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Determinants of Fintech Adoption among the Elderly: Perspectives from an Emerging Economy, India

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KEYWORDS

UTAUT, TTF, Digital Literacy, Financial Literacy, Elderly Population, Structural Equation Modelling (SEM)

ABSTRACT

The present study explores the key determinants influencing fintech adoption among the elderly population in India an important yet often overlooked demographic within an emerging economy. Employing a cross-sectional survey design, data was collected from 424 elderly individuals aged 60 and above residing in Indian metropolitan cities through a structured questionnaire. Three additional contextual constructs-financial literacy, digital literacy, and perceived risk were added to the theoretical framework along with the key constructs adapted from the Unified Theory of Acceptance and Use of Technology (UTAUT) and Task-Technology Fit (TTF) frameworks to offer a more nuanced understanding of fintech adoption among the elderly. Structural Equation Modelling (SEM), was performed using SmartPLS 4.0, and the results highlight facilitating conditions, task-technology fit, digital literacy, and perceived risk as significant predictors of fintech adoption for this demographic. However, the influence of effort expectancy, performance expectancy, and social influence was found to be negligible. This underscores the necessity of tailored, assistive, and capacity-building interventions to create an all-inclusive adaptive environment. Moreover, concerted efforts from fintech enablers and policymakers are indispensable to ensure the effective inclusion of elderly populations in the progressing digital financial ecosystem.

1. INTRODUCTION

The fusion of advanced technology with the financial ecosystem has led to the emergence of a transformative domain referred as fintech (Tun-Pin et al., 2019). At global level, this confluence has fueled the development of innovative business models, the realignment of organizational structures, and the creation of new architectures (Singh et al., 2020). The technology-driven financial ecosystem is leading to a profound and transformative shift in the delivery of financial services in a secure, affordable, and user-friendly manner. Specifically, advancements in digital remittances reflect this trend. Consequently, in emerging economies, the gender- based inequalities in access to finance have narrowed by nine percentage points to six percentage points (Demirgüç-Kunt et al., 2022).

India is positioned as a global leader in fintech expansion, standing as the third-largest and fastest-growing fintech market, coupled with an adoption rate of 87%, significantly surpassing the worldwide average of 64% (Sreenu, 2025). By 2030, the Indian market is estimated to manage $1 trillion in assets under management (AUM) and deliver $200 billion in revenue. Moreover, India's digitalization trajectory is expected to advance further by 2025, propelled significantly by middle-aged and senior users.

India's elderly population was estimated at 138 million in 2021, and is projected to reach 194 million by 2031 (NSO, 2021). According to the India Ageing Report (UNFPA, 2023), this figure is expected to further rise from 153 million to 347 million

by 2050. This demographic transition has significant implications for financial service providers, as individual's aged 60 and above is currently accounting for 10% of India's population, and are projected to double by 2050. Globally, the geriatric population is expected to increase from 1 billion (13.5% of the global population) in 2020 to 2.1 billion by 2050 (Benu, 2023). Against this backdrop, "aging" and "digitalization" emerge as two defining global phenomena, reshaping both demographic and technological landscapes.

The convergence of these trends has led to the advent of digital financial integration, with fintech driving transformative changes in the financial sector (Hassan et al., 2023). However, without a strong consideration for financial inclusion, especially regarding the older adult segment (60+), this digital transformation might not achieve all it could. Yet, fintech is a great facilitator. Although fintech holds significant promise, however, addressing the specific challenges faced by this dynamic cohort including socio- technological, and cognitive barriers is essential to fully unlock the potential of this growing market segment. The existing literature challenges digital financial inclusion based on differing population segments, but none with older adults specifically. Thus, this research attempts to bridge this gap by exploring the determinants of fintech adoption for older adults aged 60+ years in India.

While most of the literature focused on the older population's financially exclusionary aspects, this paper attempts to shift the narrative toward understanding how they can include themselves in financial inclusion through digital means. This research offers pragmatic suggestions for major stakeholders like regulating authorities, fintech enablers, policymakers, and strategic business conglomerates for designing and rendering fintech solutions for onward preparedness and sustenance during old age (Singh et al., 2020).

This study attempts to determine fintech adoption determinants among India's elderly through a modified model of the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) and the Task-Technology Fit (TTF) (Goodhue & Thompson, 1995). The UTAUT model was selected for its comprehensiveness and effectiveness in explaining the determinants of technology adoption across diverse contexts. Given that the TTF model evaluates how well tasks align with technological attributes, integrating TTF with UTAUT is expected to provide deeper comprehensions into fintech adoption.

This study makes three strategic contributions. First, it focuses exclusively on fintech adoption among the elderly (aged 60 and above), a topic that remains unexplored in the literature, particularly within the fintech adoption context. Second, while existing research on fintech adoption mostly emphasizes users' technology perception, it frequently ignores the aspect of task-technology fit. To mitigate this gap, the present study combines the UTAUT and TTF frameworks to explore the fintech adoption determinants specifically among the elderly. Third, to offer a more in-depth understanding of digital financial inclusion for this demographic, the study incorporates three additional variables digital literacy, financial literacy, and perceived risk acknowledging their significant influence on fintech adoption as identified in the literature. This extended model is conceptualized to generate advanced perspectives into the fintech adoption behavior of the elderly population. The flow of the study is as follows: Section 2 reviews the relevant literature, Section 3 describes the research design and methodology, Section 4 presents the analysis and findings, Section 5 offers a detailed discussion, and Section 6 concludes with practical implications for Asian businesses.

2. LITERATURE REVIEW

Fintech is defined as an array of contemporary digital financial innovations designed to leverage technology to deliver personalised and efficient financial services (Hassan et al.,2022; Hua & Huang, 2021), thereby promoting fintech adoption across the demographic labyrinth (Wong et al., 2021). Yet socio-cultural contexts with different technological socialization across demographic subgroups create different patterns of fintech adoption (Venkatesh et al., 2012).

The Unified Theory of Acceptance and Use of Technology is a general, all-encompassing model that boasts support through practicality (Yohanes et al., 2020); ability to integrate with various theoretical models (Huang, 2023; Merhi et al., 2019) and adopt variables relative to the context of research (Cai et al., 2023). This adaptability enhances its predictive power, making it a particularly suitable and extensively used model for studying user's perspectives on technology adoption (Al-Nawayseh, 2020). In addition, scholars indicate that the Task-Technology Fit framework (TTF) relative to this UTAUT model favoured enhancing comprehension of technology adoption (Tarhini et al., 2016; Oliveira et al., 2014). The following section illustrates the constructs of the UTAUT model as established by Venkatesh et al. (2003).

Effort expectancy

Effort expectancy (EE) assesses an individual's belief about the level of effort required to use technology (Venkatesh et al., 2003). Simple and easy to navigate technology is more likely to be embraced, as it reduces the efforts required to accomplish the intended task (Rabaa'i, 2023; Wang et al., 2020; Al-Saedi et al., 2020). Particularly, in the fintech sector, technology that

alleviates techno-stress and simplifies operational complexity is regarded as competent (Aseng, 2020), hence enhancing probability of its adoption among users (Ojiaku et al., 2024). Empirical evidences from prior studies has established EE as a central explanatory variable for fintech adoption (Mensah & Khan, 2024; Sleiman et al., 2022; Saha & Kiran, 2022), positively influencing users' attitudes toward incorporating technology into their everyday financial habits (Jena, 2023; Patil et al., 2020). In light of this analysis, the following hypothesis was formulated:

H1: Effort expectancy significantly influences fintech adoption.

Performance Expectancy

Performance expectancy (PE) measures an individual's conviction that task performance will be augmented by using a particular technology (Rahi et al., 2019; Venkatesh et al., 2003). Previous studies have reckoned PE as a significant predictor of technology adoption (Merhi et al., 2019), as it is able to capture the user's willingness to adopt mobile payment systems (Rabaa'i, 2023; Wang et al., 2020), and e-banking services (Rahman et al., 2021), driven by the belief that these technologies improve the efficiency and effectiveness of financial transactions (Chan et al., 2022). Additionally, studies by Abegao Neto & Figueiredo, (2023), Lu & Kosim, (2022), and Giovanis et al., (2019) have reported a positive correlation between PE and fintech adoption. This gives rise to the development of the following hypothesis:

H2: Performance expectancy has a significant influence on fintech adoption.

Social influence

Social influence (SI) refers to a psychological state in which an individual feels assured of receiving implicit support from their social circle when adopting technological innovations (Venkatesh et al., 2003).This perceived reinforcement from the social ecosystem increases self-assurance and self-belief (Srivastava & Singh, 2020), motivating individuals to embrace technological advancements (Joa & Magsamen-Conrad, 2022; Rahman et al., 2021). However, research findings are inconsistent pertaining to the effect of SI on technology adoption across different demographic and socio-cultural contexts (Mei, 2024). Some indicate a positive association (Abegao Neto & Figueiredo 2023; Sleiman et al. 2022; Saha & Kiran 2022; Lu & Kosim 2022), whereas others establish its insignificant impact (Al-Saedi et al., 2020; Huang & Chang, 2017). The authors therefore hypothesized as follows:

H3: Social influence significantly influences fintech adoption.

Facilitating conditions

Facilitating conditions (FC) refer to an individual's belief in the availability of supportive organizational and technical resources (Alkhwaldi & Al-Ajaleen, 2022) that enhance confidence in technology adoption (Venkatesh et al., 2003). In fintech, FC encompasses a holistic ecosystem, including facilitator's architectural support, user's competencies, and familiarity with assistive tools that drives seamless adoption (Xie et al., 2021). Empirical research on FC and fintech adoption yielded mixed findings. While Rabaa'i (2023), Kurniasari et al. (2022), Rahman et al. (2021), Wang et al. (2020), Patil et al. (2020), and Zhou et al. (2010) reported a positive correlation, Ali et al. (2018) reported a weak association in emerging economies, and Oliveira et al. (2014) reported insignificant relationship attributing these variations to differences in demographics and specific contexts. The present study proposed the following hypothesis:

H4: Facilitating conditions significantly influence fintech adoption.

Task-Technology Fit

The Task-technology fit (TTF) framework assesses (Goodhue & Thompson, 1995) how well a technology's capabilities align with intended tasks, underlining the interaction between task demands and technology characteristics (Wang et al., 2020). Synergies among tasks, technology and users results in effective TTF, while increased technological complexity deters task performance and reduces TTF. Task characteristics (TAC) encompass processes that transform inputs into outputs (Al-Maatouk et al., 2020), whereas, Technology characteristics (TEC), enhance user's performance by reducing effort (Ojiaku et al., 2024). Prior research confirms that task and technology characteristics predicts TTF (Tam & Oliveira, 2016). In fintech, a strong task-technology fit (such as quick and convenient digital financial transaction) drives technology adoption (Zhou et al., 2010), while poor or weak TTF discourages adoption (Lin & Huang, 2008) or in some cases, shows non-significant effect (Wang et al., 2020). The following hypotheses are proposed based on the literature review:

H5: Task characteristics significantly affect the task-technology fit.

H6: Technology characteristics significantly affect the task-technology fit.

H7: Task-technology fit significantly influences fintech adoption.

Digital Literacy

Digital literacy (DL) refers to the proficiency to navigate intricate digital platforms, manage digital resources, and leverage

advanced digital tools and settings for effective outcomes (Yetti, 2024; Zhang et al., 2023). DL enhances an individual's ability to assess, appraise, participate and operate digital platforms effectively (Ullah et al., 2022) and identified as a significant predictor of technology adoption (Adel, 2024). Comparative studies revealed that digitally literate individuals are more likely to adopt fintech (Nguyen et al., 2024; Islam & Khan, 2024; Bergdahl et al., 2020). Thus, the following hypothesis is tested:

H8: Digital literacy (DL) has a significant influence on fintech adoption.

Financial Literacy

Financial Literacy (FL) enables individuals to make logical financial decisions and efficiently manage personal financial objectives (Koskelainen et al., 2023). Individuals with an adequate level of financial literacy are more likely to use fintech applications (Long et al., 2023), as FL empowers their ability to appraise, believe, and engage effectively with digital financial products, make sound financial choices and ensure secure inclusion in the fintech ecosystem (Ullah et al., 2022). FL also reinforces users' belief in fintech adoption, facilitating portfolio analysis, investment planning (Farida et al., 2021), and retirement savings management (Gallego-Losada et al., 2022). Moreover, earlier research highlights a statistically significant positive association between financial literacy and fintech adoption (Abdallah et. al., 2025; Islam & Khan, 2024; Alkhwaldi, 2024). Hence, the following hypothesis is presented:

H9: Financial literacy (FL) significantly influences the fintech adoption.

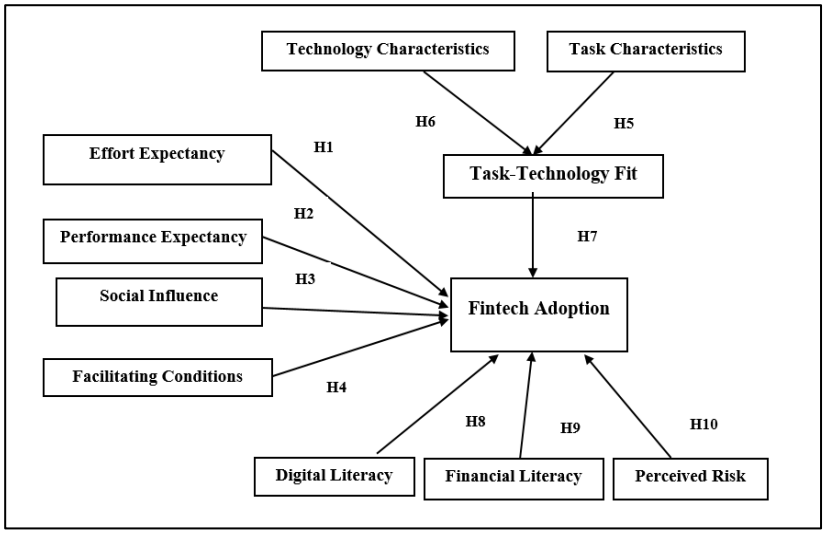
Perceived Risk

Perceived Risk (PR) is the user's notion of loss while using the technology (Widyanto et al., 2022). Thus, a substantial relationship exists between perceived risk and future adoption of the technology (Yang et al., 2023). For instance, perceived risks associated with transaction failure, privacy concerns, internet addiction, and strong psychological attachment were seen as major obstacles of fintech (Xie et al., 2017; Luo et al., 2010). Yet at the same time, perceived risk is relative; it depends upon the user's prior usage experience, digital literacy, and trust in the system (Yang et al., 2023). Therefore, these determinants must be rendered minimal in the fintech realm since they greatly influence the adoption and continued use of such services to effectively ensure a lower PR in this area (Abegao Neto & Figueiredo, 2023). Thus, the decrease of PR is relative to the positive success of fintech integrations (Rabaa'i, 2023). Thus, it is hypothesized that:

H10: Perceived risk has a significant effect on Fintech adoption.

Grounded on existing literature, this study hypothesizes an integrated model by combining TTF with UTAUT to account for the fintech adoption of the elderly. While TTF deals with task-technology fit, UTAUT deals with elderly perception of technology. Both theories account for an inclusive account of fintech adoption, incorporating both individual and task-based perspectives. Moreover, to fill knowledge gaps in fintech functionality, the model includes variables like digital literacy (DL), financial literacy (FL), and perceived risk (PR). Following Ojiaku et al. (2024) recommendation, these inclusions were intended to capture the driving factors of fintech adoption. Based on the formulated hypotheses, the study's conceptual framework is presented in Figure I.

Figure I: Conceptual Framework



Source: Author's Representation

3. 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

4. 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

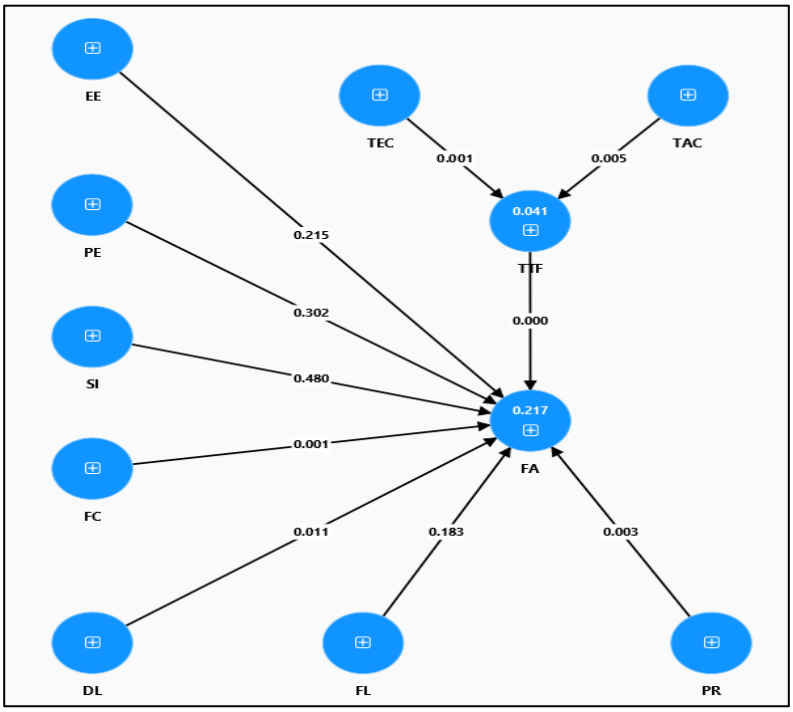
TTF	0.041	0.021	1.931	0.027

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. The structural model is depicted in Figure II.

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.

5. 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 (Ojiaku et al., 2024; Bhatnagar & Rajesh, 2023), 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 ($\beta = -0.003, t = 0.05, p = 0.0.48$) with fintech adoption were weak and statistically insignificant leading to the rejection of H1, H2, and H3. The findings were congruent with earlier research in Saudi Arabia (Bajunaied et. al., 2023); Malaysia (Jin et al., 2020); Africa (Baptista & Oliveira, 2015), Portugal (Oliveira et al., 2014), and China (Zhou et al., 2010).

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. For elderly users, usual financial tasks include pension management, bill payments, receiving subsidies, money transfers, and checking bank balances. These tend to be routine, necessary, and time-sensitive tasks, making the compatibility between the technology and the task particularly important.

Nonetheless, aged users usually experience difficulties in dealing with intricate processes, ambiguous instructions, and multi-step authentication processes. If fintech applications streamline these activities with simplified workflows, auto-fill features, and simple navigation, the perceived applicability between technology and task improves, fostering higher adoption rates. Thus, fintech developers should focus on task simplification, reducing the number of steps required to complete essential financial operations, and offering customizable options that meet the specific preferences and needs of elderly.

Technology characteristics (TEC) includes the technological attributes, structures, and functionalities that enable users to perform specific tasks. The significant relationship between TEC and TTF in this study reinforces that fintech platforms must be perceived as supportive and accommodating of the unique needs of elderly users to foster a positive task-technology fit. Elderly individuals often face cognitive, sensory, and physical limitations, such as reduced vision, hearing difficulties, slower processing speeds, and lack of familiarity with digital environments. To address these issues, fintech applications should integrate senior-friendly design features, including larger font sizes and high-contrast visuals for better readability, simplified transaction processes, voice-enabled services, larger fonts, and minimal cognitive load interfaces.

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. This result aligns with previous research (Fadhilla & Purwanto, 2022; Ullah et al., 2022) and underscores the substantial role of digital competence in facilitating fintech adoption among the elderly.

The inferences drawn from the research state that digitally proficient elderly individuals are more self-assured in navigating fintech platforms due to their familiarity with digital interfaces, whereas poor digital skills make the elderly hesitant or incapable of doing so. This observation highlights the necessity of age-specific digital literacy interventions for elderly individuals. Since many elderly individuals lack the basic skills required to navigate online transactions securely, enhancing their digital competencies is crucial. 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.

Beyond digital divides, cultural and generational factors significantly influence fintech adoption. The older generation in India generally prefer direct interactions with banking personnel, like to have tangible transactions, and rely on family members for digital financial transactions. Such dependence reduces their willingness to use fintech solutions independently, regardless of their financial literacy. Additionally, the apprehension of making costly mistakes online discourages elderly generation from using fintech platforms, even if they are financially literate. Elderlies may understand savings or investments, many lack the digital proficiency to open an e-wallet, make UPI payments, or navigate online banking services securely. This gap suggests that future interventions should be an integrated strategy, combining digital skills training with financial education to facilitate fintech adoption among the elderly.

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. In this case, higher risk perception seems to propel the elderly toward fintech adoption to manage and mitigate these risks effectively. One plausible interpretation is that elderly individuals who are more aware of risks also become more proactive in learning about and using fintech platforms to mitigate those risks for instance, using apps for secure payments or monitoring transactions. This reflects a risk-awareness-driven adoption behavior, suggesting that educational campaigns highlighting how fintech can reduce fraud and improve security might encourage adoption. These insights necessitate a shift from a one-size-fits-all technology promotion strategy to context-specific, assistive, and experiential interventions that address the elderly's specific needs.

6. CONCLUSION

The researched article, "Determinants of Fintech Adoption among the Elderly: Perspectives from an Emerging Economy, India", contributes to relevant practical considerations for fintech enablers and regulators in Asia, particularly in emerging economies that are rapidly developing amid technological advancements. The findings suggest that the determinants of fintech adoption for older adults are facilitating conditions, task-technology fit, digital literacy, and perceived risk; the insignificant determinants are effort expectancy, performance expectancy, and social influence. These insights have significant practical implications for stakeholders focusing to enhance fintech adoption among the elderly and promote inclusive digital advancement in Asia.

1. Elder-Centric Infrastructure and Assistive Tools

A strategic insight from this study underscores the need for elder-centric fintech infrastructure to enable elderly adoption. Asian policymakers and businesses must prioritize simplified apps, larger fonts, voice navigation, and affordable smartphone and internet access, particularly for rural and semi-urban elderly users, through collaboration and inclusive design.

2. Align Fintech Solutions with Elderly Needs

The study's finding that task-technology fit (TTF) strongly influences fintech adoption highlights the need for solutions that align with elderly users' daily financial tasks. Asian fintech firms should design services like pension tracking, bill reminders, and voice-enabled transactions. Simplified authentication, like replacing complex passwords with biometrics. In addition, family-linked accounts and shared access features can aid elderly users, particularly in Asia's family-centric cultures, in making fintech services more accessible and usable for older adults.

3. Digital Literacy Training for the Elderly

Digital literacy (DL) is a significant influencer in fintech adoption, and personalised training can encourage elderly users to embrace fintech platforms. Fintech companies and initiatives such as Digital India, need to supply the foundational tutorials and elementary app designs, while NGOs, and local offshoots can assist with hands-on implementation. Utilizing visuals and vernacular languages throughout Asia, where much of the elderly population is uneducated or undereducated, helps comprehension for more successful digital literacy endeavors that give them the power they need to utilize fintech.

4. Improvised Trust and Security Processes

Results indicate that a perceived risk increases elders' intention to use fintech as they're expected to use safe financial alternatives. Therefore, fintech enablers should strive for security measures and establish trust through promotions and real-use reviews, to prove that fintech is a reasonable and secure choice for everything related to financial transactions.

5. A paradigm shift from the conventional UTAUT framework toward elderly-inclusive interventions

Fintech enablers in Asia should focus on elderly-inclusive interventions in fintech platforms that ensure secure transactions, and cognitive-friendly fintech applications instead of relying upon social influence or novel, ground-breaking technologies.

6. Stakeholders Collaboration for Inclusive Growth

An inclusive fintech ecosystem requires efforts from all significant stakeholders. It involves age-friendly policy regulations, specially designed solutions, and joint digital literacy initiatives. An overall, holistic approach in the form of an integrated technological innovation, training initiatives, and policy interventions is the demand of the time for elderly inclusion in the Asian digital economy.

In effect, an integrative approach that involves user-centered design, age-centered digital literacy initiatives, and trust-building interventions is the key to inclusive fintech expansion in Asia. Addressing these operational challenges allows fintech firms and policy-makers to capitalize on the expanding elderly clientele while fulfilling wider agendas of digital empowerment and financial inclusion in Asia.

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