Factors Affecting Nepalese Consumers' Adoption of Online Payments: Analyzing Behavior Intention as a Mediating Factor through the Unified Theory of Acceptance and Use of Technology

Risal, N[1], Pandey, D.L[2],
[1]Assistant Professor, Nepal Commerce Campus, Tribhuvan University
[2]Professor, Central Department of Management, Tribhuvan University
[1]nischalrisal@gmail.com, [2]p.dhruba@yahoo.com,

Abstract

Behavioral intention is shaped by technology acceptance factors, which in turn influence the adoption of online payment systems. The study identifies the major technology acceptance constructs as performance expectancy, effort expectancy, social influence, and facilitating conditions. The study aims to analyze the impact of these constructs on the adoption intention of online payment among consumers in Nepal. The descriptive and causal-comparative research design was adopted. Using convenience sampling, responses were collected from 384 Nepalese users of online platforms. The questionnaire survey data were preprocessed in Excel, and the analysis was conducted using SPSS and SmartPLS 4. Confirmatory factor analysis was applied to determine the reliability and validity of the model, and factor loadings. Structural equation modeling (SEM) was applied in the study. The findings reveal that the four constructs have a positive and significant impact on the adoption of online payment among consumers. Behavioral intention plays a key mediating role in explaining the relationships between the variables. Social influence does not exhibit a significant association with adoption when mediated by behavioral intention, indicating that consumers' perceptions of using online payments are not significantly impacted by peers, family, or friends. To encourage adoption, policymakers and corporate executives in Nepal should consider customer needs and demographics while also promoting awareness, accessibility, and trust in online payment systems. Moreover, increasing digital literacy and ensuring inclusive access could encourage broader participation in digital transactions, supporting a shift toward a cashless economy.

Keywords: *Online Payment; Behavioural Intention; Performance Expectancy; Effort Expectancy; Social Influence; Facilitating Conditions.*

JEL Classifications: *C0; D85; D91; E27; G40*

Received: 07th December 2025 / **Accepted:** 22nd April 2026
Correspondence: p.dhruba@yahoo.com

ORCID of authors: Risal, N- https://orcid.org/0000-0002-8193-4096
Pandey, D.L- https://orcid.org/0000-0002-1323-7758

DOI: https://doi.org/10.4038/kjm.v15i1.7920

Introduction

The rapid advancement of technology has significantly transformed the way individuals and businesses conduct transactions, leading to the widespread adoption of online payment systems. These systems offer numerous benefits, including convenience, speed, and the ability to conduct transactions remotely (Al-Saedi et al., 2020). E-payments have increasingly replaced cash and credit cards due to consumers' demand of quick, easy, and affordable payment options (Koghut & AI-Tabbaa, 2021; Kumar & Yadav, 2022). The proliferation of smartphones and user-friendly mobile applications has further driven the adoption of mobile payment systems, offering improved transactional services for users and generating revenue for service providers at relatively low costs (Park et al., 2019). In Nepal, electronic payment systems include credit cards (introduced by Nabil Bank in 1990 AD), debit cards, automated teller machines (Himalayan Bank in 1995 AD), EFTPOS, internet banking (Kumari Bank in 2002 AD), and mobile banking (Laxmi Bank in 2004 AD). Additionally, non-bank intermediaries such as F1 soft (e-sewa, FonePay), Paybill, and i-pay 2 support digital transactions. The growth of e-commerce in Nepal, particularly since the late 2000s AD, has provided opportunities for businesses to increase sales and for consumers to engage in convenient digital transactions. the adoption of ICT, internet services, and mobile technologies has enables financial inclusion, facilitated money circulation, and contributed to economic development by reducing communication costs and improving information flow (Makun et al., 2022; Jayaraman & Makun, 2020; Osah & Kyobe, 2017; Plyler et al., 2010). The acceptance and use of information system (IS) and information technology (IT) innovations have been a major concern in research and practice. Several theoretical models have been proposed to examine IS/IT adoption, including the Theory of Reasoned Action, Technology Acceptance Model (TAM), Theory of Planned Behaviour (TPB), and the Model of Personal Computer Utilization (Ajzen 1991; Davis 1989; Davis et al. 1989; Fishbein and Ajzen 1975; Thompson et al. 1991). Based on a synthesis of these models, Venkatesh et al., (2003) developed the Unified Theory of Acceptance and Use of Technology (UTAUT), which identifies four key determinants of technology acceptance: performance expectancy, effort expectancy, social influence, and facilitating conditions, with behavioral intention mediating their effect on actual usage. Despite the benefits of electronic payment systems, adoption levels remain suboptimal, partly due to concerns about security and potential financial loss (Al-Smadi, 2012). Without understanding the factors that motivate consumers, businesses cannot effectively promote the use of these services. Given the widespread use of technological constructs on online payment adoption and behavioral intention in the Nepalese context. Thus, this study aims in addressing the gap by analyzing the associations between the key UTAUT constructs and the adoption of online payment systems.

Literature Review

The Unified Theory of Acceptance and Use of Technology

In 1986 AD, the technology acceptance model (TAM) was introduced by Davis to determine the behavior of computer usage for the first time. In addition to TAM, the unified theory of acceptance and use of technology, or UTAUT, was used for identifying motivation on the use of technology, developed by Venkatesh et al., (2003). The UTAUT had suggested that four core constructs (performance expectancy, effort expectancy, social influence, and facilitating conditions) were the direct determinants of behavioral intention and ultimately behavior, and that these constructs were in turn moderated by gender, age, experience, and voluntariness of use. It is argued that by examining the presence of each of these constructs in a real world environment, researchers and practitioners would be able to assess an individual‘s intention to use a specific system, thus allowing for the identification of the key influences on acceptance in any given context. The theory was developed through the review and integration of eight dominant theories and models, namely, Theory of Reasoned Action (TRA), Technology Acceptance Model (TAM), Motivational Model, Theory of Planned Behavior (TPB), a combined TBP/TAM, the Model of PC Utilization, Innovation Diffusion Theory (IDT), and Social Cognitive Theory (SCT). These contributing theories and models were widely and successfully utilized by a large number of previous studies of technology or innovation adoption and diffusion within a range of disciplines, including information systems, marketing, social psychology, and management. Venkatesh et al. (2003) presented results from a six-month study of four organizations, which revealed that the eight contributing models explained between 17 and 53 percent of variance in user intentions to use IT. However, UTAUT was found to outperform the eight individual models with an adjusted R-square of 69 percent. In the years since its introduction, UTAUT has been widely employed in technology adoption and diffusion research as a theoretical lens by researchers conducting empirical studies of user intention and behavior. UTAUT was developed on the basis of eight theories and models that explain the acceptance of technology. Like previous theories of acceptance to use technology, the UTAUT had assumed that behavioral intention was the factor that exerts the most significant influence on real behavior of a customer. The study had emphasized that behavioral intention could be explained for 70 percent of cases of real-use behavior, being superior to the earlier studies (with their explanation at 30 to 45 percent). Martín and Herrero (2012) also used the UTAUT to examine the impact of the user‘s psychological factors on the online purchase intention in rural tourism. The results reported that the online purchase intention was correlated to the levels of performance expectancy and effort expectancy. On the contrary, there was no statistically significant influenced of social influence and facilitating conditions on the online purchase intention. Likewise, based on the UTAUT, Escobar-Rodiguez and Carvajal-Trujillo (2014) had analyzed the key factors affecting the intention and behavior to use websites of low-cost airlines to book a flight. The findings also revealed four key drivers of the intention to book flights, which were performance expectancy, effort expectancy, social influence, and facilitating conditions. These were consistent with the study by Abrahao et al., (2016), Sarfaraz et al., (2017), Singh et al., (2017), and Isaac et al., (2019). It could be concluded that the UTAUT was superior theory among all. Therefore, the UTAUT has been adopted to determine factors that would be associated to the online purchase intention of Nepalese customers.

Performance Expectancy and Adoption/Usage Behavior

Performance expectancy, a pivotal construct in technology adoption theories such as UTAUT, reflects users' beliefs about the extent to which adopting a technology would enhance their task performance and efficiency (Davis, 1989; Venkatesh et al., 2003). Empirical studies consistently highlighted that higher levels of perceived usefulness and effectiveness, and components of performance expectancy had significantly predict users' behavioral intention to adopt and their subsequent actual usage behavior of technology, including online payment systems (Dahlberg et al., 2015; Kim et al., 2009; Luarn & Lin, 2005; Lai & Li, 2005). For example, Dahlberg et al., (2015) emphasized that users' positive perceptions of online payment systems' efficiency and convenience were strong drivers of adoption decisions and sustained usage. Moreover, Luarn and Lin (2005) found that perceived usefulness had significantly influenced users' behavioral intention to use mobile banking services, indicating a robust relationship between perceived performance benefits and technology adoption. Similarly, Lai and Li (2005) had explored the factors influencing consumer adoption of internet banking and highlighted the pivotal role of perceived usefulness in shaping adoption behavior. These studies had collectively underscored the critical role of enhancing performance expectancy to foster the widespread adoption and continued usage of online payment technologies. They had informed both theoretical advancements, such as the extension of UTAUT, and practical strategies for technology developers and service providers in enhancing user experience and acceptance.

Effort Expectancy and Adoption/Usage Behavior

Effort expectancy, another critical construct in technology adoption frameworks like UTAUT had referred to users' perceptions of the ease of use and simplicity associated with adopting and using a technology (Venkatesh et al., 2003; Davis, 1989). Empirical studies consistently demonstrated that higher levels of perceived ease of use had significantly predicted users' behavioral intention to adopt and their subsequent actual usage behavior of technology, including online payment systems (Kim et al., 2009; Luarn & Lin, 2005; Lai & Li, 2005; Venkatesh et al., 2003). For instance, Venkatesh et al., (2003) found that users' positive perceptions of the ease of use of a technology had directly influenced their adoption decisions. Similarly, Luarn and Lin (2005) highlighted the importance of perceived ease of use in influencing users' behavioral intention to adopt mobile banking services. Moreover, Lai and Li (2005) had explored factors influencing consumer adoption of internet banking and emphasized that perceived ease of use had significantly impacted the adoption behavior. These findings underscored the critical role of enhancing effort expectancy to promote the widespread adoption and continued usage of online payment technologies. The previous literature had provided insights for both theoretical advancements in understanding technology adoption, practical strategies for developers, and service providers to simplify user interfaces and enhance user experience.

Social Influence and Adoption/Usage Behavior

Social influence, a key construct in technology adoption theories such as UTAUT had referred to the degree to which individuals perceived that friends, family, or colleagues believed they should use a particular technology (Venkatesh et al., 2003; Davis, 1989). Empirical studies consistently demonstrated that social influence had significantly impacted the users' behavioral intention to adopt and their subsequent actual usage behavior of technology, including online payment systems (Venkatesh et al., 2003; Luarn & Lin, 2005; Lai & Li, 2005; Kim et al., 2009). Venkatesh et al., (2003) found that social influence from peers and colleagues had played a crucial role in shaping users' decisions to adopt new technologies. Luarn and Lin (2005) highlighted the influence of social norms and recommendations from friends and family on users' behavioral intention to adopt mobile banking services. Moreover, Lai and Li (2005) explored the impact of social influence on consumer adoption of internet banking and emphasized its significant role in adoption behavior. These findings had underscored the importance of understanding and leveraging social influence mechanisms to promote the widespread adoption and continued usage of online payment technologies. The previous literature had provided valuable insights for both theoretical advancements in technology adoption and practical strategies for marketers and service providers to harness social networks and endorsements to enhance adoption rates and user engagement.

Facilitating Conditions and Adoption/Usage Behavior

Facilitating conditions, a fundamental construct in technology adoption models such as UTAUT had referred to the resources, support, and infrastructure available to users that had facilitated the use of a technology (Venkatesh et al., 2003; Davis, 1989). Empirical studies consistently demonstrated that higher levels of facilitating conditions had significantly predicted users' behavioral intention to adopt and their subsequent actual usage behavior of technology, including online payment systems (Kim et al., 2009; Luarn & Lin, 2005; Lai & Li, 2005; Venkatesh et al., 2003). Venkatesh et al., (2003) found that the availability of technical support and resources had greatly influenced users' decisions to adopt new technologies. Luarn and Lin (2005) had highlighted the importance of infrastructure and accessibility in influencing users' behavioral intention to adopt mobile banking services. Moreover, Lai and Li (2005) had explored the impact of facilitating conditions on consumer adoption of internet banking and emphasized their significant role in adoption behavior. These findings had underscored the critical role of enhancing facilitating conditions to promote the widespread adoption and continued usage of online payment technologies. The previous literature had provided the valuable insights for both theoretical advancements in technology adoption and practical strategies for organizations and policymakers to improve infrastructure, support mechanisms, and accessibility to enhance adoption rates and user satisfaction.

Behavioral Intention and Adoption/Usage Behavior

Behavioral intention, a central construct in technology adoption models such as UTAUT had represented an individual's readiness and willingness to engage in specific behaviors related to technology use (Venkatesh et al., 2003; Davis, 1989). Empirical studies had consistently demonstrated that stronger behavioral intentions significantly predicted users' subsequent actual usage behavior of technology, including online payment systems (Kim et al., 2009; Luarn & Lin, 2005; Lai & Li, 2005; Venkatesh et al., 2003). Venkatesh et al., (2003) found that users with higher behavioral intentions to use a technology were more likely to actually adopt and used it over time. Luarn and Lin (2005) highlighted the predictive power of behavioral intention in shaping users' adoption decisions and ongoing usage of mobile banking services. Moreover, Lai and Li (2005) had explored the influence of behavioral intention on consumer adoption of internet banking and underscored its critical role in adoption behavior. Additionally, recent studies had expanded on this relationship, emphasizing the mediating role of behavioral intention between initial technology acceptance and actual usage behavior (Venkatesh & Bala, 2008; Bhattacherjee, 2001). These findings had underscored the importance of understanding and enhancing users' behavioral intentions to foster the widespread adoption and continued usage of online payment technologies. The previous literature had provided valuable insights for both theoretical advancements in technology adoption and practical strategies for marketers and service providers to promote positive user attitudes and intentions through effective communication, usability enhancements, and personalized user experiences.

Mediating Role of Behavioral Intention

Several studies had explored the mediating role of behavioral intention in technology adoption, particularly in understanding users' actual usage behavior of information systems. Bhattacherjee (2001) introduced an expectation-confirmation model where behavioral intention had mediated the relationship between perceived usefulness and technology continuance. Venkatesh and Bala (2008) had extended the Technology Acceptance Model (TAM) to include behavioral intention as a mediator between perceived ease of use, perceived usefulness, and actual usage behavior. Taylor and Todd (1995) had provided empirical evidence supporting behavioral intention as a mediator between perceived usefulness and technology usage, emphasizing its crucial role in adoption decisions. Mathieson (1991) had compared TAM with the Theory of Planned Behavior (TPB) and highlighted that behavioral intention had mediated the impact of perceived usefulness on technology adoption. Venkatesh et al., (2012) had extended the UTAUT to incorporate behavioral intention as a mediator between predictors performance expectancy, effort expectancy, social influence, facilitating conditions, and actual usage behavior. Collectively, these studies had underscored the significance of understanding and enhancing users' behavioral intentions to foster technology adoption and usage, providing valuable insights for both theoretical advancements and practical strategies in promoting the adoption of technologies such as online payment systems. In the context of UTAUT, the mediating role of behavioral intention was actually central to the model. It would be the core mechanism explaining the turning of perceptions into actual behavior. In the study, the mediating role of behavioral intention in UTAUT had explained the factors expectancy performance, effort expectancy, and social influence. In the context of Nepalese consumers, perceptions about the usefulness and ease of online payments did not immediately lead to adoption, instead, they first shaped a user's intention to use these systems, which had driven actual behavior. Thus, behavioral intention acted as a crucial relation that had explained how these factors translate into the adoption of online payment technologies.

Research Gap

The studies in technology adoption, particularly concerning constructs like performance expectancy, effort expectancy, social influence, facilitating conditions, and behavioral intention, had significantly advanced through UTAUT and TAM (Venkatesh et al., 2003; Davis, 1989). However, several research gaps were remain untouched. Firstly, there was a need for studies that integrated contextual factors specific to diverse cultural, economic, and demographic contexts, as current models often generalized findings from Western settings without considering nuanced differences (Venkatesh et al., 2012). Longitudinal studies were lacking, particularly in understanding the perceptions of these adoption factors evolved over time and influenced sustained usage behavior of technologies like online payment systems (Venkatesh & Bala, 2008; Bhattacherjee, 2001). While facilitating conditions were discussed, there was limited studies on the role of trust and security concerns in shaping users' intentions and behaviors towards technology adoption (Kim et al., 2009; Lai & Li, 2005). Furthermore, comparative studies across different technologies such as mobile payments, and internet banking were scarce, which could offer insights into unique adoption dynamics and challenges across these platforms (Luarn & Lin, 2005; Mathieson, 1991). Lastly, the influence of regulatory environments on technology adoption remained underexplored, particularly in fintech sectors such as online payments, warranting further investigation into the regulatory factors interaction with user perceptions and adoption behaviors (Venkatesh et al., 2012; Taylor & Todd, 1995). Addressing these gaps could provide a more nuanced understanding of the complexities surrounding technology adoption and inform strategies to enhance adoption rates and user engagement in Nepal.

Theoretical Framework

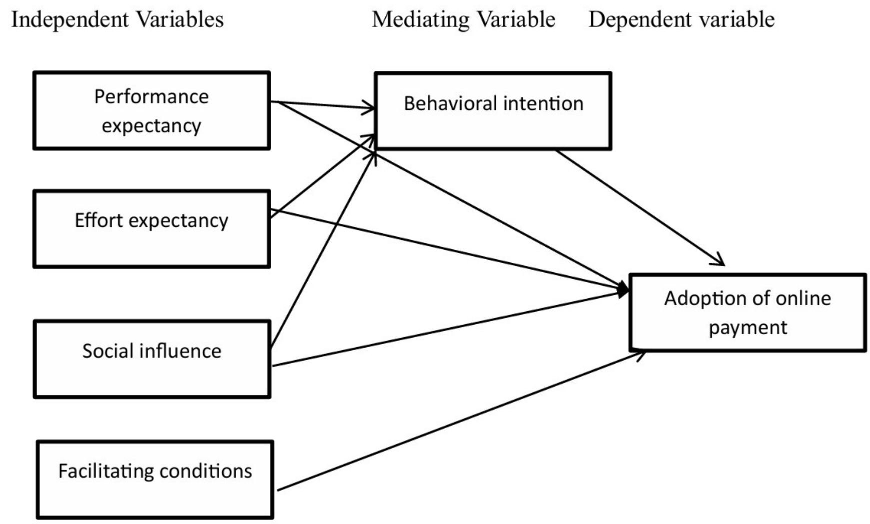

Figure 1: Theoretical Framework
Source: *Rahmiati (2020); Venkatesh et al., (2003)*

Research Methods

The study had adopted a causal-comparative research design. Casual comparative research design was adopted to analyze the factors affecting the adoption of online payment among Nepalese consumers. The study population consisted of all the Nepalese individuals users of online payment platforms or sources. Absence of a comprehensive sampling frame of Nepalese online payment users and the practical limitations of time, cost, and accessibility would be the reason for using non-probability sampling procedure. The main focus was to analyze the relationships between constructs rather than to generalize findings to entire population. Therefore, non-probability sampling would appropriate for obtaining meaningful insights into factors influencing behavioral intention and the adoption of online payments in the Nepalese context. The number of participants required to estimate a proportion with an approximate 95 percent confidence level was used to determine the sample size, and 384 was the number suggested by Godden (2004). 5-point Likert scale questionnaires were used to collect data. The questionnaire was administered using Google Forms. For the performance expectancy, the responses were taken from three different sources. Among the seven questions of each driver, four items were taken from Venkatesh et al., (2012), two from Martín and Herrero (2012), and also taken from Sarfaraz (2017). Similarly, for effort expectancy, four items were taken from Venkatesh et al., (2012), one item from Martin and Herrero (2012), one from Sarfaraz (2017), and one item from Isaac et al. (2019). For social influence, three items were taken from Venkatesh et al., (2012), one item from Martín and Herrero (2012), one item from Escobar-Rodríguez and Carvajal-Trujillo (2014), one item from Abrahao et al., (2016) and one from Sarfaraz (2017). For facilitating conditions, three items were taken from Venkatesh et al., (2012), one item from Martin and Herrero (2012), one item from Escobar-Rodríguez and Carvajal-Trujillo (2014), one item from Abrahao et al. (2016), and one from Sarfaraz (2017). Similarly for behavioral intention, seven items were taken from Venkatesh et.al., (2003; 2012). Lastly, for adoption, four items were taken from Venkatesh et al., (2012), one from Martin and Herrero (2012), one from Sarfaraz (2017), and one item from Liu and Gao (2008). The descriptive analytical tools, normality test, Cronbach alpha, discriminent validity, Fornell and Larcker test, cross-loading, structural model (SEM), correlation and regression analysis were the tests used in the study to analyze the data. Though, the study is prediction-oriented and involves analyzing complex relationships, including the mediating role of behavioral intentions, the study had used SMART PLS rather than AMOS. SMART PLS had provided greater flexibility and robustness for achieving the objectives of the study.

Results

Table 1: Normality Test

	Kolmogorov-Smirnov			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
PE	.165	384	.000	.886	384	.000
EE	.146	384	.000	.906	384	.000
SI	.168	384	.000	.902	384	.000
FC	.173	384	.000	.874	384	.000
BI	.106	384	.000	.935	384	.000
AI	.123	384	.000	.900	384	.000

All the variables p-values, as determined by the Shapiro-Wilk and Kolmogorov-Smirnov tests, were less than 0.05. This demonstrated that data was not normally distributed.

Measurement Model

The measurement model, or outer model in PLS-SEM, clarified the relationship between concept and indicator variables. Convergent validity, discriminant validity, and construct reliability were examined using this approach (Pandey et al., 2023).

Table 2: Reliability and Convergent Validity

Variables	Cronbach's Alpha	Composite Reliability	Composite Reliability (rho_c)	AverageVariance Extracted (AVE)
AI	0.892	0.892	0.916	0.608
BI	0.846	0.847	0.886	0.565
EE	0.887	0.888	0.912	0.596
FC	0.822	0.826	0.875	0.584
PE	0.896	0.900	0.920	0.659
SI	0.820	0.822	0.874	0.582

Every variable's Cronbach's alpha and composite reliability value had surpassed the minimum 0.7 threshold recommended by Fornell and Larcker (1981). The constructs' reliability was confirmed by the Cronbach's alpha values of 0.892, 0.847, 0.887, 0.822, 0.896, and 0.82 for adoption of online payment, behavioral intention, effort expectancy, facilitating conditions, performance expectancy, and social influence, respectively. Average Variance Extracted (AVE) was found greater than 0.5, verified the convergent validity. Overall, these findings had affirmed the validity and reliability of the measurement model. In addition, the values for composite reliability had shown strong internal consistency. It had implied that the indicators for each construct were reliably measuring the same concept. Thus, the measurement model had demonstrated good reliability and was acceptable for further analysis.

Discriminant Validity

As per Hair et al., (2019), the discriminant validity of a construct was used to evaluate its empirical dissimilarity from other constructs in the structural model.

Table 3: Fornell-Larcker Test

Variables	AI	BI	EE	FC	PE	SI
AI	**0.78**					
BI	0.761	**0.751**				
EE	0.723	0.731	**0.772**			
FC	0.776	0.722	0.762	**0.764**		
PE	0.723	0.682	0.698	0.716	**0.811**	
SI	0.693	0.608	0.628	0.675	0.752	**0.763**

The diagonal values shown the square roots of AVE, and the highlighted values for adoption, behavioral intention, effort expectancy, facilitating conditions, performance expectancy, and social influence were 0.78, 0.751, 0.772, 0.764, 0.811, and 0.763, respectively. As AVE's square root was greater than the equivalent correlation estimates, it had satisfied the requirements for discriminant validity set forth by Fornell and Larcker (1981). This had indicated the validity of the measurement model and implied that the constructs being used were accurately capturing the aspects of the study.

Cross Loading

Table 4: Cross Loading

Variables	AI	BI	EE	FC	PE	SI
AI1	**0.729**	0.591	0.51	0.623	0.555	0.512
AI2	**0.795**	0.601	0.549	0.583	0.525	0.519
AI3	**0.803**	0.598	0.591	0.585	0.583	0.566
AI4	**0.737**	0.585	0.564	0.643	0.563	0.526
AI5	**0.816**	0.586	0.571	0.609	0.599	0.579
AI6	**0.787**	0.62	0.52	0.575	0.506	0.502
AI7	**0.789**	0.572	0.634	0.612	0.61	0.572
BI1	0.672	**0.744**	0.586	0.599	0.509	0.489
BI2	0.594	**0.747**	0.562	0.537	0.574	0.524
BI3	0.554	**0.756**	0.531	0.53	0.527	0.451
BI4	0.528	**0.741**	0.52	0.493	0.44	0.354
BI5	0.547	**0.765**	0.533	0.548	0.505	0.458

BI7	0.515	**0.754**	0.554	0.539	0.508	0.446
EE1	0.596	0.653	**0.748**	0.586	0.564	0.496
EE2	0.563	0.555	**0.787**	0.604	0.549	0.506
EE3	0.578	0.618	**0.769**	0.595	0.54	0.497
EE4	0.58	0.545	**0.816**	0.592	0.556	0.457
EE5	0.493	0.499	**0.763**	0.587	0.503	0.448
EE6	0.526	0.517	**0.764**	0.544	0.485	0.468
EE7	0.552	0.535	**0.755**	0.604	0.561	0.515
FC1	0.607	0.635	0.662	**0.782**	0.556	0.474
FC3	0.651	0.616	0.653	**0.809**	0.545	0.512
FC4	0.615	0.528	0.482	**0.751**	0.659	0.651
FC5	0.558	0.506	0.526	**0.756**	0.526	0.536
FC7	0.522	0.46	0.585	**0.72**	0.436	0.395
PE2	0.625	0.6	0.563	0.638	**0.807**	0.657
PE3	0.593	0.612	0.644	0.592	**0.796**	0.574
PE4	0.572	0.532	0.572	0.582	**0.815**	0.607
PE5	0.651	0.597	0.607	0.629	**0.871**	0.662
PE6	0.532	0.457	0.476	0.463	**0.77**	0.566
PE7	0.531	0.496	0.514	0.559	**0.807**	0.584
SI1	0.541	0.474	0.485	0.53	0.616	**0.804**
SI2	0.557	0.454	0.453	0.525	0.552	**0.763**
SI3	0.503	0.432	0.442	0.457	0.547	**0.766**
SI4	0.474	0.435	0.432	0.514	0.509	**0.721**
SI6	0.559	0.517	0.573	0.546	0.633	**0.758**

Each component was shown with its maximum loading on the corresponding construct. It would be important to remember that an indicator was considered unsuitable for usage, if it scored better on constructs other than the one it was meant to measure (Pandey et al., 2023). The highest loadings were shown by the highlighted values. The established values had supported discriminant validity since each construct showed greater scores on its own construct than on any other.

Assessment of Structural Model

Table 5: Assessment of Structural Model

Constructs	VIF
BI -> AI	2.655
EE -> AI	3.015
EE -> BI	2.047
FC -> AI	3.182
PE -> AI	3.123
PE -> BI	2.847
SI -> AI	2.544
SI -> BI	2.416

After the construct's validity and reliability were established, the structural model was evaluated. This process started with observation in the structural models for problems related to collinearity, making sure there were no collinearity issues. Collinearity was examined using VIF as shown in Table 5. James et al., (2013) and Craney and Surles (2002) mentioned that the VIF > 5 indicated moderate correlation, whereas VIF > 10 indicated extreme correlation and was problematic and proceeded for further analysis. The value of VIF for all the constructs was below 5, satisfying that multicollinearity did not exist. Thus, with reference to James et al., (2017) and Craney and Surles (2002), the constructs (performance expectancy, effort expectancy, social influence, facilitating conditions, behavioral intention, and adoption of usage behavior) were free from the problem of multicollinearity.

Analysis of Association between Behavioral Intention, Effort Efficiency, Facilitating Conditions, Performance Expectancy, and Social Influence

Table 6: Relationship between Variables

Variables	AI	BI	EE	FC	PE	SI
AI	1	0.761	0.723	0.776	0.723	0.693
BI	0.761	1	0.731	0.722	0.682	0.608
EE	0.723	0.731	1	0.762	0.698	0.628
FC	0.776	0.722	0.762	1	0.716	0.675
PE	0.723	0.682	0.698	0.716	1	0.752
SI	0.693	0.608	0.628	0.675	0.752	1

The matrix presented in Table 6 depicted the relationships between constructs of the study; Adoption (AI), Behavioral Intention (BI), Effort Expectancy (EE), Facilitating Conditions (FC), Performance Expectancy (PE) and Social Influence (SI). Analyzing the matrix, the observe positive correlations between PE and other constructs, including EE (0.698), FC (0.716), SI (0.752), BI (0.682) and AI (0.723). This had suggested that higher levels of Performance Expectancy tend to be associated with increased levels of Adoption (AI), Behavioral Intention (BI), Effort Expectancy (EE), Facilitating conditions (FC) and Social Influence (SI). Similarly, EE had exhibited positive correlations with PE (0.698), FC (0.762), SI (0.628), BI (0.731) and AI (0.723), indicating that heightened Effort Expectancy aligned with increased levels of Adoption (AI), Behavioral Intention (BI), Performance Expectancy (PE), Facilitating Conditions (FC) and Social Influence (SI). FC had exhibited positive correlations with PE (0.716), EE (0.762), SI (0.675), BI (0.722) and AI (0.776), indicating that heightened Effort Expectancy (EE) aligned with increased levels of Adoption (AI), Behavioral Intention (BI), Effort Expectancy (EE), Performance Expectancy (PE), and Social Influence (SI). SI had shown a positive correlation with PE (0.752), EE (0.628), FC (0.675), BI (0.608) and AI (0.693), indicating that heightened Effort Expectancy (EE) aligned with increased levels of Adoption (AI), Behavioral Intention (BI), Effort Expectancy (EE), Performance Expectancy (PE), and Facilitating Conditions (FC). BI had shown positive correlations with PE (0.682), EE (0.731), FC (0.722), SI (0.608), and AI (0.761), indicating that heightened Effort Expectancy (EE) aligned with increased levels of Adoption (AI), Social Influence (SI), Effort Expectancy (EE), Performance

Expectancy (PE), and Facilitating Conditions (FC). AI had shown positive correlations with PE (0.723), EE (0.723), FC (0.776), SI (0.693), and BI (0.761), indicating that heightened Effort Expectancy (EE) aligned with increased levels of Behavioral Intention (BI), Social Influence (SI), Effort Expectancy (EE), Performance Expectancy (PE), and Facilitating Conditions (FC). The positive correlations between Social Influence (SI), Effort Expectancy (EE), Performance Expectancy (PE), Facilitating Conditions (FC), and Adoption (AI) had suggested that higher levels of PE, EE, SI, and FC were associated with better Behavioral Intention (BI). Social Influence (SI), Effort Expectancy (EE), Performance Expectancy (PE), and Facilitating Conditions (FC) might contribute to an improved adoption of online payment among consumers.

Structural Equation Model Analysis

Figure 2: Structural Model of Variables

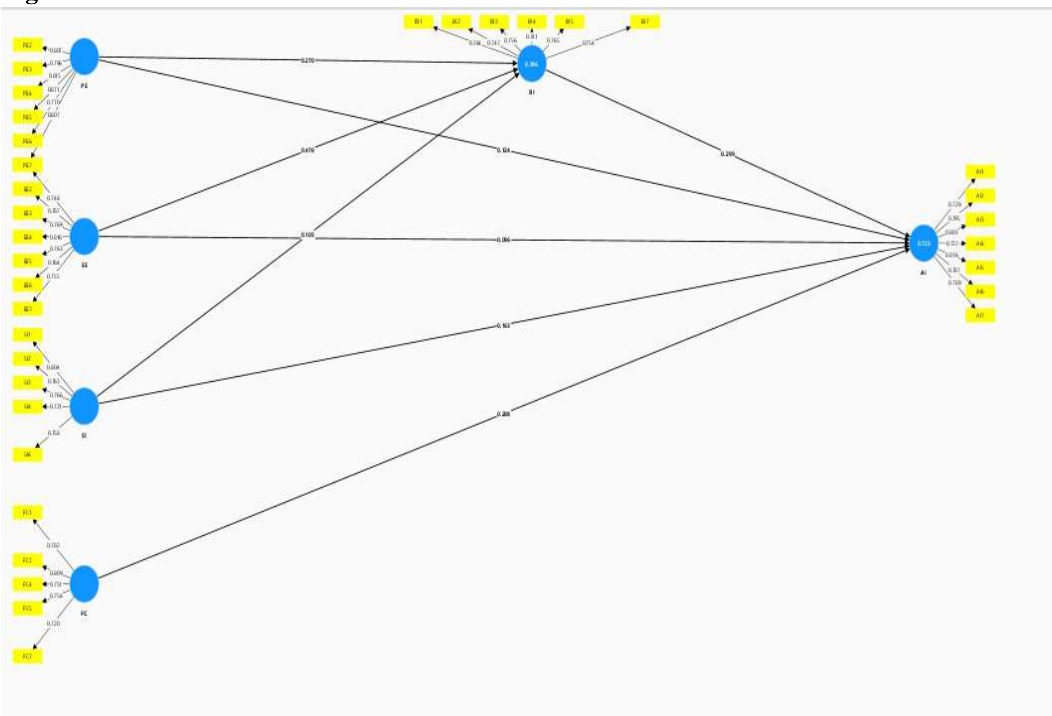

Figure 2 illustrated the path coefficient and R^2 value of the developed structural model. The R^2 value served as an indicator of the model's predictive power, representing the amount of explained variance of the endogenous construct in the model (Hair et al., 2017). R^2 value for Behavioral Intention (BI) was observed to be 0.596, indicated a moderate predictive power (Hair et al., 2017). This R2 value had suggested that 59.6 percent of the variation in Behavioral Intention (BI) was explained by the independent variables. Additionally, the path analysis had revealed a moderate predictive power for Adoption, as reflected in R^2 value of 0.723 (Hair et al., 2017). This had signified that approximately 72.3 percent of the variance in Job Performance was explained by the model.

Path Coefficient

Table 7: Path Coefficient

Paths	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	t-Statistics	P-Values
BI -> AI	0.299	0.3	0.047	6.417	0.000
EE -> AI	0.238	0.24	0.065	3.644	0.000
EE -> BI	0.476	0.476	0.034	13.922	0.000
FC -> AI	0.288	0.29	0.073	3.956	0.000
PE -> AI	0.205	0.2	0.056	3.656	0.000
PE -> BI	0.27	0.268	0.065	4.133	0.000
SI -> AI	0.195	0.195	0.048	4.042	0.000
SI -> BI	0.105	0.111	0.068	1.54	0.123

Table 7 indicated that all independent variables had exerted a significant impact on adoption (P-value < 0.05). Similarly, all independent variables had significantly affected behavioral intention (P-value < 0.05), except SI. This indicated that PE, EE, FC, and SI had significant relationships with adoption both through direct and indirect paths. The mediating role of behavioral intention was significant in this relationship. This meant, these factors not only had direct effects on adoption but also influenced adoption through their impact on behavioral intention. Specifically, Effort Expectancy, Performance Expectancy, and Facilitating Conditions had positively affected Behavioral Intention, which in turn significantly influenced Adoption. Therefore, the presence of a strong behavioral intention had enhanced the likelihood of actual adoption. However, in this study, social influence did not significantly impact behavioral intention, suggesting that its effect on adoption was primarily direct rather than mediated through BI.

Mediation Effect

Mediation takes place between two related constructs in the context of a third mediator variable. In the PLS structural model, any alteration in an exogenous variable had caused an alteration in the mediator, which then caused an alteration in the endogenous construct. As a result, a mediator variable had affected the underlying connection between the independent (performance expectancy, effort expectancy, social influence and facilitating conditions) and dependent variable (Adoption of online payment). SmartPLS 4 was used in mediation analysis to analyze and understand these complex relationships.

Analysis of Association between Performance Expectancy, Adoption and Mediation Effect of Behavioral Intention

Table 8: Direct Effect, Indirect Effect and Total Effect of PE on AI

Effect	Path	Original Sample (O)	Sample Mean (M)	Standard Deviation	t-Statistics	P-Values

				(STDEV)		
Direct Effect	PE -> AI	0.124	0.056	0.056	2.227	0.026
Indirect Effect	PE -> BI - > AI	0.081	0.08	0.023	3.496	0.000
Total Effect	PE -> AI	0.205	0.2	0.056	3.656	0.000

Table 8 presented the total effect, direct effect, and indirect effect of performance expectancy on adoption. The results indicated that the total effect of performance expectancy on adoption was statistically significant (β=0.205, 0.2, t=3.656, P=0.000). Also, the direct effect of performance expectancy adoption was significant (β=0.124, 0.056, t=2.227, P=0.026). Similarly, the indirect effect of performance expectancy on adoption through behavioral intention was significant (β=0.081, 0.205, t=3.656, P=0.000). This had suggested that the relationship was partially mediated by BI. Since both the direct and indirect effects were significant, it shown that behavioral intention had partially mediated the relationship between performance expectancy and adoption. This partial mediation implied that while Behavioral Intention (BI) played a role in this relationship, performance expectancy still had a direct impact on adoption beyond its effect through behavioral intention.

Analysis of Association between Effort Expectancy, Adoption and Mediation Effect of Behavioral Intention

Table 9: Direct Effect, Indirect Effect and Total Effect of EE on AI

Effect	Path	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	t-Statistics	P-Values
Direct Effect	EE -> AI	0.096	0.097	0.064	1.486	0.137
Indirect Effect	EE -> BI -> AI	0.143	0.143	0.026	5.410	0.000
Total Effect	EE->AI	0.238	0.240	0.065	3.644	0.000

Table 9 presented the total effect, direct effect, and indirect effect of Effort Expectancy on Adoption. The results indicated that the total effect of Effort Expectancy on Adoption was statistically significant (β=0.238, 0.24, t=3.644, P=0.000). The direct effect of Effort Expectancy on Adoption was not statistically significant (β=0.096, 0.097, t=1.486, P=0.137). Similarly, the indirect effect of Effort Expectancy on Adoption through Behavioral Intention was significant (β=0.143, 0.143, t=5.41, P=0.000). This had suggested that the relationship was fully mediated by BI. This had indicated that effort expectancy impacted adoption solely through its effect on behavioral intention, rather than having a direct influenced on adoption. In other words, effort expectancy had affected adoption indirectly by first altering behavioral intention, which then influenced adoption. Hence, behavioral intention acted as a complete mediator in the relationship between effort expectancy and adoption.

Analysis of Association between Social Influence, Adoption and Mediation Effect of Behavioral Intention

Table 10: Direct Effect, Indirect Effect and Total Effect of SI on AI

Effect	Path	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	t-Statistics	P-Values
Direct Effect	SI-> AI	0.163	0.162	0.046	3.575	0.000
Indirect Effect	SI-> BI -> AI	0.032	0.033	0.021	1.480	0.139
Total Effect	SI -> AI	0.195	0.195	0.048	4.042	0.000

Table 10 presented the total effect, direct effect, and indirect effect of social influence on adoption. The results had indicated that the total effect of social influence on adoption was statistically significant (β=0.195, 0.195, t=4.042, P=0.000). The direct effect of social influence on adoption was statistically significant (β= 0.163, 0.195 t=3.575, P=0.000). The indirect effect of social influence on adoption through behavioral intention was insignificant (β=0.032, 0.033, t=1.48, P=0.139). This had suggested that the relationship was not mediated by BI. Despite social influence having a significant total effect and a direct effect on adoption, the indirect effect through behavioral intention was insignificant. This indicated that social influence had affected adoption directly, rather than through its impact on behavioral intention. Therefore, behavioral intention did not mediate the relationship between social influence and adoption; the effect of social influence on adoption occurred independently of behavioral intention.

Analysis of Association between Facilitating Conditions and Adoption

Table 11: Direct Effect and Total Effect of FC on AI.

Effect	Path	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	t-Statistics	P-Values
Direct Effect	FC-> AI	0.288	0.29	0.073	3.956	0.000
Total Effect	FC -> AI	0.288	0.29	0.073	3.956	0.000

Table 11 presented the total effect and direct effect facilitating conditions on adoption. The results indicated that the total effect of FC on adoption was statistically significant (β=0.288, 0.29, t=3.956, P=0.000). This indicated FC had a significant positive effect on adoption. Facilitating conditions did not have an indirect effect on adoption through other variables; its effect was entirely direct. Therefore, the influence of facilitating conditions on adoption was direct and significant, with no additional mediating effects accounted for in this analysis.

Summary of Hypothesis Test

Table 12: Hypothesis Testing Summary

Hypothesis	Beta coefficient	P values	Decision
H1: PE -> AI	0.205	0.000	Accepted
H2: PE -> BI-> AI	0.081	0.000	Accepted
H3: EE -> AI	0.238	0.000	Accepted
H4: EE -> BI -> AI	0.143	0.000	Accepted
H5: SI -> AI	0.195	0.000	Accepted
H6: SI -> BI -> AI	0.032	0.139	Rejected
H7: FC -> AI	0.288	0.000	Accepted
H8: BI -> AI	0.299	0.000	Accepted

Table 12 exhibited the result of hypothesis testing based on beta coefficients and p-value. For Hypothesis H1, the beta coefficient of 0.205 had suggested a positive relationship. The p-value indicated statistical significance, supporting the hypothesis that there was a positive and significant relationship between performance expectancy and adoption. It had implied that there was a positive significant relationship between PE and AI. Similarly, for hypothesis H2, the beta coefficient of 0.081 had suggested a positive relationship. The p-value indicated statistical significance, supporting the hypothesis that the sequential relationship from performance expectancy through behavioral intention to adoption was positively significant. That implied that behavioral intention had partially mediated the relationship between performance expectancy and adoption. In the same way, for hypothesis H3, the beta coefficient of 0.238 indicated insignificant positive relationship. The p-value indicated statistical significance, supporting the hypothesis. Thus, hypothesis H3 was accepted, that implied a positive significant relationship between effort expectancy and adoption. The beta coefficient of 0.143 for H4 had suggested a positive relationship. The p-value indicated statistical significance, supporting the hypothesis that the sequential relationship from effort expectancy through behavioral intention to adoption was significant. That meant behavioral intention had mediated the relationship between effort expectancy and adoption. In H5, the beta coefficient of 0.195 suggested a positive relationship. The p-value indicated strong statistical significance, supporting the hypothesis that there was a positive and significant relationship between social influence and adoption. In H6, the beta coefficient of 0.288 had suggested a positive relationship. The p-value indicated a statistical insignificance, thus rejecting the hypothesis that the sequential relationship from social influence through behavioral intention to adoption was significant. In H7, the beta coefficient of 0.288 had suggested a positive relationship. The p-value indicated strong statistical significance, supporting the hypothesis. This implied that facilitating conditions had a significant positive effect on the adoption of online payment. Finally, in H8, the beta coefficient of 0.299 had suggested a positive relationship. The p-value had indicated strong statistical significance, supporting the hypothesis, implying the positively significant impact of behavioral intention on the adoption of online payment.

Discussions

The analysis specifically considered performance expectancy, effort expectancy, social influence, and facilitating conditions as the drivers of adopting usage behavior. The findings confirmed that performance expectancy, effort expectancy, social influence, and facilitating conditions have a positive, significant relationship with the adoption of online payment. This finding is consistent with the studies by Chand et al., (2024); Aligarh (2023); Doan (2020); Rahmiati (2020); Rosnidah et al., (2018); Alalwan et al., (2018); Junadi (2015); and Attuquayefio (2014). One plausible reason for the consistency in findings with studies might be the shared theoretical framework and use of the same base theory, i.e., Venkatesh et al., (2003), the Unified Theory of Acceptance and Use of Technology (UTAUT). It is argued that by examining the presence of each of these constructs in a real-world environment, researchers and practitioners would be able to assess an individual‘s intention to use a specific system, thus allowing for the identification of the key influences on acceptance in any given context. As per the third objective of this study, to find the mediating role of behavioral intention between performance expectancy, effort expectancy, social influence, facilitating conditions, and adoption of usage of online payment, it is revealed that behavioral intention mediates the relationship between all four constructs (performance expectancy, effort expectancy, social influence, and facilitating conditions) and the adoption and usage of online payment. The finding is consistent with the findings by Chand et al., (2024); Aligarh (2023); and Rosnidah et al., (2018). This findings contrasts with the findings by Bagozzi (2007) and Bhattacherjee (2010) that behavioral intention does not mediate the relationship between the four constructs and adoption of usage of online payment. These studies suggest that while behavioral intention is a significant mediator in many contexts, there are situations where its mediating role may be less pronounced or where other factors might directly influence usage behavior. The effectiveness of behavioral intention as a mediator can depend on the specific technology, context, and individual differences among users. The Unified Theory of Acceptance and Use of Technology (UTAUT) model posits that behavioral intention mediates the relationship between key antecedents performance expectancy, effort expectancy, social influence, and facilitating conditions and usage behavior. Numerous empirical studies have validated this mediating role across various contexts, including mobile banking, online learning platforms, and e-commerce, reinforcing the model's robustness and applicability. However, some research critiques the deterministic nature of UTAUT, suggesting that behavioral intention may not always serve as an effective mediator in all situations. These contrasting findings underscore the importance of context-specific analysis and suggest that while UTAUT provides a valuable framework, it may need to be adapted or extended to account for the nuances of different technological environments and user behaviors. Overall, while behavioral intention remains a critical mediator in many studies, its role is not universally definitive, highlighting the need for ongoing research and model refinement. The study reinforces the robustness of UTUAT while highlighting the context-specific naunces that may influence the strength of behavioral intention as a mediator. Additionally, the findings provide empirical evidence supporting the generalizability of UTUAT constructs in predicting technology adoption in emerging digital markets.

Conclusions

The study analyzed the factors influencing the adoption of online payment among Nepalese consumers and explored the mediating role of behavioral intention between the four constructs of usage behavior (performance expectancy, effort expectancy, social influence, and facilitating conditions) and adoption of online payment among Nepalese consumers using digital payment platforms. The study addressed key questions on these variables and their impact. The analysis revealed that performance expectancy, effort expectancy, social influence, and facilitating conditions significantly and positively contributed to the adoption of online payment among Nepalese consumers in a direct relationship. However, social influence has not exhibit statistically significant indirect effect on adoption, suggesting that consumers are not strongly influenced by the opinions of close contacts. Instead, they tend to try the technology independently and then evaluate its usefulness. It is concluded that Nepalese consumers consider factors such as platform performance, ease of use, influence of family and friends, and support from service providers when deciding whether to adopt online payment methods. However, their adoption decisions are not solely determined by their stated behavioral intentions. This understanding is valuable for practitioners in formulating effective policies to ensure everyone is familiar with some sort of online payment platform. Ever since the COVID-19 pandemic, the whole world has been moving towards cashless and all or some form of digital transaction. Soon, cryptocurrency will be the new norm, replacing physical forms of monetary transactions for good. Not only are digital transactions more efficient and safer, but they are also less time-consuming, thus allowing consumers to shift their focus towards goods rather than payment methods.

Implications

The study provides valuable insights for policymakers and leaders to lead Nepal towards a future of online transactions. The implications of this study hold considerable significance, particularly for Nepal. Future researchers are encouraged to delve deeper into this type of study, as it has the potential to provide further insights. Given that this study focused on behavioral intention as a mediator between drivers of adoption and usage behavior among Nepalese consumers, it becomes imperative to conduct additional research for generalizing the findings. Incorporating more variables like gender, age, experience, and voluntariness of use as mediators and moderators would enhance the precision of predicting usage behavior like adoption of online payment, especially considering the four constructs as independent variables. Additionally, the study focused only on four constructs taken from UTAUT and behavioral intention to explain the adoption of online payment; future study could benefit from exploring additional factors to provide a more comprehensive understanding of online payment adoption. Also, analyzing the impact of age, marital status, gender, and other demographic factors on the relationship could yield valuable insights. In addition, this study fully focused on the customers‘ perspective, yet it has not looked at this problem from the service providers‘ perspective. Furthermore, since this study focused solely on customer perspective, analyzing service providers’ views could provide a more complete understanding of the successful implementation and adoption of online payments in Nepal.

References

Abrahao, R. D. S., Moriguchi, S. N., & Andrade, D. F. (2016). Intention of adoption of mobile

payment: An analysis in the light of the Unifified Theory of Acceptance and Use of Technology (UTAUT). *RAI Revista de Administracao E Inovacao, 13*, 221-230. https://doi.org/10.1016/j.rai.2016.06.003

Ajzen, I. (1985). From intention to actions: A theory of planned behavior. In J. Kuhl, & J.

Beckman (Eds.), Action control: From cognition to behavior (pp. 11-39). New York: Springer-Verlag. http://doi.org/10.1007/978-3-642-69746-3_2

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50* (2), 179-211. https://doi.org/10.1016/0749-5978(91)90020-T

Al-Smadi, M.O. (2012). Factors affecting adoption of electronic banking: an analysis of the perspectives of banks customers. *International Journal of Business and Social Science, 3*. https://doi.org/10.4236/ojbm.2020.81020

Bhattacherjee, A. (2001). Understanding information systems continuance: An expectation-confirmation model. *MIS Quarterly, 25*(3), 351-370. http://doi.org/10.2307/3250921

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

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1992). Extrinsic and intrinsic motivation to use computers in workplace. *Journal of Applied Social Psychology*, *22*, 1111–1132.

Fishbein, M., & Ajzen, I. (1974). Attitudes towards objects as predictors of single and multiple behavioral criteria. *Psychological Review, 81*(1), 59–74. https://doi.org/10.1037/h0035872

Fishbein, M., & Ajzen, I. (1975). *Belief, Attitude, Intention, and Behavior: In an Introduction to Theory and Research Reading*. Addison- Wesley.

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., & Thiele, K. O. (2017). Mirror, mirror on the wall: A comparative evaluation of composite-based structural equation modeling methods. *Journal of the Academy of Marketing Science*, *45*(5), 616-632. https://doi.org/10.1007/s11747-017-0517-x

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed, a silver bullet. *Journal of Marketing Theory and Practice*, *19*(2), 139-152. https://doi.org/10.2753/MTP1069- 6679190202

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2-24. https://doi.org/10.1108/EBR-11-2018-0203.

Hong, S. J., Thong, J., & Tam, K. (2006). Understanding continued information technology usage behavior: A comparison of three models in the context of mobile internet. *Decision Support Systems, 42*, 1819-1834. http://doi.org/10.1016/j.dss.2006.03.009.

Isaac, O., Abdullah, Z., Aldholay, A. H., & Ameen, A. A. (2019). Antecedents and outcomes of internet usage within organizations in Yemen: An extension of the Unified Theory of Acceptance and Use of Technology (UTAUT) model. *Asia Pacific Management Review*, *24*(4), 335-354. https://doi.org/10.1016/j.apmrv.2018.12.003

Jayaraman, T. K., & Makun, K. K. (2020). Tourism–growth nexus in pacific island countries: A panel study on information and communication technology as a contingent factor. *Tourism Economics, 26*(3), 371–388. https://doi.org/10.1177/1354816619836332

Koghut, M., & AI-Tabbaa, O. (2021). Exploring consumers discontinuance intention of remote mobile payments during post-adoption usage: An empirical study. *Administrative Sciences, 11*(1), 18-24.

Kumar, R. (2014). *Research Methodology: A Step-by-Step Guide for Beginners (4/E).* SAGE Publications Ltd.

Kumar, N. K., & Yadav, A. S. (2022). A Systematic Literature Review and Bibliometric. https://doi.org/ 10.31893/multirev.2024029

Lai, P. C., & Li, Y. C. (2005). Technology acceptance model for Internet banking: An invariance analysis. *Information & Management, 42*(2), 373-386. https://doi.org/ 10.1016/j.im.2004.01.007.

Lin, C., & Bhattacherjee, A. (2010). Extending technology usage models to interactive hedonic technologies: A theoretical model and empirical test. *Information Systems Journal*, *20*(2), 163-181. https://doi.org/10.1111/j.1365-2575.2007.00265.x

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.

Makun, K. K., & Jayaraman, T. K. (2020). Spread of ICT and economic growth in pacific island countries: A panel study. *Bulletin Ekonomi Moneter Dan Perbankan, 23*, 109-28. https://doi.org/10.21098/bemp.v23i0.1178

Makun, K., Singh, R., Lal, S., & Chand, R. (2022). Information and communications technology, health, and gender equality: Empirical evidence from a panel of pacific developing economies. https://doi.org/10.1371/journal.pone.0269251

Martín, H. S., & Herrero, A. (2012). Influence of the user‘s psychological factors on the online purchase intention in rural tourism: Integrating innovativeness to the UTAUT framework. *Tourism Management, 33*, 341–350. https://doi.org/10.1016/j.tourman.2011.04.003

Nunnally, J.C. (1978). *Psychometric Theory (2/E).* McGraw-Hill.

Osah, O., & Kyobe, M. (2017). Predicting user continuance intention towards M-Pesa in Kenya. *African Journal of Economic and Management Studies*, *8*(1), 36–50.

Pandey, D. L., Uprety, S. K., & Risal, N. (2023). Personality traits and their impact on the social entrepreneurial intentions of management students: A test of big five personality approach. *Journal of Innovation and Entrepreneurship*, *12*(1), 1-25. https://doi.org/10.1186/s13731-023-00342-8

Park, J., Amendah, E., Lee, Y. and Hyun, H. (2019). M-payment service: interplay of perceived risk, benefit, and trust in service adoption. *Human Factors and Ergonomics in Manufacturing and Service Industries, 29* (1), 31-43. https://doi.org/10.1002/hfm.20750

Sarfaraz, J. (2017). Unified Theory of Acceptance and Use of Technology (UTAUT) Model-mobile banking. *Journal of Internet Banking and Commerce*, *22*(3), 1–20.

Sheeran, P. (2003). Predicting behavior from perceived behavioural control: Tests of the accuracy assumption of the theory of planned behavior. *British Journal of Social Psychology 42,* (3), 393-410. https://doi.org/10.1348/014466603322438224

Sheeran, P., & Orbell, S. (1998). Do intentions predict condom use? Meta-analysis and examination of six moderator variables. *British Journal of Social Psychology, 37*(2), 231–250. https://doi.org/10.1111/j.2044-8309.1998.tb01167.x

Singh, A., Alryalat, M. A. A., Alzubi, J. A., & Sarma, H. K. D. (2017). Understanding Jordanian consumers' online purchase intentions: Integrating trust to the UTAUT framework. *International Journal of Applied Engineering Research, 12*(20), 10258-10268.

Sutton, S. (1998). Predicting and explaining intentions and behavior: How well are we doing? *Journal of Applied Social Psychology, 28*(15), 1317-1338. https://doi.org/10.1111/j.1559-1816.1998.tb01679.x

Taylor, S., & Todd, P. (1995). Decomposition and crossover effects in the theory of planned behavior: A study of consumer adoption intentions. *International Journal of Research in Marketing, 12,* 137-155. https://doi.org/10.1016/0167-8116(94)00019-K

Thong, J. Y. L., Hong, S. J., and Tam, K. Y. (2006). The effects of post-adoption beliefs on the expectation confirmation model for information technology continuance. *International Journal of Human-Computer Studies, 64* (9),799-810.https://doi.org/10.1016/j.ijhcs.2006.05.001

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of technology acceptance model: Four longitudinal field studies. *Management Science, 46*(2), 186-204.

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.

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), 157-1