FACTORS INFLUENCING FINTECH ADOPTION AMONG THE ELDERLY: INSIGHTS FROM AN EMERGING ECONOMY IN INDIA

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Abstract

The adoption of financial technology (fintech) among elderly populations in emerging economies, such as India, remains a critical yet under-explored area of research. This study aims to identify and analyze the factors influencing fintech adoption among the elderly in India, with a focus on their financial inclusion and accessibility to digital financial services. The research draws on the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) to examine factors such as perceived ease of use, perceived usefulness, trust, financial literacy, and socio-cultural influences. Data was collected through surveys and interviews with elderly individuals across urban and rural areas of India, assessing their attitudes toward using digital financial platforms for transactions, investments, and savings. Findings reveal that while technological trust, financial literacy, and ease of use significantly influence adoption, socio-cultural barriers, including reluctance towards technology and limited internet access, remain significant challenges. Additionally, familial support and targeted governmental initiatives play a pivotal role in encouraging fintech usage among the elderly. The study highlights the need for customized fintech solutions, educational programs, and supportive policies to enhance adoption rates among the elderly population in India, ultimately promoting financial inclusion.

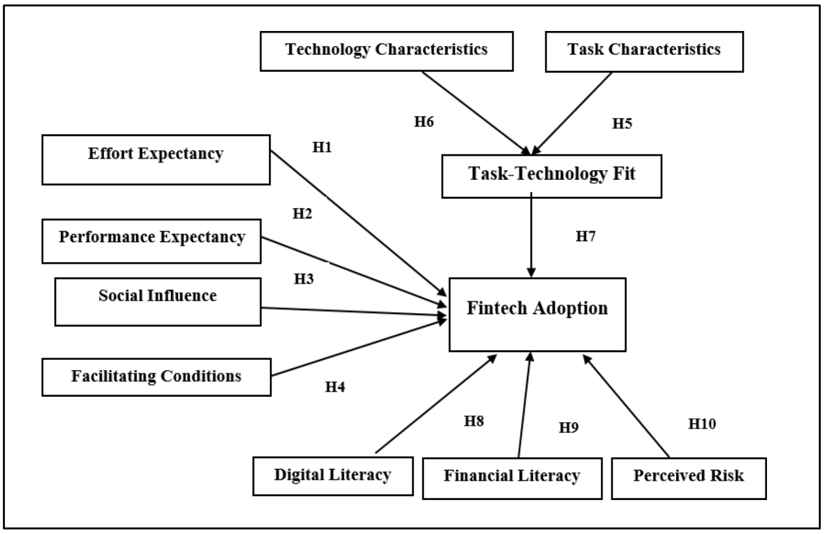
INTRODUCTION

The rapid evolution of financial technology (fintech) has revolutionized how individuals access and manage financial services worldwide. As digital platforms gain prominence, the adoption of these technologies has become a key driver of financial inclusion, particularly in emerging economies such as India. The Indian fintech landscape is expanding at an unprecedented rate, fueled by initiatives aimed at promoting digital payments, online banking, and mobile-based financial services. While fintech adoption has been particularly high among younger, tech-savvy individuals, the elderly population remains underrepresented in this digital revolution. This demographic, often marginalized in the context of technological advancements, faces unique challenges in embracing fintech solutions, which may exacerbate existing financial exclusion. India's elderly population, defined as individuals aged 60 and above, is growing at a significant pace due to increased life expectancy and declining birth rates. According to the 2011 Census of India, the elderly population constituted 8.6% of the total population, and this figure is expected to rise to over 12% by 2026. As the elderly population continues to increase, it is essential to address their financial needs and ensure they are not left behind in the digital transformation of the financial sector. However, a majority of this demographic group remains hesitant or unable to adopt digital financial services due to various factors such as technological barriers, lack of digital literacy, trust issues, and limited access to mobile and internet facilities, especially in rural and remote areas. The concept of financial inclusion emphasizes the need to provide affordable and accessible financial services to all segments of society, regardless of age, income, or geographical location. In this regard, fintech has the potential to enhance financial inclusion by offering easy-to-use, cost-effective, and secure solutions for managing finances. However, for fintech adoption to be effective among the elderly, it is essential to understand the unique barriers and enablers that influence their decision to embrace or reject digital financial tools. The elderly population, due to their life stage, often faces distinct challenges in terms of health, mobility, social connectivity, and technology familiarity. These factors, combined with generational differences in technological exposure and preferences, play a crucial role in shaping the adoption of fintech solutions. Financial literacy is another significant determinant of fintech adoption among the elderly. Many older adults may have limited exposure to modern digital technologies or may lack the skills necessary to navigate online financial platforms. In a country like India, where digital financial services are still in the process of widespread adoption, low levels of digital literacy can be a considerable barrier. On the other hand, enhancing financial literacy through targeted education programs can play a pivotal role in empowering the elderly to utilize fintech tools effectively, ensuring they are not excluded from the benefits of digital finance. Moreover, trust in the security and reliability of digital financial services is a critical issue for the elderly, particularly in India, where concerns over fraud and scams are prevalent. Given the limited trust in digital platforms and the risk of exploitation, older adults are more likely to remain hesitant in adopting fintech services. The role of social influence, including the guidance and support from younger family members, peers, and local community groups, also plays an important role in shaping the attitudes and behaviors of the elderly toward fintech adoption. Family members and close-knit social circles often act as mediators, helping the elderly navigate unfamiliar digital platforms and building trust in these services. The advent of government initiatives, such as the Digital India campaign, has been pivotal in encouraging digital inclusion across the population. However, for the elderly, these initiatives must be adapted to address their specific needs and challenges. The government, financial institutions, and fintech companies must collaborate to create an environment that fosters inclusivity by developing fintech solutions that are user-friendly, secure, and tailored to the needs of older adults. This study aims to explore the key factors influencing fintech adoption among the elderly in India, with a focus on understanding their unique challenges and the potential solutions that can foster their inclusion in the digital economy. By examining factors such as financial literacy, perceived ease of use, trust, accessibility, and socio-cultural influences, this research seeks to provide insights into the obstacles and enablers that shape the elderly's engagement with fintech.

1. LITERATURE REVIEW

The adoption of financial technology (fintech) among the elderly has been explored in several studies worldwide, offering valuable insights into the factors that influence their participation in digital financial services. While research on this topic is still developing, international literature provides a foundation for understanding how elderly populations in both developed and developing countries engage with fintech. These studies often examine various factors such as digital literacy, trust, accessibility, and social influences, which shape the willingness and ability of older adults to adopt and utilize fintech services. A key barrier to fintech adoption among the elderly is digital literacy. In a study by Davidson et al. (2016), the authors found that older adults often experience difficulties in navigating digital technologies, which hinders their adoption of fintech services. This challenge is compounded by age-related cognitive and sensory decline, making it harder for the elderly to understand and use digital financial tools. Similarly, Chiu et al. (2019) identified that elderly individuals are less likely to use fintech services due to unfamiliarity with digital devices, a lack of proper training, and the complexity of financial applications. These technological barriers are especially prevalent in developed economies, where older adults often have limited exposure to technology compared to younger generations. In contrast, kim et al. (2020) studied fintech adoption in india and found that the elderly were less digitally literate, and many still preferred traditional face-to-face banking. Their findings suggest that digital literacy programs and training are essential to bridging this gap and enhancing fintech adoption among older populations. Similarly, Al-Adwan et al. (2020) observed that elderly users in Jordan experienced a high level of discomfort with online financial platforms, citing challenges in navigation and information overload, further highlighting the need for more intuitive and user-friendly fintech solutions for the elderly. To mitigate these concerns, Zhou & Lee (2020) argue that fintech platforms must implement robust security features, such as multi-factor authentication and user-friendly fraud prevention tools, to build trust among older users. Furthermore, trust can be fostered through positive experiences with fintech services and endorsements from family members or peers. Research by Herzog et al. (2021) in the U.K. highlighted that trust in fintech increases when older adults receive assistance from younger generations, reinforcing the importance of social support networks in encouraging technology adoption. Financial literacy is a major determinant of fintech adoption among the elderly in many developed countries. According to Lusardi & Mitchell (2014), older adults with low financial literacy are less likely to understand or effectively use digital financial tools, such as online banking, payment platforms, or investment apps. In the U.S., Brown & Weigand (2019) found that elderly individuals with low financial literacy are often excluded from the benefits of fintech because they lack the necessary knowledge to evaluate digital financial services effectively. This knowledge gap results in a high level of financial anxiety and resistance to adopting new financial technologies. To address this issue, studies like Gnanadass (2020) emphasize the need for comprehensive financial literacy programs targeted at the elderly. Such programs should not only teach the basics of digital financial services but also provide ongoing support and resources to ensure that older adults feel confident and secure in using fintech tools. Atkinson & Messy (2012) highlighted that increasing financial literacy among older populations can significantly enhance their willingness to adopt digital financial services and manage their finances more effectively. Socio-cultural factors are essential in understanding fintech adoption among the elderly. In cultures where traditional values and interpersonal interactions dominate, older adults may be less inclined to adopt digital financial services. A study by Lim et al. (2019) in Singapore found that the elderly are more likely to use digital services when their social circles, including family members and peers, encourage them. The support of younger generations, particularly in family-oriented societies, plays a crucial role in helping older adults navigate the complexities of fintech platforms. Williams et al. (2017) also noted that elderly individuals in Australia were more likely to trust and use digital financial services if their children or grandchildren were active users of the technology. In contrast, Kuo et al. (2020) found that in some European countries, elderly people with higher levels of cultural conservatism exhibited a greater reluctance to adopt fintech services, preferring face-to-face interactions in traditional banking settings. In these cases, the challenge is not only technological but also deeply rooted in cultural attitudes towards technology and change. Norton & McFarlane (2020) argue that understanding these socio-cultural factors is crucial for developing fintech solutions that resonate with older adults and address their specific needs and preferences. Government support and policy interventions have been critical in promoting fintech adoption among the elderly. In the U.K., Robinson et al. (2019) found that the government's efforts to integrate older adults into the digital economy, such as providing subsidies for digital devices and internet access, were essential in reducing barriers to fintech adoption. Similarly, in South Korea, Choi & Lee (2020) reported that government-backed initiatives designed to enhance digital literacy and provide elderly-friendly financial services were successful in improving fintech adoption among older adults. In the case of emerging economies, Tan et al. (2020) argue that government policies aimed at reducing digital inequalities are essential for ensuring that the elderly are not left behind in the fintech revolution.

Figure I: Conceptual Framework



Source: Author's Representation

2. RESEARCH METHODOLOGY FRAMEWORK

Measures

This research employs a deductive approach and a cross-sectional survey design for data collection from elderly respondents. The survey was conducted using a standardised questionnaire, which was adapted and customized using scales from existing literature (Table I). The constructs were measured on a five-point Likert scale ranging from "strongly disagree" to "strongly agree.

Table I: Sources of Constructs

Constructs	Adapted from the following sources
UTAUT Framework Effort Expectancy, Performance Expectancy, Social Influence, Facilitating Conditions	Venkatesh et al., (2003); Zhou et al., (2010); Boonsiritomachai, (2019)
TTF Framework Task Characteristics, Technology Characteristics	Lin & Huang, (2008)
Digital Literacy	Ullah et al., (2022)
Fintech Adoption	Nugraha et al., (2022)
Perceived Risk	Kim et al., (2009); Zhou et al., (2010)
Financial Literacy	Rahman et al., (2021); Foster & Johansyah, (2021)

Source: Author's Representation

Sample and Sampling Design

The target population encompasses fintech users above the age group of 60 years (elderly) living in metro cities in India. Data collection was conducted offline from respondents (elderly population) residing in metro cities in the Indian provinces of Delhi, Gujarat, Maharashtra, Uttar Pradesh, and West Bengal (NSO, 2021). The non-random sampling method, precisely convenience and snowball sampling, was adopted to ensure a diverse representation of respondents in reference to demographics such as age, gender, annual income, employment, and education. A sample size of more than 400 respondents was considered adequate, as determined by G*Power software calculations (Faul et al., 2007) to ensure statistical robustness and reduce sampling error. Pilot testing was carried out with 30 respondent's sample to evaluate the reliability and validity of the survey instrument prior to large-scale data collection. Feedback, led to minor refinements, including rewording ambiguous questions and refining measurement scales for clarity. The final instrument was optimized for clarity, reducing respondent bias and improving data accuracy. This procedure ensured that the questionnaire effectively captured the envisioned constructs for SmartPLS 4.0 analysis. A sample size of 550 was chosen for further analysis to minimize non-response errors, missing values, and outlier biases (Hair et al. 2011). 77% was the response rate, yielding 424 valid responses. Males predominate among the respondents (68%). Most of the respondents were 60–70 years old, graduates, and retired from government employment. Table II provides information about the demographics of elderly fintech adopters in India.

Table II: Demographic Composition

Variable	**Frequency**	**Percentage**
Annual Income (Lakhs)		
Between ₹ 1- ₹ 2 Lakh	125	29.48%
Between ₹ 2 to ₹ 3 Lakh	145	34.20%
Between ₹ 3 to ₹ 4 Lakhs	108	25.47%
Above ₹ 4 Lakhs	46	10.85%
Profession		
Government Employee (Retired)	139	32.78%
Private Sector or Corporate Employee	131	30.90%
Business Owner or Entrepreneur	87	20.52%
Self-employed	67	15.80%
Education		
Secondary	65	15.33%
Senior Secondary	97	22.88%
Graduation	119	28.07%
Post-Graduation	74	17.45%
Professional / others	69	16.27%
Age (in Years)		
Between 60 to 70	262	61.79%
Between 71 to 80	119	28.07%

81 & Above	43	10.14%
Gender		
Male	289	68.16%
Female	135	31.84%

Source: Author's Representation

3. RESULTS

Data Analysis

The research applies PLS-SEM to test the relationships between the constructs (Hair et al., 2017). SmartPLS 4.0 will run the following for the analyses: a. measurement model evaluation (validity and reliability); b. structural model evaluation (hypotheses and path coefficients); c. bootstrapping for determining the significance of paths. Therefore, such an approach will statistically confirm the findings for practical insights into the factors determining fintech adoption. In a regression model, a strong correlation among variables can lead to multicollinearity (Hair et al., 2011), and becomes an issue if VIF exceeds 10 (Kline, 2015). Table III, shows all VIF values below 10, confirming no concerns for multicollinearity. Kock (2022) suggests that if VIFs in the inner model are ≤ 3.3 in a full collinearity test, the model is free from common method biases. Since all VIF values are < 3.3, this model meets that criterion.

Table III: Overall Constructs Collinearity

Construct	Overall collinearity VIF
Effort Expectancy	2.041
Performance Expectancy	2.166
Social Influence	2.104
Facilitating Conditions	1.046
Digital Literacy	2.236
Financial Literacy	1.762
Perceived Risk	1.250
Technology Characteristics	1.028
Task Characteristics	1.028
Task-Technology Fit	1.006

Source: Author's Representation

Common method variance (CMV) was assessed using Harman's single factor test in IBM SPSS 29. Exploratory factor

analysis confirmed that the first factor's loading (23.88%) was below the 50% threshold, indicating no CMV concerns.

Measurement Model

The outer model (measurement model) was assessed for construct validity and reliability. Confirmatory factor analysis (CFA) confirmed that all factor loadings (outer) were > than the 0.5 threshold (Bagozzi et al., 1991), ensuring the retention of all variables for further analysis. The Composite Reliability (CR) and Cronbach's Alpha values of all constructs were above the 0.7 cut-off (Hair et al., 2011), indicating strong reliability and adequate internal consistency (Nunnally & Bernstein, 1994). Furthermore, the average variance extracted (AVE) values exceeded the minimum threshold of 0.5 (Bagozzi & Yi, 1988), confirming the construct's convergent validity. Table IV presents a summary of Measurement Model.

Table IV: Summary of Measurement Model

Constructs	**Variable Items**	**Outer Loadings**	**Cronbach's alpha**	**Composite reliability**	**Average variance extracted**
Effort Expectancy (EE)	EE1	0.797	0.831	0.889	0.664
	EE2	0.792			
	EE3	0.814			
	EE4	0.854			
Performance Expectancy (PE)	PE1	0.817	0.783	0.86	0.606
	PE2	0.767			
	PE3	0.786			
	PE4	0.743			
Social Influence (SI)	SI1	0.845	0.756	0.86	0.673
	SI2	0.835			
	SI3	0.779			
Facilitating Conditions (FC)	FC1	0.842	0.867	0.909	0.715
	FC2	0.857			
	FC3	0.854			
	FC4	0.828			
Task-Technology Fit (TTF)	TTF1	0.827	0.768	0.866	0.683
	TTF2	0.826			
	TTF3	0.827			
Task Characteristics (TAC)	TAC1	0.831	0.779	0.872	0.694
	TAC2	0.814			
	TAC3	0.854			
Technology Characteristics (TEC)	TEC1	0.84	0.781	0.873	0.696
	TEC2	0.828			
	TEC3	0.834			
Financial Literacy (FL)	FL1	0.814	0.856	0.902	0.698
	FL2	0.831			
	FL3	0.841			
	FL4	0.856			
Perceived Risk (PR)	PR1	0.821	0.764	0.864	0.679
	PR2	0.841			

	PR3	0.81			
Digital Literacy (DL)	DL1	0.771	0.845	0.89	0.617
	DL2	0.806			
	DL3	0.806			
	DL4	0.784			
	DL5	0.761			
Fintech Adoption (FA)	FA1	0.804	0.883	0.914	0.681
	FA2	0.835			
	FA3	0.817			
	FA4	0.842			
	FA5	0.826			

Source: Author's Representation

The Fornell-Larcker Criterion was used to assess discriminant validity, which requires that the square root of the AVE for each construct exceed its correlation with other constructs. The off-diagonal values should be lower than the diagonal values (square roots of AVE) in corresponding rows and columns. The reported values confirm adequate discriminant validity. The discriminant validity values are tabulated in Table V as per the Fornell-Larcker Criterion.

Table V: Discriminant Validity (Fornell-Larcker Criterion)

	DL	EE	FC	FL	PE	PR	SI	TAC	TEC	TTF
DL	**0.786**									
EE	0.604	**0.815**								
FA	0.262	0.26								
FC	0.157	0.192	**0.846**							
FL	0.534	0.552	0.15	**0.836**						
PE	0.614	0.594	0.153	0.588	**0.779**					
PR	0.288	0.376	0.106	0.328	0.369	**0.824**				
SI	0.655	0.578	0.167	0.476	0.597	0.371	**0.82**			
TAC	0.039	-0.031	-0.081	0.032	0.006	-0.098	-0.029	**0.833**		
TEC	0.063	-0.012	-0.036	0.024	0.03	-0.07	0.024	0.164	**0.834**	
TTF	-0.018	0.016	-0.016	0.001	-0.038	-0.041	-0.016	0.138	0.158	**0.827**

Source: Author's Representation

In summary, the measurement model is valid and exhibits adequate reliability, and good construct validity. Hence, we proceed with hypothesis testing using the structural path model.

Structural Model

The assessment of structural model (inner model) reveals significant insights into the relationships among constructs. The bootstrapping method was used for assessment, focusing on the determination coefficient (R^2), predictive relevance (Q^2), and hypothesis testing. This non-parametric procedure tests the statistical significance of PLS-SEM outcomes, including R^2 (coefficient of determination) values, which indicate the explained variance for each predicted variable (Table VI) in the conceptualised model.

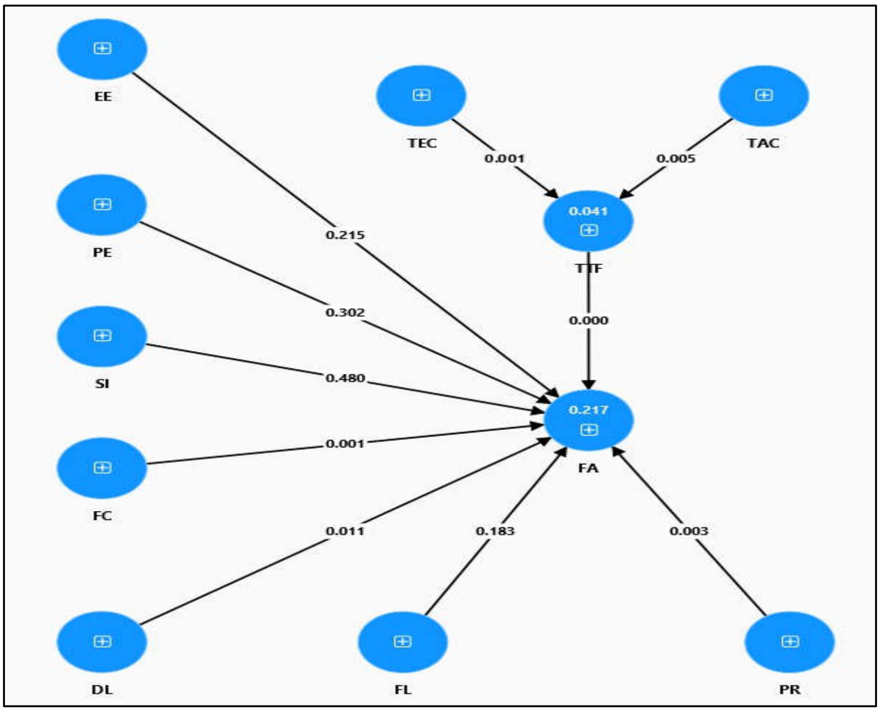
Table VI: R-Square values

	Coefficients (β)	Standard deviation	t-statistics	P values
FA	0.217	0.039	5.563	0
TTF	0.041	0.021	1.931	0.027

Source: Author's Representation

In this study, the R^2 for the construct "FA" (Fintech Adoption) is 0.217, indicating that the independent variables explain approximately 21.7% of its variance. The R^2 value for "TTF" (Task-Technology Fit) is 0.041, indicating low explanatory power, with only 4.1% variance explained by the regressors. These values indicate that while the model captures some of the variance in FA, but has limited explanatory power for TTF. The Q^2 values, which assess the model's predictive relevance, are noteworthy. The Q-squared for FA is 0.129, indicating a moderate level of predictive relevance for this construct. Conversely, the Q^2 for TTF is 0.027, suggesting that the model's predictive relevance for TTF is weak. This disparity underscores the need for further exploration of factors influencing TTF. Large, medium, and small predictive relevance correspond to Q^2 values of 0.35, 0.15, and 0.02, respectively (Hair et al., 2017).Thus, while FA shows moderate predictive relevance, TTF does not meet the threshold for meaningful predictive capability. This disparity suggests potential improvement in the model's structure or construct relationships for TTF.

Figure II: The Structural model with P values



Source: Author's Representation

Hypothesis testing results indicate several significant direct effects. The path coefficient (Table VII) from FC to FA is 0.121 ($p = 0.001$), demonstrating a strong positive association. Similarly, the path from PR to FA has a coefficient estimate of 0.143 ($p = 0.003$), confirming significance. However, EE and FL to FA, yielded non-significant results, with p-values of 0.215 and 0.183, respectively.

Table VII: Path Coefficient

Hypotheses	**Paths**	**Coefficients (β)**	**Standard deviation**	**t statistics**	**P values**	**Decision**
H1	**EE -> FA**	0.049	0.062	0.789	0.215	Insignificant
H2	**PE -> FA**	0.034	0.066	0.52	0.302	Insignificant
H3	**SI -> FA**	-0.003	0.064	0.05	0.48	Insignificant
H4	**FC -> FA**	0.121	0.039	3.081	0.001	Significant
H5	**TAC -> TTF**	0.123	0.047	2.611	0.005	Significant
H6	**TEC -> TTF**	0.143	0.048	2.978	0.001	Significant
H7	**TTF -> FA**	0.309	0.044	7.024	0	Significant
H8	**DL -> FA**	0.142	0.062	2.285	0.011	Significant
H9	**FL -> FA**	0.05	0.055	0.906	0.183	Insignificant
H10	**PR -> FA**	0.143	0.052	2.778	0.003	Significant

Source: Author's Representation

The indirect effects also present significant findings, particularly the paths from TAC to FA (0.038, $p = 0.014$) and from TEC to FA (0.044, $p = 0.006$). This suggests that both TAC and TEC have meaningful impacts on FA through their respective mediators. Table VIII presents the specific indirect effects.

Table VIII: Specific Indirect Effects

Paths	**Coefficients (β)**	**Standard deviation**	**t statistics**	**P values**
TEC -> TTF -> FA	0.044	0.018	2.507	0.006
TAC -> TTF -> FA	0.038	0.017	2.187	0.014

Source: Author's Representation

In conclusion, the structural model demonstrates varying degrees of explanatory power and predictive relevance for the constructs under study. While some direct effects are statistically significant, others are not, indicating areas for future research and model refinement. The results underscore the complexity of the relationships among constructs in technology adoption.

4. DISCUSSION

The present study aimed to explore the key determinants of fintech adoption among elderly Indians using the UTAUT and TTF models, along with contextual constructs like DL, FL, and PR. Valuable insights indicate elderly Indian's perspectives on fintech adoption, underscoring distinctive behavioral patterns that differ from broader technology adoption trends. Unlike findings from UTAUT-based researches, effort expectancy (EE), performance expectancy (PE), and social influence (SI) were not identified as statistically significant predictors of fintech adoption among the Indian elderly. The relationships of EE (*$\beta = 0.049$, $t = 0.789$, $p = 0.215$*), PE (*$\beta = 0.034$, $t = 0.52$, $p = 0.302$*), and SI (*β= -0.003, t= 0.05, p = 0.0.48*) with fintech adoption were weak and statistically insignificant leading to the rejection of H1, H2, and H3. Among elderly Indians, EE and PE failed to create a concrete impact. One likely explanation for this idiosyncrasy is lack of self-confidence in the elderly and poor knowledge of new technology. Because of limited exposure and experience with smart devices and digital financial platforms, the majority of elderly users require assistance and support in operating fintech applications despite improvised user interfaces. Social influence (SI) did not have much effect on adoption, since peer groups of this age may lack digital adoption or continue to cling to traditional banking systems. Therefore, trust mechanisms, customized assistance, and security promises to be more significant than functional usability or performance promises to encourage the elderly to adopt fintech services. The UTAUT construct facilitating conditions (FC) exhibited a significant positive correlation (*$\beta = 0.121$, $t = 3.081$, $p < 0.001$*) with fintech adoption, supporting H4. The findings align with prior studies (Rahman et al., 2021; Patil et al., 2020) and underscore the profound role of tech-enabled architecture, customer assistance services, and institutional frameworks in strongly boosting the likelihood of fintech adoption. Moreover, the perceived support from fintech facilitators is significant in overcoming adoption hurdles among elderly users. This accentuates the importance of establishing robust assistive systems on behalf of fintech facilitators. The empirical evidence supports the Task-Technology Fit (TTF) model as a strong explanatory variable in elderly's fintech adoption. Specifically, task characteristics (TAC) and technology characteristics (TEC) both significantly impact task- technology fit (TTF), thereby supporting H5 (*$\beta = 0.123$, $t = 2.611$, $p < 0.005$*) and H6 (*$\beta = 0.143$, $t = 2.978$, $p < 0.001$*). These findings highlight that adoption behaviour is driven by the alignment between the tasks the elderly users seek to accomplish and the technological capabilities of fintech platforms. The study's finding revealed a strong and statistically significant direct association between TTF and fintech adoption (*$\beta = 0.309$, $t = 7.024$, $p < 0.00$*), validating H7. The finding is in alignment with previous studies and demonstrates that when fintech platforms effectively support the specific financial management tasks of elderly users through appropriate technological features, the likelihood of adoption increases substantially. Digital literacy (DL) was identified as a noteworthy determinant of fintech adoption ($\beta = 0.142$, $T = 2.285$, $p < 0.01$), thereby supporting H8, highlighting an essential dimension of technology adoption in the Indian context. Interventions using real-world examples, repetitive task-oriented learning, and simple content can empower the elderly to interact comfortably with fintech platforms. For fintech facilitators, this finding underscores the need to design product and outreach strategies that address the digital literacy gap among the elderly. In contrast to expectations and previous research (Long et al., 2023), financial literacy (FL) was not a key determinant of fintech adoption (*$\beta = 0.05$; $t = 0.906$, $p = 0.183$*), leads to the rejection of H9. This indicates that while elderly users may possess basic financial knowledge such as familiarity with basic banking, interest rates, or financial products does not necessarily translate into a willingness or capability to use fintech platforms. They might remain hesitant unless they are digitally proficient and confident in using technology. Thus, financial knowledge alone is insufficient without digital competencies and trust in the digital environment. Notably, perceived risk (PR) exhibits a statistically significant positive association with fintech adoption (*$\beta = 0.143$; $t= 2.778$, $p < 0.003$*), supporting H10. This finding aligns with prior studies (Jena, 2023) but contrary with the common belief that perceived risk generally serves as a barrier to technology adoption.

5. CONCLUSION

The adoption of financial technology (fintech) among the elderly in India is influenced by several complex factors, reflecting the unique challenges and opportunities this demographic faces in an increasingly digital world. While fintech holds the potential to significantly enhance financial inclusion, the elderly population in India is often hesitant to embrace digital financial tools due to barriers such as limited digital literacy, concerns over security, and socio-cultural factors that shape their perceptions and interactions with technology. Digital literacy remains a key barrier to fintech adoption, with many elderly individuals lacking the necessary skills to navigate complex digital platforms. This digital divide is especially pronounced in rural areas, where access to smartphones, stable internet connections, and technical training are limited. Although initiatives such as the Digital India campaign have made strides in increasing internet penetration and digital literacy, a significant gap remains. For elderly individuals who have limited experience with technology, the absence of user-friendly, intuitive digital platforms makes fintech adoption even more challenging. Tailored digital literacy programs, particularly those aimed at older adults, are critical to bridging this gap and fostering confidence in using digital financial tools. The elderly’s reluctance to trust digital platforms is compounded by their preference for face-to-face interactions, which offer a sense of security and personal connection. To overcome these barriers, fintech platforms must prioritize transparency, robust security features, and customer support systems that cater specifically to the elderly. By educating the elderly on security protocols and demonstrating the reliability of digital services, fintech providers can build trust and encourage adoption. Financial literacy plays a crucial role in enabling the elderly to effectively use fintech tools. In India, many older adults still have limited exposure to financial services, especially digital ones. While urban elderly populations may have some familiarity with basic banking, rural and semi-urban elderly individuals are often excluded from these services due to a lack of knowledge.

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