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Digital Economy and FinTech in Facilitating Financial Inclusion in Rural India

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Abstract

Purpose: This research focuses on to identify the role of Fintech in digital economy and financial inclusion in India. The descriptive and exploratory research design were used in the study to frame out the structured questionnaire to collect the primary responses from rural areas of different cities of Delhi-NCR and UP West. There were total 530 responses finalized for the analysis purpose. The higher order structural equation modelling was performed to test the hypotheses and validate the measurement model. The findings of the research explain the mediating role of fintech in digital economy and financial inclusion. The mediating effect of fintech and total effect of each variable on other variable were found significant. This study concludes the role of technology in finance is required and significant in order to enhance the financial inclusion in the country. Policy makers and industrialist can make the policies to upliftment of Fintech for the exponential growth of digital economy on financial inclusion. This study is helpful to make various decisions for financial industry and helps in growing the technology and digital economy in the country.

Keywords: Financial Inclusion (FI), FinTech, Digital Economy, Technology Model

1. Introduction

The service sector has driven India's economic progress for decades. Lack of access to financial services, particularly in remote areas, is a major problem in India notwithstanding this progress. The Indian government and financial institutions have increasingly looked to industry 5.0 and FinTech solutions as a means to combat these issues. The IoT, big data, and AI are just a few examples of the cutting-edge technologies that will be incorporated into traditional manufacturing processes as part of Industry 5.0, the next stage in the evolution of manufacturing. FinTech is the term for the financial industry's adoption of technology to create new and improved financial products and services.

Financial technology (FinTech) leaders in India including Paytm, PhonePe, Google Pay, and MobiKwik have been instrumental in expanding access to banking services across the country, especially in rural areas. Digital payment solutions provided by these businesses, such as the Unified Payment Interface (UPI), mobile banking, and biometric payment systems, have been crucial in expanding access to banking services among India's rural poor.

However, the success of digital financial inclusion depends on several factors, including user awareness, perceived utility (PU), perceived usefulness (PUF), interpersonal impact, external influence, knowledge and experience in the operation of robots, financial inclusion via digital technology (FID), digital economy business models (DEBM), user value proposition (UVP), intention to use, attitude, and perceptions of digital wallets (like Paytm, PhonePe, Google Pay, and MobiKwik's),

Rural India has long faced financial exclusion, limiting economic growth and social development. This study seeks to investigate how digital economy tools and FinTech innovations can bridge this gap. The paper will examine user awareness, perceived utility,

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perceived usefulness, interpersonal impact, external influence, knowledge and experience in robot operation, FID, DEBM, UVP, intention to use, attitude, and perceptions of rural Indian digital wallet, UPI, mobile banking, and biometric payment system users. To comprehend the topic, the study will use mixed approaches, including qualitative and quantitative methods.

This work contributes to financial inclusion and digital technology literature by examining rural India's digital financial inclusion success factors.

This paper's focus is on the role that Industry 5.0 and financial technology (FinTech) play in bringing digital financial services to India's rural areas. This study will analyse the impact that major FinTech firms like Paytm, PhonePe, Google Pay, and MobiKwik have had on bringing banking to undeserved areas. The paper will also address the obstacles these businesses encounter in their pursuit of financial inclusion in rural areas, as well as the possible solutions to those obstacles. This study's findings may have significant consequences for policymakers, financial institutions, and other stakeholders interested in fostering financial inclusion in developing nations. The study aims to address an unexplored area by utilising a novel conceptual framework, specifically how to assess Industry 5.0's impact on industrial processes and the potential for FI. How to examine Industry 5.0 may enable novel financial solutions for rural FI? To examine Fin Tech's role in rural digital financial inclusion and access. How to measure the levels of user awareness, perceived utility, perceived usefulness, intention to use, attitudes, and perceptions related to digital wallets, UPI, Mobile banking, and Biometric payment systems in rural areas of India.

2. Literature Review & Theoretical Background

User awareness and its impact on technology adoption and utilization have been examined by (Wu & Wang, 2006). Access to financial services is limited, particularly in rural areas. Researchers discovered a crucial link between user awareness and the acceptance and usage of technology. Additionally, Arora & Aggarwal, (2018) identified that user awareness can be influenced by factors such as media coverage, word-of-mouth, and personal experience with the technology. Davis (1989)studied the idea of perceived usefulness has been linked to technological uptake and use. Davis found that individuals' perception of usefulness directly affects their adoption and utilization of technology. (Venkatesh et al., 2003) noted that simplicity of use, compatibility with current systems, and perceived costs and advantages affect PUF. PUF, as defined by Davis (1989), is the degree to which a person anticipates that the use of a certain technological tool would improve their efficiency at work. Interpersonal impact, another aspect of technology, has been subject to investigation. (Katz & Rice, 2002) found that the impact of technology on interpersonal connections can be varied. It can either promote communication and cooperation, as demonstrated by (Nie et al., 2008), or isolate individuals and limit face-to-face interaction. External influences, including Technology adoption and use are influenced by societal norms and media attention (Rogers, 2003). User awareness and perception of technology can be shaped by media coverage and societal norms. Knowledge and experience in robot operation also play a crucial role. (Arora & Aggarwal (2018) discovered that individuals who have practical experience and theoretical understanding of robotic technology exhibit a higher inclination towards learning and utilizing it. Financial Inclusion via Digital Technology (FID) utilizes mobile banking and e-wallets to provide financial services to underprivileged populations. The World Bank has substantiated the effectiveness of FID in enhancing financial inclusion and fostering economic growth (Appaya, 2021). Digital Economy Business Models (DEBM), as suggested by (Brynjolfsson & McAfee, 2014), have the potential to disrupt established businesses while promoting innovation and entrepreneurial endeavors. The Unique Value Proposition (UVP) of a product or service is a crucial factor in adoption and usage. (Osterwalder et al., 2014) conducted extensive research showing that a strong UVP significantly enhances the adoption and usage of products and services. Adoption and usage of technology are greatly influenced by people's anticipation of benefiting from it. Venkatesh et al. (2003) found that technology adoption and usage are strongly correlated with INT_USE. PU in light of digital wallets refers to consumers' beliefs about the extent to which using a digital wallet improves convenience, security, and efficiency. PEU, in contrast, pertains to consumers' perception of how easy it is to utilize a digital wallet.

2.1 Theoretical Perspectives related to Attitude and perceptions for the use of digital wallets. Digital wallet adoption is dependent on attitudes. The variables related to attitudes in this context have been studied using TAM, UTAUT, and TRA.

The TAM was established by Davis in 1989 and is a widely used paradigm for assessing technological adoption and use. It emphasizes the importance of users' attitudes and intentions, with a specific focus on perceived utility and accessibility (Davis, 1989). When considering digital wallets, PU refers to users' belief advantages of utilizing a digital wallet, such as convenience, security, and efficiency. However, PEU is about consumers' perception of a digital wallet's simplicity and usability.

Venkatesh et al. (2003) introduced the UTAUT as a comprehensive framework for technological adoption and use. UTAUT incorporates various models and theories. The TAM takes into account four key dimensions that influence users' attitudes and intentions towards technology use. These dimensions are PE, EE, SI, and FF. When considering digital wallets, performance expectancy relates to users' belief in the ability of a digital wallet to facilitate easy and quick transactions. Effort expectancy, on the other hand, pertains to users' perception of the simplicity and ease of using a digital wallet.

TRA has been widely utilized to understand and predict human behavior in various contexts. TRA suggests that attitudes and subjective norms play a major part in assessing a person's purpose to do something(Fishbein & Ajzen, 1975). In terms of digital wallets, attitudes encompass an overall evaluation of the usefulness of using a digital wallet, while subjective norms encompass the perceived societal pressure to use a digital wallet.

In conclusion, users' attitudes and perceptions of digital wallets are significant factors influencing their adoption and use. Theoretical models and frameworks such as TAM, UTAUT, and TRA can provide insights into these aspects. Understanding these factors can assist service providers in developing and deploying user-friendly digital wallets that meet consumers' needs and expectations.

While the study emphasizes the potential of Industry 5.0 and FinTech in boosting financial inclusion in semi-urban India. Apparently, research is lacking on the constraints and challenges faced by rural Indians in adopting digital financial services. Additional research might look into the elements that influence rural Indians' access to and use of FinTech solutions, such as literacy levels, digital skills, technological trust, and cultural norms. A comparison investigation of the effectiveness of various FinTech models and their influence on eliminating financial exclusion in rural areas would also be beneficial to the study.

Hypotheses:

H1: The Digital economy has a significant impact on FI.

H2: Fintech has meaningful association with the Digital economy.

H3: Fintech mediate Digital economy and financial inclusion.

3. Research Methodology

The present study focuses on the relationship between the Fintech, Digital Economy and Financial Inclusion. In this research, descriptive and exploratory research design were used. The study employed stratified random sampling, which divided the population into categories according to their location and demographic and socio-economic characteristics. Every stratum in the study, including specific areas of UP West rural regions and Delhi-NCR and certain demographic categories, was adequately reflected in the sample selection.

This sampling technique benefits the study as it enabled them to accurately evaluate digital economy and FinTech adoption habits in rural India despite significant variations in technology accessibility and general education levels as well. The methodology implemented by this method allowed researchers to detect unique implementation obstacles and market potentials within each member segment. The structured questionnaire was prepared to collect the primary responses from respondents of rural cities of UP west. After the data collection, demographic details were analyzed followed by measurement model and structural equation modelling (SEM) performed using SMART-PLS 4. In the measurement model, confirmatory factor analysis (CFA) was performed and analyzed the internal strength of the model including, reliability and validity of the questionnaire. Later on, SEM was performed to test the hypotheses.

Table 1.
sample characteristics

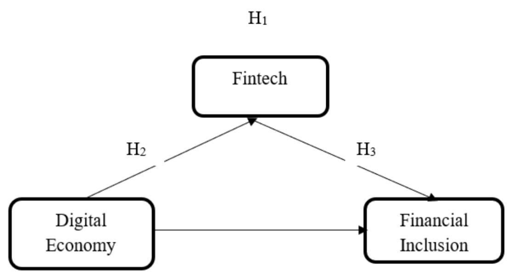

Figure 1.
Proposed Model

Source: Author's Presentation

Sample size and distribution

Rural areas of UP west and Delhi-NCR has been considered for the study. The total population of selected cities as Ghaziabad (1,729,000), Faridabad (1,809,733), Noida (1,648,115) and Greater Noida (102,054) as per the census 2011. The data has been collected from mentioned cities. The sample size distribution was based on the following formula:

$$n = \frac{N}{1+N\,(e)^2}$$

In this formula, n = sample size, N = population size, e = level of precision. The level of significance was 5% therefore, p = 0.05. The suggested sample size for this research was 385 which was calculated from the above formula. The questionnaire was circulated among people of rural areas of such cities and got the total responses 530. In table 1, the city wise distribution is mentioned.

Table 1.
Area-Wise Sampling Detail

Place	Literacy Ratio (2011)	Residents	Estimation	Representatives
Ghaziabad	85.05%	1,729,000	1,729,000/5,288,902 * 530	173
Faridabad	81.70%	1,809,733	1,809,733/5,288,902 * 530	181
Noida	68.14%	1,648,115	1,648,115/5,288,902 * 530	165
Gr. Noida	86.47%	102,054	102,054/5,288,902 * 530	11
Total		**5,288,902**		**530**

Source: Author's own representation

4. Data Analysis, Results and Discussions

Table 2.
Demographic Profile

Variables	Frequency	Percentage (%)
Gender		
Male	345	65
Female	185	35
Age		
Under 30 years	143	27
Between 30 to 45 years	239	45
Between 45 to 55 years	85	16
Above 55 years	63	12
Education		
Upto secondary	58	11
Senior secondary	43	8
Graduation	279	53
Post-graduation	137	26
Professional/Doctorate	13	2
Occupation		
Government Job	76	15
Private Sector Job	281	53
Business	133	25
Self-Employed	22	4
Student	18	3
Annual Income		
Up to Rs. 5 Lakh	458	86
Between Rs. 5-10 Lakh	50	9
Between Rs. 10-15 Lakh	12	3
More than Rs. 15 Lakh	10	2

Source: Author's own representation

This study incorporates a higher order model consisting of twelve first-order variables, namely Business model (BM), Customer Value Proposition (CVP), Awareness (AWE), Infrastructure (INFRA), Digital Financial Inclusion (DFI), Perceived Ease of Use (PEU), Perceived Usefulness (PU), Intention to Use (INTEN), Familiarity with the robots (FAM), Attitude (ATT), External Influence (EXT_INF), and Internal Influence (INT_INF). There are also two second-order hidden variables, DE and Fintech, making a total of 47 variables that can be seen.

The concept of the digital economy (DE) is widely recognized as a ubiquitous, multidimensional, interactive, and constantly evolving notion (Bukht & Heeks, 2018; McAfee & Brynjolfsson, 2018; Zhao et al., 2015). Nonetheless, the literature makes clear that there is no consensus on a clear and concrete concept of DE, nor are there widely accepted standard theoretical measurements. Consequently, this proposed paradigm defines DE is feasible, sustainable, and cost-effective, using technology to improve supply side and stakeholder participation (Barefoot et al., 2018). Four first-order variables characterize DE: the business model (BM), which considers the value proposition, value delivery, value creation, value communication, and value capture (ABDELKAFI et al., 2013); the availability of payment infrastructure, which is a safe, inexpensive, and user-friendly transactional interface that enables customers to send or receive payments, store information digitally, and connect devices through contemporary digital channels; and the level of digitalization of the economy. Another second-order construct in the model is artificial intelligence, which is supported by extensive literature review. Various studies support the reflective nature of the first-order constructs: PUF and PEU (Bhattacherjee, 2000; Davis, 1989), external influence and interpersonal influence (Belanche et al., 2019; Bhattacherjee, 2000), attitude (Bhattacherjee, 2000; Taylor & Todd, 1995), intention to use (Bhattacherjee, 2000; Mathieson, 1991), and in the field of artificial intelligence, reflective models include things like prior experience with robots (Casaló et al., 2008; Flavián et al., 2006).

Measurement Model

Smart PLS 4's CFA confirmed the measurement model. In the measurement model, three constructs viz, Digital Economy (DE), Fintech and Financial Inclusion (FI) were considered. DE has been considered as reflective-formative model, whereas Fintech and FI are reflective-reflective model.

Convergent and discriminant validity have assessed scale reliability for reflective constructs. In order to assess the CV, CR values, which include α and rho, and AVE were examined. Bagozzi & Yi (1988) suggested that a CR value of at least 0.70 and an AVE value of at least 0.50 are considered ideal (Hair et al., 2019). Furthermore, α should be equal to or higher than 0.70 (Hair et al., 2019). The Heterotrait-monotrait ratio (HTMT) test and the Fornell-Larcker criteria were used to assess discriminant validity.

For formative constructs, the various parameters are there viz. redundancy analysis, the value of r should $\leq$ 0.7; multi collinearity or VIF value which should be $\leq$ 3 shows no collinearity, but in any case, it should not be greater than 5 which shows there is multi collinearity; and these formative constructs should be significant to latent variable (Hair et al., 2019).

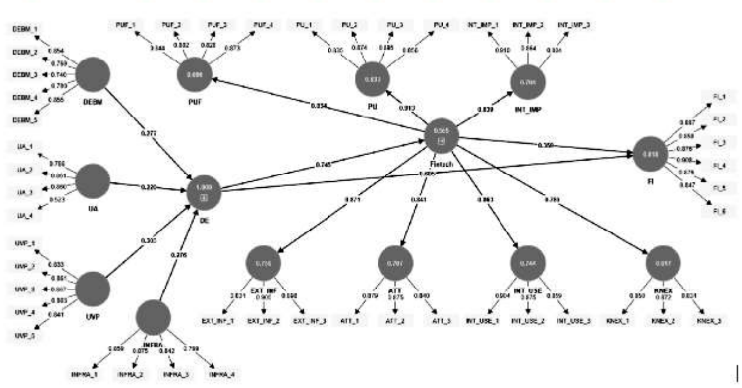

Figure 1.
Measurement Model

Internal Consistency

Reliability and Convergent Validity

Table 3 provides evidence of internal consistency and convergent validity, as indicated by loading values of each indicator with its latent variable that are equal to or greater than 0.708. In only one statement of awareness has the loading value 0.518 but it can be retained as value of alpha and AVE are satisfactory. The value of Cronbach alpha and rho explain internal consistency reliability, which is found satisfactory. The model also satisfies the criteria of convergent validity as AVE values are $\geq$ 0.5.

Table 3.
Internal Consistency and Convergent Validity

Variables	α	rho_a	rho_c	AVE
ATT	0.832	0.836	0.899	0.748
DE	0.955	0.959	0.960	0.574
DEBM	0.860	0.867	0.899	0.642
EXT_INF	0.852	0.856	0.910	0.773
FI	0.939	0.941	0.952	0.767
Fintech	0.961	0.963	0.964	0.543
INFRA	0.865	0.868	0.908	0.713
INT_IMP	0.823	0.831	0.895	0.740
INT_USE	0.854	0.857	0.911	0.773
KNEX	0.810	0.814	0.887	0.724
PU	0.888	0.889	0.923	0.749
PUF	0.880	0.884	0.917	0.735
UA	0.760	0.803	0.849	0.593
UVP	0.896	0.898	0.924	0.707

Source: Author's own representation

Discriminant Validity

To test the discriminant validity of the measurement model, the HTMT values of reflective constructs should preferably be less than 0.85, while values up to 0.90 may be acceptable in certain cases. Table 6 shows discriminant validity exists in the model as values are < 0.90. Another parameter is Fornell-Larcker test, shows in table 7, which also explains the discriminant validity, the values of AVE > MSV. In the results, the Fornell-Larcker criteria also satisfies the condition of discriminant validity (Hair et al., 2019).

Measurement Model (Manual Calculation-Higher order constructs)

Because the measuring model used in this work is of higher order, higher-order constructs cannot be analyzed by using smart-pls because Smart-PLS measure the higher-order constructs as the latent variable and it calculates the values on the basis of items are in the construct. Therefore, the manual calculation of higher-order reflective construct will be considered (Sarstedt et al., 2019).

The composite reliability is computed as follows:

$$\rho C = \frac{\left(\sum_{i=1}^{M} l_i\right)^2}{\left(\Sigma_{i=1}^{M} l_i\right)^2 + \Sigma_{i=1}^{m} var\,(e_i)}$$

$$\text{Cronbach's } \alpha = \frac{M \,.\, \bar{r}}{(1+(M-1)\,.\bar{r}}$$

The symbol r shows the average connection between the lower-order components, while M shows how many lower-order components there are in total. The calculated value of α coefficient is 0.936. Additionally, the manually computed AVE value is 0.715, which exceeds the specified cut-off value. It can be calculated by considering average square root of beta values of each lower-order constructs viz. ATT, EXT_INF, FAM, INTEN, INT_INF, PEU and PU with AI, which is a higher-order reflecting system.

Dijkstra & Henseler (2015) were proposed methods to compute the reliability metric pa, ie.

$$\rho_A = (\hat{w}'\hat{w})^2 \frac{\hat{w}'(S-diag\,(S))\hat{w}}{\hat{w}'(\hat{w}\hat{w}'-diag\,(\hat{w}\hat{w}'))\hat{w}}$$

The predicted weight vector of the latent variable, designated as w , is calculated using the indications that are directly related to the latent variable. In this calculation, the empirical covariance matrix of these indicators, indicated as S, is used. The weight estimates w is computed in the context of PLS-SEM to establish the relationship between the lower-order and higher-order components, hence tailoring the computation to reflective-reflective type (and formative-reflective type) higher-order constructs. Using the ratings of the latent variables of the lower-order components, the empirical covariance matrix S is constructed. This formula yields a value of 0.942. Because of this, the measuring approach has enough reliability and validity for both primary and secondary outcomes (Sarstedt et al., 2019).

Structural Model

The second phase involves dissecting the model's framework. The structural model is useful for analyzing data and testing hypotheses about the constructs. In this step, formative-reflective model and mediation effect will be analyzed.

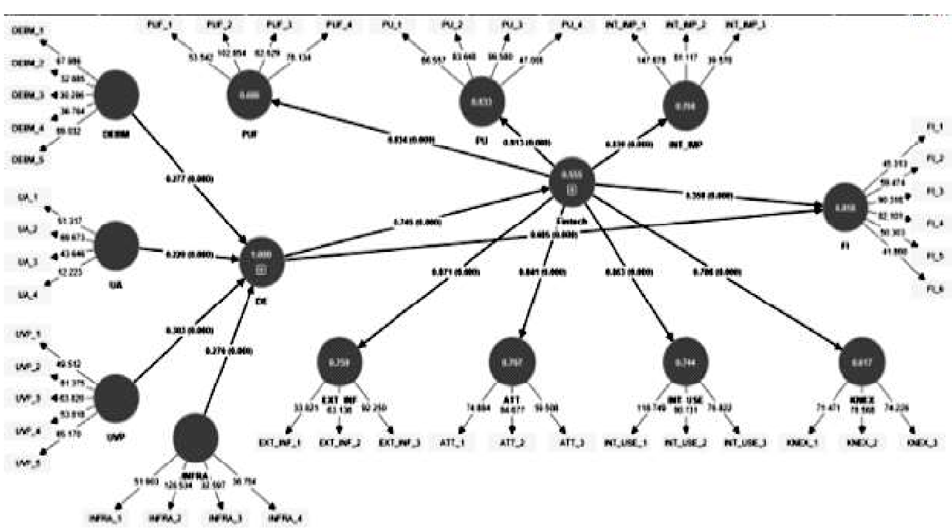

Figure 3. Structural Equation Modelling using Smart-PLS

The initial phase is to examine the direct impact of the DE on FI and the impact of the DE on Fintech. At the 5% level of significance, the data show that DE has a major influence on financial inclusion and also on Fintech. Therefore, H1 and H2 are rejected and it can be summarized that DE has the significant impact on FI

Table 4. Mediation effect among DE, Fintech and FI by showing hypothesis P values i.e., significant

Special Indirect Effect	(O)	(M)	(STDEV)	T statistics (|O/STDEV|)	P values
DE -> Fintech -> FI	0.267	0.266	0.033	8.195	0.000

Source: Author's own representation

Table 4 presented in the study demonstrates the presence of a significant mediating effect among DE, Fintech, and FI. This finding suggests that Fintech acts as a mediator between DE and FI. Studying how DE (the dependent variable) affects FI (the independent variable) is essential for this investigation. R squared is also used to quantify how much of a given independent variable's variance can be accounted for by the dependent variable. In particular, the study says that FI has an R-square value of 0.818 and Fintech has an R-square value of

0.555. This shows how much of each variable's variation is explained by the independent variable DE. The 5% level of significance is used to figure out how important this connection is from a statistical point of view.

Table 5.
Total Effect

Path Coefficients/Total Effect	(O)	(M)	(STDEV)	T statistics (|O/STDEV|)	P values
DEBM -> DE	0.277	0.277	0.005	53.004	0.000
INFRA -> DE	0.276	0.276	0.007	37.132	0.000
UA -> DE	0.22	0.22	0.005	42.238	0.000
UVP -> DE	0.303	0.303	0.006	48.791	0.000

Source: Author's own representation

The next step was to run indirect effect having mediating variable i.e., Fintech (Baron & Kenny, 1986). The results indicate the significant impact of mediating variable on dependent variable. It means fintech has significant impact between digital economy and financial inclusion. Table 5 shows the special indirect effect among DE, Fintech and FI. It explains the partial mediating effect of artificial intelligence on financial inclusion. Partial mediating effect refers to the fact that although DE had a substantial influence on FI, Fintech also had a significant effect on FI as a mediating variable. Therefore, it can be summarized Fintech has played the partial mediating role between DE and FI.

5. Conclusion

The Research findings highlight the pivotal role of the digital economy and (Financial Technology) FinTech innovations in bridging financial inclusion gaps in rural India. Research analyzes three districts from UP West combined with the four cities of Ghaziabad and Faridabad and Noida and Greater Noida in Delhi-NCR. A total of 530 participants participated in the study, which reveals the key elements that determine financial inclusion.

The collected data demonstrates varying levels of literacy and technology awareness throughout the regions since mobile banking along with digital payment platforms have started to gain popularity. The usage of digital financial products among people 30 years or younger stands out as a main study result. Higher numbers of male respondents adopt financial products more than females therefore it is essential to concentrate upon empowering female members of rural financial systems.

Digital wallets together with micro lending platforms operate as part of a system that boosts service accessibility and minimizes transaction fees for those who are financially marginalized. Digital literacy creates difficulties since older demographics resist change while the number of available internet connections remains limited.

The research presents evidence that rural financial inclusion in India can undergo significant transformation through digital economic and FinTech technologies. Stakeholders along with policymakers need to spend money on digital infrastructure as well as financial literacy programs and inclusive FinTech solutions to guarantee equitable access to financial services and economic growth and decrease economic inequalities between urban and rural populations.

Theoretical Implications

Firstly, it underscores the transformative potential of digital technologies and FinTech in addressing longstanding issues of financial exclusion in rural areas. By highlighting the positive impact of these innovations on financial inclusion, the study provides a theoretical framework for policymakers, economists, and researchers to explore similar interventions in other regions grappling with similar challenges.

Secondly, the research sheds light on the importance of adapting global financial concepts and technologies to suit the unique socio-economic context of rural India. This adaptation is crucial for the successful implementation of inclusive financial strategies, as a one-size-fits-all approach may not be effective in diverse, culturally rich environments.

Furthermore, the study encourages a deeper examination of the role of government policies and regulatory frameworks in promoting digital financial inclusion. Theoretical discussions emerging from this research could guide governments and financial institutions worldwide in designing policies that foster inclusive growth through technology-driven financial services.

In sum, the research on the role of digital economy and FinTech in rural Indian financial inclusion enriches the theoretical discourse on technology's impact on financial systems, providing valuable insights that can inform strategies for financial inclusion globally.

Social & Managerial Implications

Financial service providers may play an important part in this transformation by developing successful FinTech solutions that are tailored to the unique demands and challenges of rural Indians. Further study, taking into account aspects such as digital literacy, digital skills, technical trust, and cultural norms, can aid in this process. To increase the acceptance of digital financial services, financial service providers can change their marketing methods and education programmes to better address the barriers and difficulties to adoption. Finally, assessing the efficacy of various FinTech models in promoting financial inclusion in rural areas can aid in identifying the most effective techniques and facilitating their scaling up, so contributing to a more equal and sustainable future for all.

6. Future Scope

Future studies should investigate how blockchain technology and artificial intelligence can help improve rural financial access and understand how these technologies affect various regions as well as the permanent economic impact of digital financial transformation. Academic investigations need to explore gender-based obstacles in monetary inclusion as well as evaluate educational financial awareness initiatives together with approaches that combine FinTech providers with financial institutions and public officials to boost digital money service quality.

7. Limitations

During our investigation, we discovered some crucial findings that are both practical and theoretically relevant, but we also identified certain limitations. The research report solely examines how Industry 5.0 and FinTech affect financial inclusion in rural India and cannot be applied elsewhere. The study's limited sample size, which primarily interviewed rural Indians, may not represent the total rural population, limiting generalizability. The absence of a control or comparison group may also hinder cause-effect interactions. Finally, using only interviews and Smart PLS software may reduce the research's validity and reliability.

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