Exploring the Innovativeness of Street Vendors in Embracing AI-powered FinTech services: A Comparative Study

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Abstract. The integration of AI-powered FinTech services into daily life is increasingly crucial, with the Indian Government's Digital India initiatives driving rapid adoption, particularly among post-pandemic street vendors. This study focuses on understanding the determinants that shape the intention for using AI-powered FinTech facilities through mobile platforms, a critical component of Digital Financial Services (DFS). It employs an modified Technology Acceptance Model (TAM) to explore determinants that impact or inhibit AI-powered FinTech adoption. Gathering 580 responses, with 415 actively using these services, this research utilizes Partial Least Squares-Structural Equation Model (PLS-SEM) analysis. Notably, this research pioneers validated evidence on AI-powered FinTech adoption, emphasizing perceived value over perceived ease of use. Educational qualifications negatively impact ease of use, making technology acceptance a crucial predictor for street vendors.

Keywords: Artificial intelligence, FinTech; post pandemic; street vendors; TAM.

1 Introduction

India leads the digital economy with the highest FinTech adoption rate [4], driven by government-led initiatives, events like demonetization, and a youthful population. Tech giants like Amazon and Flipkart offer diverse financial technology products, making adoption easier. At the time of COVID-19, street vendors engaged as a vital part in maintaining supplies, but their digital literacy lagged behind customer demand. To address this, vendors are slowly embracing digital payments, with AI-powered FinTech services facing hurdles related to education and digital literacy. Empirical research focuses on understanding the determinants of street vendors' "behavioral intention" towards AI-powered FinTech adoption, shedding light on key factors that drive or hinder adoption within this group. This study aims to uncover what significantly influences AI-powered FinTech adoption among street vendors.

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2 Literature Review

Throughout history, the methods of payment have evolved from ancient barter systems and the use of valuable commodities like gold and silver in monarchies to the prevalence of digital payment modes in the twenty-first century. The emergence of digitalization, accelerated by the COVID-19 pandemic, has transformed various sectors, including online payments. Previous studies have explored the adoption of AI-powered FinTech services from different angles, with the pandemic drawing attention to the online payment sector amid disruptions in major industries like trade, tourism, and transportation [18]. While major tech companies like Amazon and Flipkart have introduced customers to AI-powered FinTech services, the pandemic underscored the vital role of street vendors in ensuring the availability of essential goods, but their adoption of these services varied due to factors like ease of use, privacy, job security, and trust [12], [16], [3]. Adoption determinants also depend on the target population and location, with TAM, self-efficacy theory, and critical mass theory explaining behavioral intentions [14], [11]. User satisfaction, influenced by trust and security, significantly affects customer behavior, and trust is crucial for continued usage of AI-powered FinTech services [15]. Government regulation, brand value, and trust in the platform also influence usage [5]. Some studies argue that trust, comfortability, and social value have limited impact on usage [17]. The adoption and usage of AI-powered FinTech services involve a complex interplay of factors, from historical evolution to user satisfaction and trust, and understanding these dynamics is essential for effective implementation and future development.

3 Proposed Framework

3.1 Research Objectives

The main golas of the research work includes (1) To learn about the current level of adoption of AI-driven fintech services from street vendors. (2) To discern the variables that lead to the heightened utilization of AI-powered FinTech facilities. (3) To gain insights into the tangible challenges encountered by street vendors in embracing and integrating AI-powered FinTech services.

3.2 Research Framework & Hypothesis

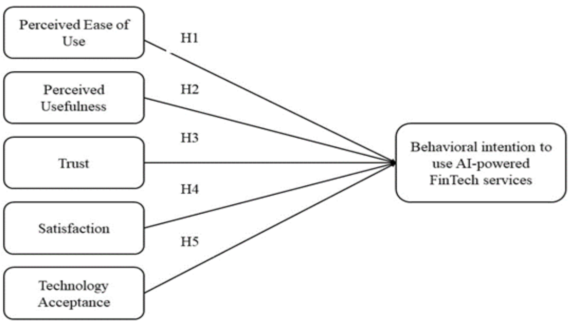

Fig. 1. Proposed Model.

Fig 1 describes framework for the adoption of AI-powered FinTech services among street vendors, building upon the TAM with additional variables. This extended model integrates trust, satisfaction, and technology acceptance alongside the existing TAM components, aiming to analyse their effect on the adoption behaviour of AI-driven FinTech services. Perceived Usefulness, Perceived Ease of Use, Trust, Satisfaction, and Technology Acceptability are among the independent variables.

3.3 Research Methodology

This study focuses on street vendors in Bangalore, India, using a quantitative approach with a structured survey. Data collection occurred in January 2023 through convenience sampling. The survey was administered in English, with translations in native languages (Kannada and Tamil) for accessibility. In total, 580 responses were collected for validation and feedback, with 415 vendors confirming the use of AI-powered fintech services. This study, which is based on the TAM, uses a two-part survey to gather demographic data and investigate the acceptance of AI-powered banking services among street sellers. A five-point Likert scale (1 for "disagree" to 5 for "strongly agree") was deployed to analyse key adoption criteria.

4 Results and Discussions

The study employed the PLS-SEM method in two phases: one focused on measuring model validity and reliability, and the other on testing hypotheses. PLS-SEM is favored for its accuracy [2]. Data from 580 respondents, including 415 AI-powered FinTech-using street vendors, revealed 45.5% adoption post-COVID-19, with PhonePe at 11.8%. Rigorous validation of the participant model demonstrated high reliability, with Cronbach's alpha readings varying from 0.855 to 0.971 and Composite Reliability ratings from 0.895 to 0.981, exceeding the 0.7 threshold, confirming internal dependability. Construct validity is assessed using factor loading and AVE values [1], with a selected threshold of above 0.5 for factor loadings, consistently met in Table 1. Calculated AVE numbers ranged from 0.630 to 0.945 [7], all surpassing the proposed 0.5 threshold, confirming convergent validity. For discriminant validity, the HTMT method developed by Hensler and colleagues [9] was employed, aligning with guidelines [8]. As be seen in Table 2, the HTMT numbers are less than the established standard of 0.9 [6], validating the presence of discriminant validity.

Table 1. Measurement Model Values.

Variables	Items	Factor Loadings	Cronbach's Alpha	Composite Reliability	Average Variance Extracted
Behavioural Intention	BIU1	0.970	0.971	0.981	0.945
	BIU2	0.973			
	BIU3	0.973			
Perceived Ease of Use	PEUS1	0.949	0.961	0.970	0.866
	PEUS2	0.974			
	PEUS3	0.853			
	PEUS4	0.927			
	PEUS5	0.947			
Perceived Usefulness	PUS1	0.902	0.894	0.919	0.660
	PUS2	0.889			
	PUS3	0.904			
	PUS4	0.564			
	PUS5	0.667			

	PU6	0.882			
Satisfaction	SAT1	0.800	0.855	0.895	0.630
	SAT2	0.702			
	SAT3	0.763			
	SAT4	0.839			
	SAT5	0.856			
Technology acceptance	TAC1	0.935	0.918	0.948	0.858
	TAC2	0.911			
	TAC3	0.934			
Trust	TRU1	0.961	0.948	0.963	0.865
	TRU2	0.935			
	TRU3	0.910			
	TRU4	0.914			

The structural model is examined by determining the coefficient of determination (R2) and path coefficients with 5000 resamples using the bootstrapping approach outlined by [7]. Analysis of the structural (Inner) model based on Table 3 conducted for hypothesis testing. The findings in Table 3 show that Perceived Ease of Use had no impact on street vendors' behavioural intention to utilize AI-powered FinTech services. As a result, H1 is unsupported ($\beta = -0.010$, $t = 0.270$). The data reveal that trust has little effect on behavioural intention for using AI-powered FinTech services, resulting in a lack of support for H3 ($\beta = -0.045$, $t = 0.884$). The outcomes suggest that perceived usefulness, satisfaction, and technology acceptance significantly impact the behavioural intention to use AI-powered FinTech services among street vendors. H2 ($\beta = 0.388$, $t = 8.772$), H4 ($\beta = 0.352$, $t = 6.209$), and H5 ($\beta = 0.324$, $t = 5.171$) are supported. In terms of the model's impact size (f2), Table reveal that perceived ease of use (0.000) and trust (0.003) have no significant impact on "behavioural intention" to utilise AI-powered FinTech services. Perceived utility (0.177), satisfaction (0.174), and technology acceptability (0.172) moderate effect on "behavioural intention" for utilising AI-powered FinTech services.

Table 2. Heterotrait - Monotrait (Htmt) Ratio

	BI	PEU	PU	SA	TA	TR
BI						
PEU	0.543					
PU	0.736	0.796				
SA	0.817	0.38	0.57			
TA	0.787	0.434	0.535	0.802		
TR	0.704	0.515	0.7	0.767	0.708	

Table 3. Results of Hypotheses Testing

Hypothesis	Standardized. Beta	Std. Error	t-value	p-value	Result	f^2
H1 - The perceived ease of use influences street vendors' behavioural intention to adopt AI-powered FinTech services.	-0.010	0.036	0.270	0.787	Not supported	0.000
H2 - The perceived usefulness of AI-powered FinTech services influences street vendors' behavioural intention to use them.	0.388	0.044	8.772	0.000	Supported	0.177
H3 - Trust influences street vendors' behavioural intention to use AI-powered FinTech services.	-0.045	0.050	0.884	0.377	Not supported	0.003
H4 - Satisfaction influences street vendors' "behavioural intention" to employ AI-powered FinTech services.	0.352	0.057	6.209	0.000	Supported	0.174
H5 - Technology acceptance positively affects the "behavioural intention" to use AI-powered FinTech services among street vendors.	0.324	0.063	5.171	0.000	Supported	0.172

The extended TAM in this research investigates the adoption of AI-powered FinTech services among street vendors, focusing on key variables like prceived ease of use, perceived usefulness, satisfaction, trust, and technological acceptance. The study reveals that perceived ease of use doesn't impact street vendors' intention for adopting AI-powered FinTech services, possibly due to their limited educational background. This underscores the need for more user-friendly solutions from FinTech providers. Notably, perceived usefulness has a substantial effect on the intention for adopting AI-powered FinTech services, highlighting the importance of innovative features to enhance user engagement. Trust has minimal impact, emphasizing the need for consistent and reliable service delivery. Additionally, satisfaction positively affects the intention for adopting AI-powered FinTech services, emphasizing importance for user-friendly designs and platforms. Technology adoption is also a significant determinant for street vendors who see these services as useful [10], [13].

4 Conclusion

The findings make substantial contributions to both theory and practical applications. The extended TAM sheds light on critical elements, explaining 75.2% of the divergence in street vendors' intention for adopting AI-powered FinTech services, enhancing our theoretical understanding. From a practical perspective, the study identifies determinants influencing AI-powered FinTech adoption among street vendors, offering valuable insights for service providers and strategies for post-pandemic adoption. These implications can extend to technology adoption among less educated populations, emphasizing the need for improved digital financial literacy in the broader context of a digitally empowered society. The research highlights the increased use of AI-powered FinTech services by street vendors in the times of COVID-19, with perceived usefulness, satisfaction, and technological acceptance being key drivers. Further research and studies could inspect the role of demographic and socioeconomic drivers on broader AI-powered FinTech adoption.

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