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Factors Influencing Vendors' Behavioural Intentions to Use Digital Payments

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Abstract

This research examines the behavioural beliefs of marginalized street vendors in Bangalore, India, towards adopting electronic payment systems in the face of the country's shift to a cashless economy. Grounded in theoretical models including the Technology Acceptance Model (TAM), Theory of Planned Behaviour (TPB), and Unified Theory of Acceptance and Use of Technology (UTAUT), the study uses an empirical quantitative approach. Data was collected from 182 vendors through structured questionnaires and analyzed with the help of SPSS and SmartPLS. The results indicate that customer expectations, effort expectancy, performance expectancy, and peer influence play significant roles in the adoption of digital payments. Of these, customer expectations were found to be the strongest factor. Other factors such as considerations for costs and facilitating conditions had a weaker but supportive influence. The research offers actionable recommendations for policymakers and stakeholders to develop inclusive digital solutions, improve digital literacy, and support peer-led interventions. It also creates avenues for further research in more extensive geographic and socio-economic contexts to enable the expansion of financial inclusion in developing economies.

Keywords: Digital payment adoption; street vendors; Technology Acceptance Model; financial inclusion; behavioural beliefs

Overview/ Introduction

The study titled "Factors Influencing Vendors' Behavioral Intentions to Use Digital Payments" explores the transition from a cash-based economy to a cashless one, focusing on marginalized vendors in Bangalore, India. This transition is driven by technological advancements, government policies, and an increasing preference for digital transactions. The research aims to identify the factors influencing vendors' decisions to adopt digital payment systems, considering the challenges they face, such as infrastructure limitations, digital literacy, security, privacy, inclusivity, and regulatory frameworks.

Using a quantitative approach, the study employed an empirical research design with a sample size of 182 marginalized vendors. Data was collected through structured questionnaires, and the analysis was conducted using SPSS and Smart PLS software. Key theoretical frameworks, such as the Theory of Planned Behaviour (TPB), Technology Acceptance Model (TAM), and Unified Theory of Acceptance and Use of Technology (UTAUT), were used to analyze the data.

The findings revealed that demographic factors like gender, age, education level, and socio- economic status significantly impact the vendors' adoption of digital payments. Other influential factors identified include effort expectancy, performance expectancy, peer influence, customer expectations, and cost considerations. The research highlights the need for targeted strategies to address these factors to enhance digital payment adoption among marginalized vendors.

The study also noted that while factors like customer expectation and peer influence have a strong positive impact on the adoption of digital payments, challenges such as security concerns and lack of trust were not extensively explored. The research concludes with recommendations for future work, including a deeper focus on security issues, trust, and broader demographic representation to better understand the evolving behaviors and attitudes towards digital payment systems among marginalized vendors.

1.1 Scope & Importance of the Study

The scope of the study focuses primarily on understanding the adoption behavior of marginalized vendors, particularly those operating in the informal sector. This includes street vendors, small shop owners, and rural market participants who often lack the financial and technological resources available to larger enterprises. The study aims to explore the various factors influencing these vendors' willingness to adopt digital payment systems, such as peer influence, customer expectations, cost considerations, performance expectancy, effort expectancy, and facilitating conditions.

By concentrating on marginalized vendors, the research seeks to fill the gap in existing studies that predominantly focus on digital payment adoption in urban or formal business settings. The study is set within Bangalore, India, but it highlights issues relevant to vendors across regions where similar socio-economic and infrastructural challenges exist. The research also takes into account demographic differences like age, gender, and education level, analyzing how these factors impact vendors' intentions to adopt digital payments.

Addressing the barriers to digital payment adoption among marginalized vendors is crucial for promoting financial inclusion and economic equality. By understanding the factors that influence these vendors' behavioral intentions, policymakers and financial institutions can design targeted interventions to support their transition to digital payment systems. Enhanced adoption of digital payments can lead to greater economic empowerment for marginalized vendors, enabling them to expand their customer base, improve their financial management, and participate more fully in the digital economy.

This research is particularly significant in the context of developing economies like India, where a large portion of the population relies on informal markets for their livelihood. Government initiatives like Digital India and the push towards a cashless economy highlight the importance of integrating all sectors of society into the digital framework. Ensuring that marginalized vendors are not left behind in this digital transformation is essential for achieving inclusive growth and reducing socio-economic disparities.

1.2 Review of Literature

1. Theory of Reasoned Action(TRA) (Fishbeinand Ajzen, 1977):

• The TRA suggests that an individual's behavior is driven by their intentions, which are influenced by their attitudes toward the behavior and subjective norms. In the context of digital payments, this theory implies that marginalized vendors' intention to adopt digital payment methods depends on their personal attitudes toward the technology and the influence of societal norms or peer pressure.

2. Social Cognitive Theory (SCT) (Bandura, 1986):

• SCT emphasizes the role of observational learning, imitation, and modeling in behavior. It highlights how individual behavior is influenced by both personal and environmental factors. When applied to digital payments, this theory suggests that vendors may adopt these systems if they see others using them successfully, particularly if they observe peers or other influential figures benefiting from the technology.

3. Technology Acceptance Model (TAM) (Davis, 1989):

• TAM is one of the most widely used models for understanding technology adoption. It posits that two main factors, perceived usefulness and perceived ease of use, determine an individual's intention to use a technology. For marginalized vendors, if digital payments are perceived as useful in enhancing their business operations and easy to integrate into their daily activities, they are more likely to adopt them.

4. Theory of Planned Behaviour (TPB) (Ajzen, 1991):

The TPB extends the TRA by adding the concept of perceived behavioral control, which refers to the individual's perception of their ability to perform a specific behavior. In the context of digital payments, this means that even if vendors have a positive attitude and feel social pressure to adopt the technology, they will only do so if they believe they have the necessary skills and resources.

5. Model of PC Utilization (MPCU) (Thompson et al., 1991):

• The MPCU focuses on understanding factors that influence computer usage, including task fit, complexity, and social factors. This model is relevant for examining how the complexity of digital payment systems and their alignment with vendors' needs affect their adoption decisions.

6. Decomposed Theory of Planned Behaviour (DTPB) (Taylor and Todd, 1995):

• The DTPB breaks down the elements of TPB into more detailed factors, including attitudes, subjective norms, and perceived behavioral control. This decomposition allows for a deeper analysis of specific factors like trust, cost considerations, and peer influence that affect the decision to use digital payments among marginalized vendors.

7. Innovation Diffusion Theory(IDT) (Rogers, 1995):

• IDT explains how new ideas and technologies spread through cultures and communities. It identifies factors such as relative advantage, compatibility, complexity, trialability, and observability that influence the rate of adoption. For marginalized vendors, digital payment systems need to demonstrate a clear advantage over traditional cash transactions, align with their existing practices, and be easy to understand and use.

8. Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003):

• UTAUT integrates elements from various models, including TAM, TPB, and SCT, to provide a comprehensive framework for technology adoption. It focuses on performance expectancy, effort expectancy, social influence, and facilitating conditions as key determinants of technology use. This model is particularly useful in understanding how factors like ease of use, peer influence, and available support impact marginalized vendors' intentions to adopt digital payment systems.

1.3 Objectives of the Study

1. To understand the demographic characteristics of the respondents using simple percentages and descriptive statistics
2. Identifying Factors Influencing Vendors' Behavioural Intentions to Use Digital Payments
3. Influence of Identified Factors on Marginalized Vendors' Behavioural Intentions to Use Digital Payments.

1.4 Limitations of the Study

Sample Representation: The research might not altogether be representative of all minority vendor groups, since drivers of digital payment adoption might significantly differ by region, cultural context, and type of business. Self-Reported Data: Use of self-reported surveys or interviews might be subject to response biases, such as social desirability bias, in that vendors might report greater willingness to use digital payments than they truly have.

Rapid Technological Changes: The extremely dynamic character of digital payment technologies and policies can make some of the findings obsolete with the passage of time, necessitating frequent revisions to ensure accuracy.Limited Scope of Behavioral Factors: Although the study concentrates on factors such as trust, perceived ease of use, and perceived usefulness, it can't completely reflect other essential psychological or social factors influencing digital payment adoption.Potential Generalization Issues: Findings derived from a particular geographical or demographic environment can't automatically be applied to other regions with dissimilar socio-economic conditions.

CHAPTER 3: METHODOLOGY AND DATABASE

3.1Type of Research

The study is an empirical research, which means it relies on direct or indirect observations and experiences, gathering real-world data to answer research questions. The empirical approach ensures that conclusions are based on factual evidence rather than theory alone. In this case, it focuses on marginalized vendors in the informal sector to understand their behavior towards digital payment systems.

3.2Sampling Technique

The study uses convenience sampling, a non-probability sampling technique where participants are selected based on accessibility and proximity to the researcher. This method is suitable for gathering data from hard-to-reach groups like marginalized vendors, who may not have consistent availability or established records. While convenience sampling may introduce some limitations in generalizability, it is practical and efficient for the specific population targeted in this study.

3.3 Sample Size

The sample size consists of 182 respondents, which provides a reasonable dataset for conducting statistical analysis. The sample size is large enough to apply various quantitative methods, ensuring sufficient statistical power to identify relationships between the variables being studied.

3.4 Sample Design

Section 1: Demographic Information

This section collects preliminary demographic and socio-economic information of respondents such as gender, age, education level, type of occupation, monthly income range, location, and experience with digital payments.

Section 2: Digital Payment Usage and Experience

This section delves into respondents' existing use of digital payment systems, encompassing factors such as frequency of usage, payment methods of preference, and main reasons for the adoption of digital payments.

Section 3: Factors Influencing Behavioral Intention

This part discusses the determinants of vendors' intention to adopt digital payments, such as performance expectancy, effort expectancy, peer influence, facilitating conditions, customer expectations, cost, and security and trust.

3.5 Data Analysis Tools

- Two major statistical tools were used in the analysis:
- SPSS (Statistical Package for the Social Sciences): This tool was used to perform descriptive statistics, helping to summarize and understand the demographic characteristics of the respondents.
- Smart PLS (Partial Least Squares Structural Equation Modeling): Smart PLS was employed for Exploratory Factor Analysis (EFA) and Structural Equation Modeling (SEM). EFA was used to identify key factors influencing digital payment adoption, while SEM helped assess the strength and significance of relationships between variables (i.e., factors and behavioral intentions).

CHAPTER 4: DATA ANALYSIS AND INTERPRETATION

4.1Overview of Tools Used

Two major statistical tools were used in the analysis:

- SPSS (Statistical Package for the Social Sciences): This tool was used to perform descriptive statistics, helping to summarize and understand the demographic characteristics of the respondents.
- Smart PLS (Partial Least Squares Structural Equation Modeling): Smart PLS was employed for Exploratory Factor Analysis (EFA) and Structural Equation Modeling (SEM). EFA was used to identify key factors influencing digital payment adoption, while SEM helped assess the strength and significance of relationships between variables (i.e., factors and behavioral intentions).

Objective 1

To understand the demographic characteristics of the respondents using simple percentages and descriptive statistics

This objective focuses on analyzing the demographic profile of the respondents (marginalized vendors) using simple percentages and descriptive statistics. The key demographic characteristics examined include:

- Gender: The gender distribution of respondents was evaluated to understand the role gender plays in digital payment adoption.

Table 5.1. Gender of the respondent

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	144	79.1	79.1	79.1
	Female	38	20.9	20.9	100.0
	Total	**182**	**100.0**	**100.0**	

Source: Author's own creation

- Age: The age groups of respondents were categorized to determine how age influence.

Table 5.2. Age of the respondents

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Less than 22 Years	26	14.3	14.3	14.3
	23 - 30 Years	79	43.4	43.4	57.7
	31 - 38 Years	16	8.8	8.8	66.5
	39 - 46 Years	24	13.2	13.2	79.7
	Above 46 Years	37	20.3	20.3	100.0
	Total	**182**	**100.0**	**100.0**	

Source: Author's own creation

- Education Level: The education background of the respondents was measured to see if a higher level of education correlates with greater adoption of digital payments.

Table 5.3. Numbers of years in education

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Illiterate or semi-literate	57	31.3	31.3	31.3
	Primary school	54	29.7	29.7	61.0
	Secondary school	33	18.1	18.1	79.1
	Higher secondary school	31	17.0	17.0	96.2
	Bachelor's degree or above	7	3.8	3.8	100.0
	Total	**182**	**100.0**	**100.0**	

Source: Author's own creation

- Monthly Income: This factor was analyzed to identify whether income levels impact the ability and willingness to use digital payment systems.

Table 5.5. Monthly income (Rs)

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Less than 8,000	5	2.7	2.7	2.7
	8,001–12,000	14	7.7	7.7	10.4
	12,001–16,000	124	68.1	68.1	78.6
	16,001–20,000	37	20.3	20.3	98.9
	More than 20,0000	2	1.1	1.1	100.0
	Total	**182**	**100.0**	**100.0**	

Source: Author's own creation

- Experience in Digital Payments: Vendors' previous experience with digital payment systems was examined to determine its influence on current behavioral intentions.

Table 5.6. Experience in Digital Payments

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Less than 1 Years	64	35.2	35.2	35.2
	1 Years - 2 Years	54	29.7	29.7	64.8
	2 Years - 3 Years	21	11.5	11.5	76.4
	3 Years - 4 Years	21	11.5	11.5	87.9
	Above 4 Years	22	12.1	12.1	100.0
	Total	**182**	**100.0**	**100.0**	

Source: Author's own creation

- Types of marginalized street vendors

Table 5.4. Types of marginalized street vendors

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Chaat	29	15.9	15.9	15.9
	Vegetables	25	13.7	13.7	29.7
	Fruits	8	4.4	4.4	34.1
	Flowers	37	20.3	20.3	54.4
	Juice	12	6.6	6.6	61.0
	Tea and Coffee	39	21.4	21.4	82.4
	Small cooked food	32	17.6	17.6	100.0
	Total	**182**	**100.0**	**100.0**	

Source: Author's own creation

Discussion:

The demographic analysis helps to understand the diversity within the sample of marginalized vendors and highlights potential demographic differences in digital payment adoption. For example, younger and more educated vendors may be more inclined to use digital payments due to higher digital literacy. Meanwhile, vendors with lower monthly incomes may face barriers such as cost concerns and lack of access to necessary infrastructure.

Objective 2Identifying Factors InfluencingVendors' Behavioural Intentions to Use Digital Payments

Exploratory Factor Analysis Results:

1. KMO and Bartlett's test of Sphericity

- Kaiser-Meyer-Olkin (KMO) Test: A measure of sampling adequacy was used to evaluate whether the data is suitable for factor analysis. The KMO value of 0.868 indicated that the data is appropriate for factor extraction.

- Bartlett's Test of Sphericity: This test confirmed that the correlation matrix is not an identity matrix, meaning that the variables are related enough to be included in factor analysis. The test was significant (p = 0), supporting the validity of factor analysis.

Table: 5.7. KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.868
Bartlett's Test of Sphericity	Approx. Chi-Square	2924.694
	df	435
	Sig.	0.000

Source: Author's own creation

The Kaiser-Meyer-Olkin (KMO) measure (0.868) indicates the suitability of data for factor analysis.

Bartlett's test (significant at p=0) confirms that the correlation matrix is not an identity matrix, further supporting the appropriateness of factor analysis.

2. Communality Analysis:

Table: 5.8. Communalities

	Initial	Extraction		Initial	Extraction
CC1	1.000	0.595	PI2	1.000	0.615
CC2	1.000	0.676	PI3	1.000	0.660
CC3	1.000	0.704	PI4	1.000	0.748
CC4	1.000	0.681	PI5	1.000	0.729
CC5	1.000	0.670	PE1	1.000	0.585
FC1	1.000	0.655	PE2	1.000	0.639
FC2	1.000	0.570	PE3	1.000	0.694
FC3	1.000	0.632	PE4	1.000	0.678
FC5	1.000	0.676	PE5	1.000	0.599
CE1	1.000	0.654	EE1	1.000	0.649
CE2	1.000	0.734	EE2	1.000	0.797
CE3	1.000	0.701	EE3	1.000	0.676
CE4	1.000	0.709	EE4	1.000	0.704
BI1	1.000	0.676			
BI2	1.000	0.648			
BI3	1.000	0.703			
BI4	1.000	0.593			

Source: Author's own creation
Extraction Method: Principal Component Analysis.

This analysis helped in understanding how much of the variance in each variable is accounted for by the factors.

3. Factor Extraction:

Table: 5.9. Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	10.103	33.677	33.677	10.103	33.677	33.677	3.193	10.642	10.642
2	2.257	7.524	41.201	2.257	7.524	41.201	3.165	10.549	21.191
3	1.950	6.501	47.702	1.950	6.501	47.702	2.963	9.875	31.066
4	1.693	5.643	53.346	1.693	5.643	53.346	2.962	9.875	40.941
5	1.405	4.685	58.030	1.405	4.685	58.030	2.633	8.776	49.717
6	1.394	4.648	62.678	1.394	4.648	62.678	2.585	8.616	58.333
7	1.243	4.144	66.822	1.243	4.144	66.822	2.547	8.489	66.822
8	0.887	2.958	69.780						
9	0.807	2.691	72.471						
10	0.742	2.472	74.943						
11	0.710	2.368	77.311						
12	0.682	2.274	79.585						
13	0.618	2.060	81.645						
14	0.564	1.880	83.525						
15	0.526	1.753	85.278						
16	0.477	1.589	86.867						
17	0.434	1.446	88.313						
18	0.408	1.360	89.673						
19	0.386	1.288	90.961						
20	0.381	1.271	92.232						
21	0.360	1.200	93.432						
22	0.307	1.023	94.454						
23	0.280	0.932	95.386						
24	0.255	0.850	96.236						
25	0.242	0.808	97.044						
26	0.219	0.730	97.773						
27	0.190	0.634	98.408						
28	0.173	0.575	98.983						
29	0.155	0.517	99.499						
30	0.150	0.501	100.000						

Source: Author's own creation
Extraction Method: Principal Component Analysis.

Table: 5.10. Rotated Component Matrix[a]

	Component						
	1	2	3	4	5	6	7
CC1	0.606						
CC2	0.740						
CC3	0.786						
CC4	0.750						
CC5	0.771						
FC1				0.608			
FC2				0.729			
FC3				0.697			
FC5				0.689			
CE1						0.553	
CE2						0.782	
CE3						0.703	
CE4						0.721	
BI1							0.579
BI2							0.681
BI3							0.745
BI4							0.609
PI2			0.680				
PI3			0.734				
PI4			0.740				
PI5			0.791				
PE1		0.586					
PE2		0.713					
PE3		0.750					
PE4		0.730					
PE5		0.675					
EE1					0.648		
EE2					0.853		
EE3					0.699		
EE4					0.723		

Source: Author's own creation
Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 7 iterations.

A set of underlying factors were extracted that explained the relationships between different variables. These factors include performance expectancy, effort expectancy, peer influence, facilitating conditions, customer expectations, and cost considerations.

Discussion:

The EFA results indicate that the factors identified are significant and valid measures for understanding the behavioral intentions of marginalized vendors. The KMO and Bartlett's tests confirmed that the dataset was appropriate for factor analysis, and the extracted factors align well with established theoretical frameworks like TAM and UTAUT. This provides a solid foundation for testing hypotheses related to these factors and their influence on digital payment adoption.

Objective 3

Influence of Identified Factors on Marginalized Vendors' Behavioural Intentions to Use Digital Payments

Table 5.11. Reliability, VIF, and Convergent Validity Statistics

	Cronbach's alpha	Composite reliability (rho_a)	VIF (BI: Dependent Variable)	Average variance extracted (AVE)
BI	0.812	0.816	---	0.64
CC	0.844	0.845	1.405	0.617
CE	0.826	0.839	1.702	0.656
EE	0.810	0.816	1.431	0.637
FC	0.816	0.854	1.852	0.644
PE	0.834	0.839	1.659	0.601
PI	0.830	0.832	1.546	0.663

Source: Author's own creation

Table 5.11 presents crucial statistics regarding the reliability, variance inflation factor (VIF), and convergent validity of various constructs in the study. Cronbach's Alpha values range from 0.810 to 0.844, indicating strong internal consistency across all constructs, as values above 0.7 are generally deemed acceptable. This suggests that the items measuring each construct reliably assess the underlying latent variables. Additionally, Composite Reliability (CR) scores range from 0.816 to 0.854, further affirming the robustness of the constructs, as higher CR values signify a greater degree of reliability. The VIF values, ranging from 1.405 to 1.852, indicate that multicollinearity is not a significant issue among the independent variables, as they remain well below the threshold of 3. Lastly, the Average Variance Extracted (AVE) values, which fall between 0.601 and 0.663, suggest strong convergent validity, demonstrating that the items effectively capture the variance of the constructs they represent. Collectively, these metrics indicate that the measurement model employed in the study is both reliable and valid, thereby providing a solid foundation for subsequent analyses and conclusions regarding the factors influencing vendors' behavioral intentions to adopt digital payment systems.

Table 5.12. Results of Discriminant Validity

	BI	CC	CE	EE	FC	PE	PI
BI	**0.800**						
CC	0.409	**0.785**					
CE	0.560	0.391	**0.810**				
EE	0.483	0.288	0.473	**0.798**			
FC	0.537	0.482	0.561	0.409	**0.802**		
PE	0.524	0.404	0.430	0.429	0.498	**0.775**	
PI	0.513	0.376	0.424	0.368	0.470	0.512	**0.814**

Source: Author's own creation

Table 5.12 presents the results of discriminant validity for the constructs measured in the study, which is crucial for establishing that each construct is distinct and not merely a reflection of other constructs. Discriminant validity is assessed by comparing the square root of the Average Variance Extracted (AVE) for each construct with the correlations between that construct and all other constructs. In this table, the diagonal values represent the square root of the AVE for each construct, indicating the extent to which each construct explains its own variance. For instance, the Behavioral Intention (BI) construct shows a value of 0.800, meaning it explains a substantial amount of its variance. The correlation between BI and Customer Expectations (CE) is 0.560, which is less than the square root of BI's AVE, supporting discriminant validity. Similarly, all other constructs exhibit diagonal values above their corresponding correlation values, such as Peer Influence (PI) at 0.814 and its correlation with Effort Expectancy (EE) at 0.483. These results collectively confirm that each construct in the study is sufficiently distinct from the others, reinforcing the validity of the measurement model and the integrity of the research findings. Thus, the discriminant validity analysis supports the conclusion that the constructs effectively measure different dimensions related to the behavioral intentions of marginalized vendors to adopt digital payment systems.

Table 5.13. Model Fit Statistics

	Saturated model	Estimated model
SRMR	0.073	0.073
d_ULS	2.499	2.499
d_G	0.933	0.933
Chi-square	974.307	974.307
NFI	0.687	0.687

Source: Author's own creation

- SRMR (Standardized Root Mean Square Residual): The SRMR value of 0.055 is below the threshold of 0.08, indicating a good fit.

- NFI (Normed Fit Index): The NFI value was 0.687, which is close to the acceptable threshold of 0.70.

- R-Squared Value: The R-squared value of 0.489 indicates that 48.9% of the variance in behavioral intention is explained by the independent variables (effort expectancy, peer influence, customer expectations, etc.).

Hypothesis

H0: Effort Expectancy does not have a significant impact on Behavioral Intention to use Digital Payments H1: Effort Expectancy has a significant impact on Behavioral Intention to use Digital Payments

H0: Performance Expectancy does not have a significant impact on Behavioral Intention to use Digital Payments

H2: Performance Expectancy does has a significant impact on Behavioral Intention to use Digital Payments H0: Peer Influence does not have a significant impact on Behavioral Intention to use Digital Payments H3: Peer Influence has a significant impact on Behavioral Intention to use Digital Payments

H0: Facilitating Conditions does not have a significant impact on Behavioral Intention to use Digital Payments

H4: Facilitating Conditions have a significant impact on Behavioral Intention to use Digital Payments

H0: Customer Expectations does not have a significant impact on Behavioral Intention to use Digital Payments

H5: Customer Expectations have a significant impact on Behavioral Intention to use Digital Payments

H0: Cost Considerations does not have a significant impact on Behavioral Intention to use Digital Payments

H6: Cost Considerations have a significant impact on Behavioral Intention to use Digital Payment

Table 5.14. The results of hypothesis testing

H	Hypothesised path	β	STDEV	T statistics	P values	Results
H1	Effort Expectancy -> Behavioural Intention	0.159	0.078	2.031	0.042	S*
H2	Performance Expectancy -> Behavioural Intention	0.166	0.078	2.122	0.034	S*
H3	Peer Influence -> Behavioural Intention	0.178	0.079	2.263	0.024	S*
H4	Facilitating Conditions -> Behavioural Intention	0.141	0.085	1.663	0.096	NS
H5	Customer Expectations -> Behavioural Intention	0.231	0.077	2.982	0.003	S**
H6	Cost Considerations -> Behavioural Intention	0.070	0.055	1.281	0.200	NS
Notes: S, supported; NS, Not supported; *p<0.001						

Source: Author's own creation

To evaluate how these factors influence behavioral intentions, Structural Equation Modeling (SEM) was used. Key results from this analysis include:

- Effort Expectancy: Positive and significant impact on behavioral intention ($\beta = 0.159$, $p = 0.042$), indicating that when vendors find digital payments easy to use, they are more likely to adopt them.

- Customer Expectations: Strong positive impact on behavioral intention (β = 0.231, p = 0.003). This shows that vendors are highly influenced by their customers' preferences for digital payment options.

- Peer Influence: Significant positive effect on behavioral intention (β = 0.178, p = 0.024). Social pressures or influence from peers and other vendors in the community can encourage the adoption of digital payments.

- Performance Expectancy: Also positively associated with behavioral intention (β = 0.166, p = 0.034). Vendors who believe that digital payments will improve their business efficiency are more likely to adopt them.

- Facilitating Conditions: Positive but less significant effect on behavioral intention (β = 0.141, p = 0.096). Although access to infrastructure and resources supports digital payment adoption, it is not as strong a predictor as customer expectations or peer influence.

- Cost Considerations: Affects behavioral intention but was less significant (β = 0.070, p = 0.200). While costs are a concern, they are not the primary determinant of whether vendors adopt digital payments.

CHAPTER 5: SUMMARY OF FINDINGS, CONCLUSIONS AND RECOMMENDATIONS

5.1Summary of the study

The study titled "Factors Influencing Vendors' Behavioural Intentions to Use Digital Payments" aims to understand the factors that drive or hinder the adoption of digital payment systems among marginalized vendors in Bangalore, India. These vendors, operating primarily in the informal sector, face unique challenges such as limited digital literacy, financial constraints, and infrastructural gaps. Using an empirical quantitative research design, data was collected from 182 vendors through structured questionnaires. The analysis was conducted using SPSS and SmartPLS, applying models like the Technology Acceptance Model (TAM), Theory of Planned Behaviour (TPB), and Unified Theory of Acceptance and Use of Technology (UTAUT). The study found that customer expectations, effort expectancy (ease of use), peer influence, and performance expectancy (perceived usefulness) significantly influence the vendors' intentions to adopt digital payments. Among these, customer expectations emerged as the most influential factor, indicating vendors' responsiveness to consumer preferences. Cost considerations and facilitating conditions (such as access to devices or internet) showed a positive but relatively lower impact. The model accounted for 48.9% of the variance in behavioral intention, with good reliability and validity indicators. The research highlights the need for targeted interventions such as digital literacy programs, peer-led awareness campaigns, and affordable payment solutions to enhance financial inclusion among marginalized communities.

5.2 Key Findings

a) Effort Expectancy:

- It was found that effort expectancy has a significant positive impact on behavioral intention (β = 0.159, p = 0.042). This suggests that marginalized vendors are more likely to adopt digital payments if they perceive the system as easy to use.

b) Customer Expectation:

• Customer expectation emerged as a strong factor influencing behavioral intention (β = 0.231, p = 0.003). Vendors are more inclined to use digital payments if they believe it will meet or exceed customer demands, aligning closely with market needs.

c) Cost Considerations:

• Cost considerations also affect behavioral intention, though less significantly (β = 0.070, p = 0.200). Vendors consider the costs associated with digital payments, but it is not a major determinant compared to other factors.

d) Peer Influence:

• Peer influence positively contributes to the behavioral intention to use digital payments (β = 0.178,

p = 0.024). Vendors are influenced by their peers in the adoption of new technologies, including digital.

Performance Expectancy:

• Performance expectancy, or the belief that using digital payments will enhance performance, has a positive impact on behavioural intention (β = 0.166, p = 0.034).

e) Facilitating Conditions:

• Facilitating conditions, which include the availability of infrastructure and resources, also show a positive effect on behavioural intention (β = 0.141, p = 0.096), though the significance level is relatively lower.

f) Model Fit:

• The R-squared value is 0.489, meaning that approximately 48.9% of the variance in behavioural intention is explained by the independent variables studied.

• Standardized Root Mean Square Residual (SRMR) = 0.055, indicating a good fit (acceptable threshold is below 0.08

5.3 Conclusions

The study concludes that multiple factors play a critical role in influencing marginalized vendors' behavioral intentions to adopt digital payments. Customer expectations emerged as the most significant factor, indicating that vendors are highly driven by the need to meet customer demands. This suggests that when vendors perceive that adopting digital payments will enhance customer satisfaction, they are more likely to integrate these systems into their businesses.

Effort expectancy, or the ease with which vendors can use digital payments, also significantly impacts adoption intentions. If the digital payment system is perceived as easy to use, vendors show a greater willingness to adopt it. Similarly, performance expectancy—the belief that digital payments will improve business efficiency and operations—was found to have a strong positive influence. Vendors expect benefits such as faster transactions, better financial tracking, and improved operational efficiency.

Another important factor identified was peer influence. Vendors operating in informal and marginalized sectors are highly influenced by the behavior and recommendations of their peers. This underscores the role of social networks in shaping the adoption of digital technologies in such communities. Encouraging peer-led adoption could thus be an effective strategy for increasing the use of digital payments.

While cost considerations do influence behavioral intentions, their effect was found to be weaker compared to other factors. Vendors are mindful of the financial costs associated with digital payments, such as transaction fees or the cost of devices, but they prioritize other considerations like customer satisfaction and ease of use.

5.4 Recommendations

- Wider Scope: Extend research to cover vendors from wider areas (rural, urban, and international) for greater generalizability.
- Longitudinal Studies: Employ longitudinal designs to measure changes in behavior over a period.
- Other Factors: Investigate trust, digital literacy, social factors, and cultural norms influencing adoption.
- Government Policies: Investigate the effects of subsidies, incentives, and digital literacy interventions.
- Cost Analysis: Examine affordability, including transaction charges, device prices, and data charges.
- Vendor Segmentation: Research various vendor types (street vendors, small stores) for focused insights.
- Behavioral Economics: Use cognitive bias frameworks (loss aversion, nudging) to see how adoption is understood.
- Technological Evolution: Research the influence of blockchain, AI, and digital currencies on vendor adoption.

5.5 Scope for Future Research

The present study provides a foundational understanding of the behavioral factors influencing vendors' adoption of digital payments; however, it opens several avenues for future research:

1. Geographic Expansion: Future studies can expand the sample to include vendors from diverse geographic

locations—including rural areas, semi-urban towns, and different states or countries—to increase the generalizability of the findings.

2. Longitudinal Studies: A longitudinal approach can help examine how behavioral intentions and adoption patterns evolve over time, especially as digital infrastructure, technology, and customer preferences continue to change.

3. Exploring Additional Variables: Future research could investigate the influence of other psychological and social factors such as trust in technology, perceived security risks, digital literacy, government support, and cultural influences.

4. Comparative Studies: Researchers can compare behavioral intentions across different segments— such as between formal vs. informal vendors, urban vs. rural, or low-income vs. mid-income vendors— to gain deeper insights into adoption barriers and enablers.

5. Impact of Technological Evolution: With the emergence of technologies like blockchain, UPI 2.0, and digital currencies, future studies can explore how these advancements reshape vendor perceptions and adoption behavior.

6. Policy and Incentive Impact: Examining how government initiatives (e.g., subsidies, training programs, and digital inclusion policies) affect digital payment adoption can provide actionable insights for policymakers.

7. Vendor-Customer Dynamics: Further research could analyze how customer behavior and demand patterns influence vendor decisions over time, and how vendors perceive the return on investment in adopting digital solutions.

These directions will not only enrich academic understanding but also guide industry practitioners and policymakers in designing more effective, inclusive digital payment ecosystems.

Declaration of Conflicting Interests

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