DIGITAL TRANSACTIONS AND THEIR INFLUENCE ON CONSUMER PURCHASING BEHAVIOUR: AN EMPIRICAL ANALYSIS

Parul Gaur [1], Dr. Ankit Saxena [2]

[1] Research Scholar, Institute of Business Management, GLA University, Mathura, Uttar Pradesh., India, 0009-0003-7138-9308

[2]Associate Professor, Institute of Business Management, GLA University, Mathura, Uttar Pradesh., India, 0000-0002-1916-2662, ankit.saxena@gla.ac.in

Corresponding author Email: gaurparul430@gmail.com

Abstract

The market is currently overflowing with internet-based services due to the internet's growing popularity, with digital transactions standing out as one of the most crucial ones. This study is based on the literature available on the theory of planned behavior (TPB). The research aims to investigate the correlation between perceived usefulness, perceived ease of use, and trust, as well as the factors that influence users' behavioral intention to use digital transactions. The objective of the study is to examine the role of perceived usefulness, perceived ease of use, and trust in the technology adoption model. We collected data from the northern part of India, specifically the Delhi NCR Region, to investigate consumer buying behavior. We used convenience sampling and collected data through a structured questionnaire, with a sample size of 200 individuals from Northern India and the Delhi NCR region. We used SmartPLS-4 to test our hypotheses. Therefore, to address the research question, we conducted a study among digital transaction users. The findings for the total sample demonstrated that behavioral intention and consumer buying behavior were favorably and significantly influenced by perceived usefulness, perceived ease of use, and trust. The findings of this study may be useful for fintech companies, banking institutions, payment gateways, governments, marketers, policymakers, and professional associates to create and design user-friendly technological innovations, policy guidelines, and frameworks to boost digital payments

Keywords: Digital transactions; Perceived usefulness, Perceived ease of use, Trust; Behavioural intention; Consumer buying behaviour; Theory of planned behaviour.

Introduction

Over time, the arrival of technology has had a significant impact on our world. Technology has a large and quick impact on every aspect of human existence. Technology has permitted the creation of remarkable tools and resources, giving everyone simple access to essential information. The internet has revolutionized business operations. Within 48 hours, you can have an Amazon delivery delivered to your door by merely clicking a button. Consumers also like the convenience of having access to a range of brands at any time of day, seven days a week. As a result, businesses are now attempting to interact with, reply to, and connect with their consumers as quickly as possible, as well as create tactics to efficiently resolve consumer complaints. The rise of digital transactions has forced merchants and manufacturers to reinvent their business strategies in unexpected ways. You can easily calculate your return on investment (ROI) using digital transactions (Rahman *et al.*, 2024).The use of digital transactions in India has grown gradually over time. The Indian government's implementation of policies such as demonetization and the Digital India program has led to an increase in digital activity. The Indian government's fundamental goal is to encourage the use of digital transaction systems so that all Indian residents can conduct secure, efficient, easy, cost-effective, and enjoyable digital transactions. The broad development of cell phones and the internet, as well as the availability of inexpensive internet bandwidth, have all aided the move to digital transactions, as have government measures. The practice of initiating and receiving financial transactions via the internet is known as digital transactions (Purnama *et al.*, 2021; Gupta and Singh, 2023).In April 2024, the global number of internet users reached 5.44 billion, accounting for 67.1 percent of the world's population. Currently, India has an incredible internet population of around 820 million. More than half of the country's 442 million people live in rural areas. The growth of digital devices, such as smartphones, tablets, and laptops, as well as the emergence of the internet, has transformed the area of digital transactions. We expect the sector of digital transactions to continue its rapid growth in the future. India's logged around 131 billion Unified Payments Interface (UPI) transactions worth □200 trillion in fiscal year 2024. In FY23, the National Payments Corporation of India (NPCI), which administers UPI, claimed that the platform completed around 83.7 crore transactions worth □139 trillion. Digital transactions, like Internet banking, can enhance the ease, speed, and efficiency of financial operations. Individuals appreciate these sorts of digital transactions since they are quick and simple. This category includes technology such as QR code scanning, electronic purses, and payment systems. An increasing number of countries have implemented digital transactions, resulting in a plethora of different digital transaction choices to meet consumers' everyday expectations (Kamate and Kumar, 2024).The introduction of digital transactions altered the global economy by increasing efficiency, speed, and convenience. Technological improvements have enhanced the convenience and efficacy of online shopping, influencing people's purchase patterns. Ideas like innovation diffusion, planned behavior, technology acceptance models (TAMs), and reasoned action theories (TRA) describe how individuals embrace new technologies. The Theory of Reasoned Action (TRA) states that motive drives conduct (Aisyah and Ali, 2023). Fishbein and Ajzen (1975) asserted that their morals and emotions shape this objective,not the action itself.The Technology Acceptance Model (TAM) states that consumers assess new technology based on ease of use and utility.Davis's (1989) ground breaking research comprehends how individuals adopt new technology. The TAM model has two main parts: perceived usefulness and ease of usage. Potential users perceive the usefulness of emerging technologies in assisting them in achieving their objectives, like boosting sales and customer base for businesses, and they find these technologies easy to use and implement. Prior studies have indicated that the installation of technology is preceded by the realization of significant advantages, such as increased productivity and job performance (Escobar and Rodriguez, 2013; Donthu and Gustafsson, 2020). This study aims to examine the influence of perceived usefulness, perceived ease of use, and trust elements on consumers' behavioral intentions, adoption of digital transactions, and their subsequent impact on consumer buying behavior.

2.0 Literature Review

The literature examined the factors that influence Indian consumers' digital transaction behavior. It proposes a conceptual model using the Technology Acceptance Model (TAM). The introduction of digital transactions is dramatically changing the business landscape (Yuen *et al.*, 2010). Bhatti and Saad (2018). Some small and medium-sized businesses in India are using digital transactions to boost their competitiveness. Mobile payment applications remain underutilized despite substantial advances in mobile technology. On a global scale, digital transaction adoption and expansion are growing at a rapid pace on a worldwide basis.Today, the introduction of digital transaction methods has revolutionized the process of acquiring and selling goods and services. Agarwal (2013) highlight the rapid shift towards digital transactions due to the convenience and accessibility of mobile phones. This shift has significantly impacted the financial environment and business operations, leading to a shift in spending habits and reduced reliance on cash (Hair *et al.*, 2015; Rathore, 2016). Due to severe competition and internet technologies, Kaur *et al.* (2018) say the conventional market has moved to digital transactions. Technology is essential to billions of people's lives (Borst and Creehan 2017). Due to security and trust problems, digital transactions have spread. Businesses must prioritize financial information security and handle security concerns to operate. Manufacturers must adapt to new digital transaction methods and ensure smooth user experiences despite equipment changes and personnel training (Darmayasa, 2022).Digital transactions have changed business paradigms, requiring organizations to adapt and generate new value. Payment networks have changed the competitive environment, compelling governments and regulators to control digital payments, safeguard consumers, and promote financial inclusion (Kajol *et al.,* 2022). Businesses may enhance goods, increase customer satisfaction, and find regulatory loopholes by assessing seller and buyer behavior. Trust, perceived ease of use (PU), and usefulness (PEOU) affect digital transactions. These characteristics and the technological adoption strategy strongly impact consumer purchase behavior (Maigari *et al.*, 2023; Bennet, 2024).

3.0 Conceptual Framework

Transaction efficiency and cost are improved by digital methods. Mobile banking and other digital transactions increased as people became more tech-savvy. PU is a person's perception of how using an item would increase productivity (Balaji and Vijayakumar, 2018). The usefulness of technology affects people's intent to use it, which applies to many non-organizational jobs. The relationship between perceived value and perceived ease of use in information system development is complex (Jeong and Yoon, 2013). Numerous social factors affect online consumer behaviour (Nandal et al., 2021). Age, wealth, employment status, and gender are some of the social factors that influence people's online shopping habits. An object's perceived ease of use (PEOU) is a critical feature. A group of academics undertook research to assess the effectiveness of digital transaction methods when compared to cash. Digital transaction methods are becoming more popular, which is good.Davis (1989) performed a study to investigate the relationship between perceived usefulness (PU), perceived ease of use (PEOU), and value. According to this research, there is a significant relationship between an item's perceived usefulness and consumer acceptance. Perceived worth heavily influences a consumer's decision to make a payment. People regularly use the technological functioning of e-commerce websites to determine their perceived value. Based on the Technology Adoption Model (TAM), the UTAUT model elucidates how factors such as perceived usefulness, perceived ease of use, trust complexity, compatibility, and visibility influence technology adoption.

3.1 Perceived Usefullness (PU)

Davis (1989) study defines perceived usefulness as an individual's belief that a technology will enhance performance or achieve desired results, while Rogers' (2014) theory equates it to perceived relative advantage. Luarn and Lin's (2005) study, "Toward an understanding of the behavioral desire to use mobile banking," provides evidence that an individual's decision to use a service is significantly influenced by its perceived usefulness. Leong *et al.* (2011) performed a study to evaluate the impact of perceived usefulness on people's decisions to embrace and use mobile banking. Perceived value refers to a consumer's view of the benefits of using a new technology over an older one. Venkatesh *et al.* (2003) investigated performance expectations, with a focus on the idea of perceived usefulness. The perceived value of Taiwan's payment system significantly influenced the views of both users and non-users (Hung *et al.,* 2006). We formulate the following hypotheses based on the discussion above:

H_1: Perceived usefulness has a significant and positive effect on behavioral intention.
H_2: Perceived usefulness has a significant and positive effect on consumer buying behavior.

3.2 Perceived Ease of Use (PEOU):

Davis (1989), perceived ease of use refers to an individual's belief that a certain piece of technology would be simple to grasp and use. Rogers (2014), assessing perceived ease of use is diametrically opposed to assessing perceived complexity in the context of idea dissemination. Venkatesh *et al.* (2003) evaluate the likelihood of expending effort, with perceived ease of use serving as one predictor. People's perception of a technology's complexity determines its adoption rate. The likelihood of someone implementing and employing a technology is directly proportional to the amount of effort required to embrace it, decreasing the perceived ease of use. Gu *et al.'s* (2009) research, perceived ease of use is a significant factor influencing people's inclinations to use mobile banking. The likelihood that a person will use electronic payments is heavily influenced by their assessment of its ease of use (Luarn & Lin, 2005). Taylor and Todd (1995) demonstrated that people's perception of an item's ease of use directly influences their willingness to utilize it. Jeong and Yoon (2013), people who used digital transaction services were most concerned with the perceived ease of use. We frame the following hypotheses based on the previous discussion:

H_3: Perceived ease of use has a significant and positive effect on behavioral intention.

3.3 Trust:

The perceived credibility, dependability, and honesty of the speaker influence the amount of interpersonal trust in digital transactions (Giffin, 1967). Sheppard and Sherman (1998) describe trustworthiness as honesty, compassion, and care. These attributes establish a significant dependency between two people, since they are concerned about the negative consequences of dishonesty, deception, mistreatment, and neglect. Numerous fields, such as organizational psychology, education, strategic management, personal ties, and commercial partnerships, have extensively studied trust. The shape and amount of trust vary depending on the circumstances. Bhattacharya et al. (1988) found that people with clear goals and expectations are more likely to develop partnerships. The desire to engage in the relationship develops as trust grows, providing a sense of security. Trust is critical in the early stages of a relationship since it significantly impacts the chance of commitment (Simpson, 2007). In India, the change to digital transactions needs a higher focus on trust, while money is still the major payment mechanism. Digital transactions improve the online purchasing experience and earn a competitive advantage through trust. Consumer retention necessitates building consumer trust. In digital transactions, trust is very vital in relationship marketing (Rizan et al., 2014).According to Lin (2011), knowledge-based trust, which includes perceived skill, compassion, and honesty, increases the likelihood that people will embrace or use mobile banking. Luarn and Lin (2005) assert that people's sense of trustworthiness positively influences their intentions to act. Perceived trustworthiness is the degree to which an individual believes digital transactions are safe and do not pose a significant privacy risk. Numerous studies have found a strong link between trust and people's views toward online banking (Al-Somali et al., 2009) and mobile payments in virtual social networks (Liébana-Cabanillas et al., 2014). The study by Lee et al. (2013) explores trust-related factors influencing consumers' electronic payment intentions, highlighting that trust mitigates perceived risk in online banking, reducing the likelihood of negative usage. Consequently, they view trust as a crucial element in the adoption of digital transactions. We formulate the following hypotheses based on the discussion above:

H_4: Trust has a significant and positive effect on behavioral intention.

H_5: Trust has a significant and positive effect on consumer buying behavior.

3.4 Behavioural Intention and Consumer Buying Behaviour:

The term "behavioral intention" (BI) refers to the consumer's willingness to use digital payment systems in digital transactions. Behavioral intention (BI) assesses an individual's readiness to participate in a certain activity. A rising number of people choose to shop online and pay using their mobile devices. We argue that digital transactions are more flexible and convenient (Daggubati, 2024). Lin (2011) discovered a positive relationship between the desire to use or deploy digital transactions and a favorable attitude toward adoption. Lee et al. (2013) discovered that an individual's attitude toward technology has a significant impact on their desire to utilize it, which then influences their decision to accept it. In 2006, Hung et al. looked at the role of perceived usefulness, perceived ease of use, trust, and behavioral intentions in the rate of adoption of digital transaction systems. They used both the technology adoption model (TAM) and the theory of planned behavior (TPB). Digital technology has significantly impacted the purchase process, making digital transactions an important component of modern shopping. Perceived value, perceived ease of use (PEOU), and trust

significantly influence consumer buying behavior.
Based on the discussion above, we formulate the following hypothesis:
H_6: Behavioral intention has a significant and positive effect on consumer buying behavior. Based on the previously discussed constructs and hypotheses, we propose the following model for the research:

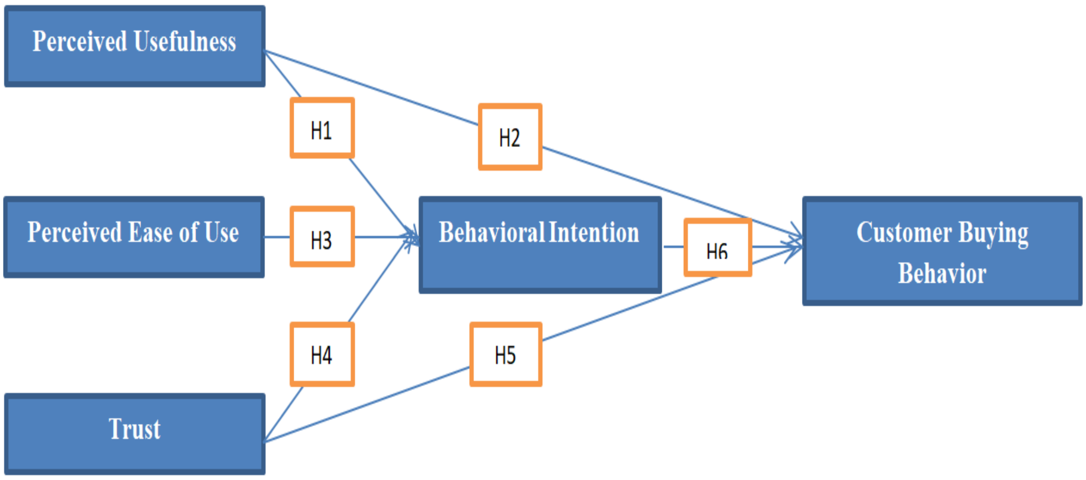


Figure 1: Research Model

4.0 Research Methodology:
We examined digital transactions and their impact on consumer purchasing behavior using SPSS software and Partial Least Squares Structural Equation Modeling (PLS-SEM) to determine how various factors affected major outcomes.

4.1 Demographic Profile
The respondents' gender, age, education, job experience, occupation, and monthly income help explain how digital transactions affect consumer behavior. As shown in Table 1, most respondents are male (59.5%), with a balanced female presence (40.5%). Younger folks dominate the age distribution, indicating tech-savvy consumers. Graduate and post-graduate education suggests a well-educated population that understands and uses digital transaction platforms. For studying how income levels affect digital transaction uptake and perception, the sample's income distribution shows economic variety.

Table 1. Demographic Profile of Respondents

Demographic Profile	Frequency(n)=200	%
Gender		
Male	119	59.5
Female	81	40.5
Age		
21-30 years	73	36.5
31-40 years	55	27.5
41-50 years	46	23
51 and above	26	13

Education		
Graduation	96	48
Post-graduation	77	38.5
Doctoral	27	13.5
Work experience		
0-5 years	57	28.5
6-10 years	48	24
11-20 years	51	25.5
21-30 years	24	12
31 and above years	20	10
Occupation		
Business/ Entrepreneur	76	38
Government Employee	62	31
Professional	38	19
Others	24	12
Monthly Income		
Less than 50,000	96	48
50,000 - 100,000	42	21
100,000 - 200,000	46	23
200,000 and above	16	8

4.2 Research instruments and Data collection

Following the completion of the pilot study, experts discussed and finalized the questionnaire, making any necessary linguistic and structural adjustments. We gathered relevant information from people living in cities and rural areas of Northern India and Delhi, NCR. Conduct an online survey using the convenience sampling approach. Individuals who used digital transactions in the previous three months answered the questionnaire. Between April 18th and July 1st, 2024, We gathered the respondents' responses using a five-point Likert scale. We assigned a five-point Likert scale rating to each item, with five indicating "strongly agree" and one indicating "strongly disagree." We manually distributed 275 questionnaires, of which 215 returned, resulting in a 78% response rate. We ultimately used 200 of these 215 questionnaires for the study.

5.0 Results

5.1 KMO and Bartlett's Test

We used the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's Test of Sphericity to ensure the data's suitability for factor analysis. (Hill, 2011). As shown in Table 2, a KMO value of 0.888 indicates that the sample size is adequate and the variables share enough common variance for factor analysis to be appropriate. The Bartlett's Test of Sphericity, with a significant Chi-Square value (883.071) and a p-value of 0.000, indicates that the variables are significantly correlated, indicating meaningful constructs.

Table 2: KMO and Bartlett's Test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.888
Bartlett's Test of Sphericity	Approx. Chi-Square	883.071
	df	171
	Sig.	.000

5.2 Reliability

According to Table 3, the study's results on the effects of trust, perceived ease of use, and perceived usefulness on behavioral intention and buying behavior are valid. This is shown by the high Cronbach's alpha and composite reliability for all constructs. All components have AVE values > 0.5, demonstrating convergent validity because each concept explains a significant amount of item variance. This ensures survey items appropriately represent their structures. High dependability and validity indices imply that the study's results on trust, perceived ease of use, and perceived usefulness on behavioral intention and consumer buying behavior are valid.

Table 3 : Cronbach's alpha, rho_a, rho_c, AVE

Constructs	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
BI	0.821	0.821	0.893	0.736
CBB	0.814	0.815	0.890	0.729
PEOU	0.762	0.763	0.863	0.778
PU	0.847	0.849	0.897	0.785
T	0.901	0.901	0.921	0.726

5.3 Discriminant Validity

Structural equation modelling and psychometrics use discriminant validity as a tool to distinguish between different concepts, assess if they are real or just shared traits, and determine if strong relationships exist between them.

5.4 Heterotrait- Monotrait Ratio (HTMT):

The HTMT values indicate whether the constructions are distinct. Table 4 shows that in this study, HTMT values are below 0.90, indicating high discriminant validity. Other components, such as behavior intention (BI), have HTMT values below 0.90 (CBB: 0.824, PEOU: 0.732, PU: 0.847, T: 0.801). Table 4 proves discriminant validity by distinguishing BI from CBB, PEOU, PU, and T. Consumer Buying Behavior (CBB) has HTMT values below 0.90, distinguishing it from PEOU, PU, and T. PEOU and PU have an HTMT value of 0.863. Though higher than other values, it is below 0.90, indicating appropriate discriminant validity. The HTMT value between PEOU and T is 0.897, close to the threshold. PEOU and T are separate, although there may be overlap that needs additional study. The HTMT score between perceived usefulness (PU) and trust (T) is 0.815, showing their distinction.

The HTMT results show that this study's constructs—behavioral intention (BI), consumer buying behavior (CBB), perceived ease of use (PEOU), perceived usefulness (PU), and trust (T)—are different. This improves research construct validity. Good discriminant validity means the model can reliably quantify the effects of trust, perceived ease of use, and perceived usefulness on behavioral intention and consumer buying behavior without overlap.

Table 4 : Heterotrait-Monotrait Ratio (HTMT)

Heterotrait-monotrait ratio (HTMT) - Matrix

	BI	CBB	PEOU	PU	T
BI					
CBB	1.041				
PEOU	0.994	1.026			
PU	1.021	0.992	1.070		
T	1.012	0.983	1.027	1.011	-

5.5 Fornell-Larcker Criterion:

Table 5 reveals strong discriminant validity between trust and behavioral intention, with the BI square root of AVE at 0.871 and the BI most correlated with trust at 0.858. However, a correlation of 0.791 (T) < 0.858 suggests potential discriminant validity concerns. In Table 5, the Fornell-Larcker criteria confirm the discriminant validity of the study's components, except for the small overlap between trust and behavioral intention. The findings confirm that behavioral intention, consumer buying behavior, perceived ease of use, and perceived usefulness are distinct entities, improving their dependability.

Table 5 : Fornell-Larcker criterion

	BI	CBB	PEOU	PU	T
BI	0.871				
CBB	0.814	0.854			
PEOU	0.824	0.808	0.860		
PU	0.855	0.825	0.823	0.886	
T	0.858	0.843	0.852	0.828	0.791

5.6 Total Variance Explained

Table 6 employs principal component analysis (PCA) to analyze and validate factors influencing constructs like trust, perceived ease of use, perceived usefulness, behavioral intention, and consumer buying behavior. PCA simplifies analysis by identifying key characteristics and dispersing variation across components. The study confirms the hypothesis that trust, perceived ease of use, and perceived usefulness have an impact on behavioral intention and consumer buying behavior.

Table 6 : Total Variance Explained

Total Variance Explained

	Initial Eigenvalues			**Extraction Sums of Squared Loadings**			**Rotation Sums of Squared Loadings**		
Component	**Total**	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**
1	5.762	30.327	30.327	5.762	30.327	30.327	2.676	14.083	14.083
2	1.199	6.309	36.636	1.199	6.309	36.636	2.605	13.710	27.793
3	1.141	6.003	42.639	1.141	6.003	42.639	2.157	11.352	39.145
4	1.050	5.525	48.165	1.050	5.525	48.165	1.714	9.020	48.165

Extraction Method: Principal Component Analysis.

5.7 Factor Loading

Factor loadings establish correlations between latent variables (factors) and observable variables (items). Table 7 indicates how well an object portrays a given aspect. High-loading items are reliable indicators of their components. The table lists BI, CBB, PEOU, PU, and T (trust) components. BI1, BI2, and BI3 have high loadings (0.862, 0.862, and 0.850) and are reliable markers of behavioral intention. These indicators consistently indicate that respondents want to use digital transactions. CBB1, CBB2, and CBB3 exhibit strong loadings (0.887, 0.832, and 0.841), showing they accurately capture consumer buying behavior in digital transactions. PEOU1, PEOU2, and PEOU3 have loadings of 0.840, 0.813, and 0.817. These ratings indicate that the items accurately portray simplicity of use, highlighting their relevance in shaping behavioral intention and purchase behavior. PU1, PU2, PU3, and PU4 have loadings of 0.811, 0.835, 0.846, and 0.820. This implies that perceived utility is critical, as these things effectively reflect how beneficial digital transactions are to people. Items T1–T7 had loadings between 0.757 and 0.803, indicating a good trust assessment. Trust has an impact on digital transaction acceptability and participation. Trust significantly influences the behavior and intentions of their consumers.

Table 7 : Factor Loading

Factor Loading					
Items	**BI**	**CBB**	**PEOU**	**PU**	**T**
BI1	0.862				
BI2	0.862				
BI3	0.850				
CBB1		0.887			
CBB2		0.832			
CBB3		0.841			
PEOU1			0.840		
PEOU2			0.813		
PEOU3			0.817		
PU1				0.811	
PU2				0.835	
PU3				0.846	
PU4				0.820	
T1					0.802
T2					0.803
T3					0.795
T4					0.757
T5					0.790
T6					0.798
T7					0.795

5.8 Correlations

Table 8 indicates a strong correlation between behavioral intention (BI) and consumer buying behavior, suggesting that digital transaction enthusiasts will buy more of them. Using behavioral intention (BI) is positively associated with perceived ease of use. People are more likely to use digital transactions if they think they're simple. Perceived usefulness strongly correlates with behavioral intention. Trust establishes the best link, demonstrating its importance in driving digital transaction participation. The strong correlation with behavioral intention (BI) indicates that ease of use influences behavioral intentions. According to CBB, user-friendliness influences consumer purchase behavior. The correlations reveal that all categories affect digital contact behavior, demonstrating substantial interconnection. Trust influences buying behavior and the motivation to act. This shows the importance of trust in digital transactions.

Table 8: Correlations

Correlations					
Constructs	**BI**	**CBB**	**PEOU**	**PU**	**T**
BI	**1.000**	0.814	0.824	0.855	0.871
CBB	0.814	**1.000**	0.808	0.825	0.843
PEOU	0.824	0.808	**1.000**	0.860	0.852
PU	0.855	0.825	0.860	**1.000**	0.886
T	0.871	0.843	0.852	0.886	**1.000**

5.9 Covariances

Table 9 demonstrates that the correlation coefficient between behavioral intention (BI) and itself is 1.000, indicating a perfect relationship. Perceived ease of use strongly correlates with this statistic, indicating that usability influences the use of digital transactions. Trust's significant association with behavior and intention emphasizes its role in intention-setting. The covariance between PEOU and itself is 1.000, indicating a perfect positive relationship. Changes in object convenience often affect people's planned actions. Consumer buying behavior (CBB) strongly correlates with user friendliness, indicating that ease of use influences consumer purchase behavior. The covariance between the PU and itself is 1.000, indicating a perfect relationship. High correlations with behavioral intention (BI) imply that perceived value affects people's intentions and all categories significantly depend on digital purchasing behavior, as indicated by the covariances. avior. Trust influences consumer buying behavior and motivation to act.

Table 9 : Covariances

Covariances					
Constructs	**BI**	**CBB**	**PEOU**	**PU**	**T**
BI	**1.000**	0.814	0.824	0.855	0.871
CBB	0.814	**1.000**	0.808	0.825	0.843
PEOU	0.824	0.808	**1.000**	0.860	0.852
PU	0.855	0.825	0.860	**1.000**	0.886
T	0.871	0.843	0.852	0.886	**1.000**

5.10 Common Method Bias (Collinearity statistics (VIF)

The VIF measures the degree of multicollinearity that inflates a regression coefficient's variance. As shown in Table 10, all constructs had VIF values between 1.478 and 2.122, below the standard threshold of 5. These values indicate that predictors are not strongly associated and do not significantly increase the variance of predicted regression coefficients. Acceptable VIF values make regression models more stable and reliable by making sure that correlations between independent and dependent variables are not multicollinear. We recommend monitoring VIF values for additional variables or data analysis.

Table 10 : Collinearity statistics (VIF)

Collinearity Statistics (VIF)	
Items	**VIF**
BI1	1.845
BI2	1.877
BI3	1.790
CBB1	2.122
CBB2	1.641
CBB3	1.833
PEOU1	1.629
PEOU2	1.478
PEOU3	1.553
PU1	1.881
PU2	2.038
PU3	2.032
PU4	1.860
T1	2.114
T2	2.122
T3	2.070
T4	1.872
T5	2.043
T6	2.062
T7	2.019

5.11 R-square

The R-square (R^2) quantifies the amount of variation in the dependent variable that is predicted from the independent variables. A score of 0 implies no explanatory power, whereas 1 represents full power. The adjusted R-square takes into account the model predictors. It is especially useful in multiple regressions because it compares models with a wider range of predictors more accurately. In Table 11, trust, perceived ease of use, and perceived usefulness explain 79.8% of behavioral intention variation, according to the R-square value of 0.798. BI's adjusted R-square is 0.795, somewhat lower than the R-square due to the model's predictors. This indicates that the model is well-fitted, and the explanatory factors predict BI well. Trust, perceived ease of use, and perceived usefulness explain 75.1% of consumer buying behavior variation (R-square = 0.751). After correcting for predictors, CBB's adjusted R-square is 0.747, somewhat lower than the R-square. This suggests that independent factors strongly predict CBB. The strong R-square values for both BI and CBB indicate that trust, perceived ease of use, and perceived usefulness explain much of the variance in the dependent variables. This means that these elements are critical to consumer behavior in digital transactions. We fit the model because the differences between the R-square and adjusted R-square values are minimal. This supports the model's robustness and generalizability.

Table 11 : R-square

Constructs	**R-square**	**R-square adjusted**
BI	0.798	0.795
CBB	0.751	0.747

5.12 f-square

The f-square (f^2) statistic helps to determine how a variable affects the endogenous construct. According to Cohen (1988), f^2 values of 0.02, 0.15, and 0.35 indicate modest, medium, and large impacts, respectively. In Table 12, the BI-CBB relationship ($f^2 = 0.046$) suggests a minimal impact of behavioral intention on consumer buying behavior. It's important, but not the main cause of CBB. A minor effect size ($f^2 = 0.038$) indicates that perceived ease of use has a minimal impact on behavioral intention. It means that PEOU is essential, but other factors also affect BI. Perceived usefulness has a moderate impact on behavioral intention ($f^2 = 0.075$), indicating a small to medium effect size. It shows how PU influences consumers' digital transaction inclinations. A moderate to medium effect size ($f^2 = 0.055$) suggests that perceived usefulness has a minor impact on consumer buying behavior. PU influences consumers' digital transactions. Trust significantly affects behavioral intention ($f^2 = 0.187$), indicating a medium-to-high effect size. Consumers' digital transaction intentions depend on trust. T -> CBB ($f^2 = 0.107$): Trust significantly affects consumer buying behavior with a modest to medium effect size. Trust affects consumers' buying habits. The f-square values illustrate how each component affects BI and CBB. This helps prioritize digital transaction platform improvements. This supports the theoretical framework and has practical implications for organizations seeking to increase consumer involvement with digital transactions.

Table 12: f-square

Constructs	f-square
BI -> CBB	0.046
PEOU -> BI	0.038
PU -> BI	0.075
PU -> CBB	0.055
T -> BI	0.187
T -> CBB	0.107

5.13 Model fit

SRMR measures the difference between model predictions and observed correlations. We consider an absolute fit value of 0.08 to be satisfactory. The saturated and estimated models had SRMR values of 0.052. As shown in Table 13, the predicted model fits the data well, with an SRMR of 0.052. This implies that the model properly depicts trust, perceived ease, usefulness, behavioral intention, and consumer buying behavior. The d_ULS model measures the disagreement of the Unweighted least squares (ULS). Fitting lower values is better. Both models have low d_ULS values, indicating a strong fit. The saturated and estimated models differ little, suggesting the estimated model is closest to the ideal fit. d_G measures the discrepancy in the geodesic distance model. Like d ULS, smaller numbers suggest a better fit. Both models have low d_G values, indicating a good fit. The estimated model's value is close to the saturated model, suggesting it represents the data well. To assess model fit, the Chi-square test compares the observed and model-implied covariance matrices. Lower Chi-square values per degree of freedom suggest a better fit. Low Chi-square values indicate a good match. The estimated model's Chi-square value is somewhat higher than the saturated model's, but the difference is small, indicating a satisfactory model fit. The NFI calculates the proportional fit improvement from null to recommended models. Fit is best with values closer to 1. Both models had NFI values over 0.80, suggesting a strong fit. Given the minimal discrepancy between the saturated and estimated models, it appears that the estimated model reflects the data structure. The model fit statistics show that the research paper's hypothesized model fits the data well. The SRMR, d_ULS, d_G, Chi-square, and NFI results indicate that the model properly depicts trust, perceived ease of use, perceived usefulness, behavioral intention, and consumer buying behavior. This validates the hypothesized linkages and the study's theoretical framework. This research's credible findings and conclusions, based on a good model fit, can aid in understanding the impact of digital transactions on consumer purchasing behavior.

Table 13: Model fit

Values	Saturated model	Estimated model
SRMR	0.052	0.052
d_ULS	0.566	0.573
d_G	0.445	0.451
Chi-square	470.943	474.769
NFI	0.843	0.842

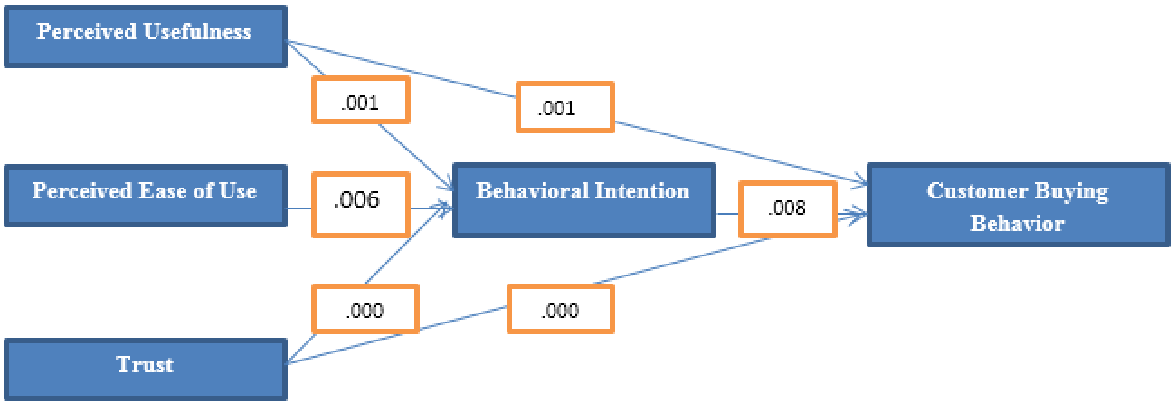
5.14 Hypothesis Results

Table 14 shows the hypothesis results. Behavioral intention (BI) should improve consumer buying behavior (CBB). The path coefficient (O) of 0.234 implies a moderately positive association. A T statistic of 2.643, larger than the threshold value of 1.96 for a two-tailed test, and a p value of 0.008 (less than 0.05) imply this link is statistically significant. We support the premise that BI enhances CBB. This concept suggests that PEOU improves behavioral intention. The 0.186 path coefficient (O) indicates a moderately positive effect. This impact is statistically significant, as evidenced by the T statistic of 2.730 and the p value of 0.006. PEOU has a positive impact on BI, supporting the idea. Perceived usefulness (PU) could increase behavioral intention (BI). A path coefficient (O) of 0.295 suggests a significant positive association. The T statistic of 3.365 and the p value of 0.001 indicate strong significance. Therefore, it is clear that PU favorably affects BI. This theory suggests that perceived usefulness (PU) boosts consumer buying behavior. The path coefficient (O) of 0.271 is quite positive. This link is statistically significant, with a T statistic of 3.233 and a p value of 0.001. We support the notion that PU enhances CBB. This hypothesis states that trust (T) increases behavioral intention. The path coefficient (O) of 0.452 suggests a significant positive association. The T statistic of 5.398 and the p value of 0.000 suggest substantial statistical significance. Trust has a significant and positive impact on BI, supporting the idea.

Table 14: Mean, STDEV, T values, p values

Mean, STDEV, T values, p values					
Hypothesis	**Original sample (O)**	**Sample mean (M)**	**Standard deviation (STDEV)**	**T statistics (|O/STDEV|)**	**P values**
BI -> CBB	0.234	0.227	0.089	2.643	0.008
PEOU -> BI	0.186	0.189	0.068	2.730	0.006
PU -> BI	0.295	0.291	0.088	3.365	0.001
PU -> CBB	0.271	0.274	0.084	3.233	0.001
T -> BI	0.452	0.452	0.084	5.398	0.000
T -> CBB	0.400	0.403	0.087	4.593	0.000

This hypothesis states that trust (T) improves consumer buying behavior. The path coefficient (O) of 0.400 indicates a high positive impact. This link is statistically significant because it has a T statistic of 4.593 and a p value of 0.000. Therefore, there is strong support for the influence of trust on CBB. This study found strong correlations between trust, perceived ease of use, usefulness, behavioral intention, and consumer buying behavior. All hypotheses have statistically significant T values and low p values, indicating robust and meaningful correlations. These findings highlight the importance of trust, convenience of use, and perceived utility in driving consumer intentions and buying behaviors in digital transactions.



Trust, PEOU, and PU impact consumer buying behavior (CBB) and behavioral intention (BI), according to "Digital Transactions and Their Influence on Consumer Purchasing Behavior: An Empirical Analysis." Marketers, legislators, e-commerce platforms, and consumers will benefit from this empirical study. Trust had a significant impact on buying behavior and urges to act. Thus, marketers understand the importance of consumer trust. Digital trading platforms, cutting-edge encryption, and security upgrades are excellent ways to protect consumer data. Clear privacy, data usage, and security policies may boost consumers' trust in transaction security. Consumer feedback, endorsements, and assistance can foster brand trust. CSR may increase a brand's reputation. E-commerce platforms must create trust to attract and retain consumers. We must use rigorous authentication methods to prevent fraud and ensure only valid transactions. When consumer service agents can rapidly fix issues, consumers feel more comfortable and assured. Tight online transaction security and regulatory compliance can increase consumer trust (Bauman and Bachmann, 2017). We should enhance consumer protection laws to shield consumers from fraudulent activities and unauthorized access to their personal data, while also offering them legal redress. This association between perceived ease of use, behavioral intention, and consumer buying behavior emphasizes the necessity for user-friendly and transparent systems (Kasuma et al., 2020). To improve usability, e-commerce systems should consider: We should regularly update the user interface (UI) based on consumer input to satisfy their demands. Reducing the number of stages in the checkout process would lessen the risk of consumers abandoning their carts. Usability improves purchasing experiences. Simplifying processes boosts user engagement and loyalty. Easy-to-use websites attract consumers. The high influence of perceived usefulness on consumer purchase behavior and behavioral intention suggests that individuals appreciate product functionality and usability (Hasbullah et al., 2016).Digital transaction methods may improve shopping experiences, convenience, and speed; therefore, marketers must properly communicate their benefits. To meet changing consumer needs, constantly update the platform (Susiang et al., 2023). E-commerce websites should offer loyalty programs, personalized recommendations, and seamless integration with other digital tools to improve platform performance. To maximize tool performance and reliability, continuously evaluate and improve efficiency. Consumers appreciate shopping on beneficial websites because they offer realistic solutions that fit their needs. This could boost their happiness and sales. Understanding behavioral intention is essential to predicting and changing consumer buying behavior. Marketers should target ads that emphasize utility, usability, and trustworthiness, which influence consumer choices. Engage consumers with personalized messaging and offers based on their interests and spending habits (Daoud et al., 2023).With predictive analytics, you can predict your customers' preferences and customize their buying experience. Enhance the characteristics that encourage individuals to repeat actions in order to strategically retain customers. Tax advantages or subsidies may encourage digital payment system usage (Tahat et al., 2023). Implement educational activities to increase public awareness of the benefits and security of digital interaction. The report fully explains consumer internet-buying behavior. Perceived usefulness, perceived ease of use, and trust can all assist stakeholders in improving digital transactions. This will boost consumer engagement and satisfaction. The insights can inform consumer relationship management, product development, and marketing strategy decisions (Ahmed et al., 2024).Emphasizing key inquiry components can improve the consumer experience. This will ensure long-term success and consumer loyalty. The study lays the groundwork for future research on technology, social influence, and cultural differences' effects on digital transaction behavior. This study informs politicians, e-commerce platforms, consumers, and marketers, making it influential. Stakeholders can enhance digital transactions and the digital economy by understanding how trust, perceived ease of use, and perceived value affect purchase decisions and behaviors.

7.0 Limitations and Scope of Future Research

The sample size was sufficient for the study, but it may not exactly represent the population. The sample's age, gender, income, and education may restrict generalizability. A future study should use larger, more diverse participant groups to improve external validity. The research was restricted to one part of the country; therefore, its findings may not apply to other places with different economic, technical, and cultural conditions. Comparative research in different countries may help us understand how digital transactions affect consumer purchasing behavior. This study collects data over a certain period using cross-sectional methods. This design makes it harder to detect changes in causation and consumer behavior. For tracking behavioral changes and demonstrating direct links between components, longitudinal studies are essential. We may better understand digital transaction behavior by including perceived risk, social impact, technical innovation, and consumer personality features in the study framework. The interplay between these elements and current systems may yield new insights. Future academic research should examine how digital platforms and technology affect human behavior. User experience disparities between mobile apps, the web, and emerging technologies like virtual reality and voice assistants might reveal consumer preferences and behavior (Skoulikas, 2024). Live messaging and consumer assistance can provide instant feedback on consumer thoughts and habits. A future study may examine how consumer input affects behavior using real-time data. Banking, retail, and healthcare case studies can shed light on digital trade trends and concerns. Industry-specific research can advise businesses in several areas (Adeleye *et al.,* 2024). Consumer education and awareness campaigns' effects on digital transaction platform use and acceptability can help promote digital literacy. To fully understand digital transaction systems, one should examine their environmental effects, including digital infrastructure energy consumption, as well as their influence on individual rights such as data privacy and algorithm fairness.

8.0.Conclusion

Trust predicts consumer purchasing behavior (CBB) and behavioral intention. According to an empirical study, trust significantly improves behavioral intention (BI), consumer behavior, and loyalty. The structures studied had the highest path coefficients, BI at 0.452 and CBB at 0.506. This emphasizes the importance of consumer trust in digital payment system security, privacy, and reliability. Trust reduces doubt and anxiety, increasing the likelihood of online purchases (Rao and Sahani, 2022). While perceived ease of use affects behavioral intention, it has little effect on consumer buying behavior. The PEOU has a slight direct effect on CBB (0.043) and BI (0.186), according to the path coefficients. An effective tool can increase the chance of digital transactions, but it has minimal influence on purchase habits. In contrast, the secondary effects of behavioral intention (BI) focus on user-friendly solutions for consumer interaction. Perceived usefulness influences both behavioral intention (BI) and consumer buying behavior (CBB). The study indicated that PU significantly affected BI (0.295) and CBB (0.339). Thus, consumers are more likely to use digital platforms for transactions and purchases if they help them achieve their buying goals (Chaudhuri *et al.*, 2021). Many consumers prioritize convenience, speed, and efficacy in their purchases. Behavioral intention mediates trust, perceived ease of use, perceived utility, and consumer purchasing behavior. The 0.234 path coefficient from BI to CBB shows a strong correlation between digital transaction desire and purchase. Trust, usability, and helpfulness are critical to influencing people's actions as a mediator. Digital platform firms and enterprises must create and maintain trust (Rohn *et al.*, 2021). This aim requires strict data privacy, reliable consumer service, constant performance, and solid security. To encourage digital transaction services, it is crucial to provide clear security requirements and guarantee that the platform is free from fraud and security breaches. Developing user-friendly and intelligible systems is crucial. Speeding transaction processing, enhancing navigability, and ensuring cross-device compatibility can improve user friendliness. Regular user experience testing and comment feedback may improve the program's usability (Forward, 2021).Highlighting digital commerce platforms' benefits and functionalities is crucial. Companies supporting digital transactions should emphasize efficiency, speed, and simplicity (Lee and Lee, 2020). Personal recommendations, incentive schemes, and seamless integration with other digital platforms may boost a service's value and consumer engagement. Proper marketing planning must include these reasons. Campaign security, direction, and ideas can develop trust.

References:

1.Adeleye, R. A., Awonuga, K. F., Ndubuisi, N. L., Oyeyemi, O. P., & Asuzu, O. F. (2024). Reviewing big data's role in the digital economy: USA and Africa focus. World Journal of Advanced Research and Reviews, 21(2), 085-095.

2.Agarwal, S. (2013). Study of factors affecting online shopping behaviour of consumers in Mumbai region. Tactful Management Research Journal, 7, 98-104.

3.Ahmed, S., Ahmed, R., Ashrafi, D. M., Ahmed, E., & Annamalah, S. (2024). Building trust in cybernetic payment network: Insights from an emerging economy. Journal of Open Innovation: Technology, Market, and Complexity, 100331.

4.Aisyah, S. N., & Ali, H. (2023). The Effect Of Digital Transaction Effectiveness, Financial Inclusion And Customer Satisfaction On Company Profits. Dinasti International Journal of Economics, Finance & Accounting, 4(3), 454-464.

5.Ajzen, I., & Fishbein, M. (1975). Belief, attitude, intention and behavior: An introduction to theory and research.

6.Al-Somali, S. A., Gholami, R., & Clegg, B. (2009). An investigation into the acceptance of online banking in Saudi Arabia. *Technovation, 29*(2), 130-141. https://doi.org/10.1016/j.technovation.2008.07.004

7.Balaji, R. P., & Vijayakumar, D. T. (2018). Diffusion of digital payment system in rural India. *Global Journal of Management and Business Research: G, 14*(4), 29-32.

8.Bauman, A., & Bachmann, R. (2017). Online consumer trust: Trends in research. Journal of technology management & innovation, 12(2), 68-79.

9.Bennet, D., Maria, L., Sanjaya, Y. P. A., & Zahra, A. R. A. (2024). Blockchain technology: Revolutionizing transactions in the digital age. ADI Journal on Recent Innovation, 5(2), 192-199.

10. Bhattacharya, R., Devinney, T. M., & Pillutla, M. M. (1998). A formal model of trust based on outcomes. *Academy of Management Review, 23*(3), 459-472. https://doi.org/10.5465/amr.1998.926621

11. Bhatti, A., & Saad, S. (2018). Convenience risk, product risk, perceived risk influence on online shopping: Moderating effect of attitude. International Journal of Business Management, 3(2), 1-11.

12. Borst, N., & Creehan, S. (2017). Banking: How technology can build trust for the newly banked.

Federal Reserve Bank of San Francisco. Retrieved from https://www.frbsf.org/banking/asia-program/pacific-exchanges-podcast/how-technology-can-build-trust-for-the-newly-banked/

13. Chaudhuri, N., Gupta, G., Vamsi, V., & Bose, I. (2021). On the platform but will they buy? Predicting customers' purchase behavior using deep learning. Decision Support Systems, 149, 113622.
14. Daggubati, L. S. (2024). Designing Digital Payment Experiences: The Crucial Role of User-Centered Design and Effective User Feedback Integration. International journal of computer trends and technology, 72(2), 27-29.
15. Daoud, M. K., Al-Qeed, M., Ahmad, A. Y. B., & Al-Gasawneh, J. A. (2023). Mobile marketing: Exploring the efficacy of user-centric strategies for enhanced consumer engagement and conversion rates. International Journal of Membrane Science and Technology, 10(2), 1252-1262.
16. Darmayasa, I. N. (2022, December). The fundamental taxation design of digital transaction. In International Conference on Applied Science and Technology on Social Science 2022 (iCAST-SS 2022) (pp. 524-529). Atlantis Press.
17. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *Management Information Systems Quarterly, 13*(3), 319-340. https://doi.org/10.2307/249008
18. Donthu, N., & Gustafsson, A. (2020). Effect of COVID-19 on business and research. Journal of Business Research, 117, 284-289.
19. Escobar, T., & Rodriguez, E. C. (2013). Online drivers of consumer purchase of airline tickets. Journal of Air Transport Management, 32, 58-64.
20. Forward, S. (2021). Speeding behaviour of adolescents and the image of a typical person who speeds. Transaction on Transport Sciences, 11(3), 12-24.
21. Giffin, K. (1967). The contribution of studies of source credibility to a theory of interpersonal trust in the communication process. Psychological bulletin, 68(2), 104.
22. Gu, J. C., Lee, S. C., & Suh, Y. H. (2009). Determinants of behavioral intention to mobile banking. Expert Systems with Applications, 36(9), 11605-11616.
23. Gupta, A., & Singh, S. (2023). Barriers of digital transaction in rural areas: an interpretive structural modelling and MICMAC analysis. International Journal of Electronic Business, 18(1), 108-128.
24. Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2015). *Multivariate data analysis* (7th ed.). Pearson Education Limited.
25. Hasbullah, N. A., Osman, A., Abdullah, S., Salahuddin, S. N., Ramlee, N. F., & Soha, H. M. (2016). The relationship of attitude, subjective norm and website usability on consumer intention to purchase online: An evidence of Malaysian youth. Procedia Economics and Finance, 35, 493-502.
26. Hill, B. D. (2011). The sequential Kaiser-Meyer-Olkin procedure as an alternative for determining the number of factors in common-factor analysis: A Monte Carlo simulation. Oklahoma State University.
27. Hung, S. Y., Chang, C. M., & Yu, T. J. (2006). Determinants of user acceptance of the e-Government services: The case of online tax filing and payment system. Government information quarterly, 23(1), 97-122.
28. Hung, S.-Y., Chang, C.-M., & Yu, T.-J. (2006). Determinants of user acceptance of the e-Government services: The case of online tax filing and payment system. *Government Information Quarterly, 23*(1), 97-122. https://doi.org/10.1016/j.giq.2005.11.005
29. Jeong, B. K., & Yoon, T. E. (2013). An empirical investigation on consumer acceptance of mobile banking services. Business and management research, 2(1), 31-40.An empirical investigation on consumer acceptance of mobile banking services. Business and management research, 2(1), 31-40.
30. Jeong, B.-K., & Yoon, T. E. (2013). An empirical investigation on consumer acceptance of mobile banking services. *Business and Management Research, 2*(1), 31-40.

https://doi.org/10.5430/bmr.v2n1p31
31. Kajol, K., Singh, R., & Paul, J. (2022). Adoption of digital financial transactions: A review of literature and future research agenda. Technological Forecasting and Social Change, 184, 121991.
32. Kamate, V., & Kumar, A. (2024). RBI WORKING PAPER SERIES.
33. Kasuma, J., Razak, F. L. A., Omar, N., Naim, A. S. A., Naimullah, B. S. S., & Darma, D. C. (2020). Attitude, Perceived Usefulness and Perceived Ease of Use towards Intention to Use M-Commerce: A Case of Grocery Shoppers in Kuching, Sarawak. Journal of Entrepreneurship & Business, 8(1).
34. Kaur, S., Tandon, N., & Malik, S. (2018). Impact of Digital Market on Consumer Buying Behaviour'. In National Conference on People, Planet and Profit in Sustainable Development & contribution in IT, Media and Management (pp. 1-14).
35. Lee, B. C., Cho, J., & Hwang, D. (2013). An integration of social capital and tourism technology adoption—A case of convention and visitors bureaus. *Tourism and Hospitality Research, 13*(3), 149-165. https://doi.org/10.1177/1467358414522055
36. Lee, S. M., & Lee, D. (2020). "Untact": a new customer service strategy in the digital age. Service Business, 14(1), 1-22.
37. Leong, L. Y., Ooi, K. B., Chong, A. Y. L., & Lin, B. (2011). Influence of individual characteristics, perceived usefulness and ease of use on mobile entertainment adoption. International Journal of Mobile Communications, 9(4), 359-382.
38. Liébana-Cabanillas, F., Sánchez-Fernández, J., & Muñoz-Leiva, F. (2014). The moderating effect of experience in the adoption of mobile payment tools in virtual social networks: The m-payment acceptance model in virtual social networks (MPAM-VSN). *International Journal of Information Management, 34*(2), 151-166. https://doi.org/10.1016/j.ijinfomgt.2013.12.006
39. Lin, H.-F. (2011). An empirical investigation of mobile banking adoption: The effect of innovation attributes and knowledge-based trust. *International Journal of Information Management, 31*(3), 252-260. https://doi.org/10.1016/j.ijinfomgt.2010.07.006
40. Luarn, P., & Lin, H. H. (2005). Toward an understanding of the behavioral intention to use mobile banking. Computers in human behavior, 21(6), 873-891.
41. Luarn, P., & Lin, H.-H. (2005). Toward an understanding of the behavioral intention to use mobile banking. *Computers in Human Behavior, 21*(6), 873-891. https://doi.org/10.1016/j.chb.2004.03.003
42. Maigari, M. A., & Yelwa, M. M. (2023). Digital Transaction: A Catalyst for Financial Inclusion and Job Creation. Journal of Digital Marketing and Halal Industry, 5(1), 57-76.
43. Nandal, D. N., Nandal, M. N., Mankotia, D. K., & Jora, M. N. (2021). Investigating digital transactions in the interest of a sustainable economy. International Journal of Modern Agriculture, 10(1), 1150-1162.
44. Purnama, S., Bangun, C. S., & Faaroek, S. A. (2021). The effect of transaction experience using digital wallets on user satisfaction in millennial generation. Aptisi Transactions on Management, 5(2), 161-168.
45. Rahman, I., Muhtar, M. H., Mongdong, N. M., Setiawan, R., Setiawan, B., & Siburian, H. K. (2024). Harmonization of Digital laws and Adaptation Strategies in Indonesia focusing on E-Commerce and Digital transactions. Innovative: Journal Of Social Science Research, 4(1), 4314-4327.
46. Rao, A., & Sahani, S. K. (2022). Adoption and Diffusion of Big Data Innovations: A Cross-Industry Analysis of Enabling Factors. International Journal of Social Analytics, 7(12), 26-38.
47. Rathore, H. S. (2016). Adoption of digital wallet by consumers. *BVIMSR's Journal of Management Research, 8*(1), 69-75.
48. Rizan, M., Warokka, A., & Listyawati, D. (2014). Relationship marketing and customer loyalty: Do customer satisfaction and customer trust really serve as intervening variables?
49. Rogers, E. M., Singhal, A., & Quinlan, M. M. (2014). Diffusion of innovations. In An integrated approach to communication theory and research (pp. 432-448). Routledge.

50. Rohn, D., Bican, P. M., Brem, A., Kraus, S., & Clauss, T. (2021). Digital platform-based business models–An exploration of critical success factors. Journal of Engineering and Technology Management, 60, 101625.
51. Sheppard, B. H., & Sherman, D. M. (1998). The grammars of trust: A model and general implications. Academy of management Review, 23(3), 422-437.
52. Simpson, J. A. (2007). Psychological foundations of trust. *Current Directions in Psychological Science, 16*(5), 264-268. https://doi.org/10.1111/j.1467-8721.2007.00517.x
53. Skoulikas, N. A. (2024). Assessment of Mobile Apps' User Experience Design, Consumer Behavior, Brand Awareness and Market Dynamics: A Case Study Analysis in the Travel Sector.
54. Susiang, M. I. N., Suryaningrum, D. A., Masliardi, A., Setiawan, E., & Abdillah, F. (2023). Enhancing customer experience through effective marketing strategies: The context of online shopping. SEIKO: Journal of Management & Business, 6(2), 437-447.
55. Tahat, L., Almasri, N., Tahat, T., Ismail, D., & Al-Ahmad, A. S. (2024). Assessing the influence of mobile direct social media advertising on consumer attitudes: a study of Kuwaiti consumers. Cogent Business & Management, 11(1), 2351107.
56. Taylor, S., & Todd, P. (1995). Assessing IT usage: The role of prior experience. MIS quarterly, 561-570.
57. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS quarterly, 425-478.
58. Yuen, Y. Y., Yeow, P. H., Lim, N., & Saylani, N. (2010). Internet banking adoption: Comparing developed and developing countries. Journal of Computer Information Systems, 51(1), 52-61.