eISSN: 2408-1906© 2020 JIR.
https://assumptionjournal.au.edu/index.php/eJIR/index

A Study on Behavioral Intention and Use Behavior Toward Mobile Payment Among University Students in Nanning, China

Zehua Tang*

Received: February 25, 2025. Revised: March 27, 2025. Accepted: April 16, 2025.

Abstract

Purpose: The study examines key factors influencing behavioral intention and actual use of mobile payment services among university students in Nanning, China. The proposed framework explores the relationships among Social Influence (SI), Effort Expectancy (EE), Trust (TS), Perceived Usefulness (PU), Perceived Risk (PR), Habit (HB), Behavioral Intention (BI), and Use Behavior (UB). **Research design, data and methodology:** The researcher conducted a questionnaire survey among 500 university students in Nanning, China. Participants were purposefully selected from four main colleges of Guangxi University, following stratified random sampling guidelines. Data were collected online using a convenience sampling approach. For analysis, CFA and SEM were applied to evaluate model fit, reliability, and structural validity. **Results:** The findings indicate that social influence, effort expectancy, trust, perceived usefulness, perceived risk, and habit significantly affect behavioral intention. Behavioral intention, in turn, strongly influences use behavior. Among these factors, perceived usefulness had the greatest impact on behavioral intention, followed by trust and social influence. **Conclusions:** The statistical results supported all seven research hypotheses, confirming that the study successfully met its objectives. To enhance mobile payment adoption, policymakers and service providers should prioritize key influencing factors and implement effective optimization strategies.

Keywords: Mobile Payments, Perceived Usefulness Behavioral Intention, Use Behavior, Higher Education

JEL Classification Code: A22, I23, L86, O30

1. Introduction

Mobile payment enables users to conduct financial transactions via mobile devices through secure communication channels (Qasim & Abu-Shanab, 2015). According to a Boston Consulting Group (BCG) report, global mobile payment revenue is projected to grow by 7.3% from 2020 to 2025, reaching $2.9 trillion by 2030. Popular methods include e-wallets, near-field communication (NFC), and quick response (QR) codes (Karjaluoto et al., 2019). Mobile payments offer convenience for online shopping (Mukherjee & Roy, 2017) and everyday transactions (Rastogi et al., 2021). Data from the China Business Industry Research Institute show a rising trend in mobile payment adoption, with users aged 25 and below relying on it for over 98% of their total consumption. Deng and Lu (2017) argue that mobile payment has become essential for daily transactions, including utility bills and public transport.

China leads the global mobile payment market (Chen & Wang, 2021), with Alipay and WeChat Pay dominating due to their convenience, security, and broad application. Mobile payments cover food services, transportation, and daily expenses (Smith & Chen, 2015). Studies suggest that mobile payments encourage higher consumer spending (Falk et al., 2016) and provide retailers with valuable consumer insights for targeted marketing (Singh et al., 2020). Despite its advantages, some users remain hesitant. Limited acceptance and trust (Oliveira et al., 2016), security concerns (Singh et al., 2020), phishing threats, and fraud risks (Ha, 2020) hinder adoption. Users expect mobile payments to be simple, time-saving, and secure (Hossain &

[1]*Zehua Tang, Innovative Technology Management, Graduate School of Business and Advanced Technology Management, Assumption University, Bangkok, Thailand. Email : 573067923@qq.com

Mahmud, 2016). Adoption depends on technology maturity, market promotion, and user habit formation (Haritha, 2022). Mulia (2019) noted that reluctance to embrace new technology can lead to abandonment of mobile payment usage.

Although prior studies have applied theoretical models such as the Technology Acceptance Model (TAM) (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2012) to understand technology adoption, there remains a notable research gap concerning how these models apply specifically to university students in regional Chinese contexts like Guangxi. Few studies have holistically examined the combined influence of trust, habit, perceived risk, and social influence in this demographic, despite their growing role as key contributors to the digital economy.

This study addresses that gap by examining the behavioral drivers of mobile payment adoption among university students at Guangxi University, integrating constructs such as social influence, effort expectancy, trust, perceived usefulness, perceived risk, and habit, along with behavioral intention and actual usage behavior. Understanding these factors is crucial, as students represent both early adopters of technology and future economic participants. The research aims to identify the key variables influencing their behavioral intention and real-world usage of mobile payment systems. By doing so, it seeks to provide actionable insights for service providers, app developers, and policymakers to design more effective, secure, and user-centered mobile payment solutions. Ultimately, this study contributes to the enhancement of mobile payment adoption and retention strategies, supporting the long-term growth and innovation of the mobile financial services industry.

2. Literature Review

2.1 Factors Impacting on Behavioral Intention and Use Behavior

Use behavior refers to the actual adoption and application of mobile payment technology (Palash et al., 2022). Upadhyay et al. (2022) noted that it includes payments and transfers. Li et al. (2011) described it as the consumer's mode of conducting transactions across different settings. Zhou et al. (2010) outlined the process from initial awareness to habitual use. Pal et al. (2021) found that use behavior is strongly influenced by perceived usefulness, habit, and trust. Yu (2012) emphasized its role in assessing mobile payment adoption and market potential.

Sobti (2019) identified social influence as a key determinant of mobile payment adoption, emphasizing the impact of others' opinions and behaviors. Qasim and Abu-Shanab (2015) defined social influence as the extent to which a person's social environment affects their likelihood of using mobile payments. Chen et al. (2019) elaborated that perceived pressure from others can drive adoption. Baishya and Samalia (2019) described it as the importance consumers place on technology based on peer opinions, while Koenig-Lewis et al. (2015) noted that people adjust their behavior to align with social expectations. Venkatesh et al. (2012) highlighted the influence of social networks on individual behavior.

Kasri and Yuniar (2021) defined effort expectancy as the ease of learning and using mobile payments. Tossy (2014) stated that it includes operational simplicity, such as downloading, installing, and setting up payment credentials. Lower complexity increases effort expectancy, making mobile payments more appealing (Chopdar & Sivakumar, 2018). Venkatesh et al. (2003) found that effort expectancy positively impacts behavioral intention, as users prefer simple, efficient payment systems (Musyaffi et al., 2021).

Trust is crucial in mobile payment adoption (Chauhan, 2015). Lu et al. (2011) described trust as confidence in meeting one's needs, while Upadhyay et al. (2021) emphasized its role in early adoption. Palash et al. (2022) defined trust as users' perception of security and reliability. Khalilzadeh et al. (2017) suggested trust positively influences adoption, and Shi and Chow (2015) stressed that building trust is vital for long-term user retention.

Davis (1989) described perceived usefulness as the belief that mobile payments improve usability and efficiency. Venkatesh et al. (2003) linked it to enhanced performance in transactions. Palash et al. (2022) defined it as the degree to which technology adoption enhances daily efficiency. Kim et al. (2010) found that perceived usefulness influences intention, while Tan et al. (2014) identified it as a key factor in adoption.

Perceived risk encompasses concerns about security, privacy, and financial losses (Alalwan, 2020). Choi (2018) defined it as consumers' perception of uncertainties in mobile payments. Baptista and Oliveira (2016) highlighted financial, time, and psychological risks affecting adoption. Slade et al. (2015) found that security concerns significantly impact remote payment acceptance, while Schierz et al. (2010) confirmed its role in adoption decisions.

Habit plays a significant role in mobile payment usage (Upadhyay et al., 2022). Palash et al. (2022) described it as an unconscious behavioral predisposition. Choi (2018) linked habit to repeated practice and effortless engagement. Baptista and Oliveira (2015) found that habit influences intention and behavior, while Alalwan (2020) highlighted its impact on decision-making.

Behavioral intention reflects a user's likelihood of adopting mobile payments (Zhao & Bacao, 2021). Upadhyay et al. (2022) described it as a deliberate intention to use the technology. Negm (2023) emphasized commitment and purpose in adoption decisions. Venkatesh et al. (2012) linked behavioral intention to actual use, while Gefen et al. (2003) confirmed the influence of social influence and trust. Understanding behavioral intention helps identify adoption barriers and incentives (Negm, 2023).

2.2 Research Hypothesis and Relationship between Variables

2.2.1 Relation between Social Influence and Behavioral Intention

Research by Venkatesh et al. (2003) demonstrated that social influence significantly shapes behavioral intention toward adopting new technologies. Oliveira et al. (2016) emphasized its critical role in influencing users' adoption decisions. Pham and Ho (2015) suggested that individuals tend to follow a herd mentality when mobile payments become widely adopted within their social circles. Tossy (2014) identified social influence as a key driver of mobile payment adoption.

Shin and Lee (2014) highlighted social influence as an essential factor in mobile payment uptake. Dahlberg et al. (2015) found that young users' behavioral intention is particularly affected by social influence. Alalwan et al. (2017) provided evidence that expectations and recommendations from significant others strongly impact users' willingness to adopt mobile payment systems. Slade et al. (2015) confirmed that social influence is a strong predictor of behavioral intention in mobile payment adoption. Yang et al. (2021) noted that theoretical frameworks exploring social influence continue to show significant effects on behavioral intention. Numerous studies validate the strong relationship between social influence and behavioral intention, reinforcing its critical role in technology adoption. This assertion is elaborated in the following hypothesis:

H1: Social influence has a significant impact on behavioral intention.

2.2.2 Relation between Effort Expectancy and Behavioral Intention

Venkatesh et al. (2003) found that effort expectancy positively influences technology adoption. Li et al. (2017) suggested that ease of use enhances users' intention to adopt mobile payment platforms. Palash et al. (2022) confirmed that the simplicity of mobile payment apps significantly improves effort expectancy. Hew et al. (2016) validated effort expectancy as a key factor in mobile wallet adoption.

Chen (2008) identified effort expectancy as a critical component of mobile payment acceptance. Kim et al. (2010) emphasized its role in technology adoption, working alongside performance expectancy, social influence, and facilitating conditions to shape behavioral intention. Pavlou and Fygenson (2006) further validated its significant impact. However, Liu and Zhang (2022) found a negative relationship between effort expectancy and behavioral intention. Venkatesh et al. (2003) established effort expectancy as a fundamental factor in the UTAUT model, which was later extended by Venkatesh et al. (2012), reaffirming its influence on mobile payment adoption. This assertion is elaborated in the following hypothesis:

H2: Effort expectancy has a significant impact on behavioral intention.

2.2.3 Relation between Trust and Behavioral Intention

Alalwan et al. (2017) emphasized the importance of establishing trust before consumers adopt mobile payments, highlighting its role in ensuring long-term confidence in security. Anggraini and Rachmawati (2019) identified trust as a key predictor of behavioral intention, while Kim et al. (2008) demonstrated that trust fosters word-of-mouth and positive adoption behavior. Alyabes and Alsalloum (2018) confirmed that trust drives both initial adoption and continued use, shaping a positive mobile payment experience.

Dahlberg et al. (2015) recognized trust as a major factor influencing behavioral intention toward mobile payments. Baptista and Oliveira (2016) found that users' willingness to adopt technology depends on their level of trust. Choi et al. (2018) and Oliveira et al. (2016) both highlighted that higher trust levels significantly enhance consumers' intention to use mobile payments by alleviating concerns about potential risks. Slade et al. (2015) suggested that trust enhances users' confidence in technology performance. Yang et al. (2012) and Thakur (2013) emphasized trust's crucial role in shaping behavioral intention, particularly among professionals. Tran and Corner (2016) further noted that trust levels evolve over time based on user experience. This assertion is elaborated in the following hypothesis:

H3: Trust has a significant impact on behavioral intention.

2.2.4 Relation between Perceived Usefulness and Behavioral Intention

Perceived utility plays a key role in influencing behavioral intention to adopt technology. Choi et al. (2018) found a strong positive correlation between perceived usefulness and the intention to adopt technological applications. Chawla and Joshi (2019) identified perceived utility as a primary driver of mobile payment adoption, while Shin (2009) noted that consumers who find mobile payments useful are more likely to integrate them into daily activities.

Baptista and Oliveira (2015) confirmed that perceived usefulness significantly impacts mobile payment adoption. Gao and Waechter (2015) emphasized its central role in shaping behavioral intention. Oliveira et al. (2016) highlighted perceived usefulness as an essential component of expected utility, positively influencing users' willingness to adopt mobile payments. Slade et al. (2015) further reinforced its importance in driving adoption. Thakur (2013) found that professionals' inclination to use mobile payments is strongly influenced by perceived utility, underscoring its appeal in professional settings. Zhou (2014) also demonstrated that users with higher perceived utility are more likely to adopt mobile payments, especially if they believe it enhances convenience and saves time. This assertion is elaborated in the following hypothesis:

H4: Perceived usefulness has a significant impact on behavioral intention.

2.2.5 Relation between Perceived Risk and Behavioral Intention

Alyabes and Alsalloum (2018) and Pham and Ho (2015) identified perceived risk as a crucial factor affecting consumers' willingness to adopt mobile payments. Thakur (2013) highlighted its significance, particularly among professionals. Shin (2009) found that confidence in financial institutions reduces perceived risk, increasing users' inclination to accept mobile payments.

Kim et al. (2010) noted that security concerns and transaction costs influence users' behavioral intentions. Venkatesh et al. (2012) suggested that when users perceive mobile payments as efficient and reliable, their perceived risk decreases, leading to higher adoption rates. Lee (2009) emphasized that biometric authentication and encryption can significantly lower perceived risk and enhance usage intention. Slade et al. (2015) further confirmed its impact on mobile payment adoption. Pavlou and Fygenson (2006) demonstrated that perceived risk negatively affects behavioral intention. Luarn and Lin (2005) proposed that a strong brand image, quality customer service, and transparent transactions help mitigate risk. Chawla and Joshi (2019) reinforced that reducing perceived risk is essential for increasing users' intention to adopt mobile payments. This assertion is elaborated in the following hypothesis:

H5: Perceived risk has a significant impact on behavioral intention.

2.2.6 Relation between Habit and Behavioral Intention

Choi (2018) found that habit not only strengthens users' behavioral intention toward mobile payments but also increases actual use behavior. Sinha et al. (2019) noted that as mobile payments become more convenient, habitual use lowers associated costs, further encouraging adoption. Oliveira et al. (2016) identified habit as a key factor influencing users' inclination to adopt mobile payments. Limayem et al. (2007) suggested that habit enhances ease and comfort, increasing users' willingness to use mobile payment services.

Wood and Neal (2007) and Slade et al. (2015) confirmed that habit plays a crucial role in shaping behavioral intentions. Baptista and Oliveira (2015), Gao and Waechter (2015), and Chawla and Joshi (2019) all reinforced that habit significantly impacts users' intention to adopt mobile payments.

Li and Zhang (2020) emphasized that once users develop the habit of using mobile payments, their intention to continue using them strengthens. Aarts and Dijksterhuis (2001) demonstrated that specific payment environments, such as malls or online shopping, trigger habitual mobile payment use. Chen and Wang (2021) further confirmed a strong positive correlation between habit and mobile payment behavior, underscoring its significant influence on behavioral intention. This assertion is elaborated in the following hypothesis:

H6: Habit has a significant impact on behavioral intention.

2.2.6 Relation between Behavioral intention and use behavior

Lin et al. (2020) proposed that behavioral intention is a key predictor of actual use behavior in mobile payments, with stronger intentions increasing the likelihood of usage. Sinha and Singh (2022) confirmed that positive attitudes and intentions toward mobile payments translate into actual use. Sobti (2019) also identified behavioral intention as an effective indicator of mobile payment adoption. Kim et al. (2010) found that promotions and incentives, such as coupons and rewards, enhance behavioral intention, which in turn drives actual use.

Kumari and Biswas (2023) noted that users who perceive high value in mobile payments are more likely to use them after forming strong behavioral intentions. Shin and Lee (2021) emphasized that technological advancements and improved user experiences strengthen behavioral intention, leading to higher adoption rates. Makanyeza and Mutambayashata (2018) highlighted the link between habit formation, behavioral intention, and actual use, suggesting that cultivating user habits fosters long-term adoption.

Istijanto and Handoko (2022) argued that behavioral intention directly precedes use behavior, with strong intentions increasing the likelihood of adoption. Esawe (2022) reinforced that behavioral intention is the primary driver of mobile payment usage. Lu et al. (2011) described behavioral intention as a key predictor of future use trends and mobile payment system development. Alalwan et al. (2017) and Upadhyay et al. (2022) confirmed that behavioral intention plays a critical role in forecasting and shaping actual use behavior in mobile payments. This assertion is elaborated in the following hypothesis:

H7: Behavioral intention has a significant impact on use behavior.

3. Research Methods and Materials

3.1 Research Framework

The following theoretical foundations form the basis of the conceptual framework in this study: the Technology Acceptance Model (TAM) by Davis (1986), the Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh et al. (2003), and the Theory of Planned Behavior (TPB) by Hsu and Chiu (2004). These frameworks serve as the foundation for analysis. Based on these theories, the researcher developed a conceptual framework for the study, as illustrated in Figure 1.

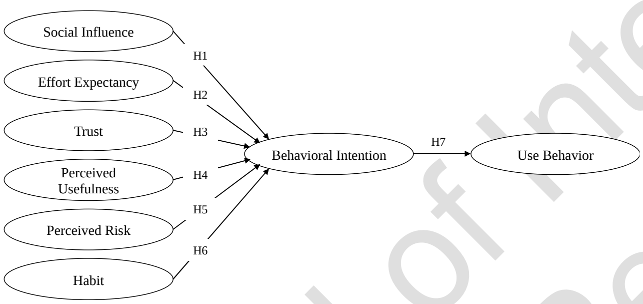

Figure 1: Conceptual Framework

This study aimed to investigate the factors influencing the behavioral intention and usage patterns of university students in Nanning, China, regarding mobile payment. The variables examined included social influence (SI), effort expectancy (EE), trust (TS), perceived usefulness (PU), perceived risk (PR), habit (HB), behavioral intention (BI), and use behavior (UB). The study analyzed the relationships among these variables to identify key determinants of mobile payment adoption among university students.

3.2. Research Methodology

This research employed a quantitative analysis method, utilizing a questionnaire as the primary tool for data collection. The researcher administered the questionnaire to university students in Nanning, China, selecting participants from four colleges of Guangxi University through purposive sampling. The sample size was determined using stratified random sampling parameters, while the actual distribution of questionnaires was conducted online via convenience sampling. The collected data were analyzed to identify the factors influencing students' behavioral intention and usage of mobile payment systems.

The research instrument—a structured questionnaire—consisted of three main sections: (1) screening questions to qualify respondents, (2) a 5-point Likert scale measuring variables related to the study's seven hypotheses, and (3) demographic information. To ensure the instrument's validity and reliability, several steps were taken. A pilot test involving 30 participants was conducted prior to the main survey. Reliability was assessed using Cronbach's Alpha, with all coefficient values exceeding the acceptable threshold of 0.6 (Sekaran, 1992). In addition, expert evaluations were used to assess item-objective consistency (IOC), and all dimensions achieved IOC scores above the standard threshold of 0.67, indicating acceptable content validity (Rovinelli & Hambleton, 1976).

Following the pilot phase, a total of 500 completed questionnaires were collected. Data analysis was performed using SPSS AMOS, employing structural equation modeling (SEM) and confirmatory factor analysis (CFA) to evaluate construct validity, reliability, and overall model fit. These analytical methods confirmed the suitability and robustness of the conceptual framework used in this study.

3.3 Population and Sample Size

Purposive sampling was used to select participants from four main colleges of Guangxi University, while stratified random sampling criteria determined the sample size. Data were collected through convenience sampling.

From July to December 2024, the researcher conducted a questionnaire survey. A data screening process ensured that the target population—students from Guangxi University's four major colleges with experience using mobile payments—was appropriate. Teachers from these colleges supported and encouraged student participation in the online survey. Table 1 presents the specific sampling details of this study.

Table 1: Sample Size Distributed to College Students

College	Population Size	Proportional Sample Size
Electrical Engineering College	2,005	135
Civil Engineering College	1,871	126
Resources, Environment and Materials College	1,861	125
Computer and Electronic Information College	1,694	114
Total	**7,431**	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Profile

This study collected 500 valid questionnaires from undergraduate students in the four major colleges of Guangxi University. The respondents included 153 males (30.6%) and 347 females (69.4%). Age distribution was as follows: 355 students (71.0%) were aged 19–21, 132 (26.4%) were 22–23, and 13 (2.6%) were over 23 years old. All participants were undergraduate students. Regarding monthly expenses, 51 students (10.2%) spent less than 1,000 yuan, 371 (74.2%) spent 1,001–2,000 yuan, 61 (12.2%) spent 2,001–3,000 yuan, and 17 (3.4%) spent more than 3,000 yuan. In terms of preferred mobile payment methods, 103 respondents (20.6%) used Alipay, 378 (75.6%) used WeChat Pay, 12 (2.4%) used Cloud Flash Pay, and 7 (1.4%) used China Union Pay.

A summary of the study participants' demographic details is presented in Table 2.

Table 2: Demographic Characteristics of Respondents

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	153	30.6
	Female	347	69.4
Age	19-21 years old	355	71.0
	22-23 years old	132	26.4
	more than 23 years old	13	2.6
Monthly Expenses	Less than 1,000 yuan	51	10.2
	1,001-2,000 yuan	371	74.2
	2,001-3,000 yuan	61	12.2
	More than 3,000 yuan	17	3.4
Most Common MPS Method	Ali-pay	103	20.6
	WeChat-pay	378	75.6
	Cloud Quick pay	12	2.4
	China Union pay	7	1.4

Source: Constructed by author

4.2 Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis (CFA) was conducted to evaluate each variable in the conceptual framework. The analysis confirmed that all scale items corresponding to each variable were statistically significant.

The results showed that all Composite Reliability (CR) values exceeded 0.8, Average Variance Extracted (AVE) values were above 0.5, and Cronbach's Alpha (CA) values were above 0.8. The factor loading values for all items ranged from 0.705 to 0.856, indicating strong correlations between observed variables and their respective latent constructs. This suggests that the indicators used effectively represent their underlying theoretical constructs. These findings confirmed the validity and reliability of the conceptual framework. A summary of these values is presented in Table 3.

Convergent and discriminant validity were confirmed in with all values deemed acceptable. These measurements collectively validate the structural model used in this study.

Table 3: Confirmatory Factor Analysis (CFA), Composite Reliability (CR), and Average Variance Extracted (AVE) Results

Variable	Source of Questionnaire (Measurement Indicator)	No. of Item	Cronbach's Alpha	Factor Loading	CR	AVE
Social Influence (SI)	Esawe (2022)	5	0.879	0.735-0.801	0.879	0.594
Effort Expectancy (EE)	Sobti (2019)	4	0.868	0.743-0.847	0.869	0.624
Trust (TS)	Chawla and Joshi (2019)	4	0.859	0.741-0.794	0.859	0.604
Perceived Usefulness (PU)	Phonthanukitithaworn et al. (2016)	3	0.855	0.779-0.856	0.856	0.664
Perceived Risk (PR)	Sobti (2019)	4	0.871	0.756-0.823	0.871	0.628
Habit (HB)	Gupta and Arora (2019)	4	0.869	0.738-0.813	0.869	0.625
Behavioral Intention (BI)	Shah and Khanna (2023)	4	0.854	0.732-0.807	0.854	0.594
Use Behavior (UB)	Dahlberg et al. (2015)	3	0.831	0.705-0.834	0.833	0.626

Note: CR = Composite Reliability, AVE = Average Variance Extracted

Model fit was assessed using several fit indices, including the chi-square ratio with degrees of freedom (CMIN/DF), Goodness-of-Fit Index (GFI), Adjusted Goodness-of-Fit Index (AGFI), Normalized Fit Index (NFI), Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), and Root Mean Square Error of Approximation (RMSEA).

Table 4: Goodness of Fit for Measurement Model

Index	Criterion	Statistical Value
CMIN/DF	< 3.00 (Hair et al., 2006)	1.195
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.942
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.929
NFI	≥ 0.80 (Wu & Wang, 2006)	0.942
CFI	≥ 0.80 (Bentler, 1990)	0.990
TLI	≥ 0.80 (Sharma et al., 2005)	0.988
RMSEA	< 0.08 (Pedroso et al., 2016)	0.020

Note: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, NFI = normalized fit index, CFI = comparative fit index, TLI = Tucker Lewis index and RMSEA = root mean square error of approximation

To assess the relationships between variables, the square root of the AVE was compared with the correlation coefficients. As presented in Table 5, all variables demonstrated correlations within an acceptable range, as confirmed by the square root of the AVE values.

Table 5: Discriminant Validity

Variable	Factor Correlations							
	SI	EE	TS	PU	PR	HB	BI	UB
SI	**0.771**							
EE	0.440	**0.790**						
TS	0.315	0.265	**0.777**					
PU	0.286	0.249	0.425	**0.815**				
PR	0.270	0.227	0.309	0.363	**0.792**			
HB	0.319	0.237	0.269	0.290	0.390	**0.791**		
BI	0.312	0.278	0.353	0.396	0.301	0.289	**0.771**	
UB	0.318	0.260	0.232	0.306	0.221	0.327	0.381	**0.791**

Note: The diagonally listed value is the AVE square roots of the variables

4.3 Structural Equation Model (SEM)

Hair et al. (2006) recommended that a CMIN/DF value below 3 indicates a good model fit, reflecting a strong alignment between the model and the data. Sica and Ghisi (2007) stated that an acceptable GFI should be ≥ 0.85, while AGFI should be ≥ 0.80. Wu and Wang (2006) suggested that NFI should meet or exceed 0.80, and Bentler (1990) proposed that CFI should also be ≥ 0.80. Sharma et al. (2005) recommended a TLI value of 0.80 or higher, while Pedroso et al. (2016) indicated that RMSEA should be < 0.08 for an acceptable model fit.

Using SPSS AMOS, the researchers evaluated the structural equation modeling (SEM) fit. The results confirmed a good model fit with the following indices: CMIN/DF = 2.460, GFI = 0.856, AGFI = 0.832, NFI = 0.873, CFI = 0.920, TLI = 0.913, RMSEA = 0.054. These values are presented in Table 6.

Table 6: Goodness of Fit for Structural Model

Index	Criterion	Statistical Value
CMIN/DF	< 3.00 (Hair et al., 2006)	2.460
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.856
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.832
NFI	≥ 0.80 (Wu & Wang, 2006)	0.873
CFI	≥ 0.80 (Bentler, 1990)	0.920
TLI	≥ 0.80 (Sharma et al., 2005)	0.913
RMSEA	< 0.08 (Pedroso et al., 2016)	0.054

Note: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, NFI = normalized fit index, CFI = comparative fit index, TLI = Tucker Lewis index and RMSEA = root mean square error of approximation

4.4 Research Hypothesis Testing Result

Regression weights and R^2 variances were analyzed to assess the significance of the relationships within the conceptual model. The results, summarized in Table 7, confirmed support for all seven proposed hypotheses. Each factor demonstrated a statistically significant influence (p-value < 0.05), validating the model's predictive capability regarding behavioral intention and use behavior in mobile payment adoption among university students.

Table 7: Hypothesis Testing Result

Hypothesis	Standardized path coefficients (β)	t-value	Test Result
H1: SI → BI	0.160	3.242*	Supported
H2: EE → BI	0.131	2.648*	Supported
H3: TS → BI	0.196	3.890*	Supported
H4: PU → BI	0.280	5.456*	Supported
H5: PR → BI	0.115	2.339*	Supported
H5: HB → BI	0.138	2.802*	Supported
H6: BI → UB	0.447	7.771*	Supported

Note: *=p-value<0.05

The results for H1 confirm that social influence (SI) significantly affects behavioral intention (β = 0.160, t = 3.242). This supports findings from Venkatesh et al. (2003), Oliveira et al. (2016), and Dahlberg et al. (2015), who emphasize that users often adopt mobile payments based on peer behavior and social norms. Among university students, the impact of friends and influencers can be especially persuasive.

H2 revealed that effort expectancy (EE) positively influences behavioral intention (β = 0.131, t = 2.648), aligning with the UTAUT model (Venkatesh et al., 2003) and studies by Palash et al. (2022) and Chen (2008). This suggests that ease of learning and using mobile payment systems encourages students to adopt the technology, though its effect is moderate compared to other variables.

H3 confirmed that trust (TS) has a significant impact on behavioral intention (β = 0.196, t = 3.890). This supports previous research by Dahlberg et al. (2015), Alalwan et al. (2017), and Choi et al. (2018), who underscore the importance of trust in overcoming users' concerns about privacy, fraud, and system reliability—especially in financial technology.

The strongest predictor of behavioral intention in this study was perceived usefulness (PU), supporting H4 (β = 0.280, t = 5.456). This finding aligns with the works of Choi et al. (2018), Shin (2009), and Gao and Waechter (2015), who established that when users believe mobile payment improves their efficiency or convenience, they are more likely to adopt and continue using it.

H5 was also supported, showing that perceived risk (PR) negatively impacts behavioral intention (β = 0.115, t = 2.339). Although the effect size was smaller than other variables, it remains significant, consistent with the studies of Slade et al. (2015), Kim et al. (2010), and Chawla and Joshi (2019). This indicates that students may hesitate to adopt mobile payments if they perceive potential financial or security risks.

The result for H6 confirms that habit (HB) influences behavioral intention (β = 0.138, t = 2.802). This supports findings from Choi (2018), Oliveira et al. (2016), and Baptista and Oliveira (2015), suggesting that repeated, automatic use of mobile payment forms positive behavioral patterns that encourage continued adoption.

Finally, H7 was strongly supported, with behavioral intention (BI) significantly predicting use behavior (UB) (β = 0.447, t = 7.771), making it the most influential relationship in the model. This is in agreement with prior studies by Lin et al. (2020), Sinha and Singh (2022), and Alalwan et al. (2017), who consistently demonstrate that behavioral intention is a strong determinant of actual usage.

These results validate the integrated conceptual framework, showing that behavioral intention is shaped by a combination of social influence, ease of use, trust, perceived usefulness, habit, and risk perception. Behavioral intention, in turn, plays a crucial role in driving actual mobile payment use. The consistency of these findings with established literature strengthens the theoretical contribution of this study and offers practical insights for stakeholders aiming to improve mobile payment adoption among university students.

5. Conclusions and Recommendation

5.1 Conclusions

This study investigated the factors influencing behavioral intention and actual usage of mobile payments among university students in Nanning, China. As mobile payment usage continues to expand rapidly across the country, young consumers—especially university students—have emerged as a key demographic driving this growth. Understanding the behavioral patterns and influencing factors within this group is essential for improving mobile payment services, informing technology adoption strategies, and supporting financial inclusion and digital transformation in higher education contexts.

A total of 500 valid responses were collected from undergraduate students across four major colleges at Guangxi University. The majority of respondents were female (69.4%), aged 19–21 (71%), with monthly expenses ranging from 1,001–2,000 yuan (74.2%). Most students preferred WeChat Pay (75.6%) as their mobile payment method. These demographic insights highlight a digitally engaged, youth-dominated population that is well-integrated with mobile financial tools.

Using Structural Equation Modeling (SEM) and Confirmatory Factor Analysis (CFA), the study tested seven hypotheses examining the relationships among key factors: social influence, effort expectancy, trust, perceived usefulness, perceived risk, habit, and behavioral intention. The model showed strong construct validity and reliability, confirming the robustness of the conceptual framework.

The findings revealed that perceived usefulness was the most significant predictor of behavioral intention, indicating that students are more likely to adopt mobile payments when they perceive them as efficient and beneficial. Trust also had a substantial impact, emphasizing the need for secure and reliable systems to gain user confidence. Social influence played a meaningful role, particularly among young users influenced by peers and social norms. Effort expectancy showed a moderate effect, suggesting that ease of use remains important, though not as critical as usefulness or trust. Habit was confirmed as a strong behavioral driver, reinforcing the role of routine in sustaining mobile payment usage. Perceived risk, while less influential, still negatively affected behavioral intention, highlighting the continued importance of addressing security concerns. Finally, behavioral intention was shown to significantly predict actual use behavior, affirming its central role in determining mobile payment adoption.

This study provides a comprehensive understanding of the behavioral dynamics behind mobile payment use among university students. By identifying and validating the key influencing factors, it offers valuable insights for service providers, policymakers, and educators aiming to promote sustained engagement with mobile financial technologies.

5.2 Recommendations

Leveraging the insights from this study, we recommend several strategies to increase university students' adoption of mobile payments. It is essential to harness social influence and build trust by fostering collaboration between universities and mobile payment providers. Launching awareness campaigns that emphasize the benefits and security of mobile payment systems can enhance students' confidence. Peer influence plays a significant role in shaping behavioral intentions, so encouraging student ambassadors to share positive experiences can drive adoption. Transparent communication about data security and privacy measures is also crucial in building trust, which significantly impacts both behavioral intention and actual usage behavior.

Effort expectancy and perceived usefulness are pivotal in shaping students' attitudes toward mobile payments. Mobile payment platforms should prioritize user-friendly interfaces and seamless integration with services frequently used by students, such as campus facilities and online shopping. Providing tutorials and customer support can help reduce the perceived effort required to use these systems. Additionally, emphasizing the convenience and efficiency of mobile payments in everyday transactions can enhance their perceived usefulness, further strengthening behavioral intention and actual usage.

To mitigate perceived risk, mobile payment providers should implement robust security measures and offer clear guidelines on protecting personal information. Regular updates and prompt responses to security concerns can reassure users and reinforce trust. Incentives such as discounts, cashback offers, and loyalty programs can encourage consistent use, helping students develop the habit of using mobile payments. This habitual use, in turn, reinforces behavioral intentions and sustains long-term adoption among university students.

5.3 Limitation and Further Study

One of the study's limitations is that the sample was restricted to students from specific colleges, which may limit the generalizability of the findings to other demographic groups. Additionally, the variables assessed were based on self-reported data, which could introduce biases related to social desirability and memory recall. Furthermore, data collection occurred within a concentrated timeframe (Glick, 1985), potentially affecting the study's scope. Future research should consider expanding the sample to include a more diverse population, employing longitudinal or experimental methodologies, and collecting data at multiple time intervals to provide a more comprehensive understanding of the subject.

References

Aarts, H., & Dijksterhuis, A. (2001). The automatic activation of goal-directed behavior: The case of travel habit. *Journal of Environmental Psychology, 20*(1), 75-82. https://doi.org/10.1006/jevp.1999.0156

Alalwan, A. A. (2020). Mobile food ordering apps: An empirical study of the factors affecting customer e-satisfaction and continued intention to reuse. *International Journal of Information Management, 50*, 28-44. https://doi.org/10.1016/j.ijinfomgt.2019.11.002

Alalwan, A. A., Dwivedi, Y. K., & Rana, N. P. (2017). Factors influencing adoption of mobile banking by Jordanian bank customers: Extending UTAUT2 with trust. *International Journal of Information Management, 37*(3), 99-110. https://doi.org/10.1016/j.ijinfomgt.2017.01.002

Alyabes, A. F., & Alsalloum, O. (2018). Factors affecting consumers' perception of electronic payment in Saudi Arabia. *European Journal of Business and Management, 10*(27), 36-45.

Anggraini, E. L., & Rachmawati, I. (2019). Analysis of factors influencing the adoption of mobile payment using the UTAUT2 model: A case study of OVO in Indonesia. *International Journal of Scientific Research and Engineering Development, 2*(3), 168-175.

Baishya, K., & Samalia, H. V. (2019). Extending the unified theory of acceptance and use of technology with perceived monetary value for smartphone adoption at the bottom of the pyramid. *International Journal of Information Management, 51*, 102036. https://doi.org/10.1016/j.ijinfomgt.2019.11.004

Baptista, G., & Oliveira, T. (2015). Understanding mobile banking: The unified theory of acceptance and use of technology combined with cultural moderators. *Computers in Human Behavior, 50*, 418-430. https://doi.org/10.1016/j.chb.2015.04.024

Baptista, G., & Oliveira, T. (2016). A weight and a meta-analysis on mobile banking acceptance research. *Computers in Human Behavior, 63*, 480-489. https://doi.org/10.1016/j.chb.2016.05.074

Bentler, P. M. (1990). Comparative fit indexes in structural models. *Psychological Bulletin, 107*(2), 238-246. https://doi.org/10.1037/0033-2909.107.2.238

Chauhan, S. (2015). Acceptance of mobile money by poor citizens of India: Integrating trust into the technology acceptance model. *Info, 17*(3), 58-68. https://doi.org/10.1108/info-02-2015-0018

Chawla, D., & Joshi, H. (2019). Consumer attitude and intention to adopt mobile wallet in India: An empirical study. *International Journal of Bank Marketing, 37*(7), 1590-1618. https://doi.org/10.1108/ijbm-09-2018-0256

Chen, L. (2008). A model of consumer acceptance of mobile payment. *International Journal of Mobile Communications, 6*(1), 32-52. https://doi.org/10.1504/ijmc.2008.015997

Chen, X. M., & Wang, L. (2021). Exploring the linkage between mobile payment habits and customer loyalty. *Marketing Letters, 32*(3), 345-358.

Chen, Y., Dai, R., Yao, J., & Li, Y. (2019). Donate time or money? The determinants of donation intention in online crowdfunding. *Sustainability, 11*(16), 4269. https://doi.org/10.3390/su11164269

Choi, J. H. (2018). Determinants of continuous intention to use over extended use of smartphone apps. *Telematics and Informatics, 35*(5), 1133-1144. https://doi.org/10.1016/j.tele.2018.01.006

Choi, S., Kim, H., Chung, M., & Lee, S. Y. (2018). Online donation experiences, donation awareness, and intention of future donation among teenagers in South Korea. *Journal of Social Service Research, 45*(5), 622-633. https://doi.org/10.1080/01488376.2018.1487363

Chopdar, P. K., & Sivakumar, V. J. (2018). Understanding continuance usage of mobile shopping applications in India: The role of espoused cultural values and perceived risk. *Behaviour & Information Technology, 38*(1), 42-64. https://doi.org/10.1080/0144929x.2018.1513563

Dahlberg, T., Guo, J., & Ondrus, J. (2015). A critical review of mobile payment research. *Electronic Commerce Research and Applications, 14*(5), 265-284. https://doi.org/10.1016/j.elerap.2015.07.006

Davis, F. D. (1986). *A technology acceptance model for empirically testing new end-user information systems: Theory and results* [Doctoral dissertation]. MIT Sloan School of Management, Cambridge, MA.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319-340. https://doi.org/10.2307/249008

Deng, Z., & Lu, Y. (2017). An empirical analysis of user acceptance of mobile payment in China. *International Journal of Mobile Communications, 15*(3), 233-252.

Esawe, A. T. (2022). Understanding mobile e-wallet consumers' intentions and user behavior. *Spanish Journal of Marketing - ESIC, 26*(3), 363-384. https://doi.org/10.1108/sjme-05-2022-0105

Falk, T., Kunz, W. H., Schepers, J. J. L., & Mrozek, A. J. (2016). How mobile payment influences the overall store price image. *Journal of Business Research, 69*(7), 2417-2423. https://doi.org/10.1016/j.jbusres.2016.01.011

Gao, L., & Waechter, K. A. (2015). Examining the role of initial trust in user adoption of mobile payment services: An empirical investigation. *Information Systems Frontiers, 19*(3), 525-548. https://doi.org/10.1007/s10796-015-9611-0

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. *MIS Quarterly, 27*(1), 51-90. https://doi.org/10.2307/30036519

Glick, W. H. (1985). Conceptualizing and measuring organizational and psychological climate: Pitfalls in multilevel research. *The Academy of Management Review, 10*(3), 601. https://doi.org/10.2307/258140

Gupta, K., & Arora, N. (2019). Investigating consumer intention to accept mobile payment systems through unified theory of acceptance model. *South Asian Journal of Business Studies, 9*(1), 88-114. https://doi.org/10.1108/sajbs-03-2019-0037

Ha, H. (2020). The cashless economy in Vietnam - The situation and policy implications. *Journal of Reviews on Global Economics, 9*, 216-223. https://doi.org/10.6000/1929-7092.2020.09.20

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2006). *Multivariate data analysis* (6th ed.). Pearson Prentice Hall.

Haritha, P. H. (2022). Mobile payment service adoption: Understanding customers for an application of emerging financial technology. *Information & Computer Security, 31*(2), 145-171. https://doi.org/10.1108/ics-04-2022-0058

Hew, J.-J., Lee, V.-H., Ooi, K.-B., & Lin, B. (2016). Mobile social commerce: The booster for brand loyalty? *Computers in Human Behavior, 59*, 142-154. https://doi.org/10.1016/j.chb.2016.01.027

Hossain, R., & Mahmud, I. (2016). Influence of cognitive style on mobile payment system adoption: An extended technology acceptance model. *International Conference on Computer Communication and Informatics (ICCCI)*, 1-6. https://doi.org/10.1109/iccci.2016.7479973

Hsu, M.-H., & Chiu, C.-M. (2004). Internet self-efficacy and electronic service acceptance. *Decision Support Systems, 38*(3), 369-381. https://doi.org/10.1016/j.dss.2003.08.001

Istijanto, A., & Handoko, Y. I. (2022). Customers' continuance usage of mobile payment during the COVID-19 pandemic. *Spanish Journal of Marketing - ESIC, 26*(3), 345-362. https://doi.org/10.1108/SJME-02-2022-0016

Karjaluoto, H., Shaikh, A. A., Leppäniemi, M., & Luomala, R. (2019). Examining consumers' usage intention of contactless payment systems. *International Journal of Bank Marketing, 38*(2), 332-351. https://doi.org/10.1108/ijbm-04-2019-0155

Kasri, R. A., & Yuniar, A. M. (2021). Determinants of digital zakat payments: Lessons from Indonesian experience. *Journal of Islamic Accounting and Business Research, 12*(3), 362-379. https://doi.org/10.1108/jiabr-08-2020-0258

Khalilzadeh, J., Ozturk, A. B., & Bilgihan, A. (2017). Security-related factors in extended UTAUT model for NFC-based mobile payment in the restaurant industry. *Computers in Human Behavior, 70*, 460-474. https://doi.org/10.1016/j.chb.2017.01.001

Kim, C., Mirusmonov, M., & Lee, I. (2010). An empirical examination of factors influencing the intention to use mobile payment. *Computers in Human Behavior, 26*(3), 310-322. https://doi.org/10.1016/j.chb.2009.10.013

Kim, D. J., Ferrin, D. L., & Rao, H. R. (2008). A trust-based consumer decision-making model in electronic commerce: The role of trust, perceived risk, and their antecedents. *Decision Support Systems, 44*(2), 544-564. https://doi.org/10.1016/j.dss.2007.07.001

Koenig-Lewis, N., Marquet, M., Palmer, A., & Zhao, A. L. (2015). Enjoyment and social influence: Predicting mobile payment adoption. *The Service Industries Journal, 35*(10), 537-554. https://doi.org/10.1080/02642069.2015.1043278

Kumari, N., & Biswas, A. (2023). Does M-payment service quality and perceived value co-creation participation magnify M-payment continuance usage intention? Moderation of usefulness and severity. *International Journal of Bank Marketing, 41*(6), 1330-1359. https://doi.org/10.1108/ijbm-11-2022-0500

Lee, M. C. (2009). Factors influencing the adoption of internet banking: An integration of TAM and TPB with perceived risk and perceived benefit. *Electronic Commerce Research and Applications, 8*(3), 130-141. https://doi.org/10.1016/j.elerap.2008.11.006

Li, H., Sarathy, R., & Xu, H. (2011). The role of affect and cognition on online consumers' decision to disclose personal information to unfamiliar online vendors. *Decision Support Systems, 51*(3), 434-445. https://doi.org/10.1016/j.dss.2011.01.017

Li, Y. N., & Zhang, H. (2020). Cognitive and affective factors in the formation of mobile payment habits and their impact on behavioral intentions. *Journal of Consumer Behaviour, 19*(6), 590-603.

Li, Y.-Z., He, T. L., Song, Y. R., Yang, Z., & Zhou, R.-T. (2017). Factors impacting donors' intention to donate to charitable crowdfunding projects in China: A UTAUT-based model. *Information, Communication & Society, 21*(3), 404-415. https://doi.org/10.1080/1369118x.2017.1282530

Limayem, M., Hirt, S. G., & Cheung, C. M. K. (2007). How habit limits the predictive power of intention: The case of information systems continuance. *MIS Quarterly, 31*(4), 705. https://doi.org/10.2307/25148817

Lin, W. R., Lin, C. Y., & Ding, Y. H. (2020). Factors affecting the behavioral intention to adopt mobile payment: An empirical study in Taiwan. *Mathematics, 8*(10), 1851. https://doi.org/10.3390/math8101851

Liu, L., & Zhang, J. (2022). Understanding mobile payment adoption: An empirical study in China. *Journal of Electronic Commerce Research, 19*(4), 1-18.

Lu, Y., Yang, S., Chau, P. Y. K., & Cao, Y. (2011). Dynamics between the trust transfer process and intention to use mobile payment services: A cross-environment perspective. *Information & Management, 48*(8), 393-403. https://doi.org/10.1016/j.im.2011.09.006

Luarn, P., & Lin, H. H. (2005). Toward an understanding of the behavioral intention to use mobile banking. *Computers in Human Behavior, 21*(6), 873-891. https://doi.org/10.1016/j.chb.2004.03.003

Makanyeza, C., & Mutambayashata, S. (2018). Consumers' acceptance and use of plastic money in Harare, Zimbabwe. *International Journal of Bank Marketing, 36*(2), 379-392. https://doi.org/10.1108/ijbm-03-2017-0044

Mukherjee, M., & Roy, S. (2017). E-commerce and online payment in the modern era. *International Journal of Advanced Research in Computer Science and Software Engineering, 7*(5), 1-5. https://doi.org/10.23956/ijarcsse/sv7i5/0250

Mulia, D. (2019). The differences in risk perception between millennials and baby boomers in online transactions. *Jurnal Manajemen, 23*(3), 375. https://doi.org/10.24912/jm.v23i3.570

Musyaffi, A. M., Sari, D. A. P., & Respati, D. K. (2021). Understanding digital payment usage during the COVID-19 pandemic: A study of the UTAUT extension model in Indonesia. *The Journal of Asian Finance, Economics and Business, 8*(6), 475-482. https://doi.org/10.13106/jafeb.2021.vol8.no6.0475

Negm, E. M. (2023). *Consumers' acceptance intentions regarding e-payments: A focus on the extended unified theory of acceptance and use of technology (UTAUT2)*. Management & Sustainability: An Arab Review. https://doi.org/10.1108/msar-04-2023-0022

Oliveira, T., Thomas, M., Baptista, G., & Campos, F. (2016). Mobile payment: Understanding the determinants of customer adoption and intention to recommend the technology. *Computers in Human Behavior, 61*, 404-414. https://doi.org/10.1016/j.chb.2016.03.030

Pal, A., Herath, T., De, R., & Rao, H. R. (2021). Why do people use mobile payment technologies and why would they continue? An examination and implications from India. *Research Policy, 50*(6), 104228. https://doi.org/10.1016/j.respol.2021.104228

Palash, A. S., Talukder, S., Islam, A. K. M. N., & Bao, Y. (2022). Positive and negative valences, personal innovativeness, and intention to use facial recognition for payments. *Industrial Management & Data Systems, 122*(4), 1081-1108. https://doi.org/10.1108/imds-04-2021-0230

Pavlou, P. A., & Fygenson, M. (2006). Understanding and predicting electronic commerce adoption: An extension of the theory of planned behavior. *MIS Quarterly, 30*(1), 115-143. https://doi.org/10.2307/25148720

Pedroso, R., Zanetello, L., Guimarães, L., Pettenon, M., Gonçalves, V., Scherer, J., Kessler, F., & Pechansky, F. (2016). Confirmatory factor analysis (CFA) of the Crack Use Relapse Scale (CURS). *Archives of Clinical Psychiatry (São Paulo), 43*(3), 37-40. https://doi.org/10.1590/0101-60830000000081

Pham, T. T. T., & Ho, J. C. (2015). The effects of product-related, personal-related factors, and attractiveness of alternatives on consumer adoption of NFC-based mobile payments. *Technology in Society, 43*, 159-172. https://doi.org/10.1016/j.techsoc.2015.05.004

Phonthanukitithaworn, C., Sellitto, C., & Fong, M. W. L. (2016). An investigation of mobile payment (m-payment) services in Thailand. *Asia-Pacific Journal of Business Administration, 8*(1), 37-54. https://doi.org/10.1108/apjba-10-2014-0119

Qasim, H., & Abu-Shanab, E. (2015). Drivers of mobile payment acceptance: The impact of network externalities. *Information Systems Frontiers, 18*(5), 1021-1034. https://doi.org/10.1007/s10796-015-9598-6

Rastogi, S., Panse, C., Sharma, A., & Bhimavarapu, V. M. (2021). Unified payment interface (UPI): A digital innovation and its impact on financial inclusion and economic development. *Universal Journal of Accounting and Finance, 9*(3), 518-530. https://doi.org/10.13189/ujaf.2021.090326

Rovinelli, R. J., & Hambleton, R. K. (1976). On the use of content specialists in the assessment of criterion-referenced test item validity. *Dutch Journal of Educational Research, 2*(1), 49-60.

Schierz, P. G., Schilke, O., & Wirtz, B. W. (2010). Understanding consumer acceptance of mobile payment services: An empirical analysis. *Electronic Commerce Research and Applications, 9*(3), 209-216. https://doi.org/10.1016/j.elerap.2009.07.005

Sekaran, U. (1992). *Research methods for business: A skill-building approach*. John Wiley & Sons.

Shah, J., & Khanna, M. (2023). Determining the post-adoptive intention of millennials for MOOCs: An information systems perspective. *Information Discovery and Delivery, 52*(2), 243-260. https://doi.org/10.1108/idd-11-2022-0109

Sharma, G. P., Verma, R. C., & Pathare, P. (2005). Mathematical modeling of infrared radiation thin layer drying of onion slices. *Journal of Food Engineering, 71*(3), 282-286. https://doi.org/10.1016/j.jfoodeng.2005.02.010

Shi, S., & Chow, W. S. (2015). Trust development and transfer in social commerce: Prior experience as a moderator. *Industrial Management & Data Systems, 115*(7), 1182-1203. https://doi.org/10.1108/imds-01-2015-0019

Shin, D.-H. (2009). Towards an understanding of the consumer acceptance of mobile wallet. *Computers in Human Behavior, 25*(6), 1343-1354. https://doi.org/10.1016/j.chb.2009.06.001

Shin, S., & Lee, W. J. (2014). The effect of technology readiness and technology acceptance on NFC MPS in Korea. *Journal of Applied Business Research (JABR), 30*(6), 1615-1625. https://doi.org/10.19030/jabr.v30i6.8873

Shin, S., & Lee, W. J. (2021). Factors affecting user acceptance for NFC mobile wallets in the U.S. and Korea. *Innovation & Management Review, 18*(4), 417-433. https://doi.org/10.1108/inmr-02-2020-0018

Sica, C., & Ghisi, M. (2007). The Italian versions of the Beck Anxiety Inventory and the Beck Depression Inventory-II: Psychometric properties and discriminant power. In M. A. Lange (Ed.), *Leading-edge psychological tests and testing research* (pp. 27-50).

Singh, N., Sinha, N., & Liébana-Cabanillas, F. J. (2020). Determining factors in the adoption and recommendation of mobile wallet services in India: Analysis of the effect of innovativeness, stress to use, and social influence. *International Journal of Information Management, 50*, 191-205. https://doi.org/10.1016/j.ijinfomgt.2019.05.022

Sinha, M., Majra, H., Hutchins, J., & Saxena, R. (2019). Mobile payments in India: The privacy factor. *International Journal of Bank Marketing, 37*(1), 192-209. https://doi.org/10.1108/ijbm-05-2017-0099

Sinha, N., & Singh, N. (2022). Moderating and mediating effect of perceived experience on merchants' behavioral intention to use mobile payments services. *Journal of Financial Services Marketing, 28,* 448-465. https://doi.org/10.1057/s41264-022-00163-y

Slade, E., Williams, M., Dwivedi, Y., & Piercy, N. (2015). Exploring consumer adoption of proximity mobile payments. *Journal of Strategic Marketing, 23*(3), 209-223. https://doi.org/10.1080/0965254x.2014.914075

Smith, J., & Chen, H. (2015). Understanding mobile payment use behavior: A study of Chinese consumers. *Journal of Electronic Commerce Research, 16*(2), 145-162.

Sobti, N. (2019). Impact of demonetization on diffusion of mobile payment service in India. *Journal of Advances in Management Research, 16*(4), 472-497. https://doi.org/10.1108/jamr-09-2018-0086

Tan, G. W.-H., Ooi, K.-B., Chong, S.-C., & Hew, T.-S. (2014). NFC mobile credit card: The next frontier of mobile payment? *Telematics and Informatics, 31*(2), 292-307. https://doi.org/10.1016/j.tele.2013.06.002

Thakur, R. (2013). Customer adoption of mobile payment services by professionals across two cities in India: An empirical study using modified technology acceptance model. *Business Perspectives and Research, 1*(2), 17-30. https://doi.org/10.1177/2278533720130203

Tossy, T. (2014). Modelling the adoption of mobile payment system for primary and secondary school student examination fees in developing countries: Tanzanian experiences. *International Journal of Information Technology and Business Management, 27*(1), 1-12.

Tran, H. T. T., & Corner, J. (2016). The impact of communication channels on mobile banking adoption. *International Journal of Bank Marketing, 34*(1), 78-109. https://doi.org/10.1108/ijbm-06-2014-0073

Upadhyay, N., Upadhyay, S., Abed, S. S., & Dwivedi, Y. K. (2022). Consumer adoption of mobile payment services during COVID-19: Extending meta-UTAUT with perceived severity and self-efficacy. *International Journal of Bank Marketing, 40*(5). https://doi.org/10.1108/ijbm-06-2021-0262

Upadhyay, N., Upadhyay, S., & Dwivedi, Y. K. (2021). Theorizing artificial intelligence acceptance and digital entrepreneurship model. *International Journal of Entrepreneurial Behavior & Research, 28*(5). https://doi.org/10.1108/ijebr-01-2021-0052

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425-478. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly, 36*(1), 157-178. https://doi.org/10.2307/41410412

Wood, W., & Neal, D. T. (2007). A new look at habits and the habit-goal interface. *Psychological Review, 114*(4), 843-863. https://doi.org/10.1037/0033-295x.114.4.843

Wu, J.-H., & Wang, Y.-M. (2006). Measuring KMS success: A respecification of the DeLone and McLean's model. *Information & Management, 43*(6), 728-739. https://doi.org/10.1016/j.im.2006.05.002

Yang, M., Mamun, A. A., Mohiuddin, M., Nawi, N. C., & Zainol, N. R. (2021). Cashless transactions: A study on intention and adoption of e-wallets. *Sustainability, 13*(2), 831. https://doi.org/10.3390/su13020831

Yang, S., Lu, Y., Gupta, S., Cao, Y., & Zhang, R. (2012). Mobile payment services adoption across time: An empirical study of the effects of behavioral beliefs, social influences, and personal traits. *Computers in Human Behavior, 28*(1), 129-142. https://doi.org/10.1016/j.chb.2011.08.019

Yu, C. S. (2012). Factors affecting individuals to adopt mobile banking: Empirical evidence from the UTAUT model. *Journal of Electronic Commerce Research, 13*, 104-121.

Zhao, Y., & Bacao, F. (2021). How does the pandemic facilitate mobile payment? An investigation on users' perspective under the COVID-19 pandemic. *International Journal of Environmental Research and Public Health, 18*(3), 1-22. https://doi.org/10.3390/ijerph18031016

Zhou, T. (2014). Understanding the determinants of mobile payment continuance usage. *Industrial Management & Data Systems, 114*(6), 936-948. https://doi.org/10.1108/imds-02-2014-0068

Zhou, T., Lu, Y., & Wang, B. (2010). Integrating TTF and UTAUT to explain mobile banking user adoption. *Computers in Human Behavior, 26*(4), 760-767. https://doi.org/10.1016/j.chb.2010.01.013