it easier for me to conduct transactions. 3. I find mobile payments a useful possibility for making payments. *Adopted from Kim et al. (2010)*

APPENDIX 4:

INFORMATION LETTER
for a Research study entitled
"Factors Affecting Consumers' Behavioral Intentions toward Mobile Payments"

You are invited to participate in a research study to help better understand the technology acceptance under individual usage context. The study is being conducted by Mr. Lin Jia, a doctoral student, under the direction of Dr. Dianne Hall, an associate professor, from the Department of Aviation & Supply Chain Management, Auburn University. You were selected as a possible participant because you are currently users or potential users of mobile payment and are age 19 or older.

Your participation is completely voluntary. If you decide to participate in this research study, you will be asked to rate the importance of numerous items about your behavior intention of mobile payment. Your total time commitment will be approximately 10-15 minutes.

There are no discomforts associated with participating in this study. No personal information will be collected, nor do we collect URLs or IP addresses that could be used to discover your identity. If you decide to participate, having read the information above, please click on the link below.

If you change your mind about participating, you can withdraw at any time by simply closing your browser window. Your decision about whether to participate or to stop participating will not jeopardize your future relations with Auburn University, or the Department of Aviation and Supply Chain Management.

Any data obtained in connection with this study will remain anonymous. We will protect your privacy and the data you provide by storing on secured servers. Information collected through your participation may be used to publish in academic journals, and/or present at a professional meetings.

If you have any questions, please contact me by e-mail at lzj0011@auburn.edu or my advisor, Dr. Dianne Hall at halldia@auburn.edu.

If you have questions about your rights as a research participant, you may contact the Auburn University Office of Human Subjects Research or the Institutional Review Board by phone 334-844-5966 or e-mail at hsubjec@auburn.edu or IRBChair@auburn.edu.

IF YOU DECIDE TO PARTICIPATE, PLEASE CLICK ON THE LINK BELOW. YOU MAY PRINT A COPY OF THIS LETTER TO KEEP.

Survey Link: https://auburn.qualtrics.com/SE/?SID=SV_e3e3HzebKZD7vJH

Lin Jia 12.12.2013
Investigator Date

The Auburn University Institutional Review Board has approved this document for use from November 3, 2013 to November 2, 2016. Protocol #13-376 EX 1311.