INTERNATIONAL JOURNAL OF BUSINESS, 29 (4), 2024 ISSN: 1083-4346

Determinants Influencing Behavioral Intentions towards Digital Wallets in Saudi Arabia

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ABSTRACT

This study examines the factors influencing consumer behavioral intentions towards digital wallet services in the Kingdom of Saudi Arabia. Based on the Technology Acceptance Model and the Diffusion of Innovation theory, 472 valid survey responses are analyzed in order to develop a model that explores consumers' attitudes towards the adoption and ongoing use of digital wallets in the focal context. Further, SEM-AMOS is used to test multiple hypotheses and investigate the impact of the COVID-19 pandemic on consumers' adoption of digital wallets, thereby providing the first evidence indicating this impact in the context of Saudi firms. The study explores the direct and indirect influence of "intention to use" on "continuous use" with empirical support found for the mediation mechanism through actual use. Consequently, an empirical basis is established for understanding how an individual's intentions play a significant role in determining actual and continuous use. The refined model contributes to the literature by furthering the field's understanding of the factors that influence the acceptance rate of this innovative technology.

JEL Classifications: D12, G20, G21, L86, M15, O33

Keywords: technology adoption, digital wallet, technology acceptance model (TAM), diffusion of innovation theory (DIO), COVID-19 pandemic, vision 2030

https://doi.org/10.55802/IJB.029(4).003

I. INTRODUCTION

In the present-day commercial environment, one of the greatest challenges facing companies inheres in understanding and accounting for the decision processes of potential buyers of new products. In determining how best to introduce potential consumers to a new product or service, companies engage in market research that may include surveys and focus groups with the ultimate goal of implementing a strategy to turn potential buyers into regular users (Blythe, 2006). According to Kotler and Armstrong (2016), only 2.5% of potential customers adopt new products/services immediately following their market release, with almost 50% of the expected target market adopting an innovation only when it has become well-established.

There is, of course, a strong focus on the online marketplace across all industries, including in the highly competitive realm of modern financial technology (FinTech)—a context in which enterprises are transitioning operations from a traditional product-oriented model to a customer-centered one (Al Bassam and Al Shawi, 2010; Kotler and Armstrong, 2016). This study concentrates on digital wallets or e-wallets in the context of Saudi Arabia as an easily accessible service that reflects this contemporary focus. Offered by major global market competitors such as Apple Pay, Samsung Pay, Google Pay, and PayPal (BCG, 2018), digital wallets enable the exchange of currency in order to acquire goods and services. Specifically, these services enable end-users to engage in multiple kinds of transactions, including recharging and topping up balances, transferring funds between accounts, shopping online, and paying bills (Henson, 2017).

The use of this kind of service is of particular interest, given the Saudi government's goal of achieving a 70% cashless society as stated in the KSA's Vision 2030. To realize this goal, the government is implementing various initiatives to enhance the country's digital infrastructure, which can be expected to support the development of the country's FinTech industry, including in regard to services such as digital wallets. For instance, the government is encouraging investment in the FinTech sector in order to spur the development of advanced digital wallet solutions, thereby promoting the adoption of digital payment methods. One notable initiative is the adoption of the Mada scheme in 2015, through which the Saudi Arabian Monetary Authority (SAMA) eliminated merchants' fees for installation and periodic services, provided free SIMs for connectivity and maintenance support, and introduced affordable merchant discount rates (Saudi Central Bank, 2020). Furthermore, the Saudi Central Bank has so far granted licenses to 17 companies to provide digital wallet payment services, including STC. Pay is leading the industry for this service with 8 million customers nationwide. These regulatory reforms are expected to significantly boost digital payments and online transactions, consequently driving the adoption of digital wallets across Saudi Arabia. According to Mordor Intelligence (2023), between 2024 and 2029, the Kingdom is expected to experience an 11.49% Compound Annual Growth Rate (CAGR) in non-cash payment transaction volume.

According to STATS (2021), in 2020, 67% of Saudi Arabia's population comprised children and young people, who are considered digital natives or part of Generation Z, also known as tech-savvy Zoomers. In 2019, a report from the Jeddah Chamber (2021) showed that internet usage in Saudi Arabia had risen to 95.7%, up from 93.3% in 2018, fueling the growth of FinTech services. In this context, the uptake of digital wallet services is progressing overall. However, if companies are to reach their

https://doi.org/10.55802/IJB.029(4).003

potential in the FinTech industry and other commercial environments, it is necessary to determine the factors that drive and the factors that undermine the adoption rate of this type of technology. Understanding these factors is essential to advancing towards the goal of a 70% cashless society.

To date, the literature offers very little discussion of these issues. However, the literature from the last thirty years includes multiple studies focused on understanding the factors that influence the rate at which new products are adopted, especially in regard to identifying the reasons for low adoption rates. According to Sarin and Kapur (1990), new product development studies focus on the following five concerns: the causes of new product success/failure (Zirger and Maidique, 1990), the new product development process (Cooper and Kleinschmidt, 1991), the new product development strategy-performance relationship (Dougherty, 1990), models to predict new product performance (Kendall and French, 1991), and a single factor relating to new product success/failure (Abeele and Christiaens, 1986).

Over the past decade, a number of studies have been published to further the understanding of the factors that influence the rate at which consumers adopt e-wallet and mobile payment services. Recent studies such as Aji et al. (2020) and Le et al. (2022) highlight the importance of combining technological, behavioral, and financial aspects in understanding the adoption of mobile payment services. Lin (2011) investigated the effect of innovation attributes and knowledge-based trust on mobile banking adoption. Innovativeness, perceived value, and user experience are also key factors, as shown by Hong et al. (2017) and Dwijayanti et al (2021). Additionally, Liébana-Cabanillas et al. (2018) emphasized the importance of understanding the determinants of mobile payment acceptance in their hybrid SEM-neural network approach. However, none of these studies focus specifically on digital wallets.

The purpose of the present study is to address the gap in the literature in relation to digital wallet adoption in Saudi Arabia by developing and testing a research model to predict consumers' attitudes towards and usage of this technology in particular with applicability to similar technologies more generally, with the impact of the COVID-19 pandemic taken into account. Specifically, we integrate the Technology Acceptance Model (TAM) with the Diffusion of Innovation (DOI) theory to create a hybrid TAM-DOI model. This model offers a more comprehensive understanding of technology acceptance and use, taking into account the complexities of the adoption process. Thus, we seek answers to the following key research questions:

1. What factors influence the adoption and continuous usage of digital wallets?
2. To what extent did the COVID-19 pandemic impact the adoption rate and usage of digital wallets?

By answering these questions, we provide insights that can assist policymakers in developing strategies to facilitate digital wallet adoption and support the realization of the Vision 2030 goal of a 70% cashless economy in Saudi Arabia. The refined model will advance the field's understanding of the factors identified as likely to influence the acceptance rate of these kinds of technology such that the findings could play a crucial role in informing policy and industry decisions related to promoting and adopting these payment methods. Additionally, the model can be used by both managerial practitioners and policymakers to support progress towards the development of a cashless economy.

https://doi.org/10.55802/IJB.029(4).003

The rest of the paper is organized as follows: Section 2 provides a comprehensive overview of the research conducted on digital wallet acceptance, including a literature review and the development of the central hypothesis, and a description of the conceptual framework used to explain the attributes that impact acceptance rate. In Section 3, we present the data analysis and the sample selection process together with the empirical results. Section 4 comprises our concluding remarks and an account of policy implications.

II. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

A. Literature Review

1. Underpinning Theories

The consumer behavioral literature includes a number of technology acceptance and adoption models and theories. One of the most well-established approaches to analyzing consumer behavior in the information systems field (Davis, 1989), the Technology Acceptance Model (TAM) constitutes an information system theory that explains consumers' acceptance of technological products and services. The model connects predetermined external dimensions that influence consumer acceptance of technology products/services with the perceived usefulness of the technology systems and the perceived ease of using the service. These two antecedents have been identified as major contributing factors to the formation of attitudes towards and behavioral intentions regarding a product or service, and actual use of it.

A large and growing body of literature investigates TAM across different sectors and various cultures (Anouze and Alamro, 2019). However, regardless of its popularity, TAM suffers from several major drawbacks. It has been reported that TAM does not explain more than 40% of the variance in technology system usage (Legris et al., 2003). Accordingly, it is necessary to modify the model to better serve specific purposes such that we refined it in a number of ways to better suit our investigation into the specific concern of digital wallet acceptance. It has been suggested that the attitude construct could be dropped from the standard version of TAM in order to simplify the model (Venkatesh et al., 2003). In addition, we incorporated a service attributes factor into our refined model as an external variable that ultimately influences actual use of the system.

In more detail, the TAM is combined with the Diffusion of Innovation (DOI) theory in the present study to provide a comprehensive understanding of the acceptance and utilization of the focal technology. Based on an extensive analysis of relevant literature, we integrated TAM with the Diffusion of Innovation (DOI) theory to develop the hybrid TAM-DOI model—a model that improves on current methodologies by yielding a more nuanced and multi-dimensional perspective on the multifaceted process of technology acceptance and a closer account of the complexities of technology acceptance and usage.

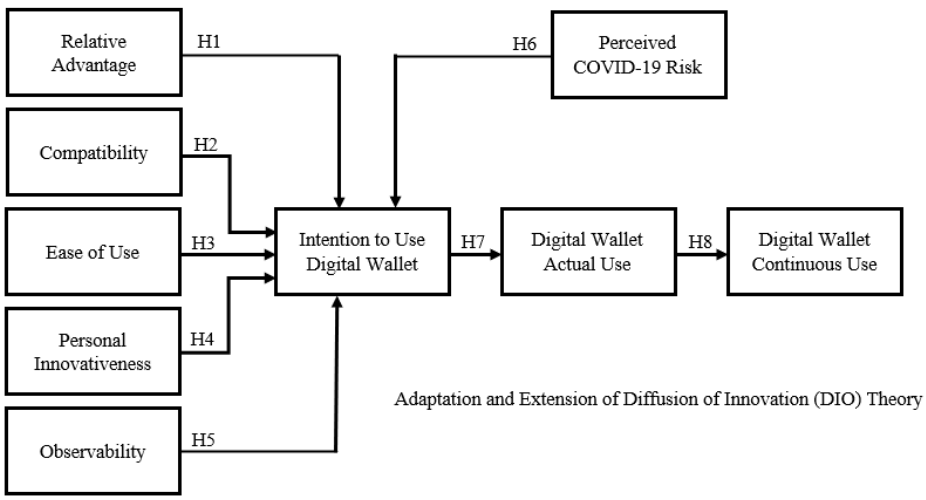
B. Hypothesis Development

This section includes an overview of the research most pertinent to the current study and the basis it provides for forming the present hypothesis. This section includes an

https://doi.org/10.55802/IJB.029(4).003

overview of the research most pertinent to the current study and the basis it provides for forming the present hypothesis (Figure 1).

Figure 1.
Research Model and Hypothesis



In multiple studies, researchers have established that factors such as relative advantage, compatibility, and image are crucial in the adoption of technology (Mallat, 2007; Kim et al., 2009; Liébana-Cabanillas et al., 2018; Aji et al., 2020). In a study of the impact of COVID-19 on the usage intention of e-wallets in Indonesia and Malaysia, Aji et al. (2020) concluded that relative advantage was positively linked to the intention to use e-wallets. Similarly, in applying a hybrid SEM-neural network method to determine the factors affecting mobile payment acceptance, Liébana-Cabanillas et al. (2018) found that relative advantage had a positive impact on the intention to use mobile payments.

In the context of mobile payments, previous research has emphasized the significance of location and time independence in the perceived relative advantage of these technologies (Mallat, 2007; Kim et al., 2009). The ability to access financial services at any time and place means it is reasonable to assume that perceived relative advantage will have a positive effect on customers' adoption of the technology. Thus, the following hypothesis is proposed:

H1: Relative advantage has a significant positive influence on use intention for digital wallet service.

As per Rogers (2003), compatibility refers to the relative alignment of an innovation with the values, prior experiences, and expectations of potential adopters. Accordingly, Hsu et al. (2007) and Shin (2010) showed that compatibility plays a significant role in shaping consumers' intention to use the internet and adopt mobile

https://doi.org/10.55802/IJB.029(4).003

networks whereas Mallat et al. (2008) found that compatibility can predict usage intention for mobile ticketing services. Further, Putzer and Park (2010) reported that compatibility greatly influences the attitudes of smartphone users and Schierz et al. (2010) discovered that compatibility has a significant relationship with the attitudes of mobile payment service users. In a number of more recent studies, researchers found significant connections between compatibility and the intention to adopt digital wallets (Liébana-Cabanillas et al., 2018; Aji et al., 2020; Le et al., 2022; Shetu et al., 2022). Thus, the following hypothesis is proposed:

H2: Compatibility has a significant positive influence on use intention for digital wallet service.

Describing perceptions of how easy or difficult it is to use a given technology, perceived ease of use is a determinant of technology adoption (Apanasevic et al., 2016). As the market has continued to demand new and innovative technologies, the number of services and devices with advanced applications and features, such as smartphones, has increased to keep pace. An important result of this demand and supply relationship is continuous improvement of mobile technologies that enable organizations and consumers to complete their daily tasks more efficiently (Daştan and Gürler, 2016). Further, as noted by Schepers and Wetzels (2007), ease of use plays a critical role in determining a consumer's willingness to use any given product or service. The connection between ease of use, consumer attitude, and intention to use is examined in numerous studies. For example, Liébana-Cabanillas et al. (2018) used a hybrid SEM-neural network approach to predict the determinants of mobile payment acceptance. The results showed that relative advantage, compatibility, ease of use, and observability have a positive effect on the intention to use mobile payments. Moreover, Shetu et al. (2022) showed that a significant relationship exists between ease of use and intention to adopt digital wallets specifically. The perceived ease of use, therefore, is used as a determinant in the present study, as it is a factor that may inhibit the adoption of an innovation (Wei et al., 2009). Thus, the following hypothesis is proposed:

H3: Ease of use has a significant positive influence on use intention for digital wallet service.

The idea of personal innovativeness, as defined by Kalinic and Marinkovic (2016), refers to an individual's willingness or inclination to experiment with new things, including new products or services. According to Rogers (2003) and the innovation diffusion theory, individuals with a high level of personal innovativeness seek information about new ideas and are among the first to adopt new innovations. As a result of their early adoption and increased technical competencies, these individuals are more likely than others to perceive information technology innovations as less complex and easier to use (Sam et al., 2014; Montazemi and Qahri-Saremi, 2015).

Iranmanesh et al. (2017) and Tech (2020) concur that individuals with high personal innovativeness (PI) tend to be early adopters and are more adaptable to uncertainty. They are open to change and more willing to embrace new technologies, even with the associated risks. This conclusion is supported by Chauhan et al. (2022), who found that individuals with high levels of innovativeness are more willing to take on higher risks. Le et al. (2022) studied the adoption of m-wallets in emerging markets and considered technological, behavioral, and financial aspects. The results showed that relative advantage, compatibility, ease of use, and personal innovativeness have a positive impact on the intention to use m-wallets. Thus, the following hypothesis is proposed:

H4: Personal innovativeness has a significant positive influence on use intention for digital wallet service.

Referred to as observability, the degree to which the outcomes of an innovation are visible to others has a direct correlation with its adoption rate (Rogers, 2003). The more noticeable the outcomes of an innovation, the more likely it will be accepted and used. According to Vishwanath and Goldhaber (1982), observability has a significant impact on an individual's intention to adopt technology products. Additionally, based on a meta-analysis of the drivers of intention and behavior, Arts et al. (2003) found partial support for the idea that observability may have a particularly strong effect on the intention phase.

In a more recent study, Liébana-Cabanillas et al. (2018) predicted the determinants of mobile payment acceptance using a hybrid SEM-neural network approach. The results showed that factors such as relative advantage, compatibility, ease of use, and observability have a positive impact on the intention to use mobile payments. Thus, the following hypothesis is proposed:

H5: Observability has a significant positive influence on use intention for the digital wallet service.

E-wallets have been identified as an effective way to mitigate the disease risk (i.e., the likelihood that individuals will be negatively affected by various epidemics (Hasan et al., 2017) of COVID-19. Further, the perception of this kind of risk has been shown to have a strong positive effect on the intention to use e-wallets (Aji et al., 2020). The authors suggest that as individuals' perceived risk of COVID-19 from handling physical cash increased, their intention to perform payment transactions using an e-wallet increased as a precautionary measure against COVID-19. Thus, the following hypothesis is proposed:

H6: Perceived COVID-19 risk has a significant positive influence on use intention for the digital wallet service.

Davis et al. (1989) connect intention to use with continuous use. According to the model, a user's intention to use a technology is determined by perception of its usefulness and ease of use, and by other factors such as subjective norm and facilitating conditions. Having formed an intention to use a technology, a user may then actually use it, at which point perceived usefulness and ease of use may lead the user to continue using it.

Overall, it is critical to understand the intention to use the technology concept, as it refers to the likelihood of an individual adopting and using a given product or service of a technological nature (Schierz et al., 2010). In fact, this intention has been shown to significantly affect actual usage behavior, as demonstrated by a number of studies

https://doi.org/10.55802/IJB.029(4).003

(Baptista and Oliveira, 2017; Alalwan et al., 2018; Zhou et al., 2020). For this reason, it is imperative that stakeholders grasp not just consumers' intention to use mobile payment solutions but also the likelihood of that intention resulting in actual usage. Thus, the following hypothesis is proposed:

H7: Use intention has a significant positive influence on actual use of digital wallet service.

Several studies have highlighted the fact that the initial adoption and usage of a technology can significantly impact its continuous use. For instance, Venkatesh et al. (2003) identified user satisfaction with a technology to be crucial in determining continued usage, concluding that users who are more satisfied with the technology are more likely to continue using it. Continuous use of a technology is with good reason considered a key measure of success (Davis et al., 1989).

TAM proposes that a user's continued use of a technology is positively associated with perceived usefulness and ease of use. In other words, users who find a technology both useful for given purposes and easy to use, they are likely to continue using it over time. This connection between intention to use and continuous use is established by linking users' perceptions of a technology to actual usage behavior.

Zhong et al. (2013) found that actual use and payment behavior are both have a determinative role in consumer adoption of mobile payments in China. More recently, using a structural analysis of the factors that impact the adoption and sustained use of mobile payment systems in India, Raman and Aashish (2021) found that the actual usage of mobile payments has a strong positive impact on continuous use. The researchers also identified factors such as service quality, attitude, ease of use expectations, and perceived risk as important determinants of the continuance intention to use mobile payment systems (MPSs) in India. The following hypothesis is, therefore, proposed:

H8: Actual use of digital wallet service has a significant positive influence on continuous use.

III. STUDY SAMPLE, DATA COLLECTION, AND SCREENING

A. Online Survey, Sampling, Data Collection, and Screening

The questionnaire was designed based on Likert-type scales in the literature, with some modifications in terms of the language used to better align the items with the Saudi context and the focal digital wallet topic. Next, content validity was examined through face validity and a pilot study. Face validity was established by consulting with academic and professional experts with significant experience in questionnaire design. The experts proved 96% of the questionnaire content, and some revisions related to language and phrasing as a result of their review. A professional editor reviewed and corrected the language and grammar used and made minor changes accordingly. Face validity was established through this overall process. Using the questionnaire reviewed and modified as described, we conducted a pilot study by surveying 25 respondents who were not part of the sample used for model analysis. The Cronbach's alpha coefficient values were all found to be above the 0.60 level for the pilot sample, such that all the scales are

https://doi.org/10.55802/IJB.029(4).003

considered reliable. In addition, Pearson correlations were examined to check for internal consistency. All the items were found to be significantly correlated to the proposed dimension, such that the survey instrument demonstrated an adequate level of consistency.

The survey was hosted on Google Form with an open link forwarded using social media platforms (WhatsApp, Twitter). Respondents were informed that participation in the survey was voluntary, that the data would be used for academic research purposes only, and that confidentiality would be ensured, given that Google Form settings do not collect users' IP addresses. The questionnaire link was live for a five-month period (January 2022–May 2022), with the data collection ending after no more surveys had been completed for some time. When the data collection was complete, the data were exported to an Excel sheet for analysis. As an open link was used to collect data through the survey instrument, a response ratio cannot be provided.

A total of 541 questionnaires were completed. Data screening established data validity. Based on the variances of each questionnaire for the Likert-type scales, 69 questionnaires were dropped from the final sample subjected to analysis: 64 questionnaires identified as having a regular pattern and a further 5 questionnaires identified as outliers based on Cook's distance values above the 0.1 cutoff proposed by Weinberg and Abramowitz (2008). Hence, the final dataset for analysis comprised 472 questionnaires. The sample size was sufficient to run a confirmatory factor analysis (CFA). The survey consisted of 39 statements, each required a minimum of 10 observations. The required total number of observations was, therefore, 390 (Bentler and Chou, 1987), given that the goodness of fit index for AMOS is sensitive to sample size. With regard to the development of energy policies and sustainability goals, the literature

B. Respondents Demographics

In line with gender disparities in Saudi Arabia's labor force, males accounted for a much larger portion of the sample (n = 417, 88.3%) than did females (n = 55, 11.7%) (Table 1). It is important, therefore, to interpret the results in this gender disparity context and to seek a more comprehensive understanding of digital wallet usage patterns in Saudi Arabia by using a more balanced sample in future research.

Further, the majority of the respondents were 18–35 years old (n = 347, 73.5%), with respondents aged 36–55 years accounting for a quarter of the sample (n = 120, 25.4%) and respondents 56 years of age or older representing a very small proportion (n = 5, 1.1%). These large differences were expected, as younger people are generally more familiar than older people with using technology applications such as e-wallets. Our respondents were highly educated, with the highest level of education they had participated in described as follows: diploma degree or lower (n = 252, 53.4%), undergraduate degree (n = 165, 35%), and graduate degree (n = 55, 11.7%). Table 1 presents the demographic profile of the sample along with distributions by gender, age group, education level, duration of digital wallet experience, and frequency of digital wallet use, reported in frequencies and percentages.

Most of the respondents, close to half, were new users of digital wallets, having used the service for less than a year (n = 220, 46.6%). Respondents with a 1- to 2-year history as users of digital wallets accounted for almost a quarter of the sample (n = 111, 23.5%), whereas those with more than 2 years of using digital wallets accounted for a

https://doi.org/10.55802/IJB.029(4).003

little less than a third of the sample (n = 141, 29.9%). The fact that most of the respondents had only a short history of using a digital wallet service was expected, as Arab countries have generally shown a low adoption rate for electronic financial services. Indeed, the movement towards the adoption of digital wallets is likely to be a result of restrictions imposed during the COVID-19 pandemic. Further, the frequency of digital wallet service use in the 12 months preceding completion of the survey is as follows: Reporting on the 12-month period immediately prior to taking the survey, the majority of respondents were light users who had used a digital wallet service fewer than 121 times (n = 293, 62.1%), followed by medium users at 121 to 182 times (n = 77, 16.3%), and then heavy users at more than 182 times (n = 102, 21.6%).

Table 1

Sample Composition (n = 472)

Demographic	Sub-group	n	%
Gender	Male	417	88.3%
	Female	55	11.7%
	Total	**472**	**100%**
Age	18–35 years old	347	73.5%
	36–55 years old	120	25.4%
	Above 55 years old	5	1.1%
	Total	472	100%
Education Level	A diploma degree or lower	252	53.4%
	Undergraduate degree	165	35%
	Graduate degree	55	11.7%
	Total	**472**	**100%**
Digital wallet experience	Less than one year	220	46.6%
	1 to 2 years	111	23.5%
	More than 2 years	141	29.9%
	Total	**472**	**100%**
Frequency of digital wallet use in the previous 12 months	Fewer than 121 times (light user)	293	62.1%
	121 to 182 times (medium user)	77	16.3%
	More than 182 times (heavy user)	102	21.6%
	Total	**472**	**100%**

C. Data Preliminary Analysis

We analyzed the quantitative data collected using the structured survey instrument described in order to identify the determining factors of e-wallet adoption and use in the context of the KSA. Data analysis was performed using the Statistical Package for Social Sciences (SPSS v.26) and the Analysis of Moment Structure (AMOS v.23). We carried out an Exploratory Factor Analysis (EFA) to explore the data adequacy for structure analysis, and a Confirmatory Factor Analysis (CFA) to verify the fit and validity of the measurement scales. SEM-AMOS is a covariance-based version of SEM that is widely used to simultaneously estimate and test complex causal models (Williams et al., 2009).

AMOS is a parametric analysis that requires a normal distribution for the dataset. Skewness and kurtosis values were computed to test for data normality, with both values found to be around zero and, therefore, within the +2.2 / -2.2 range as proposed by Sposito et al. (1983). A summary of the data normality results is presented in Table 2. Table 2 presents the determining factors of e-wallet adoption, along with their respective skewness and kurtosis values.

Table 2

Data Normality Results (n = 472)

Factor	Skewness	Kurtosis
Relative advantage	-0.622	0.314
Compatibility	-0.500	-0.216
Ease of use	-0.828	0.492
Personal innovativeness	-0.093	-0.626
Observability	-0.214	-0.085
Perceived COVID-19 risk	-0.859	0.011
Intention to use	-0.879	0.181
Actual use	-0.889	0.340
Continuous use	-1.093	.0702

Table 3

Summary of Multicollinearity Analysis (N = 472)

Factor	Tolerance	VIF	Pearson Correlation					
			1	2	3	4	5	6
Relative advantage	0.631	1.584	1					
Compatibility	0.592	1.688	0.536**	1				
Ease of use	0.703	1.422	0.477**	0.464**	1			
Personal innovativeness	0.767	1.304	0.207**	0.269**	0.231**	1		
Observability	0.635	1.576	0.382**	0.468**	0.303**	0.473**	1	
Perceived COVID-19 risk	0.895	1.117	0.160**	0.242**	0.150**	0.297**	0.303**	1

*Note: ** Correlation is significant at the (0.01) level.*

To determine whether or not a multicollinearity issue was related to the dataset, we calculated the tolerance, variance inflation factor (VIF), and Pearson correlations by regressing the predictors against each other. All the indices examined were found to be below the cut-off point, such that no multicollinearity issue was identified. The tolerance values were found to be above the cutoff point (0.10), whereas the VIF values were found to be below it. In addition, all the predictors correlated with each other; the positive correlations were significant at the 0.01 level, and the weak to moderate correlations were below the cut-off point (r = 0.90). The results of the multicollinearity analysis were in accordance with Pallant's (2020) recommendation for determining the absence of multicollinearity. A summary of the results of the analysis for multicollinearity is presented in Table 3. Table 3 provides a summary of multicollinearity analysis for a sample size of 472, showing factors' tolerance, variance inflation factor (VIF), and Pearson correlations among them, with significant correlations marked (** at the 0.01 level).

Finally, due to the use of self-reported scales, which are subject to bias, we used Harman's one-factor test to determine whether or not the data reflected a bias issue. A common variance value below the 50% cut-off point is proposed by Podsakoff et al.

https://doi.org/10.55802/IJB.029(4).003

(2012) to avoid bias. In the present study, a single factor accounted for 28.498% of the variance such that bias was not an issue in the dataset.

D. Descriptive Analysis

To illustrate relationships between proposed factors, a summary for the mean std. values and correlations is presented in Table 4. Table 4 presents descriptive statistics and correlations among factors influencing intentions, actual use, and continuous use of digital wallets in a sample of 472 participants (** at the 0.01 level).

The mean values were interpreted using the scale proposed by Sekaran and Bougie (2016) and adopted in previous studies (e.g., Al Rahahleh, 2022; Al Rahahleh et al., 2023) as follows: 3.67–5.00 indicates a high level of agreement, 2.34–3.669 indicates a moderate level of agreement, and 1–2.339 indicates a low level of agreement.

Mean values were found to be high for all the factors with the exception of personal innovativeness. The findings indicate that the respondents perceived digital wallets as providing significant relative advantage (M = 4.17), compatibility (M = 3.96), ease of use (M = 4.29), and observability (M = 3.73), but only moderate personal innovativeness (M = 3.31). Further, the respondents perceived a high level of risk due to COVID-19 (M = 3.84) in relation to using paper money. On the other hand, the respondents indicated the intention to use a digital wallet service at a high level (M = 4.33) along with actual use at a high level (M = 4.14) and intention to engage in continuous use at a high level (M = 4.41). Std. values were lower than 1 for all the factors with the exception of Perceived COVID-19 risk, thereby indicating that the respondents' assessments spanned mean values for all the factors with the exception of Perceived COVID-19 risk as disagreement was seen between the assessments. Furthermore, moderate to high correlations were found between the proposed factors and between intention and use type. Preliminary support was, therefore, found for the influence of proposed factors on intentions and actual and continuous use of digital wallets.

Table 4
Descriptive Statistics (n=472)

Factor	Mean	Std.	*Pearson correlation*								
			1	2	3	4	5	6	7	8	9
Relative advantage	4.17	0.64	1								
Compatibility	3.96	0.78	0.536**	1							
Ease of use	4.29	0.66	0.477**	0.464**	1						
Personal innovativeness	3.31	0.90	0.207**	0.269**	0.231**	1					
Observability	3.73	0.72	0.382**	0.468**	0.303**	0.473**	1				
Perceived COVID-19 risk	3.84	1.04	0.160**	0.242**	0.150**	0.297**	0.303**	1			
Intention to use	4.33	0.71	0.467**	0.395**	0.467**	0.180**	0.317**	0.443**	1		
Actual use	4.14	0.80	0.388**	0.463**	0.390**	0.217**	0.406**	0.304**	0.456**	1	
Continuous use	4.41	0.69	0.476**	0.454**	0.487**	0.195**	0.327**	0.260**	0.654**	0.545**	1

https://doi.org/10.55802/IJB.029(4).003

*Note: ** Correlation is significant at the 0.01 level.*

E. Quality of Measurement Model

We used EFA followed by CFA to test the quality of the measurement model. Using principal component analysis (PCA) based on Promax rotation, EFA was performed to determine the adequacy of the dataset for structure analysis. Based on Byrne (2016), given that the Kaiser-Mayer-Olkin value (KMO= 89.6%) was above the 60% cut-off point, the sample was sufficient for a satisfactory analysis. The dataset was found to be suitable for structure analysis, as Bartlett's Test of Sphericity was highly significant ($\chi 2$ (741) = 11503.053, Sig. = 0.000), indicating that the factors were correlated to each other, which helped in identifying underlying factors to represent a set of variables. Furthermore, many factors with eigenvalues above 1 were extracted with a total cumulative variance of 69.347%, which indicated the multi-dimensionality of the measurement model.

AMOS was used to perform CFA as a way to improve the psychometric properties of the measurement scales. In CFA, the factors were developed and the fitness of measurement scales determined based on fitness measures proposed in multiple research studies (Byrne, 1994; Hu and Bentler, 1999; Kline, 2015; Hair et al., 2019). The fitness measures comprised the following: (1) CMIN/df ($\chi 2$) for which a value below the cutoff of 3 is an excellent fit, with a value of 5 acceptable; (2) the Comparative Fit Index (CFI) for which a value above the 0.95 cutoff is an excellent fit and a value above 0.90 is acceptable; (3) the Tuker Lewis Index (TLI) for which a value above the 0.95 cutoff is an excellent fit and a value above the 0.90 cutoff is acceptable; (4) the Standardized Root Mean Residual (SRMR), for which a value below the 0.09 cutoff is an excellent fit; (5) the Root Mean Square Error of Approximation (RMSEA) for which a value below the 0.05 cutoff is a good fit and a value below 0.08 is acceptable; and (6) PClose for which a value above 0.05 cutoff is an excellent fit.

The outcomes of the original CFA revealed a poor fit: ($\chi 2$ = 3.491, CFI = 0.851, TLI = 0.834, SRMR = 0.104, RMSEA = 0.073, and PCLOSE = 0.000). Model modification was necessary to improve the model fit to the data, and modifications were made based on the guidelines established in the literature (Anderson and Gerbing, 1988; Hair et al., 2019). Individual indicator Factor Loading (FL) was executed with 0.50 as the minimum cutoff point. Four items were dropped given an FL value below the 0.50 cutoff level (C5, O1, O2, and O5). Further, the Modification Indices were executed with 20 as the maximum cutoff point, and accordingly some MIs were correlated with a focus on the standardized residual covariances executed with 0.400 as the maximum cutoff and four more items were dropped (C4, RA1, RA2, and RA3). One modification was made at each try, and a minimum of two observed items were required to retain a specific factor (Kenney, 2012).

The outcomes of the modified measurement model indicated an excellent fit: $\chi 2$ = 2.091, CFI = 0.953, TLI = 0.945, SRMR = 0.051, RMSEA = 0.048, and PCLOSE = 0.745. All the retained indicators had an FL value above the 0.50 cutoff point with the majority exceeding the preferred level, i.e., above the 0.70 cutoff point. All the MI values were low, and the squared multiple correlations were relatively high, which suggests that the indicators reflect their corresponding constructs. Further, when the revised model was pooled into a single factor, the fit was acceptable ($\chi 2$ = 13.268, CFI = 0.427, TLI = 0.383,

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SRMR = 0.147, RMSEA = 0.161, and PCLOSE = 0.000) such that the unidimensional model is not supported. A summary of the goodness of fit results for the measurement model is presented in Table 5. Table 5 presents the results of fitness measures for three models: the original model, revised model, and unidimensional model. It assesses their fit based on various criteria including CMIN (Chi-square minimum), CMIN/DF (Ratio of Chi-square minimum and DF), CFI (Comparative Fit Index), TLI (Tucker-Lewis Index), SRMR (Standardized Root Mean Residual), RMSEA (Root Mean Square Error of Approximation), and PClose (Probability Close to 1.00).

Table 5
Results of Goodness-of-fit Indices

Index	Cutoff criteria			Original model	Revised model	Unidimensional model
	Unacceptable	Acceptable	Excellent			
CMIN	--	--	--	2325.181	827.843	5731.697
DF	--	--	--	666	396	432
CMIN/ DF	>5	>3	>1	3.491	2.091	13.268
CFI	<0.90	<0.95	>0.95	0.851	0.953	0.427
TLI	<0.90	<0.95	>0.95	0.834	0.945	0.383
SRMR	>0.10	>0.08	<0.09	0.104	0.051	0.147
RMSEA	>0.08	>0.06	<0.05	0.073	0.048	0.161
PClose	<0.01	<0.05	>0.05	0.000	0.745	0.000

Based on the revised measurement model, validity and reliability assessments of the underlying factors were performed. The results are presented in Table 6. Table 6 presents the findings for CFA, including indicator reliability (FL), construct reliability (Cronbach's α), convergent validity (AVE), and MSV (Maximum Shared Variance).

Table 6
CFA Results for The Revised Measurement Model (n = 472)

Factor	Item	FL	T-value	Cronbach	CR	AVE	MSV
Relative advantage	RA4	0.67	12.997***	0.781	0.792	0.561	0.373
	RA5	0.84	14.850***				
	RA6	0.72	--				
Compatibility	C1	0.89	28.996***	0.923	0.924	0.802	0.213
	C2	0.92	--				
	C3	0.88	28.271***				
Ease of use	E1	0.70	15.174***	0.830	0.831	0.552	0.373
	E2	0.74	16.226***				
	E3	0.72	15.680***				
	E4	0.81	--				
Personal innovativeness	PI1	0.75	14.270***	0.867	0.875	0.585	0.348
	PI2	0.82	17.475***				
	PI3	0.80	17.132***				
	PI4	0.68	14.495***				
	PI5	0.76	--				
Observability	O3	0.90	--	0.892	0.892	0.805	0.348
	O4	0.89	20.299***				
Perceived COVID-19 risk	COVID1	0.85	--	0.911	0.915	0.733	0.224
	CVODI2	0.67	16.664***				

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	CVODI3	0.95	29.070***				
	COVID4	0.92	27.651***				
Intention to use	I1	0.87	--	0.837	0.847	0.651	0.492
	I2	0.85	21.649***				
	I3	0.69	16.569***				
Actual use	AU1	0.68	--	0.839	0.823	0.538	0.449
	AU2	0.80	14.309***				
	AU3	0.75	13.619***				
	AU4	0.69	12.604***				
Continuous use	CU1	0.84	--	0.905	0.906	0.763	0.492
	CU2	0.89	24.252***				
	CU3	0.88	23.983***				

Note: *** $p < 0.001$

The calculated Cronbach's alpha values were all above 0.70, which is the threshold recommended by Hair et al. (2019) for satisfactory reliability. The Cronbach's alpha values were as follows: Relative advantage (0.781), Compatibility (0.923), Ease of use (0.830), Personal innovativeness (0.867), Observability (0.892), Perceived COVID-19 risk (0.911), Intention to use (0.837), Actual use (0.839), and Continuous use (0.905). Further, the convergent validity of the model was confirmed by the following evidence: FL values for the retained items above the minimum cutoff (0.50), with most above the preferred cutoff of 0.70, t-values above the 1.96 cutoff, and P < 0.001.

The Average Variance Extracted (AVE) values were above the recommended 0.50 cutoff for adequate convergent validity: Relative advantage (0.561), Compatibility (0.802), Ease of use (0.552), Personal innovativeness (0.585), Observability (0.805), Perceived COVID-19 risk (0.733), Intention to use (0.651), Actual use (0.538), and Continuous use (0.763). Finally, Composite Reliability (CR) also supported convergent validity, as all the CR values were above the 0.70 cutoff point, thereby contributing to the internal consistency of the model. The CR values were as follows: Relative advantage (0.792), Compatibility (0.924), Ease of use (0.831), Personal innovativeness (0.875), Observability (0.892), Perceived COVID-19 risk (0.915), Intention to use (0.847), Actual use (0.823), and Continuous use (0.906).

The discriminant validity of the model was confirmed by the Maximum Shared Variance (MSV) values, which were lower than the respective AVE values (Hair et al., 2019). Further, the square root of the AVE of each factor was higher than the correlation coefficient value with other factors (Fornell and Larcker, 1981), which also supported the discriminant validity of the model (Table 7). Table 7 displays the outcomes of discriminant validity analysis conducted on a sample size of 472. Significance levels are denoted as *** for $p < 0.001$, ** for $p < 0.01$, and * for $p < 0.05$. Finally, three nested models were established in which the factors were merged to determine whether support could be found for models of this kind. By checking the model fit of all the nested models, we established an unacceptable fit, which supported the discriminant validity of the verified model. The goodness-of-fit results for the nested models are presented in Table 8. Table 8 presents the goodness-of-fit results for the nested models examining different combinations of merged and unmerged items of factors related to e-wallet adoption.

https://doi.org/10.55802/IJB.029(4).003

Table 7
Discriminant Validity Results (n = 472)

Factor	1	2	3	4	5	6	7	8	9
Relative advantage	0.749								
Compatibility	0.453***	0.896							
Ease of use	0.610***	0.400***	0.743						
Personal innovativeness	0.168**	0.276***	0.267***	0.765					
Observability	0.206***	0.401***	0.084	0.590***	0.897				
Perceived COVID-19 risk	0.087	0.219***	0.152**	0.320***	0.306***	0.856			
Intention to use	0.492***	0.343***	0.541***	0.223***	0.193***	0.474***	0.807		
Actual use	0.419***	0.461***	0.502***	0.238***	0.294***	0.333***	0.595***	0.733	
Continuous use	0.471***	0.360***	0.565***	0.218***	0.165**	0.248***	0.701***	0.670***	0.873

*Note: *p < 0.050, **p < 0.010, ***p < 0.001*

Table 8
Goodness-of-Fit Indices Results

Index	Cut-off criteria			Revised Model	Nested Model 1	Nested Model 2	Nested Model 3
	Unacceptable	Acceptable	Excellent				
CMIN	--	--	--	827.843	2864.456	2198.451	3502.146
DF	--	--	--	396	417	411	417
CMIN/ DF	>5	>3	>1	2.091	6.869	5.349	8.398
CFI	<0.90	<0.95	>0.95	0.953	0.735	0.807	0.667
TLI	<0.90	<0.95	>0.95	0.945	0.705	0.781	0.628
SRMR	>0.10	>0.08	<0.09	0.051	0.112	0.131	0.126
RMSEA	>0.08	>0.06	<0.05	0.048	0.112	0.096	0.125
PClose	<0.01	<0.05	>0.05	0.745	0.000	0.000	0.000

Notes: Model 1: The items of Relative advantage, Compatibility, Ease of use, and Personal innovativeness were merged. The items of Observability, Perceived COVID-19 risk, Intention to use, Actual use, and Continuous use were not merged.
Model 2: The items of Observability, Perceived COVID-19 risk, and Intention to use were merged. The items of Relative advantage, Compatibility, Ease of use, Personal innovativeness, Actual use, and Continuous use were not merged.
Model 3: The items of Ease of use, Personal innovativeness, Perceived COVID-19 risk, and Intention to use were merged. The items of Relative advantage, Compatibility, Observability, Actual use, and Continuous use were not merged.

F. Testing The Structural Model

We tested the hypotheses by examining the structural model. The goodness of fit was excellent for most of the indexes: $\chi 2$ = 2.211, CFI = 0.947, TLI = 0.939, SRMR = 0.066, RMSEA = 0.051, and PCLOSE = 0.391. The model quality was determined through the R^2 coefficients, and the proposed factors were found to have adequate variation relative to Intention to use (R^2 = 53%). In addition, the R^2 in Actual use was 41%, indicating that intention to use contributed to Actual use. Further, the R^2 in Continuous use was 60%, indicating that the actual use, along with Intention to use, explains a substantial amount

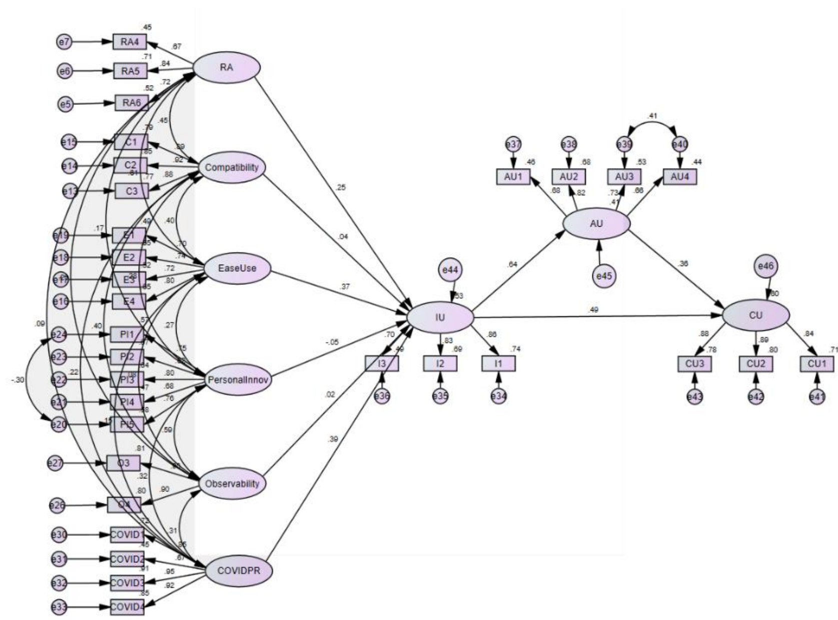
https://doi.org/10.55802/IJB.029(4).003

of the variance in Continuous use. The structural model test is represented in Figure 2.

Based on the estimates, we identified a set of significant predictors and a set of non-significant predictors. The Relative advantage → Intention to use path showed a significant positive influence (B = 0.25, P = 0.001) such that H1 was supported. The Compatibility → Intention to use path showed a non-significant influence (B = 0.04, P = 0.454) such that H2 was not supported. The Ease of use → Intention to use path was significant (B = 37, P = 0.001) such that H3 was supported. The Personal innovativeness → Intention to use path showed a non-significant relationship (B = -0.05, P = 0.376) as did the Observability → Intention to use path (B = 0.02, P = 0.707), such that neither H4 nor H5 was supported. The Perceived COVID-19 risk → Intention to use path showed a significant relationship (B = 0.39, P = 0.001) such that H6 was supported. The Intention to use → Actual use path showed a significant relationship (B = 0.64, P = 0.001), as did the Actual use → Continuous use path (B = 0.36, P = 0.001), such that both H7 and H8 were supported.

Finally, we tested for a mediation role for Actual use between Intention to use and Continuous use. Intention to use was shown to have a significant and direct influence on Continuous use (B = 0.49, P = 0.001). Further, an indirect influence was found as an indirect coefficient (B = 0.208, P = 0.000), with a total influence for Intention to use on Continuous use of 0.69, which showed that Actual use had a partial mediation role in the relationship tested. A summary of the path estimates is presented in Table 9.

Figure 2
Structural Model Testing



https://doi.org/10.55802/IJB.029(4).003

Table 9
Summary of Path Estimates (n = 472)

H	Path	Standardized coefficient	Decision
H1	Relative advantage → Intention to use	0.25*	Supported
H2	Compatibility → Intention to use	0.04	Not supported
H3	Ease of use → Intention to use	0.37*	Supported
H4	Personal innovativeness → Intention to use	-0.05	Not supported
H5	Observability → Intention to use	0.02	Not supported
H6	Perceived COVID-19 risk → Intention to use	0.39*	Supported
H7	Intention to use → Actual use	0.64*	Supported
H8	Actual use → Continuous use	0.36*	Supported
H9	Intention to use → Actual use → Continuous use	Indirect (0.208*) Direct (0.49*) Total (0.69*)	Partial mediation

Note: H9: Actual use of a digital wallet significantly mediates the influence of use intention on continuous use ($p < 0.05$)*

IV. DISCUSSION AND IMPLICATIONS

In this study, we integrated the Diffusion of Innovation (DOI) theory into the Technology Acceptance Model (TAM) to investigate the factors that determine digital wallet adoption and continuous use in the context of Saudi Arabia. This integrated approach addresses the gap in the literature by enabling a more comprehensive understanding of the factors that influence the adoption and use of digital wallets through a nuanced account of the role of intentions in determining use behavior.

We pursued a quantitative approach to this research based on the online survey responses collected, which produced a total of 472 valid responses included in the analysis. SEM-AMOS validated the measurement model, and the hypotheses were tested using the structural model, with the results showing a set of significant antecedents and a set of non-significant predictors. Further, we confirmed the robustness of the TAM-DIO used to predict the antecedents of the intention to use, actual use, and continuous use given that the model explained more than 50% of the variance of each variable. However, companies providing digital wallet services in Saudi Arabia would be well-advised to consider that many aspects related to the factors included were omitted in validating our model. Examples of these aspects—which should be considered in future research and in current commercial and marketing practices—include the compatibility of digital wallets with users' lifestyles and users' ability to manage financial transactions.

The study answered the key research questions as follows: In regard to determining the factors that influence the adoption and continuous usage of digital wallets, based on the estimates, we identified a set of significant predictors and a set of non-significant predictors: ease of use and relative advantage are the most significant predictors, and compatibility, personal innovativeness, and observability are non-significant predictors. In regard to the impact of COVID-19 on the adoption rate and usage of digital wallets, based on the estimates, we found that perceived COVID-19 risk showed a significant positive effect on the adoption of digital wallets. Further, actual use of a digital wallet was found to significantly mediate the influence of use intention on continuous use. In general, the results indicate that consumers have concerns about the security of digital wallets and also recognize them as more convenient than traditional payment methods. To encourage greater adoption and usage of digital wallets, it is recommended that the FinTech industry focuses on enhancing the security of these products. The results confirm those published by Mordor Intelligence (2023), which show that data security concerns an increased fraud in online payment services as compared to traditional banking services is hindering the growth of the mobile payments market in the region.

In greater detail, the study findings provide a foundation for guiding companies seeking to increase the number of people who adopt their e-wallet service. We found that of all the factors examined, ease of use is the strongest predictor of the intention to use followed by relative advantage. Companies should, therefore, prioritize strong ease of use values in their digital services in order to attract and retain users.

Further, factors with non-significant predictive results are not necessarily unimportant in determining adoption and use. In fact, most of the e-wallet literature emphasizes compatibility, personal innovativeness, and observability as critical. It may be, therefore, that the digital wallet services currently available do not meet the needs and expectations of users on these points. For this reason, these considerations should continue to be of great importance in companies' efforts to attract and retain users. Overall, in comparison with the original DIO factors, perceived COVID-19 risk was found to be a stronger predictor of continuous e-wallet use. Companies would, therefore, be well-advised to at least consider that the pandemic conditions drove adoption of e-wallet services rather than attributing adoption to specific aspects of the services independent of that context.

Finally, we tested for the direct and indirect influence of intention to use on continuous use through actual use. Based on the results, we found empirical support for our mediation mechanism and the systematic process through which individual intentions determine actual and continuous use. Such findings indicate the robustness of the proposed model. In addition, our findings demonstrate the importance of intentions in determining use behavior. Hence, the field would benefit from research focused on investigating the antecedents and predictors of individual intentions, given the vital role of intentions in shaping use behaviors.

The results of the study demonstrate the critical role of intentions in determining the usage of digital wallets. This finding has practical implications for policymakers, as it highlights the importance of understanding the factors that influence consumers' intentions in order to promote the widespread adoption of digital wallets. In the context of Saudi Arabia's Vision 2030, this study provides both direction for driving the adoption of digital wallets and a foundation for informing the development of policies aimed at fostering a cashless economy. It also takes into account the impact of the COVID-19 pandemic on the adoption of these services and indicates the importance of doing so as an essential consideration in the uptake of digital services in general during the focal period. The refined model developed (i.e., TAM-DOI) may also be useful for researchers, industry practitioners, and policymakers in other countries seeking to promote the adoption of digital wallets.

Funding

This project was funded by the Deanship of Scientific Research (DSR) at King Abdulaziz University, Jeddah, under grant no. (GPIP: 1498-120-2024). The authors, therefore, acknowledge with thanks DSR for technical and financial support.

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