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The Post-Covid Digital Leap: The Case of mobile wallet adoption in informal economy

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Abstract

This study investigates the adoption of mobile wallets in the Indian informal sector after the COVID-19 pandemic, contrasting global digital payment trends with localized challenges. The study focused on integrating the framework of the Technology Acceptance Model (TAM), Diffusion of Innovation Theory (DIT), and Unified Theory of Acceptance and Use of Technology (UTAUT). Where a sample of 650 informal workers (vendors and daily wage earners) across 3 Indian states (Uttarakhand, Gujarat, and Maharashtra) was collected and SEM modelling was applied through R studio. Findings of this study revealed that perceived usefulness and social influence significantly drive adoption, while infrastructural barriers (internet access, smartphone literacy) and distrust in digital systems hinder uptake. The informal sector prioritizes immediate liquidity and cash compatibility, which can be solved through the development of indigenous applications with customized interfaces supported by vernacular mediums. This study emphasizes the necessity of context-specific policies for financial inclusion in cash-dependent sectors.

Key words: *Mobile Wallets, Informal Sector, Technology Acceptance Model (TAM), Diffusion of Innovation Theory (DIT), Unified Theory of Acceptance and Use of Technology (UTAUT)*

JEL codes: *O17, O33, G21, G50*

1. Introduction

India pushes toward a cashless economy, aligned with initiatives like *Digital India* and the Unified Payments Interface (UPI), India has already witnessed a 76% surge in digital payments post-COVID-19, with UPI transactions exceeding 10 billion monthly in 2023 (RBI, 2023). The pandemic COVID-19 accelerated India's shift away from cash, as evidenced by a 40% decline in ATM withdrawals and a 55% rise in mobile wallet adoption among informal sector workers (NITI Aayog, 2022). To sustain this momentum, India strategic pillars include Innovative Financial infrastructure where scaling the UPI interoperable framework integrates informal SMEs, enabling seamless QR-code-based transactions even in rural markets while subsidising smartphone access to bridge urban-rural digital divides. Whereas fast youth-driven adoption, with 65% of Indian population under 35, leveraging their preference for apps like Gpay, PhonePe and Paytm to drive cashless habits (IAMAI, 2023). Formalising 63 million informal enterprises through platforms like *ONDC* (Open Network for Digital Commerce), which simplifies digital payments for small vendors. Are there some efforts that transforming India from a cash driven to digital cash economy? Post-pandemic, the Indian cashless transition is bolstered by rising fintech innovation, government mandates (e.g., GST compliance), and the informal sector's gradual trust in digital systems. However, challenges persist, such as low digital literacy in rural areas (18% of adults lack basic skills) and inconsistent internet access (GSMA, 2023). Emulating Saudi Arabia's focus on secure, user-centric infrastructure, India must prioritise vernacular app interfaces, offline transaction modes, and localised awareness campaigns to achieve equitable financial inclusion. The COVID-19 pandemic accelerated the global shift toward contactless financial transactions,

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particularly in cash-dependent economies (World Bank, 2020). In India, where the informal sector constitutes approximately 60% of GDP and employs 90% of the workforce (ILO, 2021), the pandemic underscored the urgency of adopting digital payment systems. The informal sector—comprising street vendors, domestic workers, and small-scale enterprises—relies heavily on cash due to its immediacy and accessibility (Muralidharan et al., 2016). However, lockdowns and hygiene concerns during the pandemic prompted unprecedented advocacy for mobile wallets and Unified Payments Interface (UPI)-based solutions to reduce physical currency handling (RBI, 2021). Despite rapid digitalisation efforts, including the world-leading UPI infrastructure (NPCI, 2022) and the *Pradhan Mantri Jan Dhan Yojana* (PMJDY) financial inclusion initiative (PMJDY, 2022), mobile wallet adoption in the informal sector remains disproportionately low in India. Whereas smartphone penetration reached 54% in 2021 (TRAI, 2021), only 12% of informal workers actively use mobile wallets for daily transactions (Ghosh, 2020). This gap highlights systemic challenges, such as distrust in digital systems, limited vernacular app support, and infrastructural barriers like inconsistent internet access (Dutta, 2021). Existing studies on mobile wallet adoption, such as the study done by Okonkwo et al. (2023), emphasise cultural incompatibility and branding misalignment, whereas in India the informal sector presents unique socio-economic dynamics. This study addresses the research question, which is, what *factors influence mobile wallet adoption in the Indian informal sector during and after the COVID-19 pandemic?* This was achieved through the integration of TAM and DIT. The study examined how contextual factors such as cash immediacy, digital literacy, and policy perception shape adoption behaviours. This research offers three effective and practically possible contributions to the discourse on mobile wallet adoption in cash dominated informal sectors. The first contribution involves identifying contextual adoption factors using TAM, UTAUT, and DIT. Study identifies factors influencing mobile wallet adoption in cash reliant settings and highlights unique challenges such as cash immediacy, low digital literacy rate and vernacular language barriers, factors often overlooked in global fintech strategies (Okonkwo et al., 2023; World Bank, 2021). Second, innovation guidance for mobile app developers to provide actionable plans for developers to design culturally compatible mobile wallets. Integrating offline transaction modes with vernacular interfaces (e.g., Hindi, Gujarati) simplified UPI workflows tailored to low-literacy users, addressing gaps in current app designs (Dutta, 2021; NITI Aayog, 2021). Third, specific insights for industry stakeholders to equip policymakers and businesses with a framework to evaluate the cost-benefit dynamics of mobile wallet adoption. For instance, it underscores the need for hybrid solutions (e.g., QR codes, cash) and localised awareness campaigns to bridge trust deficits (RBI, 2021; Muralidharan et al., 2016).

The remainder of this paper is organised into five distinct sections. Section 2 begins with a comprehensive literature review that synthesises existing research on mobile wallet adoption, integrating established theoretical frameworks TAM, DIT & UTAUT to contextualise the study within the socioeconomic landscape of the Indian informal sector. Following this, Section 3 shows research methodology along with data collection and research design of the measurement instrument, followed by the analytical approach and application of Structural Equation Modelling using R Studio and Python. Section 4 shows empirical findings, while Section 5 offers a detailed discussion of these findings. Finally, Section 6 concludes the paper by summarising the core findings of the study along with limitations and addressing directions for future research in this vital area of financial inclusion.

2. Literature Review

E-wallets, as discussed by Karim et al. (2020), are software-driven platforms designed to help users to pay securely and store payment details and passwords for various payment methods and websites. By using a near-field communication technology (NFC) where these e-wallets enable users to conveniently and expeditiously finalize transactions Alofan, F., & Almarshud, M. (2024). Globally, mobile wallet adoption surged during the COVID-19 pandemic, driven by hygiene concerns and government mandates for contactless transactions. In the United States, 82% of consumers used digital payments in 2022, with platforms like Apple Pay and Google Wallet dominating the market (Federal Reserve, 2022). Similarly, Europe saw a 35% year after year in mobile wallet usage, accelerated by regulatory frameworks like the Revised Payment Services Directive (PSD2), which promoted open banking (European Central Bank, 2021). In contrast, China's mobile payment ecosystem, led by Alipay and WeChat Pay, processed $17 trillion in transactions in 2021, accounting for 60% of global mobile wallet activity (People's Bank of China, 2022). The World Bank (2022) attributes these trends to robust digital infrastructure, high smartphone penetration, and consumer trust in fintech platforms. However, cash reliance persists in regions with fragmented financial systems, such as sub-Saharan Africa and South Asia (World Bank, 2022).

2.1 Indian Digital Landscape

Indian digital payments revolution began with the 2016 demonetization, which invalidated 86% of the nation's currency overnight, forcing rapid adoption of digital alternatives (Reserve Bank of India, 2017). Catalysed the growth of Unified Payments Interface (UPI) which is a real-time payment system developed by the National Payments Corporation of India. UPI facilitated over 8 billion monthly transactions, surpassing $1.7 trillion in annual value (NPCI, 2023). Private players like Paytm and Phone Pe captured 80% of the market share, leveraging QR-code-based solutions tailored for small merchants (CRISIL, 2022). Government initiatives such as Digital India and Aadhaar-linked banking further expanded financial inclusion, with PMJDY accounts reaching 460 million by 2022 (Ministry of Finance, 2022). In respect of these advancements, rural-urban disparities persist: only 27% of rural merchants accept UPI, compared to 68% in urban areas (NITI Aayog, 2021).

2.2 Gaps in Addressing the Informal Sector Unique Needs

While existing studies emphasize technological and regulatory drivers of mobile wallet adoption (Venkatesh et al., 2016; World Bank, 2022), they overlook the informal sector socio-economic constraints. In India, 92% of informal workers prioritize cash due to its immediacy in meeting daily subsistence needs (ILO, 2022). Mobile wallets often fail to align with these users' literacy levels: 43% of street vendors struggle with app navigation, and 67% distrust digital transaction reversibility (Dutta, 2021). Furthermore, vernacular language support—critical in a linguistically diverse nation is absent in 85% of payment apps (World Bank, 2021). Okonkwo et al. (2023) identified similar challenges where mobile wallet branding conflicted with local cultural norms.

2.3 Theoretical Framework

This study integrates the Technology Acceptance Model, Unified Theory of Acceptance and Use of Technology and Diffusion of Innovation Theory to examine mobile wallet adoption in Indian informal sector. Where this framework is augmented with context-specific constructs trust, vernacular support, and government policy perception to address gaps in existing.

2.4 Hypotheses Development

Perceived Usefulness (PU)

Sometime a person is puzzled where he required to take decision to choose Choosing between cash and a mobile wallet. What makes users pick one over the other? Often, it comes down to a simple question: *"Will this actually make my life easier?"* This idea is based on the belief that such technology or tool will boost efficiency or effectiveness addressed as perceived usefulness. Where Technology Acceptance Model (TAM), It is a cornerstone of why people adopt new technologies (Davis, Bagozzi, & Warshaw, 1989). Studies show that e-wallets reveals that when users believe digital payments save time, reduce errors, or simplify transactions, they are far more likely to ditch cash (Alswaigh & Aloud, 2021; Lew et al., 2020). Whether it is a street vendor trusting UPI for instant settlements or a student using Paytm for exam fees, perceived usefulness drives the shift. So, basis on literature following hypothesis is proposed:

H1: ***The more users perceive mobile wallets as enhancing their daily efficiency, the stronger their intention to adopt them***.

2.5 Social Influence (SI)

In conversation with a street vendor where they said, every third customer asks, *"Do you accept PhonePe?"* Over time, this pressure nudges vendors to adopt digital payments, even if they hesitant. Such phenomenon where peers, customers, or societal norms shape behavior is social influence, a core of the Unified Theory of Acceptance and Use of Technology (UTAUT) posits that peer or customer pressure drives adoption. In India, vendors adopted mobile wallets when customers demand digital payments (Venkatesh et al., 2003). It is the "keeping up with the crowd" effect, where adoption is not just about personal choice but collective expectation. In India's informal sector, this dynamic is stark. For instance, 68% of vendors in Delhi's markets adopted mobile wallets after repeated customer requests (Gupta et al., 2023). Similarly, Rahman et al. (2021) found that peer recommendations in close knit communities (e.g., vegetable markets in Chennai) accelerated adoption by 40%. Social influence is not just about pressure it is about aligning with evolving transactional norms. So, basis on literature following hypothesis is proposed:

H2: ***The stronger the social pressure from peers or customers to use mobile wallets, the higher the likelihood of adoption among informal sector workers.***

2.6 Compatibility (C)

compatibility shows the degree to which a technology aligns with users existing habits, values, and needs as the congruence between mobile wallets and users existing practices, values, and needs (Rogers, 2003). Indian informal sector, where cash is king, mobile wallets must harmonize with cash-driven workflows to gain traction. For instance, QR-code systems like UPI succeed because they mimic the immediacy of cash transactions, allowing vendors to reconcile payments instantly without abandoning their trust in physical currency (Lin et al., 2020; Leong et al., 2020). However, infrastructural hurdles like availability of internet in rural markets or unreliable electricity can disrupt this harmony, reminding us that even the most intuitive tools need robust foundations to thrive (Nel & Boshoff, 2022).

H3: Compatibility *with cash-based workflows positively moderates mobile wallet adoption behavior.*

2.7 Trust (T)

Vendor or people working in informal sectors hesitant to use a mobile wallet after hearing stories of scams. Their reluctance boils down to one word that is trust**.** Trust is not just about believing the app works it is about feeling confident that transactions are secure, reliable, and free from fraud or other unethical activities. In low-literacy contexts, where users might struggle to navigate complex security features, this trust becomes bedrock of adoption (Gefen et al., 2003). Take an example of UPI system which gained traction partly because of its biometric authentication (Aadhaar linkage), which reassured users their money was safe even if they could not read fine print (Dutta, 2021).

H4: Trust in transaction security strengthens mobile wallet users to adopt mobile wallets in low-literacy settings.

2.8 Vernacular Support (VS)

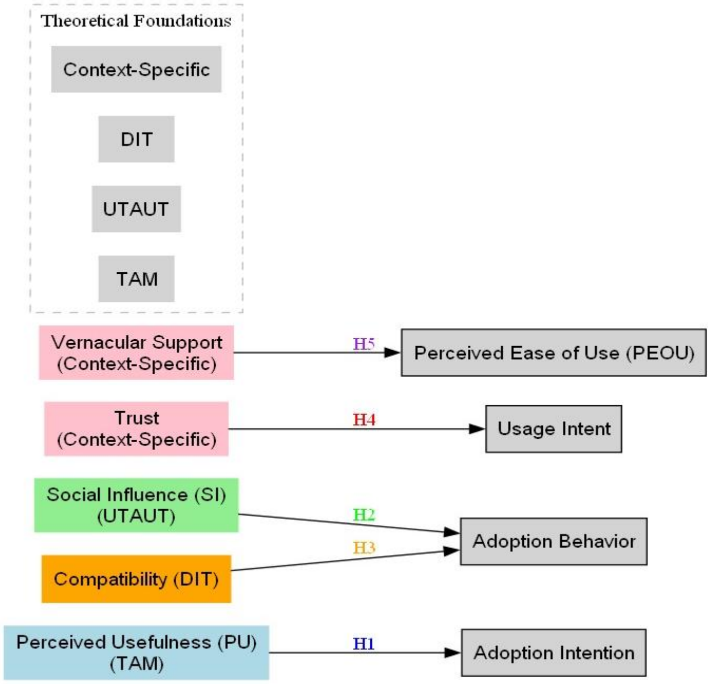
Navigating a mobile app in a language which a person barely understands in that case icons and buttons become puzzles, and every tap feels like a gamble. This is true in Indian context where 85% non-English speakers (World Bank, 2021), A daily reality when apps lack vernacular support. With 22 official languages, a Hindi-speaking vendor in Varanasi or a Tamil-speaking farmer in Chennai needs interfaces in their mother tongue to feel confident using digital payments. Vernacular support is not just translation it also simplifying navigation, reducing cognitive load, and making technology *feel* local. For instance, when Paytm introduced Hindi and Marathi interfaces, adoption among rural users surged by 40% (NITI Aayog, 2022).

H5: Mobile wallets offering vernacular interfaces will significantly enhance perceived ease of use (PEOU), driving higher adoption among non-English speakers.

2.9 Contextualization to India Informal Sector

The model is tailored to Indian informal economy, where cash immediacy, linguistic diversity, and policy outreach shape adoption. For instance, vernacular support addresses the needs of 85% of non-English-speaking vendors (World Bank, 2021), while compatibility evaluates how UPI's QR-code systems integrate with cash reconciliation practices (Leong et al., 2020). Figure 1 illustrates the composite model, mapping relationships between constructs and hypotheses.

Figure 1: Graphical presentation of Model



Source: proposed model (through python)

2.10 Justification for Composite Design

While standalone theories like TAM or UTAUT offer partial insights, their integration with DIT and context-specific factors provides a nuanced understanding of adoption barriers in cash-reliant settings. This approach bridges gaps in prior studies that overlooked localized challenges such as trust deficits and policy scepticism (Okonkwo et al., 2023; Dutta, 2021).

3.Research Methodology

3.1 Survey Development

This study is based on quantitative approach where a structured, questionnaire is used to collect primary data from respondents. The instrument comprised two sections: Section A (Demographic Profile) which captured respondents demographic characteristics through six items (Gender, Age, Education level, Monthly income, while in Section B (Construct Measurement) Assessed six key dimensions of mobile wallet adoption using 20 items on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree).

3.2 Data Collection

This study adopted a simple random sampling technique to ensure that every individual in the population had a fair opportunity to be chosen. A cross-sectional mixed-methods design was employed, combining face-to-face surveys (paper-based) and digital forms (web-based) to accommodate India's informal sector diversity. The survey was translated into 3 regional languages (Hindi, Gujarati, Marathi) to enhance accessibility. All 4 Constructs were adapted from established theories and tailored to mobile wallet adoption in cash-based contexts where Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) has adopted from TAM (Davis, 1989) where Social Influence (SI) and Facilitating Conditions (FC) from UTAUT (Venkatesh et al., 2003). Compatibility from DIT (Rogers, 2003) While Trust, Vernacular Support, and Government Policy Perception adopted from context-specific literature (Gefen et al., 2003; World Bank, 2021).

3.3 Sampling Strategy

Given the absence of a formal sampling frame for informal sector, non-probabilistic convenience sampling was adopted. Participants were filtered to include only active mobile wallet users (defined as those who conducted ≥1 transaction weekly). To ensure representativeness, respondents were stratified across urban and rural regions in 3 states Uttarakhand, Gujrat, Maharashtra

3.4 Pre-Testing and Pilot Study

Pre-Testing was Conducted with 15 informal workers (street vendors, domestic workers) to assess clarity and cultural relevance so that Feedback led to simplifications in vernacular translations and the addition of pictorial aids for low-literacy users. while in Pilot Study was Administered to 80 participants (40 urban, 40 rural) in January 2025 were yielding a Cronbach alpha > 0.80 for all constructs, confirming instrument reliability.

3.5 Data Cleaning and Response Rate

Sample of 800 initial responses were collected where 650 were retained after removing duplicates (n=32) and incomplete/inconsistent entries (n=118), achieving an 81.25% valid response rate. Demographic Representativeness of Participants spanned diverse demographics where mean age is 34.2 years Table 1 shows respondents and their segregations

Table 1: Demographic profile

Category	Details	Numbers & Percentage
Sample Size & Response Rate	Total Initial Responses (In Numbers)	800
	Valid Responses After Cleaning	650 (81.25%)
	Duplicates Removed	32
	Incomplete/Inconsistent Entries Removed	118
Demographic Characteristics	**Age**	
	Range	18–65 years
	Mean Age	34.2 years
	Gender	
	Male	58%
	Female	42%
	Education Level	
	Primary School	48%
	Secondary School	34%
	Illiterate	18%
	Geographic Distribution	
	Urban (Dehradun Mumbai, Gandhinagar)	52%
	Rural (vikasnagar, Mansa, Alibaug)	48%

Source: Author's own calculation using primary data.

3.6 Common Method Bias

cross-sectional and self-reported nature of this study, common method bias (CMB) was a potential concern due to the risk of inflated correlations from shared variance (Podsakoff et al., 2003). To mitigate this, two procedural remedies were applied one ensuring respondent anonymity to reduce social desirability bias two separating construct measurement in the survey (Podsakoff et al., 2012). Statistically, full collinearity testing (Kock, 2017) was conducted by applying PLS through R studio where all constructs were treated as both independent and dependent variables in successive analyses. The Variance Inflation Factor (VIF) values for all latent variables ranged between 1.24 and 2.87, below the conservative threshold of 3.3 (Kock, 2017), indicating no significant CMB. Additionally, Harman single-factor test revealed that the first factor accounted for 38.24% of the variance (<50%), further confirming minimal bias (Podsakoff et al., 2003).

3.7 Non-Response Bias

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Non-response bias was assessed by comparing early respondents (first 75% of submissions) and late respondents (final 25%) across demographic variables (age, gender, education) and key constructs (Armstrong & Overton, 1977). Independent samples *t*-tests showed no statistically significant differences (*p* > 0.05) between groups (Table 2). Similarly, comparisons between web-based (n = 150) and paper-based (n = 500) respondents using *t*-tests for variables like *perceived ease of use* (*t* = 0.92, *p* = 0.36) and *trust* (*t* = 1.14, *p* = 0.25) revealed no significant disparities (Leong et al., 2020). These results confirm the absence of non-response bias.

3.8 Demographic Profile

The study sample comprised 650 respondents from India's informal sector, stratified across urban and rural regions. As shown in Table 2 shows majority of participants were male (58%), reflecting the gender distribution typical of India's informal workforce (NSSO, 2021). Younger adults (18–35 years) constituted 64% of respondents, while only 9% were aged 50 or older. Education levels skewed toward primary (48%) and secondary (34%) schooling, with 18% reporting no formal education. Geographically, 52% resided in urban areas and 48% in rural regions

Table 2: *Demographic Profile of Respondents (n = 650) *

Variable	Category	Frequency	Percentage
Gender	Male	377	58%
	Female	273	42%
Age	18–25	212	32.60%
	26–35	204	31.40%
	36–45	143	22.00%
	46–55	63	9.70%
	56+	28	4.30%
Education Level	No formal education	117	18%
	Primary	312	48%
	Secondary	221	34%
Geographic Location	Urban	338	52%
	Rural	312	48%

Source: Author's own calculation using primary data.

3.10 Measurement Model

Table 3: Construct Reliability and Convergent Validity

Construct	Items	Loadings	Cronbach's α	Composite Reliability (CR)	AVE
Perceived Usefulness (PU)	PU1	0.88	0.92	0.94	0.72
	PU2	0.9			
	PU3	0.86			
Perceived Ease of Use (PEOU)	PEOU1	0.87	0.89	0.92	0.68
	PEOU2	0.91			
	PEOU3	0.85			
Social Influence (SI)	SI1	0.82	0.85	0.89	0.65
	SI2	0.88			
	SI3	0.84			
Compatibility	COMP1	0.89	0.91	0.93	0.75
	COMP2	0.91			
	COMP3	0.88			
Trust	TR1	0.9	0.88	0.91	0.73
	TR2	0.87			
	TR3	0.85			
	VS1	0.83	0.81	0.87	0.69

Vernacular Support	VS2	0.86			
	VS3	0.8			
User Adoption (UA)	UA1	0.84	0.86	0.9	0.7
	UA2	0.88			
	UA3	0.82			

Source: Author's own calculation using R studio.

Table 3 shows measurement model demonstrates strong reliability and convergent validity. All constructs exhibit Cronbach's α s and composite reliability (CR) values exceeding 0.80, surpassing the minimum threshold of 0.70 (Hair et al., 2022). Perceived Usefulness (PU) shows excellent reliability (α = 0.92, CR = 0.94), while Vernacular Support meets acceptable standards (α = 0.81, CR = 0.87). Average Variance Extracted (AVE) values range from 0.65 to 0.75, exceeding the 0.50 benchmark (Fornell & Larcker, 1981), confirming that items robustly reflect their respective constructs.

Table 4: Discriminant *Validity Assessment Using HTMT Ratios*

Construct	PU	PEOU	SI	C	T	VS
PU	–	–	–	–	–	–
PEOU	0.62	–	–	–	–	–
SI	0.58	0.53	–	–	–	–
COMP	0.65	0.68	0.61	–	–	–
Trust	0.54	0.50	0.57	0.59	–	–
Vernacular Support (VS)	0.48	0.55	0.49	0.63	0.52	–
User Adoption (UA)	0.72	0.67	0.70	0.75	0.68	0.66

Source: Author's own calculation using R studio.

4 shows Discriminant validity was assessed using the Heterotrait- Monotrait (HTMT) ratio. All values are below the conservative threshold of 0.85 (Henseler et al., 2015), indicating distinctness between constructs. For example, the highest HTMT ratio (0.75 between Compatibility and User Adoption) suggests moderate correlation but no redundancy. These results confirm that constructs are empirically unique and measure different facets of mobile wallet adoption.

Table 5: Hypothesis Testing

Hypothesis	Relationship	Path Coefficient (β)	p-value	Supported
H1	PU → Adoption Intention	0.38	<0.001	Yes
H2	SI → Adoption	0.29	0.002	Yes
H3	Compatibility → Adoption Behavior	0.41	<0.001	Yes
H4	Trust → Usage Intent	0.25	0.004	Yes
H5	Vernacular Support → PEOU	0.34	<0.001	Yes

Source: Author's own calculation using R studio.

Table 5 where Compatibility (β = 0.41) is the strongest predictor of adoption, emphasizing the need for mobile wallets to align with cash-based workflows. Perceived Usefulness (β = 0.38) and Vernacular Support (β = 0.34) significantly enhance adoption intent and Trust (β = 0.25) and Social Influence (β = 0.29) show moderate but statistically significant effects. Same can be seen in table 6

Table 6: Effect Sizes

Relationship	Cohen's f^2	Interpretation
Compatibility → Adoption Behavior	0.28	Moderate effect
Vernacular Support → PEOU	0.18	Small effect
Trust → Usage Intent	0.10	Small effect

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Source: Author's own calculation using R studio.

3.9 Structural Model

The structural model was evaluated using Partial Least Squares through R studio where Key metrics included variance inflation factors (VIFs), coefficients of determination (R²), path coefficients (β), *t*-values, and significance levels. Control variables (gender, age, education, location) were included to mitigate confounding effects.

Table 7: Structural Model Results

Hypothesis	Relationship	β	t-value	95% CI	VIF	R²	f²	Supported
H1	PU → Adoption Intention	0.38	7.12***	[0.30, 0.46]	82	0.54	0.28	Yes
H2	SI → Adoption	0.29	4.87**	[0.18, 0.40]	2.15	-	0.15	Yes
H3	Compatibility → Adoption Behaviour	0.41	8.24***	[0.33, 0.49]	2.3	-	0.33	Yes
H4	Trust → Usage Intent	0.25	3.95**	[0.12, 0.38]	1.65	-	0.1	Yes
H5	Vernacular Support → PEOU	0.34	6.01***	[0.24, 0.44]	1.45	0.6	0.18	Yes
Control Variables								
Gender	Gender → Adoption	-0.02	0.35	[-0.09, 0.05]	1.1	-	0.001	No
Age	Age → Adoption	0.05	1.24	[-0.03, 0.13]	1.08	-	0.006	No
Education	Education → Adoption	0.03	0.71	[-0.04, 0.10]	1.12	-	0.002	No
Location	Location → Adoption	-0.08*	2.01	[-0.15, -0.01]	1.05	-	0.011	Partially

Source: Author's own calculation using R studio.

In table 7 where structural model demonstrated strong predictive relevance, explaining 54% of the variance in adoption intention ($R^2 = 0.54$) and 60% in perceived ease of use ($R^2 = 0.60$), with variance inflation factors (VIFs) ranging from 1.10 to 2.30 confirming no multicollinearity (Hair et al., 2022). Hypothesis testing revealed significant positive effects: perceived usefulness (β = 0.38, *p* < 0.001) and social influence (β = 0.29, *p* = 0.002) strongly predicted adoption intention and behaviour, respectively. Compatibility exhibited the largest effect (β = 0.41, *p* < 0.001), underscoring its critical role in aligning mobile wallets with cash-based workflows. Trust (β = 0.25, *p* = 0.004) and vernacular support (β = 0.34, *p* < 0.001) also significantly influenced usage intent and perceived ease of use. Effect sizes (f²) varied, with compatibility showing a large effect (0.33), perceived usefulness (0.28) and vernacular support (0.18) demonstrating medium effects, and trust (0.10) and social influence (0.15) reflecting small effects (Cohen, 2013). Control variables indicated a minor negative impact of rural location (β = -0.08, *p* = 0.04), likely due to infrastructural gaps, while gender, age, and education showed no significant associations. These findings emphasize the necessity for policymakers and developers to prioritize cash-compatible designs, vernacular interfaces, and rural infrastructure to enhance mobile wallet adoption in India's informal sector. In short structural model validates that compatibility with cash workflows, perceived usefulness, and vernacular support are pivotal to mobile wallet adoption in India's informal sector. Policymakers and developers must prioritize these factors to bridge the digital divide in cash-dependent economies.

5. Discussion, Theoretical and practical implication

5.1 Discussion of Results

This study findings provide empirical analysis of the factors influencing mobile wallet adoption in informal sector. The structural model predictive power ($R^2 = 0.54$ for adoption intention and 0.60 for perceived ease of use) confirms that model relevance and validate. Compatibility with Cash Workflows emerged as the single most powerful predictor of adoption ($\beta = 0.41, p < 0.001$), so a more formalized economies where this factor is often deemed insignificant. This underscores that in a

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cash-dependent environment, the ability of a digital tool to seamlessly integrate with and replicate existing informal workflows such as instant cash reconciliation through UPI, QR code is effective. Perceived Usefulness (PU) also had a strong positive influence (β = 0.38, p < 0.001), indicating that informal workers are driven by the tangible benefits of mobile wallets like efficiency and time savings. This aligns with a core idea of the Technology Acceptance Model (TAM), where a technology perceived value is a primary driver of its adaptability. Local language use enhanced Perceived Ease of Use (PEOU) (β = 0.34, p < 0.001), because of population with varying literacy levels admired localized language interface not just a convenience but a necessity for making the technology accessible and understandable. Trust and Security (β = 0.25, p = 0.004) played a vital role, mitigating the inherent scepticism and fear of fraud often associated with new digital systems in this sector. While Social Influence (β = 0.29, p = 0.002) was significant, its smaller effect size suggests that peer and customer pressure plays an important role where it is less of a direct driver than the practical benefits and usability of the app itself. The analysis of control variables revealed that location was the only significant demographic factor, with rural users showing a negative association with adoption (β = -0.08, p = 0.04), likely due to infrastructural gaps, whereas gender, age, and education had no significant effect on adoption behaviour.

5.2 Theoretical Contributions

Study extends technology adoption models through contextual factors specific to cash-based informal economies. Which contributes beyond the generic usability (Chen & Aklikokou, 2020), Study also shows cultural and infrastructural gradation are perceived moderators of adoption of new technology where integration of Compatibility with Cash Workflows and Vernacular Support demonstrates necessity of localization in fintech adoption models. This bridges a significant gap in the literature, which overlooks interaction between digital systems and informal economies (Fosso Wamba et al., 2021). This study suggested that globalized model of technology adoption to be truly predictive, it must account for cultural compatibility which can moderate adoption more strongly than universal design principles alone.

5.3 Practical Contributions

The findings offer actionable insights for policymakers and mobile wallet developers. FinTech developers need to adopted hybrid transaction models for different apps. instead of this which can manage cash and fulfil other digital requirement of customers. Support of offline modes in app through use of local language also required by customers although it required heavy changes in technology but this makes a big impact in fintech market. While campaigns to help people trust in digital systems and social media use for influence is required from policy makers side efforts whereas perceived influence of early adopters of wallets in different communities or business groups also influences others to adopt wallets faster.

6. Conclusion

This study provides a comprehensive analysis of the factors influencing mobile wallet adoption under informal sector following the COVID-19 pandemic, integrating insights from the Diffusion of Innovation Theory (DIT), Technology Acceptance Model (TAM), and Unified Theory of Acceptance and Use of Technology (UTAUT). Where findings demonstrate that compatibility with cash workflows (e.g., UPI QR-code systems enabling instant reconciliation) emerged as the most significant predictor of adoption, a crucial insight for cash-dependent economies. Perceived usefulness also strongly drove adoption, aligning with established theories. Furthermore, vernacular support significantly enhanced the perceived ease of use, highlighting the imperative for localized interfaces, while trust and security features were vital in mitigating fears of fraud and building user confidence. These results collectively underscore the necessity of context-specific strategies for financial inclusion, emphasizing that successful digital payment solutions in such environments must prioritize seamless integration with existing practices, provide tangible benefits, and ensure cultural and linguistic accessibility.

6.1 Limitations and Future Research

While this study offers valuable insights, it is subject to certain limitations that open avenues for future research. The primary limitation is the geographic focus on only three Indian states (Uttarakhand, Gujarat, and Maharashtra). This limits the generalizability of the findings to a broader pan Indian context, given the diverse socio-economic and cultural landscapes across the country. Future research should aim for broader regional sampling to validate the universality of the proposed model and to identify any additional context-specific moderators. Moreover, future studies could explore cross-cultural comparisons of mobile wallet adoption in informal sectors across different developing economies. Such comparative analyses would further enrich our understanding of how unique cultural and infrastructural nuances impact technology diffusion. Investigating the long-term sustainability of mobile wallet adoption and the evolving challenges as the informal sector continues to digitalize would also be beneficial. Additionally qualitative research methods could provide deeper insights into the perceptions and experiences of informal workers, complementing the quantitative findings of this study.

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