Do you take…? The effect of mobile payment solutions on use intention: an application of UTAUT2

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Abstract

Despite the multitude of mobile payments solutions, the US still remains reluctant to adopting this payment technology. The connection between types of mobile payments and usage needs investigation. Therefore, the purpose of this study was to examine the difference in usage intentions for three types of mobile payment solutions as moderated by age and gender. The theoretical model, UTAUT2, was tested in a quantitative study using structural equation modeling, conducted in the US with a sample recruited through Qualtrics. The findings show intention to use mobile payments differ for each mobile payment type with performance expectancy and habit as strong predictors of intention and use behavior. Social influence and effort expectancy were poor predictors of intention. Additionally, facilitating conditions did not impact use behavior. The results help apparel retailers determine which mobile payment solution fits the needs and wants of their target market.

Keywords Mobile payment · Mobile commerce · UTAUT · QR code · Cloud based · NFC · Retailing industry

Abbreviations

POSIS   Point-of-sales-independent software
POSDS   Point-of-sales-dependent software
POSDH   Point-of-sales-dependent hardware
UTAUT   Unified theory of acceptance and use of technology

Introduction

The payment industry is ultra-competitive with retailers constantly needing to increase their offerings. With consumers pushing retailers to expand their payment options, it is no surprise that mobile payment adoption and usage are increasing (Hardekopf 2022; Soltes 2022). No longer new to the market, mobile payment solutions globally continue to grow as a popular payment alternative to cash and debit/credit cards (Kim et al. 2010). Despite the widespread usage of mobile devices in the United States (US), mobile payment

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usage penetration is only at 29% compared to China's 81% penetration rate (de Best 2020).

Culture, habits, innovations, and available technology depict the way consumers make payments (Keates 2020). The US has the available technology and hosts a multitude of mobile payment solutions as well as a variety of ways to classify them. Mobile pay can be conducted via the usage of barcodes, QR codes, apps, web browsers, and text messages (de Best 2020). Major players of mobile pay in the US are PayPal, Venmo, and Apply Pay (de Best 2020). Mobile pay has become more popular with younger generations (de Best 2020); however, the dominant form of payment in the US market is still debit/credit cards and cash.

The apparel e-commerce industry is projected to be a 713 billion dollar global industry by 2022 (Khusainova 2022). In the US, the same sector will grow to 153.6 billion by 2024 (Chevalier 2021). It is the fastest growing vertical e-commerce business (Chevalier 2021; Khusainova 2022), and it is ripe for mobile pay as 50% of the consumers in Worldpay's Retail Global Payments Report study (Vogue Business 2020) use it with millennials and generation z leading the way. Thus, further understanding consumers and retailers' mobile payment wants and needs will strengthen the future of mobile pay solutions, especially in the apparel industry.

Currently, 75% of retailers are offering mobile payments (Hardekopf 2022); however, these retailers are not providing educational promotions to help foster adoption (Soltes

2022). Despite research that has shown, it would increase mobile pay adoption among all generations. Additionally, just under 50% of all in store purchases are conducted via mobile devices in China; in comparison, other developed markets such as Germany are at 25%, with the US landing at 24% of in store purchases via mobile device (Keates 2020). Despite the low penetration rate, Keates (2020) predicts mobile pay in store purchases to quadruple within the next 5 years. However, none of the mobile payment solutions in the US have near as many users as their Chinese counterparts (O'Shea 2018). Furthermore, despite the plethora of mobile payment solutions, some businesses only accept one type of mobile payment, have a preferred payment partner, or choose to promote their own branded mobile payment.

In the end, consumers will use the form of payment they want. However, it is still unclear which consumer groups prefer which mobile payment types, making the decision process on which mobile payment to implement difficult for retailers. Thus, the purpose of this study was to examine the difference in usage intentions for three types of mobile payment solutions as moderated by age and gender.

This study provides several contributions for the advancement of mobile pay research in the current age of digital acceleration and will discuss direct implications for retailers and small businesses. The impact of this study is twofold. First, the study explores the effect of differing mobile payment solutions determinants utilizing Venkatesh et al. (2012) unified theory of acceptance and use of technology (UTAUT). Second, mobile payment solutions are classified and analyzed based on the technology equipment and location to allow a comparison of specific mobile payment options. Early research on mobile pay is vast with much work on adoption and usage (Loh et al. 2021; Gao and Waechter 2017; Ooi and Tan 2016); however, very few studies have used UTAUT to simultaneously compare different types of mobile payment solutions in differing age groups and gender despite the need for comparative studies (Yan et al. 2021). Understanding a consumers' intention to use mobile pay is of great value to many stakeholders especially in the current age of mobile payment services where there is an abundance of mobile payment types. Therefore, diverse user groups may perceive mobile payment advantages differently for each type of mobile pay and in turn impact their intention to use and actual use behavior (Kim et al. 2010).

Theoretical background

Unified theory of acceptance and use of technology

Venkatesh et al. (2003) formulated the UTAUT from the comparisons of eight models: the technology acceptance model (TAM), the theory of reasoned action, the motivational model, the theory of planned behavior (TPB), the combined TAM and TPB model, the model of PC utilization, the innovation diffusion theory, and the social cognitive theory. Empirical results explain that UTAUT can account for 70% of the variance in behavioral intentions to use a new technology (Ramírez-Correa et al. 2019; Zhou et al. 2020). UTAUT was later extended to form UTAUT2 (Venkatesh et al. 2012) to further describe individuals' utilization of information technology they have at their disposal (Ramirez-Correa et al. 2019). UTAUT and UTAUT2 models have been used to explore the intentions to adopt mobile pay (Slade et al. 2015; Cao and Niu 2019), online games (Ramirez-Correa et al. 2019), self-service parcel (Zhou et al. 2020), mobile banking (Baptista and Oliveira 2015; Alalwan et al. 2017), to use mobile apps (Ameen et al. 2020), and big data (Cabrera-Sánchez and Villarejo-Ramos 2020).

UTAUT identified four key constructs to influence the intention to use (behavior intention): performance expectancy, effort expectancy, facilitating conditions, and social influence. Facilitating conditions also influence the use of the new technology (use behavior). The constructs of hedonic motivation, price value, and habit were later added when UTAUT was extended (Venkatesh et al. 2012). Due to the efficient and free nature of mobile pay and in agreement with Oliveira et al. (2016) hedonic motivation and price, value will be excluded from this study. Additionally, the individual differences of age, gender, and experience were theorized to moderate various relationships. Venkatesh et al. (2012) usage of moderators shows that consumer cohorts will have different weights on a variety of factors that may influence technology usage. UTAUT2 has examined an array of technologies such as online games in mobiles (Ramirez-Correa et al. 2019), to quantitatively test behavioral intention and use (Cao and Niu 2019; Morosan and DeFranco 2016; Oliveira et al. 2016; Shaw and Sergueeva 2019); thus, it serves as the theoretical basis for this study.

Mobile payment classifications

Mobile payments or m-pay is defined as the usage of a mobile device to initiate, approve, and verify commercial transactions (Au and Kauffman 2008). Mobile payments fall broadly into two categories: payments for purchases and bill payments. This study focuses on payment for purchases with mobile pay competing directly with cash, checks, and debit and/or credit cards (Kim et al. 2010). Mobile payments can be classified with two criteria, where the payment occurs [point of sales (POS) dependent or POS independent] and the type of equipment needed for transaction (software or hardware based) (Falk et al. 2016), thus, classifying mobile payments into four types.

POS-independent software (POSIS) mobile payments are cloud based and do not require for the retailer and the

consumer to be in the same place for payment to take place. Setup is simple for consumers and retailers as software installation and account setup is all that is required (Falk et al. 2016). This form of mobile payment tends to be primarily money transfer solution such as PayPal and Venmo. However, over 80% of US retailers support PayPal as an in-app payment option (Walk-Morris 2021).

POS-dependent software (POSDS) mobile payments such as Starbucks and Chick-fil-A mobile pay features occur when both consumer and retailer are in the same location, and the consumer has installed the software on their mobile device normally via a branded app. This is a code-based mobile payment system generally working through a mobile app with the usage of a QR code containing the consumers' payment information at POS. While China's QR-based payment systems such as Alipay or WeChat have dominated their m-pay solutions (Lou et al. 2017), US-based QR-code payments are on the rise with financial giant PayPal recently introducing QR codes to supplement their payment systems (Trivedi 2021).

POS-dependent hardware (POSDH) mobile payments require a piece of hardware next to the mobile to enable data communication between retailer and consumer at POS. The hardware required is normally near field communications (NFC) chip or sticker (Falk et al. 2016). With approximately one third of the world's cellphone equipped with NFC technology (Moghavvenmi et al. 2021), NFCs are the prime example of POSDH as there are several currently on the market such as Google Wallet, Apple Pay, and Samsung Pay. Consumers and retailers exchange data communications via the NFC chip within the consumer's mobile device. POSDH are greatly different from all other mobile payments (Morosan and DeFranco 2016) and are thought to be more secure as the cardholder information is not exchanged. Every purchase has a unique transaction number, and there is no physical card swiping, thus, eliminating skimming and malware-based fraud (Morosan and DeFranco 2016; Falk et al. 2016; Kassner 2014). POS-independent hardware (POSIH) are rare (Falk et al. 2016); therefore, POSIH were excluded from the study.

Research model and hypotheses

The UTAUT model was used as the theoretical model for this study. UTAUT has been empirically tested and proven to be superior to other models (Park et al. 2007), and thus, it is used in its latest form. The comparisons of this model among mobile payment classification allow a better understanding of the current and future mobile pay environment in the US. As gender and age may have a significant impact on users' intention to use mobile pay, both are also considered.

Performance expectancy is defined as the degree to which the technology benefits the performance of consumers' activities (Venkatesh et al. 2012). In this study, performance expectancy is the extent to which consumers' usage of mobile pay aid in the transaction completion more accurately and conveniently. It is considered to be one of the most important antecedents to intention with several studies validating its influence on behavioral intention (Cabrera-Sánchez and Villarejo-Ramos 2020; Zhou et al. 2020; Cao and Niu 2019; Rahi et al. 2018; Baptista and Oliveira 2015; Oliveira et al. 2016). Therefore, consumers will use m-pay when they find it useful for their transactional needs (Kim et al. 2010).

Effort expectancy is the ease with which consumer use technology (Venkatesh et al. 2012). It has been validated as a significant antecedent of intentions in numerous UTAUT studies (Cao and Niu 2019; Ameen et al. 2020; Zhou et al. 2020). However, despite its validation, there has been a number of studies, who found non-significant relationships (Alalwan et al. 2017; Ramírez-Correa et al. 2019; Rahi et al. 2018; Baptista and Oliveira 2015). It is theorized that this effect is due to the increase of mobile phone literacy and user's adeptness with the technology (Baptista and Oliveira 2015). M-pay must provide benefits such as a simple payment process, intuitive graphic displays, and help functions to the consumer as it rivals established payment solutions (Schierz et al. 2010). While mobile pay should be easy to learn and to use (Kim et al. 2010), mobile pay usage has low saturation in the US (de Best 2020); thus, for many, this is not a direct extension of their ability to use a mobile device.

Social influence is the degree to which consumers perceive those important others believe one should use the technology (Venkatesh et al. 2012). Social influence has had a mixed effect in the literature with some finding it to be a significant predictor of intention (Ramírez-Correa et al. 2019; Alalwan et al. 2017; Cao and Niu 2019; Rahi et al. 2018; Zhou et al. 2020) while others have shown non-significance (Baptista and Oliveira 2015; Wang and Yi 2012). However, positive experiences of mobile pay solutions shared by friend and families will enhance consumers' intention to use mobile pay.

Facilitating conditions refer to the accessibility to the resources needed for the acceptance and use of a technology in addition to available support when in use (Venkatesh et al. 2012). To use mobile payment solutions, users must be able to operate a mobile device, have connection to the Internet, ability to install a mobile app, and be knowledgeable of risk factors associated with the service (Baptista and Oliveira 2015). If a user can access helpful facilitating conditions such as a chat feature or online service walkthrough, their intention to use likelihood is greater (Baptista and Oliveira 2015). Previous studies show the influence of facilitating conditions on

a variety of technology-based systems (Cabrera-Sánchez and Villarejo-Ramos 2020; Zhou et al. 2010, 2020) positive influence not only effecting intention but also actual use (Baptista and Oliveira 2017). Therefore, the following hypotheses are derived:

Hypothesis 1 Performance expectancy will positively influence intention to use mobile payments (a POSIS, b POSDS, c POSDH) moderated by age and gender.

Hypothesis 2 Effort expectancy will positively influence intention to use mobile payments (a POSIS, b POSDS, c POSDH) moderated by age and gender.

Hypothesis 3 Social influence will positively influence intention to use mobile payments (a POSIS, b POSDS, c POSDH) moderated by age and gender.

Hypothesis 4 Facilitation conditions will positively influence intention to use mobile payments (a POSIS, b POSDS, c POSDH) moderated by age and gender.

Hypothesis 5 Facilitation conditions (a POSIS, b POSDS, c POSDH) will positively influence use behavior moderated by age and gender.

Habit is the learned automatic response developed over time (Venkatesh et al. 2012). Research has noted its influence on behavioral intention and use behavior (Morosan and DeFranco 2016; Ramírez-Correa et al. 2019; Baptista and Oliveira 2017). Habit has been theorized to be the most vial antecedent to determine use behavior (Baptista and Oliveira 2015; Ramírez-Correa et al. 2019; Loh et al. 2021) that notes the importance of changing consumers payment habit to be able to switch to mobile payment and if the habit is not formed, it will yield little to no influence on intention (Ameen et al. 2020). Thus, if consumers find mobile payment to be useful, they are more likely to make it a part of their routine (Baptista and Oliveira 2017).

Intention to use is defined as the likelihood that an individual will use a technology (Schierz et al. 2010) and has a strong influence on actual use behavior (Zhou et al. 2020; Alalwan et al. 2017; Baptista and Oliveira 2017). It is vital to stakeholders to know not only if consumer would intend to use mobile payment solution, but if that intention would indeed result in actual behavior. Thus, the following hypotheses are derived.

Hypothesis 6 Habit will positively influence intention to use mobile payments (a POSIS, b POSDS, c POSDH) moderated by age and gender.

Hypothesis 7 Habit (a POSIS, b POSDS, c POSDH) will positively influence use behaviour moderated by age and gender.

Hypothesis 8 Intention to use mobile payments (a POSIS, b POSDS, c POSDH) will positively influence use behaviour.

As a result of the hypotheses previously justified, an acceptance and use model of mobile payment options can be proposed, as shown in Fig. 1.

Research methodology

An online survey was used to test the influence of UTAUT2 on usage intention of three different mobile payment options. All items, performance expectancy, effort expectancy, facilitating conditions, social influence, habit, intention to use, and actual use were adapted from Venkatesh et al. (2012) and were measured on a 7-point Likert scale. Age was measured in years and gender was coded using a 1 (female) or 2 (male). The survey also contained a series of questions regarding demographic characteristics and behaviors, e.g., gender, operating system, age, ethnicity, education, and income.

The sample was US adults over 18 years of age who owned a smartphone with mobile pay capability. Participants were recruited through Qualtrics respondents. A total of 1322 responses were found to be useable after excluding missing data. Table 1 summarizes the sample demographics for the total 1322 responses and the breakdown of each mobile pay group.

Analysis and results

Structural equation modeling (SEM) is used to test established theory (Tabachnick & Fidell 2013). This research project was grounded in the theoretical framework of UTAUT2 and mobile pay solutions. Before a structural model can be tested, confirmatory factor analysis (CFA) with 31 indicators, 7 latent variables, and 2 moderating variables was used to test the latent model showing convergent validity, composite reliability (CR), and discriminate validity. Next a structural model was tested by the three mobile pay solutions using multi-group SEM analysis to test moderation. The data were analyzed using SPSS 20 and AMOS 18 software.

Measurement model

The measurement model was examined using CFA to identify measurements composing construct (Table 2). Model fit indicates that the data fits to the model well: $x^2 = 2389.752$,

Fig. 1 Research model with hypotheses; UTAUT2 (Venkatesh et al. 2012)
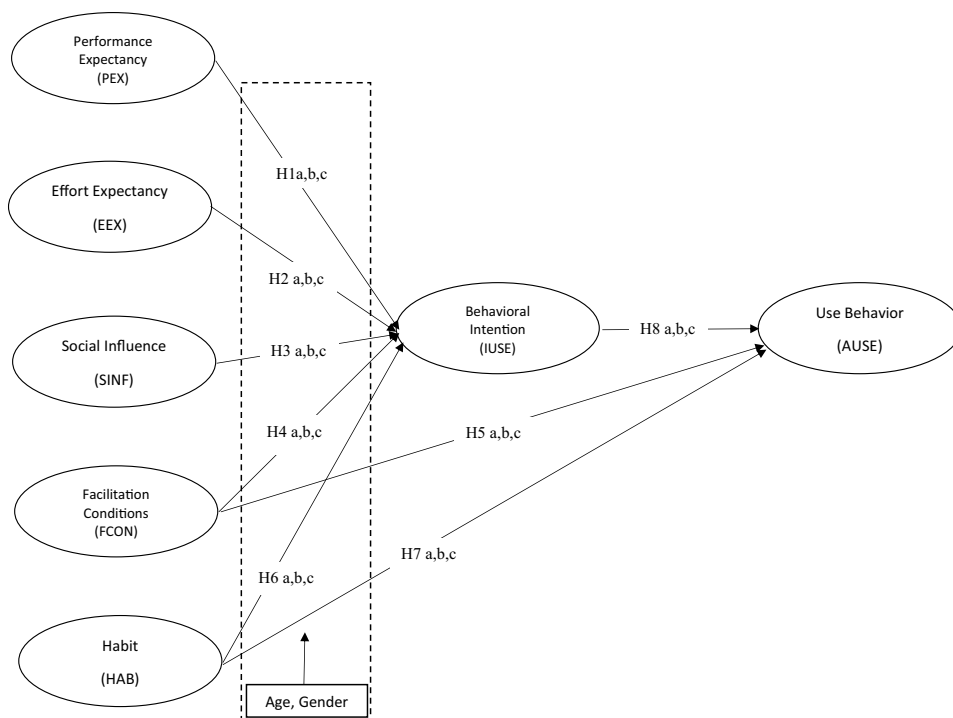
df $= 417$, x^2/df $= 5.731$, CFI $= 0.94$, TFI $= 0.929$, RMSEA $= 0.06$ (Kline 2016). To achieve an overall good model fit while performing the CFA, the moderating variable age was removed in all paths. Convergent validity is established by the following criteria; the factor loadings of items should be significant and should exceed 0.7; CR and Cronbach α should exceed 0.7; and the average variance extracted (AVE) of constructs should exceed 0.50 (Kline 2016). As shown in Table 2, convergent validity was confirmed as all factor loadings were greater than 0.70, AVE were 0.57 or greater, and all values of CR were 0.68 or greater. As shown in Table 3, the square roots of values of AVE were greater than corresponding squared correlation coefficients between the factors, confirming discriminate validity, except habit and social influence (Kline 2016).

Structural model and hypotheses testing

To test the study's hypotheses, SEM was utilized. The SEM results are shown in Table 5. First, the model was run without gender as a moderating variable, which generated a good model fit for Group 1 POSIS: $x^2 = 1491.63$, df $= 416$, $p = 0.0$, RMSEA $= 0.067$, TFI $= 0.91$, CFI $= 0.923$, Group 2 POSDS: $x^2 = 897.18$, df $= 416$, $p = 0.0$, RMSEA $= 0.068$, TFI $= 0.90$, CFI $= 0.912$, and Group 3 POSDH: $x^2 = 1092.55$, df $= 416$, $p = 0.0$, RMSEA $= 0.057$, TFI $= 0.94$, CFI $= 0.951$. Second, the model was run using gender as a moderating variable, which also generating a good model fit, specifically for Groups 1 and 3. The model fit for Group 1 POSIS: $x^2 = 2050.04$, df $= 832$, $p = 0.0$, RMSEA $= 0.051$,

TFI $= 0.90$, CFI $= 0.913$, Group 2 POSDS: $x^2 = 1660.44$, df $= 832$, $p = 0.0$, RMSEA $= 0.063$, TFI $= 0.829$, CFI $= 0.856$, and Group 3 POSDH: $x^2 = 1640.34$, df $= 832$, $p = 0.0$, RMSEA $= 0.044$, TFI $= 0.930$, CFI $= 0.941$. In addition, R^2 was checked for all responses in each group, as well as, in the gender multi-group. Results are in Table 4 showing both Group 2 POSDS and Group 3 POSDH's model accounted for more variance in behavioral intention. However, only Group 3 POSDH's model accounted for more variance in use behavior.

The model without gender as a moderating variable had the following results. For Group 1, performance expectancy ($\beta = 0.30$, $p < 0.001$) and habit ($\beta = 0.22$, $p < 0.05$) positively influenced intention to use mobile payment using PayPal and Venmo. However, effort expectancy, social influence, and facilitation conditions did not have significant influence on intention to use mobile payment using PayPal and Venmo. Habit ($\beta = 0.53$, $p < 0.001$) had a positive influence on actual use of PayPal and Venmo. For Group 2, performance expectancy ($\beta = 0.42$, $p < 0.05$) and effort expectancy ($\beta = 0.50$, $p < 0.01$), habit ($\beta = 0.44$, $p < 0.01$) had a positive influence on intention to use QR-based mobile pay such as Starbucks or Chick-fil-A. Social influence and facilitation conditions did not have a significant influence on intention to use. Habit ($\beta = 0.22$, $p < 0.05$) had a positive influence on actual use, where both facilitation conditions and intention to use did not. For Group 3, performance expectancy ($\beta = 0.64$, $p < 0.001$) and facilitating conditions ($\beta = 0.23$, $p < 0.01$) had a positive influence on intention to use NFC-based mobile payments such as Apple Pay and Samsung

Table 1 Demographics

	All ($n=1322$)	Group 1 ($n=571$)	Group 2 ($n=254$)	Group 3 ($n=498$)
Mean age	42.9	45.5	37.2	42.7
Gender (%)				
Female	74.2	78.8	67.2	72.4
Male	25.8	21.2	32.8	27.6
Race/ethnicity (%)				
White/Caucasian	69.6	73.2	55.9	72.5
Black/African American	16.5	14.7	24.8	14.3
Indigenous	1.0	0.5	1.6	1.2
Asian/Pacific Islander	3.5	2.8	5.1	3.4
Hispanic/Latino(a)	7.2	6.3	10.6	6.4
Multi-racial	2.1	2.5	2.0	1.8
Other	0.2	0.0	0.0	0.4
Education (%)				
Less than high school	2.9	2.1	3.2	3.6
High school graduate	29.8	26.3	34.0	31.8
Some college	27.6	28.5	28.9	26.0
2-Year degree	12.0	12.6	12.3	11.3
4-Year degree	18.6	21.2	16.6	16.7
Professional degree	8.0	8.2	4.7	9.3
Doctorate	1.1	1.1	0.4	1.4
Annual household income (%)				
Less than $10,000	9.2	7.7	14.6	8.2
$10,000–$19,999	11.3	10.7	10.6	12.3
$20,000–$29,999	15.2	14.9	13.4	16.3
$30,000–$39,999	13.2	12.1	11.4	15.3
$40,000–$49,999	11.6	11.8	12.2	11.1
$50,000–$59,999	10.8	10.5	11.8	10.5
$60,000–$69,999	6.4	7.0	5.1	6.4
$70,000–$79,999	5.4	5.8	5.9	4.6
$80,000–$89,999	2.7	3.0	2.8	2.4
$90,000–$99,999	3.4	3.0	4.3	3.4
$100,000–$149,999	7.4	8.8	6.3	6.4
More than $150,000	3.5	4.7	1.6	3.0
Operating system (%)				
Apple	39.1	39.2	44.5	36.3
Android	60.8	60.8	55.5	63.5
Other	0.1	0.0	0.0	0.2

Pay. Effort expectancy, social influence, and habit did not have a significant influence on intention to use. However, habit ($\beta=0.51$, $p<0.001$) had a positive influence on actual use of NFC-based mobile payments such as Apple Pay and Samsung Pay, where intention to use and facilitation conditions did not.

To test group difference between females and males, a multi-group SEM analysis was conducted for moderation. For Group 1, performance expectancy (females $\beta=0.28$, $p<0.01$; males $\beta=0.44$, $p<0.05$) and habit (females $\beta=0.20$, $p<0.05$; males $\beta=0.53$, $p=0.67$) had a positive

influence on intention to use PayPal and Venmo, where the moderation effect was stronger for females which supports H1a and H6a. Effort expectancy, social influence, and facilitation conditions did not have a significant influence on intention to use PayPal and Venmo, which rejects H2a, H3a, and H5a. Habit had a positive influence (females $\beta=0.51$, $p<0.001$; males $\beta=0.54$, $p<0.001$) on actual use of PayPal and Venmo, but not moderated by gender, which supports H7a but without moderation. Facilitation conditions and intention to use did not have a significant influence on actual use rejecting H5a and H8a.

Table 2 Measurement items and confirmatory factor analysis results

Construct	AVE	Composite reliability	Cronbach's α	Item	Loadings	t-value
Performance expectancy (PEX)	0.76	0.85	0.93	PEX1	0.85	120.37
				PEX2	0.88	128.35
				PEX3	0.88	122.42
				PEX4	0.88	130.38
Effort expectancy (EEX)	0.79	0.88	0.94	EEX1	0.88	136.46
				EEX2	0.91	139.83
				EEX3	0.89	138.11
				EEX4	0.87	137.14
Social influence (SINF)	0.61	0.68	0.86	SINF1	0.84	92.90
				SINF2	0.71	109.06
				SINF3	0.84	85.94
				SINF4	0.73	73.85
Facilitating conditions (FCON)	0.57	0.69	0.80	FCON1	0.74	145.80
				FCON2	0.76	137.75
				FCON3	0.77	143.46
Habit (HAB)	0.74	0.70	0.89	HAB1	0.80	84.01
				HAB2	0.90	64.47
				HAB3	0.89	68.87
Intention of use (IUSE)	0.85	0.88	0.95	IUSE1	0.91	102.09
				IUSE2	0.93	101.65
				IUSE3	0.93	108.82
				IUSE4	0.93	103.52

Table 3 Discriminant validity of measurement model

Latent variables	PEX	EEX	SINF	FCON	HAB	IUSE
PEX	*0.87*					
EEX	0.81	*0.89*				
SINF	0.66	0.54	*0.78*			
FCON	0.78	0.86	0.63	*0.76*		
HAB	0.54	0.47	0.86	0.475	*0.86*	
IUSE	0.80	−0.16	−0.22	0.06	0.25	*0.92*

PEX performance expectancy, *EEX* effort expectancy, *SINF* social influence, *FCON* facilitating conditions, *HAB* habit, *IUSE* intention to use. Italicized are the square root of AVE which correlations of constructs are compared

Italicized are the square root of AVE which correlations of constructs are compared

For Group 2, performance expectancy (females $\beta = 0.43$, $p = 0.17$; males $\beta = 1.00$, $p < 0.05$), effort expectancy (females $\beta = 0.59$, $p < 0.01$; males $\beta = -0.51$, $p = 0.48$), and habit (females $\beta = 0.22$, $p < 0.05$; males $\beta = 0.67$, $p = 0.07$) had positive influence on intention to use QR-based mobile pay, while the effect was stronger in males for performance expectancy and in females for effort expectancy and habit which supports H1b, H2b, and H6b. Social influence and facilitation conditions were not found to be significant rejecting H3b and H4b. Habit (females $\beta = 0.22$, $p = 0.10$; males $\beta = 0.38$, $p < 0.05$) and intention to use QR-based mobile pay (females $\beta = 0.15$, $p = 0.36$; males $\beta = 0.40$, $p < 0.05$) had a positive influence on actual use, while stronger in males, which supports H7b and H8b. Facilitating conditions was not significant rejecting H5b.

Finally, for Group 3, performance expectancy (females $\beta = 0.66$, $p < 0.001$; males $\beta = 0.61$, $p < 0.001$) had a positive influence on intention to use NFC-based mobile payments such as Apple Pay and Samsung Pay but gender did not have a moderating effect, therefore, supporting H1c without moderation. Facilitation conditions (females $\beta = 0.22$, $p < 0.001$; males $\beta = 0.37$, $p = 0.88$) had positive influence on

Table 4 Variation in behavioral intention and use behavior

	POS groups	Variable	R^2 (%)
1	POSIS: All	→ behavioral intention	24.6
	POSIS: Female		22.5
	POSIS: Male		38.4
2	POSDS: All		79.9
	POSDS: Female		84.3
	POSDS: Male		82.7
3	POSDH: All		78.4
	POSDH: Female		76.8
	POSDH: Male		82.7
1	POSIS: All	→ Use behavior	27.1
	POSIS: Female		26.3
	POSIS: Male		31.7
2	POSDS: All		22.9
	POSDS: Female		22.1
	POSDS: Male		29.2
3	POSDH: All		36.8
	POSDH: Female		35.8
	POSDH: Male		39.6

intention to use NFC-based mobile payments such as Apple Pay and Samsung Pay which was stronger in females, supporting H4c. Effort expectancy, social influence, and habit had no significant influence on intention to use, rejecting H2c, H3c, and H5c. Habit (females $\beta = 0.48$, $p < 0.001$; males $\beta = 0.38$, $p < 0.05$) had a positive influence on actual use of NFC mobile payments, which was stronger in females supporting H7c, but facilitation conditions and intention to use were found to have no significant influence rejecting H6c and H8c. Table 5 summarizes the SEM results with the hypotheses conclusions.

Discussion

With the endless options of mobile payment providers in the US, understanding the landscape is a necessity for businesses. This study aims to understand the usage intention and behavior of three mobile payment classifications using UTAUT2.

Table 5 SEM results

		All β	Female β	Male β	Conclusion
H1a: Performance expectancy	→ Intention to use mobile pay POSIS	0.30***	0.28**	0.44*	Supported
H1b: Performance expectancy	→ Intention to use mobile pay POSDS	0.42*	0.43	1.00*	Supported
H1c: Performance expectancy	→ Intention to use mobile pay POSDH	0.64***	0.66***	0.61***	Supported without moderation
H2a: Effort expectancy	→ Intention to use mobile pay POSIS	0.18	0.25	−0.56	Not supported
H2b: Effort expectancy	→ Intention to use mobile pay POSDS	0.50**	0.59**	−0.51	Supported
H2c: Effort expectancy	→ Intention to use mobile pay POSDH	−0.06	−0.09	−0.05	Not supported
H3a: Social influence	→ Intention to use mobile pay POSIS	−0.18	−0.17	−0.57	Not supported
H3b: Social influence	→ Intention to use mobile pay POSDS	−0.16	−0.54	−0.77	Not Supported
H3c: Social influence	→ Intention to use mobile pay POSDH	0.04	−0.14	−0.07	Not supported
H4a: Facilitation conditions	→ Intention to use mobile pay POSIS	−0.01	−0.06	0.80	Not Supported
H4b: Facilitation conditions	→ Intention to use mobile pay POSDS	−0.20	−0.20	0.60	Not supported
H4c: Facilitation conditions	→ Intention to use mobile pay POSDH	0.23**	0.22***	0.37	Supported
H5a: Facilitation conditions POSIS	→ Use Behavior	−0.04	−0.03	0.02	Not supported
H5b: Facilitation conditions POSDS	→ Use Behavior	−0.05	0.14	−0.28	Not supported
H5c: Facilitation conditions POSDH	→ Use Behavior	0.09	0.80	0.20	Not supported
H6a: Habit	→ Intention to use mobile pay POSIS	0.22*	0.20*	0.53	Supported
H6b: Habit	→ Intention to use mobile pay POSDS	0.44**	0.22*	0.67	Supported
H6c: Habit	→ Intention to use mobile pay POSDH	0.12	0.48	0.12	Not supported
H7a: Habit POSIS	→ Use Behavior	0.53***	0.51***	0.54***	Supported without moderation
H7b: Habit POSDS	→ Use Behavior	0.22*	0.22	0.38*	Supported
H7c: Habit POSDH	→ Use Behavior	0.51***	0.48***	0.38*	Supported
H8a: Intention to use mobile pay POSIS	→ Use Behavior	0.04	0.04	0.04	Not supported
H8b: Intention to use mobile pay POSDS	→ Use Behavior	0.33*	0.15	0.40*	Supported
H8c: Intention to use mobile pay POSDH	→ Use Behavior	0.06	0.11	−0.09	Not supported

* p<.05, ** p<.01, *** p<.001

Performance expectancy, effort expectancy, and social influence

Supporting previous research (Cao and Niu 2019; Zhou et al. 2020; Cabrera-Sánchez and Villarejo-Ramos 2020), performance expectancy had a direct impact on intention to use all mobile payment types, POSIS, POSDS, and POSDH. Additionally, the moderating influence of gender on performance expectancy was confirmed and found to be stronger for females for POSIS (e.g., PayPal, Venmo) but stronger for males for POSDS (Starbucks, Chick-fil-A). Thus, when the services of mobile payment providers such as PayPal, Venmo, Starbucks, Apple Pay, and Samsung Pay are considered useful to streamline and perform transactional demands, there is a greater intent to use.

Effort expectancy, in line with Ramírez-Correa et al. (2019) and Cabrera-Sánchez and Villarejo-Ramos (2020) was insignificant in its influence on intention to use POSIS and POSDH mobile payments. Consumers of mobile payment providers such as PayPal and Apple Pay may not find these payment systems effortless, but it did not affect their behavioral intention. POSDH payments such as Apple Pay and Samsung require effort on not only the consumers' part but also the retailer as well, since this is the only mobile payment that is hardware dependent. Therefore, both sides must work without hesitation for consumers to deem this payment method easy to use. Additionally, POSIS mobile payments such as PayPal and Venmo require consumers to set up an account for both their mobile device and laptops with each platform operating slightly different. Therefore, the insignificant findings may allude to consumer being unaffected by the complexity of mobile payments. Supporting previous research (Cao and Niu 2019; Zhou et al. 2020), effort expectancy did impact POSDS mobile payments. POSDS such as Starbucks, Chick-fil-A, McDonalds requires consumers to download each providers' mobile app, enter their card information, and keep the app and card information up to date. However, consumers find these mobile payment types easy to use, thus, proving the growing familiarity with mobile apps usage in the US.

Surprisingly, contrary to the findings of Cao and Niu (2019), Oliveira et al. (2016), and Morosan and DeFranco (2016), social influence did not impact intention to use any of the mobile payment types, POSIS, POSDS, and POSDH. If family and friends do not find value in mobile payments, they may be less likely to affect a consumer's usage. For instance, consumers may not find value in the loyalty incentives of payments such as Starbucks or Chick-fil-A. Additionally because POSDH payments are split between two operating systems, Apple vs. Samsung, the friends, and family a consumer deems important may not have the same operating system; thus, their influence is lost. Therefore, mobile payments might lack other value

added features taking away friends and family impact on consumers' intention to use.

Facilitating conditions, habit, and intention to use

Facilitating conditions were found to have a mixed effect, significant over intention to use POSDH mobile payments but not for POSIS or POSDS mobile payments. Gender was confirmed to moderate intention to use POSDH mobile payments and was found stronger for females. Several studies have found significant results over intention (Morosan and DeFranco 2016; Zhou et al. 2020; Cabrera-Sánchez and Villarejo-Ramos 2020) and some have not (Oliveira et al. 2016; Baptista and Oliveira 2015, 2017; Ramírez-Correa et al. 2019). This insignificant finding may be due to the lack of, or hard to find, support features on POSDS and POSIS (e.g., Starbucks, PayPal) mobile payments. In addition, POSDS mobile payments are provider specific; thus, consumers may not deem it necessary to learn or fix issues within the payment feature when the product price is low. POSIS mobile payments have to be set up by the consumer, and in comparison, to other payment options the setup is not as intuitive. Additionally, consumers may not find the resources easy to use when gaining an understanding of the payment system.

Contrary to previous findings (Zhou et al. 2020; Cabrera-Sánchez and Villarejo-Ramos 2020; Baptista and Oliveira 2017) but in line with Baptista and Oliveira (2015) and Ramírez-Correa et al. (2019) facilitating conditions had no influence on use behavior. The switching cost of mobile payments in the US is relatively low due to the number of mobile payment options as well as consumers dependency on credit/debit cards; therefore, if help/support resources are needed, consumers are less likely to utilize their mobile payment and instead use a payment method they are more familiar with.

Supporting the works of Baptista and Oliveira (2017) and Morosan and DeFranco (2016), habit impacted intention to use POSIS and POSDS mobile payments but not POSDH mobile payments. The moderating influence of gender on habit was confirmed and found to be stronger for females. Intention to use POSDH mobile payments was not impacted by habit. Not only mobile payments such as Apple Pay and Samsung require the consumer to have this payment method enabled on their phone, but also the business's POS system must be enabled to read NFC transactions. If a business establishment does not have their POS activated to accept the POSDH payment method or the sales associate is not knowledge, the consumers may find it difficult to use, thus, voiding habit formation.

Habit also influenced consumers' actual usage of mobile payments for all three payment types which support the findings of Baptista and Oliveira (2015). In addition, gender

moderated the relationship to actual usage but only for POSDS and POSDH with males pulling stronger for POSDS and females for POSDH. Therefore, the more likely a consumer is to form a habit with their mobile payment of choice, the more likely it will impact their actual usage behavior.

Contrary to the findings of Venkatesh et al. (2012), intention to use (POSIS and POSDH) did not influence use behavior except for POSDS mobile payments. Because the primary providers of POSDS mobile payments in the US are based in the food industry, consumers may see the advantage of their usefulness in the market where the purchase price and potential are relatively low. Additionally, the usage of the payment features is often incentivized by rewards; however, there is no incentivization to use POSIS or POSDH (PayPal, Apple Pay, etc.).

Theoretical implications

Our results revealed that the UTAUT model for each type of mobile payment has good explanatory power in predicting consumer intention to use and their actual usage behavior. Compared with other studies exploring the behavioral intentions of mobile payments, our study with 79.9% for POSDS and 78.4% for POSDH presents a stronger predictive power than similar studies, such as Oliveira et al. (2016) with 61.3%. This provides a foundation for refinement of individual models of usage intention. Direct and indirect effects of the determinants were analyzed with the most important ones identified as performance expectancy and habit. Facilitating conditions were not considered relevant to influence actual usage in any of the mobile payment types. The findings confirm the importance of analyzing mobile payment by types as their determinants differ greatly.

Practical implications

The study provides critical implications for retailers and apparel businesses who operate or plan to operate mobile payments. Currently retailers and mobile pay providers are not fully servicing the customer and could improve in many areas. POSIS and POSDH providers such as PayPal, Venmo, Apple Pay, and Samsung Pay should improve their payment systems so that consumer finds them easy to use and effortless. Recently, with PayPal's launching of a QR-code-based payment, it appears that there are some attempts at improving in this area. Furthermore, all mobile payment types lacked any impact from social influence. Retailers and mobile payment providers should consider using social media influencers to help sway the usage of mobile payments for all payment types while showcasing the benefits and usefulness of their platform. In conjunction with influencer collaboration, retailers should use signage near the point-of-sales system to educate consumers on how to use and the benefits of usage.

Furthermore, with the exception of mobile payment providers such as Apple Pay and Samsung Pay, support and resources for using mobile payment systems were lacking. Providers such as Pay Pal, Venmo, and QR-based mobile payment system need to revamp their customer service and support by adding more features to access customer service as well as making it easy to find within the platform's interface.

Moreover, small businesses especially for apparel have limited financial resources to offer a variety of mobile payments to their consumer. For small business owners who have yet to embark in the mobile pay environment, they should consider using POSDS mobile payments. This QR-based mobile payment was the only payment type that led to actual usage behavior. Additionally, consumers found this mobile payment to be useful and easy to use, and habit formation increased the likelihood of actual use.

Lastly, males found QR-based mobile payment e.g., Starbucks more useful, easy to use, and formed habits stronger in comparison to women. Currently, the biggest providers of these types of payments are in the food industry. Women are not seeing all of the advantage in this market where the purchase price is relatively low. However, if small apparel businesses would increase their usage of QR-based mobile payments, it may be more appealing for women. Thus, these providers should target the market of working women and women with children to increase their perception of QR-based mobile payments.

Limitations and future research

As with any research, there were limitations in the study; however, this leads to future research. First, in previous research, age had been on moderating variable in UTAUT2 model (Venkatesh et al. 2012; Baptista and Oliveira 2017). However, in the initial CFA modeling, age was found to have no moderating effect and the SEM model did not fit with age. One factor could be that the total sample had to be divided between three groups, affecting the group sizes, and SEM is sensitive to small sample sizes (Kline 2015). However, there could be other variables for mobile payment solutions that were not considered in this model, therefore, leading to the suggestion of future researchers considering new variables in the UTAUT2 model.

Second, Group 2, QR-code-based payment, was the smallest sample size with a total of 254 with 170 females and 83 males. Again, SEM is sensitive to smaller sample sizes. Although the model fit was fair, with additional sampling, further relationships may be found. Group 2 was a unique group, especially with males. Further research into how

QR-code-based payment is reaching males and not females could be both theoretically and practically important.

Future research should modify the model in order to include new variables and moderators, such as experience, ethnicity and culture, residence area (city vs. rural), and purchase price range. Additionally, as QR payments continue to rise, future research should look at the market potential for POSDS mobile payments. Because of the plethora of mobile payment options in the US, future research should concentrate on small business's navigation of the mobile pay environment focusing on their adoption and usage. Finally, future research should take a longitudinal approach to mobile payment usage in light of behavioral changes in consumers and retailers brought forth by the COVID 19-pandemic.

Declarations

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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