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Factors Influencing Adoption of Digital Payments: A PLS SEM and ANN Approach

Vasant Pandey[1], Gyaneshwar Singh Kushwaha[2], Shuchi Srivastava[3]

[1]Research Scholar, Maulana Azad National Institute of Technology Bhopal, Madhya Pradesh, India
[2]Associate Professor, Maulana Azad National Institute of Technology Bhopal, Madhya Pradesh, India
[3]Professor, Maulana Azad National Institute of Technology Bhopal, Madhya Pradesh, India

Abstract

This study aims to examine the factors that affect digital payment adoption. In addition to this, it also identifies the factors that will help to increase the adoption once the maturity is attained. The current study demonstrates a key driver of digital payment. The research is conclusive in nature. It utilizes a hybrid approach combining PLS SEM and ANN to illustrate the impact of various factors on the adoption of digital payments. The data is collected through a structured questionnaire. Warp PLS 7.0 is used for Structured Equation Modelling as a statistical tool analysis of the data. The findings of this study indicate that the facilitating conditions are the most influencing factor of digital payment adoption. Apart from this, social norms were identified as the factor that will influence the adoption of digital payment when there will be a fall in its adoption and usage.

Keywords: Digital payments, perceived ease of use, perceived usefulness, facilitating conditions, social norms.

Introduction

Financial inclusion is crucial for an economy both socially and financially. According to previous works, information technology-enabled payment options such as Internet banking, mobile banking, and prepaid instruments account for a huge increase in financial inclusion. In general, digital payments also referred to as "mobile payments" comprise payments using the short message service, the wireless application protocol the mobile internet, credit or charge cards stored in the phone, or the mobile wallet. Digital payment has the potential to bring the unbanked masses to a stream of banking services *(Patil et al.,2017)*. The digital payment market has experienced rapid growth globally due to the increased internet and smartphone usage, adoption of digital commerce, and consequent development in technology. Therefore, it has been increasingly popular and becoming a viable alternative to cash payments *(Liébana-Cabanillaset al., 2018)*, and is widely adopted, regardless of the transaction amount. Even small vendors now accept digital payments. Based on World Payment Report 2022, it is estimated that by 2026, about 28% of digital payments will utilize innovative payment methods, while conventional payment methods will constitute roughly 72% of other than cash transactions. Hence, the digital payment system is expected to play a crucial role in driving the shift towards a cashless society. Increased transparency, efficiency, and financial inclusion are some of the key benefits associated with digital payment adoption *(Putrevu & Mertzanis, 2023)*.

One of the biggest advantages of utilizing digital payment is that it saves time and cost compared to visiting a bank for transactions. During the demonetization period in India, when the government invalidated the currency notes of 500 and 1000. This resulted in a shortage of cash for transactions, but the

(Corresponding Author: Vasant Pandey, Research Scholar, Maulana Azad National Institute of Technology Bhopal, Madhya Pradesh, India, E-mail: pandeyvasant1996@gmail.com
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digital payment system proved to be a helpful solution to bridge the gap. Approximately 45% of businesses opted for digital payments as a tool for their transactions during that time *(Dutta et al., 2023)*. The move towards a cashless economy could lead to a decrease in government expenses. However, the full benefit of a digital economy is unrealistic unless a significant number of people consistently utilize cashless transactions because people started to shift to physical currency after the shortage of currency was over. Later on, during the COVID-19 pandemic, there was again a significant increase in digital payments in India due to restrictions on physical movement and concern over the spread of the virus through physical currency *(Sahay et al.,2020)*. This paves the way for higher adoption of digital payment, but according to *Krishna et al. (2023)* achieving this would not be easy due to various challenges and obstacles in the future. Apart from the challenges posed, the innovativeness offered by digital payment vendors such as convenience, adaptability, and quick transactions puts them in an advantageous position *(Liébana-Cabanillas et al., 2014)*. The World Bank also promotes digital payment systems as it finds them to be the most suitable way to achieve economic development *(Telukdarie & Mungar, 2023)*.

Penetration of mobile devices enabled one to send or receive money digitally without visiting a bank *(Sandhu et al., 2023)*. Digital payments offer quick, secure, and easy ways to complete transactions, benefitting companies and customers alike. They provided customers with added flexibility, mobility, and efficiency *(Sahi et al., 2021),* and disrupted monetary exchange between two parties. These disruptions caused by fintech companies lead to an improvement in the service quality of banks. Banks will have to now invest more in infrastructure to accommodate digital transactions. By doing so banks will be able to compete with fintech companies *(Kasriet al., 2022)*. The origin of digital payment can be traced back to the introduction of ATM cards from time-to-time innovative digital payment methods have evolved to the current stage of mobile payment. The widespread adoption is influenced by various factors, with ease of use and usefulness being significant factors in determining public acceptance. Technological advancement is constantly occurring, and it is important to consider its impact on the public when implementing new payment methods *(Loh et al., 2021)*. Support from the government also contributes to the development of a favourable atmosphere for adoption *(Das & Das, 2023)*. Vendors offer incentives for using digital payment apps, which encourages its adoption. Previous literature has identified various influencing factors. However, after a certain point in a product's life cycle, its adoption declines, and people start switching to other options. In such a situation, companies need to develop new strategies for promoting their products. The novelty of this study is that it examines which factors have the potential to increase adoption during this stage.

In order to propose a conceptual model for digital payment adoption, the Technology Acceptance Model *(Davis, 1989)*, Theory of Planned Behaviour *(Ajzen, 1991),* and Unified Theory of Acceptance and Use of Technology (UTAUT) *(Venkatesh et al., 2003)* have been utilized. Specifically, the factors of Perceived Ease of Use, Perceived Usefulness, Social Norms, and Facilitating Conditions are examined. The accelerated adoption of digital payment in India is attributed to various platforms such as Immediate payment system (IMPS), National Electronic Fund Transfer (NEFT), Real Time Gross Settlement (RTGS), Unified Payments Interface (UPI), Bharat Interface for Money (BHIM), Mobile Banking, Mobile Wallet, and Aadhaar Enabled Payment System (AEPS), and others *(Singh, 2016)*. These interfaces allow payments through scan-and-pay technology using bank accounts, debit cards, and payment vouchers. As the world is transitioning into a new era of digitalization where the entire landscape of business transactions has changed, many people have adopted this technology, and there is continuous innovation in the field. This paper explores the factors that influence potential users to become users and make a significant contribution to the available literature. The objectives of this study are:

- Using the TAM, TPB, and UTAUT models, this study predict which factors will influence the adoption of digital payments.

- To identify the factor that will further increase the adoption of digital payments once attaining the maturity.

Literature Review

Meaning of digital payment

A digital payment is a type of payment that involves transferring value from one account to another using digital devices or channels. In this system execution of payment is done digitally *(Bapat & Khandelwal, 2023).* According to the Indian Payment and Settlement Act 2007, digital payments are defined as electronic fund transfers. It means that when an individual uses an electronic medium to transfer funds either by themselves or by authorizing the bank to debit or credit their account, it is considered a digital payment *(Sivathanu, 2019).* According to *Sahi et al. (2021),* digital payment refers to the procurement of goods and services using digital devices. With various payment platforms as highlighted by *Singh (2016),* it has become the most preferred way of payment *(Krishna et al., 2023).* Scholars in this field have used pseudonyms like online payment *(Shankar et al., 2023),* and e-payments *(Özkan, 2010)* in their studies for digital payment. All these terms express the acceptance of money digitally.

Digital Payment Adoption

The root of the technology acceptance model propounded by *Davis (1989)* lies in the perception of users towards adopting a technology. Exercising digital payment methods has extended beyond the confines of physical currency, allowing individuals to pay for everything from coriander leaves to electricity bills. Scholars such as *Das and Das (2023)* and *Liébana-Cabanillaset al. (2014)* have identified the key factors that impact the adoption and future use of digital payments. At the initial stage, the adoption of technology does not guarantee its continuous usage. Though feasible, the user might switch from it. A significant amount of studies has been carried out by researchers exploring the event of continuous intention to use digital payments. The actual usage of the digital payment system *(Sivathanu, 2019),* the impact of dataveillance on resistance towards digital payment *(Shankar et al., 2023)* cashless transactions need for policy interventions *(Putrevu & Mertzanis, 2023)*, determinants of quick response code mobile payment by marginalized vendors are the subject on which researchers have conducted extensive studies.

Perceived Ease of Use

The ease of use of a technology is a crucial factor in determining whether a prospective user will adopt it or not. It acts as a precursor in the formation of the user's attitude towards the technology. The more effortless a technology is to use; the more likely users are to accept it. The degree to which a potential user perceives that a particular technology is easy to use plays a vital role in determining their willingness to adopt it. This factor serves as a precursor to their overall attitude towards the technology *(Davis, 1989).* In the case of digital payments, ease of use is a critical factor, as the effort required to operate them is a significant barrier to adoption. User attitude towards digital payment is influenced by ease of use, making it a crucial factor in their decision to adopt it *(Abdul Sathar et al., 2022)*. A positive ease of use is a significant determinant in accepting digital payment over cash payment. It is the primary reason why users prefer digital payment *(Haritha, 2022).* Lack of ease of use can hinder the acceptance and enhancement of payment systems, so it's crucial for these systems to be user-friendly. To ensure that the customer experience is optimal, a well-designed, user-friendly web portal, regular evaluation, and continuous updates on the basis of customer feedback are essential *(Afroze & Rista, 2022)*. The ease of use of a system significantly influences its usefulness for users, and this, in turn, affects their propensity to use it. Therefore, it's safe to say that the ease of use of digital payment systems significantly influences its adoption rate and the hypothesis proposed is that:

H1: Perceived ease of use significantly influences digital payment adoption.

Perceived Usefulness

Davis (1989) expounded the concept of perceived usefulness and defined it as the enhancement in productivity, efficiency, and effectiveness as a result of the implementation of a particular technology. In other words, it is about finding ways to make work easier and more efficient. People are more likely to embrace new technology when they perceive the personal benefits associated with its use (Safari et al., 2022). Chawla and *Joshi (2019)* and *Flavián et al. (2020)* found perceived usefulness as a significant factor in clarifying the effectiveness of digital payment methods versus cash payments. However, the results of the study by *Anggraini and Rachmawati (2019); Phonthanukitithaworn et al. (2016),* and *Teo et al. (2015)* were contrary to this they did not find the influence of perceived usefulness on digital payment adoption. On the basis of available literature, the hypothesis proposed is that:

H2: Perceived usefulness significantly influences digital payment adoption

Facilitating Conditions

Facilitating conditions as defined by *Venkatesh et al. (2003)* are the conditions that enable consumers to adopt digital payment with ease. These conditions include resources and infrastructure availability. Concerning digital payment internet connectivity, technical knowledge and easy accessibility come under this umbrella term. Several studies have suggested that facilitating conditions have a significant impact on the adoption of digital payment system. The finding of the study by *Sivathanu (2019)* was in line with the results of previous studies and concluded that conformity with available resources influences people to adopt digital payments. According to *Sobti (2019)* research, internet connectivity is the most important factor that enables digital payments. Therefore, the proposed hypothesis is that:

H3: Facilitating conditions significantly influences digital payment adoption

Subjective norm

Subjective norm is an essential factor that influences individuals to adopt new technology. It refers to the pressure felt by one's social circle or important people in their lives to perform or not to perform a specific behaviour *(Ajzen, 1991).* Before executing a certain behaviour, individuals consider the expectations of their family, friends, and acquaintances. During the initial stages of technology adoption, the potential to influence people is relatively low, and individuals are less likely to be influenced by subjective norms. However, as technology adoption progresses, subjective norm emerges as a crucial factor, as individuals feel more pressure from their social circle to adopt new technology. In a study conducted by *Aithal et al. (2023),* it was found that for small retailers the most important factor influencing technology adoption was the subjective norm. Retailers are pressurized from everywhere. For example, from their children; suppliers; and competitors using digital payment apps that attract customers. Overall, subjective norms played a key role in these retailers' adoption of digital payment systems. Social influence from important people plays a crucial role in building trust in digital payment systems. As per *Kalinić et al. (2020),* the impact of digital payment systems on individuals is based on the advice of their acquaintances. Therefore, the hypothesis proposed is that:

H4: Social norms significantly influences digital payment adoption.

Research Methodology

Measurement Items

Measurement items were selected after conducting a careful review of the literature. Each of the item was adopted to fit the specific context of the study. The measurement items used to assess perceived usefulness were taken from *De Sena Abrahão et al. (2016)*. Those used to measure perceived ease of use were taken from *Oliveira et al. (2016),* facilitating conditions items were taken from *Teo et al. (2015)* and the subjective norms were taken from *Shankar and Datta (2018)* All the items were rated using a five-point Likert scale and scored from strongly disagree 1 to strongly agree 5.

Data Collection

A diverse range of 550 individuals were surveyed to glean enlightening perspectives. Of these, 527 submissions were deemed valid and worthy of deeper deliberation. Among the respondents, the representation of each gender was nearly balanced with male participation tallying at 53.7% and females comprising 46.28%. This breakdown foregrounds the portrait of the assortment interviewed, empowering well-reasoned conclusions to emerge from this study. A bevy of reactions were procured and various themes emerged, granting perspective to the diverse viewpoints encompassed within the sample.

Measurement Model

The measurement model's effectiveness is determined through the reliability and validity of its constructs. In a PLS model, a construct can be formative, reflective, or a combination of both. Since the constructs being studied are reflective, we assessed the individual item reliability, internal consistency, as well as convergent and discriminant validity. *Table 1* shows the loading and cross-loading of the constructs, including items loading, standard error, and their respective p-values as provided by Warp PLS 7.0. It can be concluded that the items are reliable since their loading value lies between 0.75-0.89 which is higher than the threshold value of 0.7 *(Hair et al., 2011)*.

Table 1: Loading and Cross loading between variables

	PEOU	PU	SN	FC	DP	SE	VIFs	p-value
PEOU 1	(0.758)	0.143	-0.104	0.223	-0.295	0.039	1.526	<0.001
PEOU 2	(0.837)	-0.064	0.060	0.143	-0.066	0.039	1.927	<0.001
PEOU 3	(0.857)	-0.006	0.003	-0.097	0.271	0.039	2.072	<0.001
PEOU 4	(0.753)	-0.066	0.035	-0.274	0.061	0.039	1.523	<0.001
PU 1	0.137	(0.892)	-0.101	0.083	0.030	0.039	2.288	<0.001
PU 2	-0.193	(0.883)	-0.080	0.053	0.064	0.039	2.227	<0.001
PU 3	0.064	(0.763)	0.210	-0.159	-0.108	0.039	1.403	<0.001
SN 1	0.183	-0.051	(0.855)	-0.031	-0.075	0.039	1.779	<0.001
SN 2	-0.332	0.243	(0.779)	-0.049	0.116	0.039	1.414	<0.001
SN 3	0.119	-0.170	(0.858)	0.076	-0.030	0.039	1.794	<0.001
FC 1	-0.051	-0.009	0.090	(0.782)	-0.027	0.039	1.862	<0.001
FC 2	-0.020	0.003	-0.019	(0.883)	0.052	0.039	2.590	<0.001
FC 3	0.003	0.004	-0.025	(0.811)	-0.050	0.039	1.814	<0.001
FC 4	0.067	0.002	-0.041	(0.820)	0.018	0.039	2.077	<0.001
DP 1	-0.016	-0.185	0.039	-0.077	(0.810)	0.039	1.958	<0.001
DP 2	-0.094	0.082	-0.005	0.129	(0.802)	0.039	1.898	<0.001
DP 3	0.021	0.010	-0.155	0.023	(0.802)	0.039	1.976	<0.001
DP 4	-0.101	0.154	0.138	-0.118	(0.759)	0.039	1.711	<0.001
DP 5	0.173	-0.049	-0.009	0.035	(0.856)	0.039	2.358	<0.001

Note: PEOU= Perceived ease of use, PU= Perceived usefulness, SN= Subjective norms, FC= Facilitating conditions, SE= Standard error

Table 2 exhibits the composite reliability measures, Cronbach's alpha values, Average Variance Extracted, and Full Collinearity VIFs for all reflective variables. All values are greater than 0.7, thus establishing composite reliability *(Hair et al., 2011)*. To assess discriminant validity, we utilized HTMT (Heterotrait-monotrait ratio) and *Fornell and Larcker (1981)* criteria, in which we compared the Average Variance Extracted (AVE) of each construct with its correlation. Though the HTMT ratio was not available in the previous versions but WarpPLS 7.0 has it. Previous studies have found that the HTMT ratio outperforms the Fornell-Larcker criteria. In order to enhance the validity of this study we assessed the results obtained from both methods. To determine whether two constructs are distinct from each other using the HTMT ratio, the value obtained should be less than 0.90. On the other hand, when using the Fornell-Larcker criteria, the diagonal value should be greater than any other value in the same row or column. The discriminant validity is established by obtaining values from both tests. The results of discriminant validity are presented in *Tables 3* and *Table 4*.

Table 2: Latent variable coefficients

Reliability indices	PEOU	PU	SN	FC	DP
Composite reliability	0.878	0.884	0.870	0.895	0.903
Cronbach's alpha	0.814	0.802	0.776	0.842	0.865
Average Variance Extracted	0.644	0.719	0.691	0.680	0.650
Full Collinearity VIFs	1.952	1.742	1.195	1.588	2.116

Table 3: Discriminant validity: Fornell Larcker criteria

Constructs	PEOU	PU	SN	FC	DP
PEOU	0.802				
PU	0.594	0.848			
SN	0.292	0.232	0.832		
FC	0.446	0.270	0.367	0.825	
DP	0.607	0.558	0.315	0.551	0.807

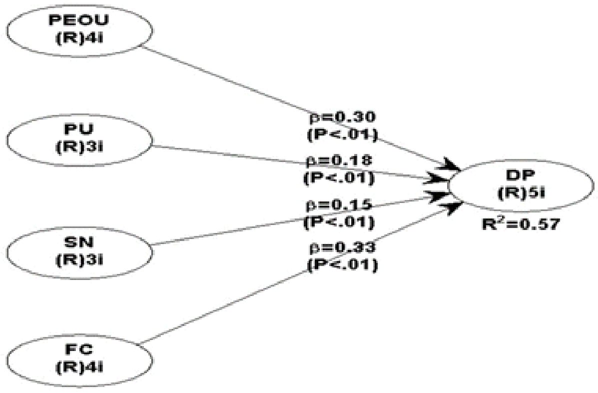
Table 4: Discriminant validity: HTMT (heterotrait-monotrait) ratio

Constructs	PEOU	PU	SN	FC	DP
PEOU					
PU	0.733				
SN	0.359	0.304			
FC	0.533	0.323	0.452		
DP	0.716	0.665	0.386	0.642	

Structural Model

The evaluation of the structural model is based on the R^2 measures in combination with the level and significance of the path coefficients. There is no specific threshold for R^2 values; the higher the *R2*, the greater the percentage of variance explained. Further based on Cohen's threshold value, the effect size was assessed. Weak, moderate, and strong influences of independent variables on dependent variables are 0.02, 0.15, and 0.35, respectively *(Cohen, 2013)*. To test the predictive relevance, Stone-Geisser's Q^2 was used, which specifies that Q^2 should be greater than 0 (Hair et al., 2011). *Figure 1* displays the diagram of the path coefficients.

Figure 1: Path diagram



In the path diagram, the path coefficient along with their respective p-values and R^2 value for the dependent variable is provided. The hypotheses were tested using the bootstrapping technique with 999 resamples. The PLS algorithm was used for outer model analysis, while the inner model analysis algorithm was WARP 3. According to *Ali et al. (2018)*, results become meaningful when the standardized paths are 0.20 or greater. However, *Hair et al. (2011)* suggested that when the research is exploratory in nature and PLS-SEM is the best statistical tool, beta values lower than 0.20 can still be considered. The results of the bootstrapping technique showed that Perceived usefulness (β = 0.18, p<0.01), Perceived ease of use (β = 0.30, p<0.01), Subjective norms (β = 0.15, p<0.01), and Facilitating conditions (β = 0.33, p<0.01) had a significant influence on the adoption of digital payment methods *Table 5*. Further, we analysed the fit indices of the model, and the results are presented in *Table 6*.

Table 5: Path coefficient of structural model

Hypothesis	Path coefficient	p-values	Remark
PEOU→DP	0.30	<0.001	Accepted
PU→DP	0.18	<0.001	Accepted
SN→DP	0.15	<0.001	Accepted
FC→DP	0.33	<0.001	Accepted

Table 6: Fit indices of structural model

Constructs	R2	f2	Q2
PEOU		0.203	
PU		0.111	
SN		0.064	
FC		0.192	
DP	0.569		0.567

One important feature of WarpPLS is its ability to present a table of path relationships that specifies the type of relationship between modelled paths as either "warped" (non-linear) or linear. The output displays the relationships between perceived usefulness, perceived ease of use, social norms and facilitating conditions with digital payment adoption as "warped". These relationships are illustrated in Figures 2 to 5, respectively.

Figure 2: Perceived ease of use and digital payment adoption

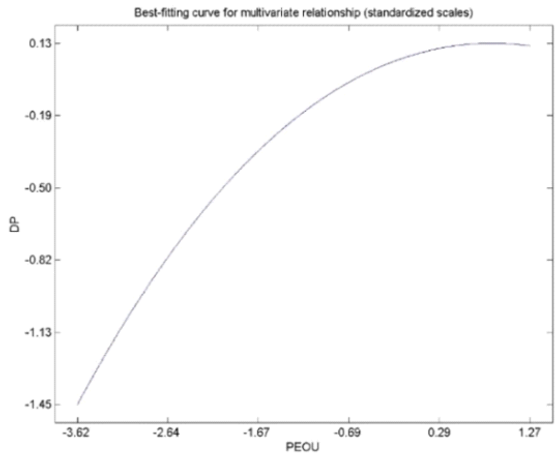


Figure 3: Perceived usefulness and digital payment

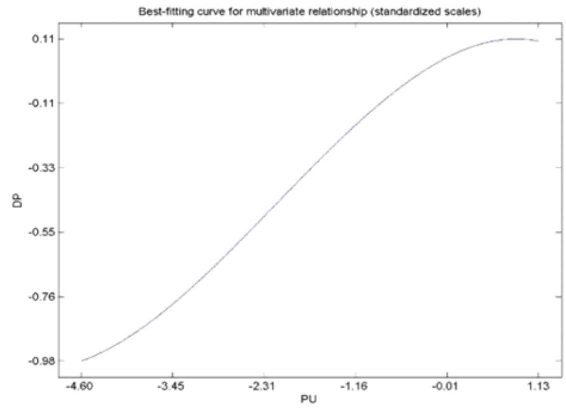


Figure 4: Social norms and digital payment adoption

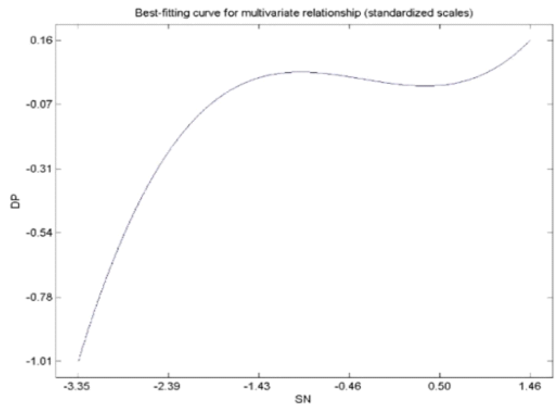
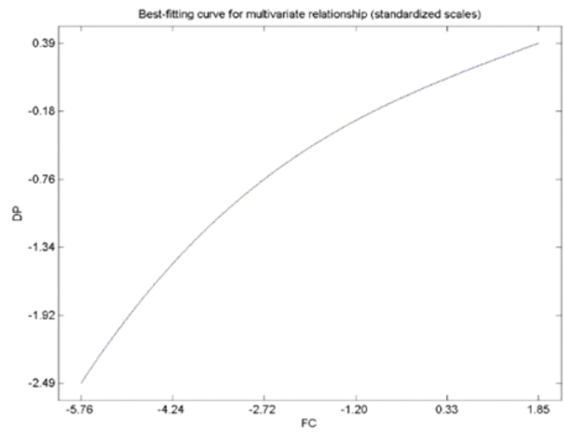


Figure 5: Facilitating conditions and digital payment adoption



In the context of the Partial Least Squares (PLS) method, there is a set of rules that determine the quality and fitness of a model. These rules are based on several indices that include the following: average path coefficient of 0.241 with a p-value of less than 0.001, average R-squared of 0.569 with a p-value of less than 0.001, average adjusted R-squared (AARS) of 0.566 with a p-value of less than 0.001, average block VIF (AVIF) of 2.649 (which is considered acceptable if less than or equal to 5, and ideally less than or equal to 3.3), average full collinearity VIF (AFVIF) of 1.718 (which is also considered acceptable if less than or equal to 5, and ideally less than or equal to 3.3), Tenenhaus GoF (GoF) of 0.621 (where a value greater than or equal to 0.1 is considered small, greater than or equal to 0.25 is medium, and greater than or equal to 0.36 is large), Sympson's paradox ratio (SPR) of 1.000 (which is acceptable if greater than or equal to 0.7, and ideally equal to 1), R-squared contribution ratio (RSCR) of 1.000 (which is acceptable if greater than or equal to 0.9, and ideally equal to 1), statistical suppression ratio (SSR) of 1.000 (which is acceptable if greater than or equal to 0.7), and nonlinear bivariate causality direction ratio (NLBCDR) of 1.000 (which is acceptable if greater than or equal to 0.7).

The digital payment adoption curve is flatter for perceived usefulness, perceived ease of use, and facilitating condition and the curve is “U” shape but the curve for the social norms influencing digital payment adoption is steeper and is a “scalloped” shape curve. Therefore, it can be stated that all the factors except social norms will decline the adoption rate after a point of time but social norms after reaching saturation will decline and have the potential to increase the adoption.

Artificial Neural Network (ANN) Analysis

Overview on ANN

The Artificial Neural Network is good in the case of both normal and non-normal distribution of data and non-linear relationships between independent and dependent variables. It is also not affected by small sample sizes, outliers, and noise, and it does not need compensatory models. This is an information processing paradigm that simulates the method by which biological nervous systems, or brains, operate information. The ANN is built of many interconnected processing units or neurons. The ANN accomplishes the designated work through its neurons working together. Each neuron is associated with the others through connection links and the links are modelled by weights that store information regarding the input signal. This study tested the neural network model using IBM's SPSS 29. The MLP used three layers of neurons namely: input layer, hidden layer, and output layer. The feedforward-backpropagation type is a general artificial neural network that utilizes a specific training algorithm called backpropagation in order to rearrange its weights and improve accuracy. The feedforward neural network transports the information starting with the input layer to the hidden layers and finally to the output layer. Each neuron in either the hidden or output layer evaluates a weighted sum of its inputs that it passes through an activation function. The neurons are given synaptic weights ranging from 0 to 1; 1 is the strongest connection the neuron can have. The output layer evaluates the difference between the actual and desired outcomes with the assistance of another activation function, and the bias information is sent backward to the input layer. This process is then repeated until the bias is minimized. Tenfold cross-validation was employed to avoid model over-fitting. We used 90% of the data for training and the remaining 10% for testing purposes. With the help of the sigmoid function, the activation function used is shown in *Figure 7.* The number of hidden units was determined automatically by computing the minimum and maximum values of the range and then determining the best number of hidden units within the range. The Bayesian Information Criterion indicated the best model fit was the one that had the smallest value. In order to evaluate the model, we calculated the root mean square error and assessed the sensitivity of the model to determine the relative importance of the predictors.

Fig 6: Conceptual ANN model

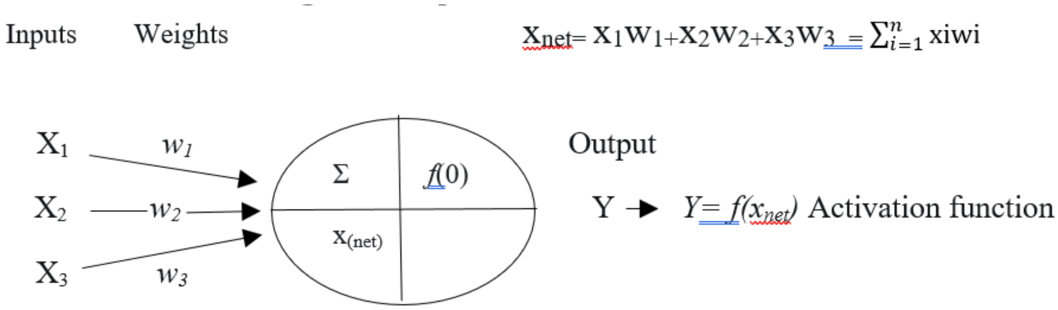
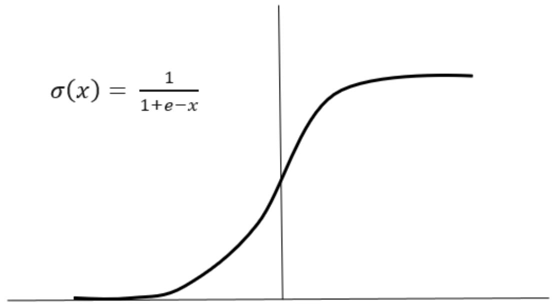


Figure 7: Sigmoid function



Source: https://machine-learning.paperspace.com/wiki/activation-function

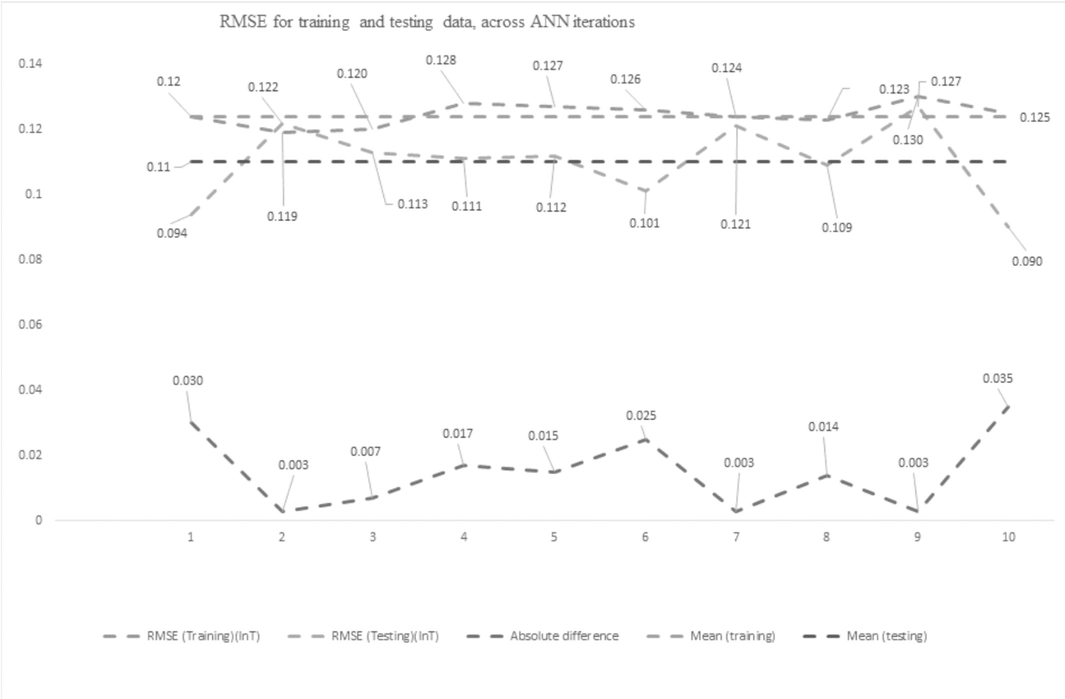
Validating ANN Models

The study conducted a measurement of prediction accuracy using RMSE and found that the ANN model is reliable and possesses a high degree of prediction accuracy. The average RMSE for training and testing were 0.12 and 0.11, respectively, indicating consistency in the results depicted in *Table 7*. Additionally, the relevancy of the constructs was validated by examining the quantity of non-zero synaptic weights directed to the hidden layers, and it was found that all predictors are relevant in predicting instructional effectiveness.

Table 7: RMSE Values (Source: Author's own creation)

Network	RMSE Training	RMSE Testing	Absolute difference	Mean Training	Mean Testing
1	0.124	0.094	0.030	0.12	0.11
2	0.119	0.122	0.003	0.12	0.11
3	0.120	0.113	0.007	0.12	0.11
4	0.128	0.111	0.017	0.12	0.11
5	0.127	0.112	0.015	0.12	0.11
6	0.126	0.101	0.025	0.12	0.11
7	0.124	0.121	0.003	0.12	0.11
8	0.123	0.109	0.014	0.12	0.11
9	0.130	0.127	0.003	0.12	0.11
10	0.125	0.090	0.035	0.12	0.11
Mean	0.12	0.11	0.01	0.12	0.11
Std Dev	0.003	0.012	0.012	0.00	0.00

Fig 8: Root mean square of errors across ANN iterations. (Source: Author's own creation)



Sensitivity Analysis

To measure the significance of the predictors, a sensitivity analysis was performed. Initially, the average relative importance was determined for ten neural networks. Next, the normalized importance of each predictor was calculated as a percentage of the average relative importance in comparison to the highest average relative importance among the predictors across the ten neural networks *(Karaca et al., 2019)*. Based on the results presented in *Table 8,* perceived usefulness was the most crucial factor with maximum normalized importance. Further in the list were social norms, followed by facilitating conditions and the least was perceived ease of use.

Table 8: Results of sensitive analysis

NN	Perceived Usefulness	Perceived Ease of Use	Social Norms	Facilitating Conditions
ANN 1	1.00	0.39	0.39	0.27
ANN 2	1.00	0.41	0.77	0.63
ANN 3	1.00	0.57	0.88	0.77
ANN 4	0.82	0.47	1.00	0.44
ANN 5	1.00	0.42	0.82	0.61
ANN 6	0.61	0.35	1.00	0.53
ANN 7	1.00	0.38	0.53	0.44
ANN 8	1.00	0.51	0.83	0.84
ANN 9	0.95	0.85	1.00	0.49
ANN 10	0.71	0.41	1.00	0.61
Average Importance	0.909	0.476	0.822	0.563
Normalised Importance %	100%	52.36%	90.42%	61.93%

Theoretical and Managerial Implications

Previous studies related to the adoption of technology were only based on a simple SEM and failed to read the underlying complexity and nonlinearity that may be encountered in the adoption of digital payments. To read the complex and non-linear relationships of digital payment adoption, this study introduced an advanced approach with Partial Least Squares Structural Equation Modeling and Artificial Neural Network. The study used deep neural network architecture to investigate the high dimensional and nonlinear connection of the model. The use of dual-stage PLS-SEM, and ANN increased better understanding and interpret the non-linear complex relationship of digital payment adoption. This study is a major progress in technology adoption and could be a guideline for future research in the same environment. This study adopted the constructs from TAM, TPB, and UTAUT to determine which factors affect digital payment adoption. The facilitating condition and ease of use have the most influence on the adoption of digital payment services. The result of this study will have implications for the service provider, highlighting the facilitating condition as the most influencing factor, and the role of social norms in increasing adoption after attaining maturity for a digital payment system. It is important to formulate and implement a strategy that concerns the user's digital payment facilities and services.

Conclusion

It is impossible to ignore that for different reasons; digital payment adoption has been taking new levels in the last few years. It is feasible due to the ease with which it is operated. Even after the adoption, it has been discovered that many people would not operate digital payment for reasons such as there is an increase in online payment gateway fraud, and there is the fear of being defrauded. This study shows that the two most critical reasons for adopting the technology are facilitating conditions (FC) and perceived use of ease (PEOU). Facilitating conditions (FC) refers to the available resources and support to enable the adoption of digital payment. This entail accessibility to technology, the creation of infrastructure for users, and a safe environment for online payment gateways. Perceived ease of use (PEOU) reflects the users' perspectives of how easy it is to use digital payment systems as compared to online payment. It also shows that digital payment systems are more user-friendly and their ease and convenience have made people more inclined to use them compared to traditional payment methods.Therefore, these findings can help the authorities in constructing the way forward in the general adoption of digital payment technology. The widespread adoption of digital payments has changed the way the economy operates, and acquiring money is more convenient. People no longer have to carry money wherever they go, eliminating fear of theft. In addition, the government benefits due to reduced counterfeit money circulation and recording each transaction made in digital form. Therefore, it aids in reducing the black money in the economy. In general, the findings of this study provide insight about the digital payment adoption and the adoption of such a payment system will improve the overall economy by boosting the people's confidence in the country's digital economy.

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