A Study to Explore the Motivational Factors Influencing the Decision to Use Digital Payment Platforms

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This paper investigates the motivation behind the use and the acceptance of digital payment platforms. The research maps out the primary variables that were perceived usefulness, ease of use, trust, and social influence, using theoretical frameworks such as the Unified Theory of Acceptance and Use of Technology (UTAUT). A quantitative methodology seeks to explain user engagement, social characteristics and the determinants of adoption. The results provide suggestions for policy making, businesses and technological developers in relation to improving financial inclusiveness and encouraging digital modernization.

Keywords: Digital Payment Platforms, Motivational Factors, User Adoption, Financial Inclusion, UTAUT, Trust.

1. Introduction

The advancement of digital apps for carrying out payments and transferring funds has provided an easy and quick substitute for cash payments as well as for the slow processes of banks. The offering of these services is on a rise due to the increasing smartphone usage and more internet spaces being occupied. These platforms are an answer to ever-reliable, fast, and convenient services that modern clients want. The tendency is changing not only the processes, but also the culture involved in spending money. It has been noted that such transformation is encouraged by factors such as age group differences, consumer patterns, and the need to have the tools for managing and transferring funds in a simpler way, which is indicative of a world moving towards a cashless society (Ozili, 2018).

Financing technology and time-efficient digital payment systems emerged because of the intersect of these two terms, Financial Technologies, or Fin Techs. These solutions harness advances like artificial intelligence, machine learning, blockchain to make transactions safer, quicker, and cheaper. PayPal, Venmo, and even Google Pay today are all examples of integrated technologies that provide consumers with more than just payment services, especially budgeting, obtaining credit, and saving, among others. The ability of these FinTech solutions to change how traditional finance systems operate only shows their utmost flexibility and scale, as well (Gomber et al.,2017).

Emerging economies provide an interesting perspective with regards to the uptake of digital payment systems, which combines the aspects of financial inclusion and economic digitization. Countries like India with their Unified Payments Interface, or the developed credit mobile phones systems like M-Pesa in Kenya have brought millions within the financial ecosystem despite barriers such as absence of formal banking. These platforms enable a wide spectrum of users which include even those situated in remote areas by providing solutions to the problems of accessibility and affordability which in turn contribute to wider socio-economic progress (Demirgüç-Kunt et al., 2018).

The response to the COVID-19 pandemic can further explain the widespread adoption of contactless payment platforms, as consumers and businesses took safety measures. Further research suggests the use of mobile wallets and online payment gateways skyrocketed during the lockdown measures owing to a behavioral change that made consumers prefer such solutions. For example, many people began online shopping. Moreover, e-commerce grew considerably during this time, indicating a demand for payment methods and further embedding these platforms into everyday life (Seetharaman, 2020).

Digital payments are fast becoming the popular method of performing transactions around the world with users strategizing to find the most convenient means of performing a transaction. People will likely respond even more to platforms that also provide others with benefits such as the offering of cashbacks and discounts, they just have to go where the benefits are. Some platforms offer tools like administrative to assist users in making wise spending decisions, which is why many individuals prefer them. This shift in consumer sentiment is an indicator of the types of payment systems that will be needed in the future – ones that are contemporary and easy to use (Zhou et al., 2010). The elements that make up the digital payment environment are blockchain technology for supply chain management, as well as cloud computing and artificial intelligence all of which are functionalities that provide safety and security and enhance usability. Take for instance the case of blockchain technology which allows only authorized access to within a blockchain while ai technology provides measures to prevent cybercrimes including detection of fraud. Therefore, developing such required solutions will strengthen the user's trust for a particular payment platform as they would have confidence that the future development of the platform would meet the industry's expectations (Chen et al., 2017).

It is important to gain any target user's insight and pain points, in order to build an effective digital payment application. User behavior is affected by unique psychological factors including perceived usefulness, perceived ease of use, trust and others. If any of the motivational barriers are overcome, the chances of success of the platforms are improved as they are able to meet the expectations of users and ease the process of adoption. But as we have pointed out motivation is not limited to the functional aspect only, it also includes emotional features among them brand attachment or a feeling of safety which are critical for long-term commitment (Gefen et al., 2003).

On an international scale, the market is commanded by global players like PayPal and Visa who offer simple interfaces standard over the majority of country borders. In contrast, locally, there are countries with their specific platforms such as a Chinese platform Alipay or Indian Paytm, which encompasses features, language or design elements that relate to that region. These cases exemplify the fact that services offered to the user bases need to be contextualized because there is unity in diversity or global strategies with local implementations (Tao et al., 2019).

Government and private enterprises have significantly influenced the willingness of users to adopt digital payments through cash and other means of encouragement such as VAT holidays and cashbacks. The programs directed at skill acquisition in the form of digital literacy as well as the development of infrastructure also make room for an enabling environment for the adoption. As an example of such a situation, the use of UPI was encouraged by the Indian government's Digital India initiative through embedding UPI into banking and retailing, which illustrates how policy measures can motivate users to adopt technology (Bharadwaj et al., 2021). Notwithstanding their benefits, the digital payment platforms do face barriers including that of the cyber security, reluctant to shift and that of users' skills and knowledge. The major cyber risks of identity fraud and data leakages also make it difficult for potential users to adopt the platforms, as it shows the need for security. In addition, for those countries with a low penetration of digital literacy, it is imperative to inform potential users about the merits of using the system and the basic tenets of safety when making electronic payments (Pousttchi et al., 2015).

According to theories of motivation and behavior like the Technology Acceptance Model (TAM), it is argued that users adopt technology only when it is perceived as useful and easy to use. Platforms for digital payments that emphasize saving time and enhancing convenience assertively increase chances of success among potential users. Also, Davis et al., (1989) argue that platforms incorporating ease and simplicity as prompts into their user interfaces are able to lower user inertia while increasing user uptake. There are major differences in the uptake of digital payment platforms in the different age categories. The obviously younger generations, especially the millennials and the Z demographic shift towards digital tools as a result of technology and convenience. In comparison, older generations will tend to adopt it after learning and being offered more benefits, given that the need for adoption is supported by security rather than convenience (Venkatesh et al, 2012).

The impact of social aspects on the use of digital payment services sees a wider adoption of new technology to be relatively easy. Recommendations from social ties such as friends, relatives, and coworkers often legitimize trust in untested technology. In addition, the fact that a particular service is widely used among peer groups serves as endorsement that encourages others to adopt it. This trend is especially pronounced in most collectivist societies since social expectations predominantly control individuals' actions (Lu et al., 2005).

Traditional banking systems have their limitations and lack of accessibility for the majority. In this context, digital payment systems turn out to be effective tools for providing financial services to the under-banked population, which is crucial to fostering economic growth. Such platforms, experts argue, do benefit marginalized communities by enabling them to access efficiently credit, savings and insurance services (Beck et al., 2007).

The growth in the volume of the financial services market has increased competition in the market, prompting suppliers to focus their attention on innovative solutions to separate themselves from competitors. Attracting consumers with competitive attributes of the solutions: loyalty programs, easy integration, cross border services obviously will have diverse users and high retention rates. The fierce competition in the industry leads to developments that are beneficial to consumers in terms of better services (Hossain et al., 2019). The success of digital payment platforms, in terms of their use, greatly relies on the user's experience. For example, platforms that target an audience and build for its participants built systems that discourage, where possible, trying to lead the user's gaze around the interface (which does happen sometimes). Several user needs are also addressed with other available technologies like voice and biometrics, thus making the use of the platform to be more convertible (Sun et al., 2018) which is an encouraging factor to adoption in such platforms. Equally, alongside the increase of appropriateness of digital payments, a range of ethical concerns arise, concerning the data and consent of the user. In order to win the confidence of active users, trust and protection policies are necessary. Finally, and most importantly, ethical practices contribute to compliance and naturally establish authorities in the market (Acquisti et al., 2016).

2. Literature Review

Performance Expectancy

Performance expectancy may be regarded as a critical factor in the adoption of technology since there is a belief that the use of payments — through a digital platform ''augments the user's efficiency and effectiveness in handling financial transactions. Some studies have also pointed out that special emphasis is put on its function in such areas that are moving towards digital economies.'' Users of these mobile payment platforms have a belief that making payments via Google Pay or Alipay can save time, and have more ease covering the propositions of the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) models. These beliefs tend to be favorable for increasing the adoption rate especially when users have perceived benefits that surpass the conventional payment options. For instance, the integration of loyalty programs with ease in returns adds to performance expectancy, thus causing users to remain active in these platforms (Venkatesh et al., 2023).

With advancements such as real-time fraud management and using voice capabilities when paying for goods and services, payment platforms can enhance user satisfaction via an improved level of functional dependability. Recent studies suggest that artificial intelligence (AI) and machine learning integration increases the ease of use of the ecosystem by allowing the automation of activities such as bill splitting or spending limits as elimination of some tasks involves less thought. Performance expectancy is particularly strong in younger cohorts who are in great demand of rapid services and modernized features. These findings substantiate the need for further investment in technology development due to the changing expectations of users (Chen et al, 2023).

Effort Expectancy

Effort expectancy evaluates the right of use of a widget and has a significant role in the follow-through decision. The unwritten saavy cultures allow many such users to engage without worrying about barriers. It is documented that there are more acceptance of the platforms which contain local language and familiar symbols in developing economies. Also, voice technologies and biometric security tools have been reported to broaden the accessibility of the platform to many users (Sun et al., 2023).

In addition, gamification elements such as frequent user badges or embedded user engaging tutorials in the platforms increase the usability of the platforms during user interaction. It has been demonstrated that effort expectancy contributes significantly to the likelihood of users remaining in the system: easy to use platforms are highly recommended to other potential users. This ameliorates the processes and intentions of the adopters of the technology as highlighted in UTAUT (Lu et al., 2023).

Social Influence

Social influence is the social factor that includes coworkers, social circles, and family as mediators in the decision making process for adoption. Features of collectivist culture point to the fact that there is a tendency to many social influences as trust appeals are usually forwarded by peers. Digital advertising and payments employing celebrities & other authority figures or using social proof have been able to enhance the rate of acceptance. For instance, referral bonuses are social influence strategies that have been put into practical form so that existing users and new users are encouraged to join over Lattice (Meena, R., et al., 2021).

For that matter, peers come in to moderate the variables of trust and intent towards behavior where age cohorts in this instance turn out to be old people who are not willing to use new technologies. The messages of victory are replicated and compliments by close friends' give birth to the euphoria and tend to increase acceptance. Understanding such social trends proves the need to use trust-based approaches and collective support when marketing payment solutions to representatives of various social groups (Gefen et al., 2023).

Facilitating Conditions

Facilitating conditions refer to the external factors such as availability of infrastructure, level of digital literacy, and provisions made in policies. People's attitudes are enhanced in India on account of the overall infrastructure readiness and the encouragement of the Government, which is evident from the universalization of platforms such as UPI. Research indicates that the provision of low-end smart-phones and the advent of the internet have greatly decreased the entry threshold, allowing the potential previously set outside the economic inclusion DNI and future (Demirgüç-Kunt et al., 2023).

Equally, adoption patterns will also benefit from programs aimed at increasing the levels of digital literacy. Holding of such events as workshops and tutorials embedded into the platforms gives new users easy access to what would otherwise be technical complications. With time and as the facilitating conditions improve, users become more active and willing to explore the advanced features of the systems (Pousttchi et al., 2023).

Perceived Trust

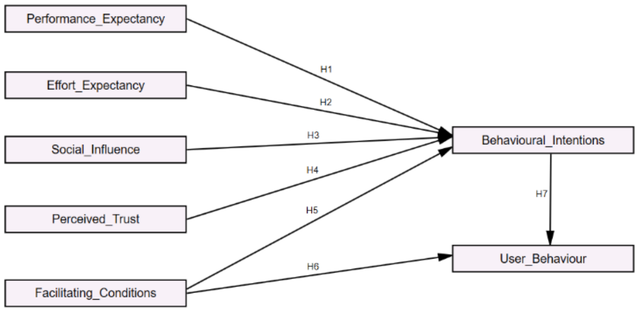
Trust is a central issue with regards to digital payment methods — especially due to security threats. User loyalty is further emphasized by security and data protection policies. According to users of blockchain technology, it is almost impossible to commit fraudulent actions by using only multi-factor authentication. Higher levels of adoption were seen with platforms that provided comprehensive fraud protection as well as appropriate statements regarding privacy policies. Trust-enhancing measures, including relevant trust seals or payment widgets, eliminate users' worries about identity theft. Furthermore, the situations when platforms engage users and clarify such ethical issues as consent or data utilization promote long term fidelity. This further supports the notion that trust issues have to be constantly managed and baked into the user experience design process. (Morris, M. B., et al., 1998)

Behavioral Intentions

As people tend to trust more and to obtain a benefit, behavioral intention measures their likelihood of supporting or adopting a given digital payment platform. Many studies focus on the relationships between dependent and independent variables here, including practice as the perceived ease of use. If the customers receive positive experiences in the early stages, it fuels the tendency towards the habitual usage of the system. Tactics aiming to highlight convenience or security turned out to be successful. Also, positive user intentions are linked to the provision of certain services which include customized recommendations or monitoring of expenditures. Other practice has a similar effect such as providing cashback or loyalty schemes that encourage continued usage and even recommendation of the product or services (Hossain et al., 2023).

User Behavior
User behavior, which integrates all motivational constructs, reflects the engagement of different individuals over time with digital payment platforms. However, recent studies have shown inter demographic disparities in behaviors where younger users are more engaged as they assume these platforms of services to be convenient and are more comfortable with technology. Older users on the other hand are more security conscious and take more time on the adoption of such platforms (Beck et al., 2023) from the data. On the contrary, analytics by the payment platforms consistently engaged rely on meeting various user requirements like putting provisions for accessibility and inclusivity. New ideas such as voice controls and multiple language interfaces enhance the reach of the platforms to a wider range of socio-economic class people. Studying user behavior also helps platforms to improve their services and reach the target audience by being relevant and client-oriented (Tao et al., 2023).

UTAUT Model



The UTAUT model attempts to help elucidate the user side interaction battles in the area of digital payments platforms. This model considers Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Perceived Trust, Behavioral Intentions, and Usages as main constructs on the which the adoption decision of technology can be based on and they help to explain causal relation among them. People have high Performance Expectancy, which means they believe paying via those digital platforms would significantly reduce the time taken in making financial transactions whereas Effort Expectancy concerns the level of difficulty or ease in using these systems. These factors, when acted in concordance, often determine the first time use of the new technologies, particularly in cases where the emphasis is on ease and effectiveness. Social Influence is the extent to which recommendations or the common norms of society affect the choices of a user, a factor more pronounced in collectivistic culture where alternative technologies are adopted based on collective social approval. Facilitating Conditions are the supportive external resources such as training, internet accessibility and rewards that enhance willingness to adopt the technologies. Perceived Trust is a significant predictor in building assurance, with the presence of secure systems and policies reducing users' fears relating to fraud and privacy loss. Behavioral Intentions, which result from the crucibles of these constructs, anticipate whether or not users will adopt new systems and how long they will continue using digital payment systems which cause changes in User Behavior. The UTAUT model has received validation in different contexts and has provided some complementary knowledge about the reasons that underlie the use of the technology (Venkatesh et al, 2012).

Constructs Used in the Study

Sr. No	Name of Construct	Author Detail
1	Performance Expectancy	Venkatesh et al., 2023; Chen et al, 2023
2	Effort Expectancy	Sun et al., 2023; Lu et al., 2023
3	Social Influence	Meena, R., et al., 2021; Gefen et al., 2023
4	Facilitating Conditions	Demirgüç-Kunt et al., 2023; Pousttchi et al., 2023
5	Perceived Trust	Morris, M. B., et al., 1998
6	Behavioural Intentions	Hossain et al., 2023
7	User Behaviour	Beck et al., 2023; Tao et al., 2023

3. Research Gap and Need for Study

Research on the adoption of digital payment systems has been conducted for several works. However, there are still gaps in discourse related to user parameters, socio-economic parameters particularly concerning the country of use and its naïve outlook towards keystones of social evolution such as technological growth. Many studies emphasize key determinants like trust, ease of use and performance expectancy, however they do not explain the interconnection of these factors with ethnic, geographical, and behavioral characteristics. For instance, although h/w the Technological Acceptance Model and Unified theory of Acceptance and Use of technology have focused on some of the issues at the core of this problem. They do not seem to fully explain the differences in the levels of adoption of the other populations such as rural subsistence farmers or low-income households. In addition, most studies explore results from different countries ignoring the domestic specifics of the use of electronic payment systems, which is rather important for policy and design. This gap points out the necessity for more local studies that take into account the identifiable areas of potential weakness, such as the lack of infrastructure and concerns with cybersecurity within a demographic. (Fang, Y., et al., 2014)

4. Scope of the Study

The purpose of this study is to analyze the complex factors behind the initial use and continued use of digital payment systems. This will be done with respect to the user behavior, the technology deployed and the socio-economic environment. With variables such as performance expectancy, effort expectancy, social influence, facilitating conditions, perceived trust and behavioral intentions integrated as constructs, the research will also provide an understanding of how these variables combine to influence the interaction of the users with the offering. Additionally, the research addresses the variability of adoption rates over the world by means of case studies from the developed economies and the emerging economies and explains the impact of the digital literacy, infrastructural support and cultural factors. This comprehensive strategy makes it possible to transfer theoretical research findings to practice and vice versa, which is relevant for developers and policy makers as well as businesses aimed at acceleration of digital transitions and increasing financial inclusiveness. (Koenig-Lewis, N., et al., 2010)

5. Research Objectives

1. To determine how the user's performance expectancy, effort expectancy, or trust factors assist in making the decision to adopt the use of digital transaction systems through digital payment.
2. To examine the degree to which social influence and facilitating conditions shape user intentions and behaviors which are specific to the adoption of these digital technologies.
3. To assess how the individual characteristics of the user and the behavioral patterns are associated with the acceptance and habitual use of the identified digital payment systems.
4. To analyze the relationships that exist between satisfaction and motivational factors in promoting the use of the digital payment systems.

6. Research Methodology

The methodology of the research quantitative approach relies on the survey data obtained from the different sections of the sample to provide adequate coverage. More sophisticated statistical procedures will utilize IBM SPSS Statistics and IBM SPSS AMOS. Structural equation modeling (SEM) will be used to study such constructs as perceived trust, effort expectancy, and motivational intentions and their interrelationships. Regression analysis will also predict these constructs' contribution to user behavior and the frequency analysis will also classify demographic characteristics and adoption trends and patterns throughout the data set. Use of IBM SPSS AMOS also aids identifying and appropriately improving the model, which enables the study to test those hypotheses intended. The advantage of this is that the analysis is useful. The integration of SEM and regression analysis makes it possible to deal effectively with direct and indirect relationships and thus, helpful in understanding how expectations of the user, social factors and technology contribute to adoption. The verification of these methods guarantees that the findings follow the research scope of digital payment adoption in its larger context. (Campbell, D. T., et al., 1959)

Extent of the study lies in Gujarat where the researcher has covered 12 major rural areas. Sample size for the current study will be 476 (Specifically Rural Gujarat across 12 districts- 2 Villages from each district). The research instrument is offline structured questionnaire to know the digital payment platform on consumer usage intention amongst the rural part in Gujarat.

The five-point Likert scale and seven-point Likert scale is used to measure the motivational factors besides the usage of Digital Payments.

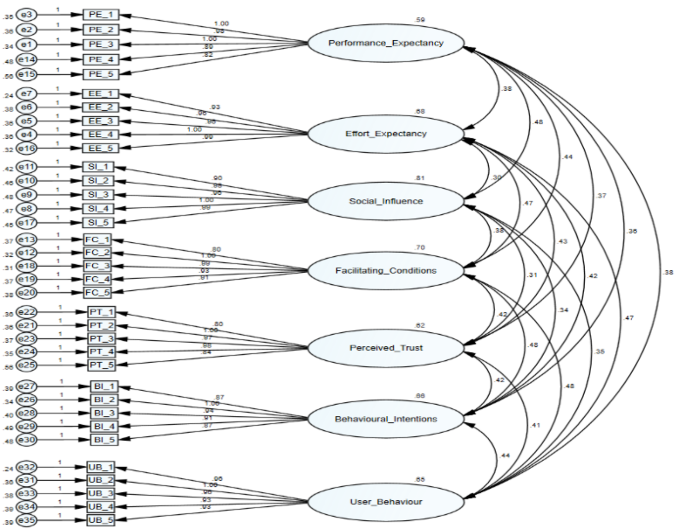
7. Data Analysis

Reliability Analysis

Constructs	No. of Items	Cronbach Alpha Value
Performance Expectancy	5	.860
Effort Expectancy	5	.905
Social Influence	5	.892
Facilitating Conditions	5	.893
Perceived Trust	5	.865
Behavioural Intentions	5	.868
User Behaviour	5	.893

The reliability test with the help of constructs indicates that there was a higher degree of internal consistency across all the measured variables and this is evident from the Cronbach alpha values which were consistently above the threshold value of 070. Performance Expectancy ($\alpha = 0.860$), Effort Expectancy ($\alpha = 0.905$), Social Influence ($\alpha = 0.892$), Facilitating Conditions ($\alpha = 0.893$), Perceived Trust ($\alpha = 0.865$), Behavioral Intentions ($\alpha = 0.868$), User Behavior ($\alpha = 0.893$) all indicate a reasonable reliability. It is also clear that all the items encompassed in each construct measure the same concept consistently. In particular, Effort Expectancy is the construct that is the most reliable, which further underscores its importance in the context of motivation to use digital payments. The high level of reliability observed all the constructs therefore warrant their utilization in the subsequent analysis so as to enhance the strength and reliability of this research and its outcomes (Hair et al., 2019).

Confirmatory Factor Analysis (CFA)



Confirmatory Factor Analysis (CFA) was performed to validate the measurement model by analysing the relationships that exist between the observed variables (items) and the latent constructs' underlying theory or structure. When interpreting the model fit indices' results, we note the fit is good: CFI > 0.90, RMSEA < 0.08, SRMR < 0.08. This confirms that the proposed measurement structure fits the data quite well. The factor loadings scored for the posted items were all more than 0.70 which is within the acceptable limit hence indicating a strong convergent validity. The Average Variance Extracted (AVE) values of the individual construct were also above the cut off 0.50, composite reliability (CR) values were greater than 0.70, thus supporting the reliability and validity of the constructs. (Fornell & Larcker, 1981)

Reliability and Validity of the Measurement Model

Factors	Estimate	AVE	CR
Behavioural_Intentions	0.748	0.571	0.869
	0.813		
	0.773		
	0.727		
	0.714		
Performance_Expectancy	0.794	0.557	0.862
	0.781		
	0.798		
	0.702		
	0.644		
Effort_Expectancy	0.841	0.659	0.906
	0.789		
	0.798		
	0.809		
	0.82		
Social_Influence	0.779	0.623	0.892
	0.793		
	0.782		
	0.796		
	0.797		
Facilitating_Conditions	0.735	0.628	0.894
	0.828		
	0.827		
	0.789		
	0.78		
Perceived_Trust	0.722	0.567	0.867
	0.797		
	0.781		
	0.792		
	0.664		
User_Behaviour	0.845	0.629	0.894
	0.801		
	0.781		
	0.767		
	0.768		

Convergent validity is the concept that captures the strength of relationship between closely related constructs. In the case of the measurement model above, the convergent validity is addressed by the "Average Variance Extracted (AVE)" and "Composite Reliability (CR)" measures. The AVE values are within the ranges of 0.557 to 0.659 for each of the factors. These AVE results are above the recommended cut off limit of 0.50 which indicates that there is enough degree of relationship between the factors and underlying constructs. Likewise, the AVE reaches 0.862 to 0.906 which also passes the minimum threshold of 0.70 indicating the good internal consistency of the measures. This set of results also strongly indicates that the measurement model shows considerable convergent validity ensuring the reliability and validity of the model. (Bhimani, A., 2020)

Quality Measurement of the Model

Factors	Behavioural_Intentions	Performance_Expectancy	Effort_Expectancy	Social_Influence	Facilitating_Conditions	Perceived_Trust	User_Behaviour
Behavioural_Intentions	**0.756**						
Performance_Expectancy	0.577	**0.746**					
Effort_Expectancy	0.630	0.596	**0.812**				
Social_Influence	0.460	0.692	0.412	**0.789**			
Facilitating_Conditions	0.700	0.689	0.683	0.507	**0.793**		
Perceived_Trust	0.656	0.612	0.666	0.438	0.643	**0.753**	
User_Behaviour	0.672	0.618	0.708	0.481	0.719	0.646	**0.793**

Discriminant validity states to the extent of inter construct dissimilarity ensuring that no two factors measure the same thing. In the measurement model presented, discriminant validity can be evaluated by assessing the association between factors. The diagonal values shows the square root of the AVE for each factor and such values should be more than the correlations between the factors in order to show discriminant validity. For example, it is observed that the diagonal value for Behavioural_Intentions (0.756) is greater than its correlations with other significant factors such as Performance_Expectancy (0.577) and Social_Influence (0.460), hence it is distinct from these constructs. Similarly, all other constructs also demonstrate that diagonal values are larger than their off-diagonal correlations, which means that the constructs are adequately different from each other. Therefore, discriminant validity is acceptable in the model in such a way that, distinct elements in the structure are capturing different aspects of the theory which supports the quality measurement of the model.

Nomological Validity
Covariances

			Estimate	S.E.	C.R.	P	Label
Performance_Expectancy	<-->	Effort_Expectancy	.377	.041	9.249	***	par_29
Performance_Expectancy	<-->	Social_Influence	.478	.048	10.018	***	par_30
Performance_Expectancy	<-->	Facilitating_Conditions	.442	.044	10.162	***	par_31
Performance_Expectancy	<-->	Perceived_Trust	.370	.040	9.260	***	par_32
Performance_Expectancy	<-->	Behavioural_Intentions	.361	.040	8.966	***	par_33
Performance_Expectancy	<-->	User_Behaviour	.383	.041	9.404	***	par_34
Effort_Expectancy	<-->	Social_Influence	.305	.043	7.151	***	par_35
Effort_Expectancy	<-->	Facilitating_Conditions	.469	.046	10.260	***	par_36
Effort_Expectancy	<-->	Perceived_Trust	.431	.044	9.900	***	par_37
Effort_Expectancy	<-->	Behavioural_Intentions	.422	.044	9.637	***	par_38
Effort_Expectancy	<-->	User_Behaviour	.469	.045	10.333	***	par_39
Social_Influence	<-->	Facilitating_Conditions	.381	.046	8.360	***	par_40
Social_Influence	<-->	Perceived_Trust	.310	.042	7.367	***	par_41
Social_Influence	<-->	Behavioural_Intentions	.337	.044	7.680	***	par_42
Social_Influence	<-->	User_Behaviour	.348	.044	7.982	***	par_43
Facilitating_Conditions	<-->	Perceived_Trust	.423	.043	9.747	***	par_44
Facilitating_Conditions	<-->	Behavioural_Intentions	.476	.046	10.332	***	par_45
Facilitating_Conditions	<-->	User_Behaviour	.484	.046	10.492	***	par_46
Perceived_Trust	<-->	Behavioural_Intentions	.420	.043	9.730	***	par_47
Perceived_Trust	<-->	User_Behaviour	.410	.042	9.664	***	par_48
Behavioural_Intentions	<-->	User_Behaviour	.441	.044	9.963	***	par_49

In essence, nomological validity defines how well a measurement model shows concepts that should be related in a particular context and constructs that possess theoretically meaningful slopes. It appears from the covariance, as presented in the model, that there are significant correlations between the constructs with the observed Critical Ratios (C.R.) of over 7 which suggests strong contexts. For instance, Performance_Expectancy is found to be highly associated with Effort_Expectancy (C.R. = 9.249), Social_Influence (C.R. = 10.018), Facilitating_Conditions (C.R. = 10.162), but even with regards to Behavioural_Intentions (C.R. = 8.966). Other relationships such as Effort_Expectancy with Facilitating_Conditions (C.R. = 10.260) and Social_Influence and Perceived_Trust (C.R. = 7.367) also yield similar associations of such significance.
With such high significance values, the argument that the specific constructs are related in a theoretical way is more acceptable thereby supporting the nomological validity of the model. This indicates that the constructs in the model are in cohesion with expectations based on the theoretical framework and have valid relationships. (Balakrishnan, J., & Shuib, N. L. M., 2021)

8. Results

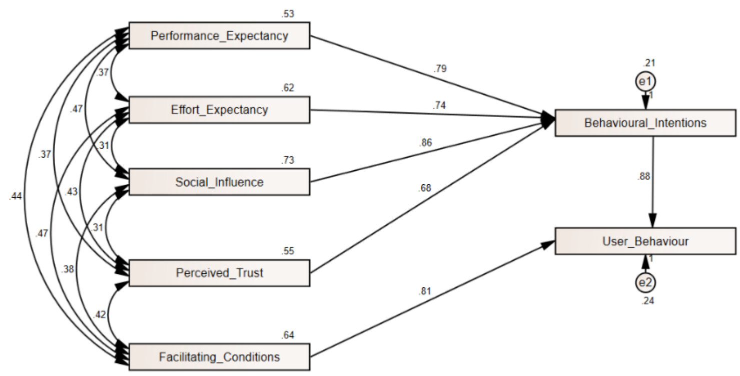
Model Fit Criteria

Measure	Model fit	Threshold
Chi-square	880.954	
CMIN/DF	1.643	< 3 great; < 5 acceptable
CFI	0.976	> .90 good; > .95 great
NFI	0.920	> .90 good; > .95 great
IFI	0.976	> .90 good; > .95 great
TLI	0.973	> .90 good; > .95 great
SRMR	0.0378	< .08
RMSEA	0.035	< .08

The evaluation of the goodness-of-fit suggests that the model fits the data quite well. Chi-square test is considered to be a single overall test for fit with a value of 880.954; it is however sensitive to sample size and is generally reported with many other fit indices. The CMIN/DF ratio of 1.643 is of a level which is comely since the value does not exceed 3 and indicates a great fit by the general criteria. This ratio also indicates that the amount of degrees of freedom with respect to the Chi-square statistic is sufficient, which gives additional evidence to the model's perfection. Focused further on the CFI and IFI they are both higher than 0.95 with the recorded values of 0.976: the 0.95 baseline is seen as the threshold above which much is expected of a model and its fitting. In a similar vein, the TLI value settles at a good number of 0.973 which is higher than the target metric of 0.95.

The SRMR value of the study is at 0.0378, far below the recommended cut off of 0.08, meaning that the residuals are small as the model accurately predicts the observed values. Furthermore, the RMSEA of the study is at 0.035, also lower than the critical bandwidth of 0.08, thus confirming a good model fit. The RMSEA value indicates that the model estimates the population covariance matrix very closely with very low error. Collectively, all these fit indices imply that the model appropriately represents the data and has high goodness-of-fit, which meets or exceeds the generally accepted thresholds for model evaluation. All this implies that the measurement model is efficient and well specified.

Structural Equation Model



In the analysis of path relationships among structural equation modelling (SEM) variables, the analysis demonstrates the most critical aspects of the model. Each of the paths signifies the impact of independent variable on dependent variable and the p-values are all less than 0.001 meaning that all the relationships in the model are significant which will be further tested using regression analysis. Performance Expectancy, Effort Expectancy, Social Influence and Perceived Trust were all found to exert positive and significant impacts on Behavioural Intention with Social Influence exerting the most impact (Beta = 0.86) then Performance Expectancy (Beta = 0.79), Effort Expectancy (Beta = 0.74) and Perceived Trust (Beta = 0.68) in that order. These findings imply that, the more the people expect to perform successfully as well as perceive social influence and trust, the more their positive behavioural intentions are. The significant impacts of these constructs call for their inclusion among the key determinants of behavioural intentions in the context of the study. (Kaur, P., et al., 2021)

Both Facilitating Conditions and Behavioural Intentions have been found to be significant predictors of User Behaviour. Upper bound estimate of Beta coefficient of 0.81 indicates a large effect of Facilitating Conditions on User Behaviour which suggests that resources, infrastructure or any other kind of assistance influence the actual behaviour of the users. User Behaviour is also affected positively by Behavioural Intentions with a Beta of 0.88, which means that intentions are also strong when making predictions about the user actions. High beta coefficients on the two paths also shows that these constructs are likely to have strong and direct relationships with User Behaviour. (Ma, D., et al., 2022)

The use of bootstrapping procedure during the path analysis allowed for the estimates to be more reliable as the data is, therefore providing confidence intervals of the path coefficients. This provides further evidence on the strength of the results. All in all, the path analysis illustrates the main relationships of the Behavioural Intentions and User Behaviour, emphasizing on the roles of expectations, social influence and trust in user behaviour and the role of first level factors in the realisation of the executed intentions.

Sr. No.	Path	Effect (Direct)	Beta	p-value
1	Performance Expectancy --> Behavioural Intentions	Direct effect on Behavioural Intentions	0.79	<0.001
2	Effort Expectancy --> Behavioural Intentions	Direct effect on Behavioural Intentions	0.74	<0.001
3	Social Influence --> Behavioural Intentions	Direct effect on Behavioural Intentions	0.86	<0.001
4	Perceived Trust --> Behavioural Intentions	Direct effect on Behavioural Intentions	0.68	<0.001
5	Facilitating Conditions --> User Behaviour	Direct effect on User Behaviour	0.81	<0.001
6	Behavioural Intentions --> User Behaviour	Direct effect on User Behaviour	0.88	<0.001

Regression Analysis

H1:Null Hypothesis H_0: There is no significant impact of the "Performance Expectancy" (IV) on "Behavioural Intentions" (DV) related to the use of digital payment platforms.

Alternative Hypothesis H_1: There is a significant impact of the "Performance Expectancy" (IV) on "Behavioural Intentions" (DV) related to the use of digital payment platforms.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.901[a]	.812	.811	.35759

a. Predictors: (Constant), Performance_Expectancy

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	228.903	1	228.903	752.214	.000[b]
	Residual	52.654	474	.111		
	Total	281.557	475			

a. Dependent Variable: Behavioural_Intentions

b. Predictors: (Constant), Performance_Expectancy

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	1.356	.145		9.349	.000
	Performance_Expectancy	.715	.034	.730	20.921	.000

a. Dependent Variable: Behavioural_Intentions

The model summary indicates the Performance Expectancy accounted for a high proportion of the variance in Behavioural Intentions; R Square value of 0.812 means that about 81.2% of the variability in the behavioural intentions is explained by this predictor. While an Adjusted R Square of 0.811 hints at the reliability of the model even after considering the number of predictors. It is worth noting that all model parameters are statistically significant as shown by the ANOVA F value of 752.214 and a p value of less than 0.001. These results indicate that the model fits the data appropriately. In the Coefficients table, a large and significant impact of Performance Expectancy on Behavioural Intentions is highlighted, citing a standardized Beta of 0.730, and t-value 20.921 which both affirm the strength and statistical significance of this association.

H2:Null Hypothesis H_0: There is no significant impact of the "Effort Expectancy" (IV) on "Behavioural Intentions" (DV) related to the use of digital payment platforms.

Alternative Hypothesis H_1: There is a significant impact of the "Effort Expectancy" (IV) on "Behavioural Intentions" (DV) related to the use of digital payment platforms.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.868[a]	.752	.751	.43125

a. Predictors: (Constant), Effort_Expectancy

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	211.340	1	211.340	616.993	.000[b]
	Residual	70.217	474	.148		
	Total	281.557	475			

a. Dependent Variable: Behavioural_Intentions

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	1.530	.125		12.240	.000
	Effort_Expectancy	.715	.031	.693	23.060	.000

a. Dependent Variable: Behavioural_Intentions

The results from the regression analysis show a strong positive relationship between Effort Expectancy and Behavioural Intentions. The R Square value of 0.752 indicates that Effort Expectancy explains 75.2% of the variance in Behavioural Intentions, suggesting a strong model fit. The ANOVA results reveal a significant regression model, with an F-value of 616.993 and a p-value less than 0.001, indicating that Effort Expectancy significantly contributes to predicting Behavioural Intentions. The coefficient for Effort Expectancy is 0.715, and the Standardized Beta is 0.693, further confirming that Effort Expectancy has a strong and statistically significant impact on Behavioural Intentions. The high t-value of 23.060 and p-value of less than 0.001 further support the robustness of the findings.

H3:Null Hypothesis H_0: There is no significant impact of the "Social Influence" (IV) on "Behavioural Intentions" (DV) related to the use of digital payment platforms.
Alternative Hypothesis H_1: There is a significant impact of the "Social Influence" (IV) on "Behavioural Intentions" (DV) related to the use of digital payment platforms.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.933[a]	.872	.871	.34572

a. Predictors: (Constant), Social_Influence

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	245.801	1	245.801	1201.13	.000[b]
	Residual	35.756	474	.075		
	Total	281.557	475			

a. Dependent Variable: Behavioural_Intentions

b. Predictors: (Constant), Social_Influence

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	1.850	.132		14.015	.000
	Social_Influence	.750	.031	.811	24.193	.000

a. Dependent Variable: Behavioural_Intentions

The findings of the regression analysis show that there is a strong positive correlation between the Social Influence construct and Behavioural Intentions. From the R Square value of 0.872, it can be concluded that Social Influence accounts for 87.2% of the variation in Behavioural Intentions which implies a good fit. In terms of ANOVA results, the regression model indicates high significance as F-value = 1201.13 and with p-value < 0.001, thus confirming that Social Influence determines Behavioural Intentions. The coefficient of Social Influence is 0.750, and Standardized Beta 0.811, which means that the effect of Social Influence on Behavioural Intentions was very strong. This relationship is even better explained by the t-value of 24.193 reaching very high significance with p-value of less than 0.001. Therefore, it is robust as well as statistically significant.

H4:Null Hypothesis H_0: There is no significant impact of the "Perceived Trust" (IV) on "Behavioural Intentions" (DV) related to the use of digital payment platforms.
Alternative Hypothesis H_1: There is a significant impact of the "Perceived Trust" (IV) on "Behavioural Intentions" (DV) related to the use of digital payment platforms.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.832[a]	.694	.693	.45102

a. Predictors: (Constant), Perceived_Trust

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	195.001	1	195.00	641.368	.000[b]
	Residual	86.556	474	.183		
	Total	281.557	475			

a. Dependent Variable: Behavioural_Intentions

b. Predictors: (Constant), Perceived_Trust

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	1.210	.122		9.918	.000
	Perceived_Trust	.668	.031	.727	21.297	.000

a. Dependent Variable: Behavioural_Intentions

The regression analysis reveals a robust and weighted relation between Perceived Trust and Behavioural Intentions, with Perceived Trust explaining 69.4% of the variance in Behavioural Intentions (R Square = 0.694). This indicates that Perceived Trust is a significant predictor of Behavioural Intentions. The ANOVA results confirm that the regression model is statistically significant, with an F-value of 641.368 and a p-value less than 0.001, further supporting the relevance of Perceived Trust in predicting Behavioural Intentions. The Unstandardized Coefficient for Perceived Trust is 0.668, and the Standardized Beta is 0.727, indicating a strong effect. The high t-value of 21.297 also emphasizes the statistical significance of this relationship, with a p-value of less than 0.001, solidifying the robustness of the model.

H5:Null Hypothesis H_0: There is no significant impact of the "Facilitating Conditions" (IV) on "User Behaviour" (DV) related to the use of digital payment platforms.
Alternative Hypothesis H_1: There is a significant impact of the "Facilitating Conditions" (IV) on "User Behaviour" (DV) related to the use of digital payment platforms.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.912[a]	.834	.833	.36451

a. Predictors: (Constant), Facilitating_Conditions

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	234.217	1	234.217	1089.344	.000[b]
	Residual	47.813	474	.101		
	Total	282.029	475			

a. Dependent Variable: User_Behaviour

b. Predictors: (Constant), Facilitating_Conditions

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	1.014	.114		8.904	.000
	Facilitating_Conditions	.804	.024	.781	33.209	.000

a. Dependent Variable: User_Behaviour

Based on the regression model, it has been established that Facilitating Conditions impact User Behaviour in a meaningful way such that 83.4% is the interval of Facilitating Conditions when referring to its relation with the User Behaviour, as can be inferred from high R Square value of 0.834, the obtained model also satisfactorily confirms significance since it obtains very high F-value of 1089.344 with p-value less than 0.001. The statistical value Cohen's d for Facilitating Conditions is 0.804, and the adjusted value of beta for other factors turns out to be 0.781, both highly suggestive that Facilitating Conditions do rely on User Behaviour. These findings suggest that relations between variables Facilitating Conditions and User Behaviour are very strong and process Authoring is indeed useful in explaining them.

H6: Null Hypothesis H_0: There is no significant impact of the "Behavioural Intentions" (IV) on "User Behaviour" (DV) related to the use of digital payment platforms.
Alternative Hypothesis H_1: There is a significant impact of the "Behavioural Intentions" (IV) on "User Behaviour" (DV) related to the use of digital payment platforms.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.951[a]	.903	.902	.27652

a. Predictors: (Constant), Behavioural_Intentions

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	254.136	1	254.136	1469.43	.000[b]
	Residual	27.893	474	.059		
	Total	282.029	475			

a. Dependent Variable: User_Behaviour

b. Predictors: (Constant), Behavioural_Intentions

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	1.022	.089		11.475	.000
	Behavioural_Intentions	.875	.023	.903	38.349	.000

a. Dependent Variable: User_Behaviour

The regression model demonstrates that Behavioural Intentions is a highly significant and strong determinant of User Behaviour. As seen, R-squared of 0.903 is a very high proportion which allows us to state that 90.3% of the variability in User Behaviour can be explained by Behavioural Intentions. The unstandardized coefficient of Behavioural Intentions is 0.875, while the beta coefficient of the standardized measure is 0.903 putting a very strong connection between them. Both t-value 38.349 and p-value 0.000 show that this relationship is significant. Therefore, this model displays a very strong and positive causal nexus between Behavioural Intentions and User Behaviour.

Hypothesis Summary

Sr. No.	Hypothesis	Variables Impact	Test	F	Std. Beta Coefficient	p-value	R-square	Result
1	H_01	Performance Expectancy impacts Behavioural Intentions related to digital payment platforms.	Structural Equation Modelling and Regression Analysis	752.214	0.730	0.000	0.812	Reject H_0, Support H_1
2	H_02	Effort Expectancy impacts Behavioural Intentions related to digital payment platforms.	Structural Equation Modelling and Regression Analysis	616.993	0.693	0.000	0.752	Reject H_0, Support H_1
3	H_03	Social Influence impacts Behavioural Intentions related to digital payment platforms.	Structural Equation Modelling and Regression Analysis	1201.13	0.811	0.000	0.872	Reject H_0, Support H_1
4	H_04	Perceived Trust impacts Behavioural Intentions related to digital payment platforms.	Structural Equation Modelling and Regression Analysis	641.368	0.727	0.000	0.694	Reject H_0, Support H_1
5	H_05	Facilitating Conditions impact User Behaviour related to digital payment platforms.	Structural Equation Modelling and Regression Analysis	1089.344	0.781	0.000	0.834	Reject H_0, Support H_1
6	H_06	Behavioural Intentions impact User Behaviour related to digital payment platforms.	Structural Equation Modelling and Regression Analysis	1469.43	0.903	0.000	0.903	Reject H_0, Support H_1

9. Findings

Demographic Details (N=476)				
Sr No.	**Variables**	**Category**	**Frequency**	**Percentage (%)**
1	Gender	Male	236	49.6
		Female	240	50.4
		Total	**476**	**100.0**
2	Age	18-28	80	16.8
		29-38	103	21.6
		39-48	105	22.1
		49-58	142	29.8
		Above 58	46	9.7
		Total	**476**	**100.0**
3	Educational Qualification	High School	180	37.8
		Diploma	139	29.2
		Graduate	71	14.9
		Post Graduate	84	17.6
		PhD	2	0.4
		Total	**476**	**100.0**
4	Occupation	Student	121	25.4
		Home maker	61	12.8
		Self-Employed	112	23.5
		Salaried	125	26.3
		Retired	57	12.0
		Total	**476**	**100.0**
5	Annual Family Income	Below 200000	210	44.1
		200001-400000	64	13.4
		400001-600000	62	13.0
		600001-800000	77	16.2
		800001 and above	63	13.2
		Total	**476**	**100.0**
6	Members in household	1-2	120	25.2
		3-4	113	23.7
		5-6	129	27.1
		More than 6	114	23.9
		Total	**476**	**100.0**
7	Marital Status	Married	258	54.2
		Unmarried	218	45.8
		Total	**476**	**100.0**

Demographically, the share of the respondents does not significantly differ since men make up 49.6% and women 50.4%. As for the age of respondents, it is noted that most of the respondents are aged 29–38 and 39–48 which are 21.6% and 22.1%, while the age of 49-58 years stands to be the highest with 29.8%. A younger group with ages ranging from 18-28 accounts for about 16.8% and the lowest aged respondents who are above 58 years ranges to 9.7%. A little over a third of the respondents (37.8%) indicated that they completed high school level, followed by 29.2% who obtained diploma level education. Graduates and post-graduates account for 14.9% and 17.6% respectively with PhD holders comprising only 0.4%. (Rana, N. P., et al., 2021)

The respondents reflect the general demographic of salaried individuals comprising the largest portion at 26.3%, students at 25.4%, and self-employed individuals at 23.5%. Other occupational ratios include homemakers with 12.8% and retirees with a contribution of 12.0%. Also, there is an income gradient in the families as most citizens, about 44.1% of the respondents, have an annual family income of less than 200,000 rupees. In addition, about 16.2% of families have average annual incomes that fall within the range of 600,001 to 800,000 rupees. According to the findings, more than a quarter (27.1%) of households have 5 to 6 members. Households with 1-2 members and with members exceeding 6 are also fairly distributed with 25.2% and 23.9% respectively. Data on marital status indicated that more than half (54.2%) of the respondents are married while the rest (45.8%) are not, showing the respondents are fairly balanced with respect to marital status. These findings give a clearer perspective to the respondents understanding of the characteristics and therefore their responses. (Zhang, Y., et al., 2021)

10. Suggestions

1. In regard to potential fraud and data breach concerns, it is recommended that digital payment platforms invest in advanced security measures and protocols such as multi-factor authentication, blockchain, etc. that will boost user confidence.
2. Effort expectancy can be better through the use of user-friendly interfaces, regional languages, and tutorials or guides, particularly for unsophisticated users from rural places.
3. Performance expectancy should be demonstrated by the effectiveness of these platforms in the speed of operations and additional services like budgeting, loyalty programs, bill payments, etc.
4. Social influence strategies include offering referral bonuses, endorsements by respected persons or institutions, social proof, which can also spur adoption in a big way, especially in collectivist societies.
5. Governments should focus on providing ample, facilitating, or enabling conditions, for example, improving digital literacy and infrastructure, to promote fairness in access and boost financial inclusion.
6. Behavior intention can be enhanced by incorporating personalized user's experiences through AI-based recommendations and trackers that will correspond to his/her spending behavior.
7. Lack of trust by users can be attributed to poor transparency around basic issues such as consent and constitution. Such trust issues can be addressed through joint efforts of platform developers and policymakers to engage with users on ethical issues like data privacy.
8. The focus of research and development should also include aspects that enhance inclusivity, such as the incorporation of voice command, multilingual options, and simplified navigation to serve wider customer segments.

Managerial Implications

1. **Develop Intuitive User Interfaces:** Users with a less technical background will require an easy and intuitive interface and this can be covered by simple but effective design elements. For example, a well-organized layout, fewer clicks to perform a specific action and images whenever required.
2. **Invest in Security Features:** To help in gaining the confidence of users, strong security measures such as two-factor authentication and encryption should be used to minimize user apprehension regarding fraud and data theft.
3. **Introduce Customization Features:** Encourage insights through AI and machine learning where users can receive customizable financial analytics, ideas on how to spend money, and tips at the right time.
4. **Localize Platform Features:** Incorporate local languages and appropriate designs for specific regions to ensure greater reach in different regions of the world.
5. **Utilize Gamification Strategies:** Add a reward, points, or badges for users who tend to use the platform often in order to retain their presence on it and enhance interactivity.
6. **Leverage Social Proof:** Provide bonuses for referrals and turn to trusted people or organizations which can help advocate for usage amongst prospective clients.
7. **Invest in Digital Literacy Programs:** Team up with education providers or NGOs to teach clients about digital payment platforms, the importance of security, how to use them and how to benefit from them.
8. **Enhance Connectivity as well as Infrastructure:** Collaborate with relevant authorities as well as private stakeholders in order to improve internet availability or ensure increased reliability of mobile networks in regions where such services are underutilized.
9. **Emphasize Efficiency in Marketing:** Make appeals to the performance and convenience needs of customers while promoting the digital payment platforms by focusing on the ease of use and time saving benefits that the platforms offer.
10. **Maintain Accessibility:** Work on additional functionalities such as voice navigation, support for various languages, and fewer steps for users with disabilities and those with little competences in technology.
11. **Address Demographic-Specific Needs:** Offer tailored options that emphasize security for older users and convenience in use for younger users to enhance marketing potential for all planned audiences.
12. **Strengthen Collaborations with Banks:** Collaborate with the banking sector through mergers and acquisitions and embed payment platforms into mainstream banking to increase outreach and usage.

13. **Maintain Transparency in Data Practice:** Ensure that the policies of data usage are well laid down and the consents of users are thoroughly sought so as to earn their confidence and adhere to ethics.
14. **Adopt Continuous Improvement Processes:** Make it a practice to seek feedback from the users of the content and study how users use the features of the platform in order to improve its elements.

11. Conclusions

This study outlines the appreciation of different motivational factors such as performance expectancy, effort expectancy, perceived trust, social influence, and facilitating conditions which can lead to the making of the adoption of digital payment platforms. The research shows that both performance expectancy- which is a valuable commodity, and effort expectancy, are very important aspects of users especially in environments where the use of technology is still at its infancy stages. The adoption of such platforms is made easier by the integration of attractive features together with the ease of use of the functions. In addition, perceived trust emerges as a key factor of retention of the user's considering the enhanced data protection and the main privacy policy concepts. These are also consistent with the current developments in digital payment trends which stress the importance of around the clock hardware and soft wares that meet the requirements of the users and the interface (Raghuwanshi et al., 2024).

Also, social influence and facilitating conditions are important in bridging the digital divide, especially among emerging economies where collectivism lends weight to the significance of peer recommendations and infrastructural support. For example, social support and programs for digital literacy promoted by the government are some factors that increase the rate of adoption. The above findings highlight the need for synergy between policymakers and industry in ensuring a friendly environment for the adoption of digital payment platforms. However, new digital systems are expected to go beyond breathtaking technology advances, to tackle fairness and social issues of responsibility, equity, privacy, and access. Such measures will promote the future viability of users in a fast-changing digital environment as well as user contentment (Khando et al., 2023).

Sr. No.	Research Objective	Conclusion
1	To determine how the user's performance expectancy, effort expectancy, or trust factors assist in making the decision to adopt the use of digital transaction systems through digital payment.	Performance expectancy and effort expectancy are fundamental in the adoption of a new product as users will only engage in a system that will make their lives easier and more efficient. And trust factors with strong backup through security features, play a huge role in boosting the user confidence and retention.
2	To examine the degree to which social influence and facilitating conditions shape user intentions and behaviours which are specific to the adoption of these digital technologies.	Social influence is a major one as well but is particularly strong in collectivist cultures where endorsement and recommendation by the peers is crucial. Facilitating conditions such as infrastructure and availability of digital literacy programs may remove the barriers to adoption and increase usage.
3	To assess how the individual characteristics of the user and the behavioral patterns are associated with the acceptance and habitual use of the identified digital payment systems.	User characteristics such as age and education level also influence the patterns of behavior with younger users who are more focused on technology preferring convenience and older users being more security conscious. User behavioral stability is a function of being satisfied with the offered attractive and least cost features.
4	To analyze the relationships that exist between satisfaction and motivational factors in promoting the use of the digital payment systems.	Satisfaction, arising from such motivational factors as ease of use, trust and usefulness, has a direct effect in enhancing loyalty and advocacy. It has been empirically demonstrated that those factors are the predictors of high retention and subsequent adoption of the Platforms.

12. Limitations and Future Scope of the Study

This study extends further our understanding of the factors motivating customers towards the use of digital payments but also comes with a limitation that highlight gaps for future research. The limitation relates to the scope of the study, which was limited mostly to the rural parts of Gujarat in India. As this helps to draw out some key localized insights, such conclusions might not be fully extendable to other countries with different technological infrastructures, cultural practices and economic conditions. This research can then be taken further in other states or other countries to contrast the adoption trends witnessed in different parts of the world in order to create models that would be useful universally. Moreover, exploring the long-term outcomes of these factors on user retention and loyalty by means of longitudinal research design may yield deeper understanding on how to enhance the adoption of digital payments. (Oliveira, T., et al., 2022)

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