

Do Demographics Shape Perceived Usefulness of Financial Technology? Evidence from an Indian Context

Rajesh Gupta¹ and Karnika Gupta^{2*} 

¹Department of Applied Science, Sri Sukhmani Institute of Engineering and Technology, Dera Bassi Campus, Mohali, Punjab, India.

²Department of Commerce, SNRL Jairam Girls College, Lohar Majra, Kurukshetra, Haryana, India.

*karnikagupta7@gmail.com (corresponding author)

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ABSTRACT

Purpose: This research aims to identify the significant demographic determinants and to examine the demographic differences that shape people's perception of the usefulness of financial technology.

Methods: Data were collected via an online survey questionnaire on perceived usefulness and demographic variables such as age, gender, marital status, place of living, education, academic field, tax-paying status, family type, family income, and occupation. After editing and outlier deletion, 412 usable responses were retained. Analysis was completed through descriptive statistics, correlation, regression, one-way ANOVA, and factor analysis.

Results: Findings indicated perceived usefulness as a unidimensional, valid, and reliable construct. It was found that demographic factors such as age, marital status, place of living, education, tax-paying status, family income, and occupation significantly influence perceived usefulness. However, gender, academic field, and family type came out as insignificant determinants. Also, older respondents, married individuals, those living in urban and semi-urban areas, highly educated individuals, those who pay taxes, those belonging to high-income families, business professionals, and corporate and bank employees reported high levels of perception regarding the usefulness of financial technology.

Implications: The study implicates building marketing and inclusion strategies according to key demographic characteristics to enhance adoption and accessibility.

Originality: It contributes to the literature by adding marital status, academic field, tax-paying status, family type, and occupation as unique demographic variables that have either not been or been minimally explored earlier. This provides unique value to the research for financial technology firms and policymakers and adds to the literature on financial technology.



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1. Introduction

Financial technology (FinTech) has provided the world with various digital solutions, which have completely transformed the financial sector. These solutions include mobile applications, digital wallets, internet banking, credit/debit cards, peer-to-peer lending, and many more. Also, they offer convenience, lower costs, improved accessibility, and promote financial inclusion, especially in developing economies (Arner *et al.*, 2020). However, the adoption of these solutions largely depends upon people's perceptions of their usefulness. Accordingly, Perceived Usefulness (PU) is studied as a key construct in the Technology Acceptance Model (TAM) developed by Davis (1989), and has been identified as one of the strongest predictors of technology

adoption (Venkatesh & Davis, 2000; Venkatesh *et al.*, 2003). PU refers to the degree to which an individual believes that using a technology will create utility in daily life. Further, according to Lee and Shin (2018), adoption rates differ across demographics, indicating that perceptions of FinTech's usefulness are shaped by individual characteristics. Likewise, Perceived Usefulness becomes the prime construct to be studied for its determinants.

Ashoer *et al.* (2024), Gupta (2024), Wu and Peng (2024), and Mittal *et al.* (2025) said that demographic factors are vital in understanding how people perceive the usefulness of FinTech applications, and despite the significance of demographic characteristics, little research effort has been put into examining the influence of demographic factors on perception. Setyanti *et al.* (2025) have also mentioned that

diffusion of FinTech innovation has remained significant in emerging economies like India; however, adoption of financial technology remains uneven across demographic segments. Undeniably, there is real potential in the field of financial technology in India due to its large population size and diverse socio-economic profile. This becomes multifold with the Government's Digital India Mission. In this way, apprehending demographic influences on Perceived Usefulness among a segment of the Indian population will be significant for recognizing that users' experiences and evaluations of technology vary considerably, and fetching this insight can help FinTech providers in creating tailored strategies to boost adoption among demographic groups. FinTech is also seen as crucial for financial inclusion among rural and lower-income segments in developing economies (Pradhan *et al.*, 2025). Hence, overlooking demographic differences could alarm existing financial inequalities, and it is a fact that policies must avoid a one-size-fits-all approach. With this backdrop, this research investigates the demographic determinants of Perceived Usefulness. The findings will be helpful for policymakers in identifying demographic groups that should be targeted for enhancing adoption of financial technology.

The paper is structured under seven sections. The first section introduces the topic. The second section details the review of literature and describes the research gap and questions. The third section is about research methodology. The fourth section, in line with the research questions, presents analysis and interpretation. The fifth section concludes the paper with discussions. Lastly, the sixth and seventh sections offer implications and further scope for research.

2. Literature Review

Various studies have mentioned that usage of financial technology has grown worldwide after the impact of COVID-19 (Fu & Mishra, 2022; Phuong *et al.*, 2022; Gupta *et al.*, 2024). So, here literature is reviewed for the time period of 2021 to 2025. The review is restricted to those papers which directly or indirectly talk about demographic influencers.

2.1. Literature: A Summarized View

Solarz and Swacha-Lech (2021) evaluated the determinants of usage of financial technology among Millennials in Poland. Data from 1236 respondents aged between 25 to 40 were collected. A logistic regression model was utilized to assess the determinants. According to the findings, young men who value technological innovations, have high income, are less influenced by traditional recommendations, and who favour social media opinions were the most receptive users.

Alshari and Lokhande (2022) focussed on Yemeni consumers and examined how demographic features influenced attitudes and intentions to use financial technology services in banks. Data were collected from 435 respondents through a questionnaire and structural equation modelling was employed on the constructs of the TAM model. It was concluded that education and income had a negative impact on perceived risks while a positive impact on perceived benefits. Further, gender, income, and risks negatively affected attitudes; and education, perceived ease of use, perceived usefulness, and trust positively influenced attitudes toward financial technology services.

Phuong *et al.* (2022) studied socio-demographic factors, trust, security, and COVID-19 perceived risk as determinants of Gen Z's intention to use FinTech payment services. Data were analysed for 568 participants. Findings revealed that performance expectancy, COVID-19 risk, security, social influence, effort expectancy, trust, and facilitating conditions had a positive impact on usage intention, and socio-demographics acted as moderators.

Kalinga and Senarathna (2023), after analysing a sample of 305 Sri Lankan undergraduates and by using partial least squares structural equation modelling, revealed that digital accessibility, convenience, and personal innovativeness significantly affected financial technology adoption. Findings had notable implications for empowering FinTech usage among the population within Sri Lanka.

Krupa and Buszko (2023) investigated the differences in attitudes towards FinTech products and services between two groups in Poland: young individuals born after 1990 and older adults. Data were analysed by using non-parametric statistical techniques and a backward stepwise logistic regression model. It was revealed that young customers, men, residents of larger households, and independent financial decision-makers showed significantly high interest in financial technology than their counterparts.

Rani and Kumar (2023) used both male and female respondents to examine the factors determining the adoption of financial technology in Haryana (India). Two cross-sectional surveys were analysed. Findings revealed that regardless of gender, perceived usefulness and ease had significant influence on attitude and behavioural intention. Another key influencing factor was perceived value. Perceived risk had a low effect. It was also interesting to note that relative advantage and trialability were not significant determinants of behavioural intention.

Mahmud *et al.* (2023) conducted a study in Bangladesh and surveyed 1282 individuals to understand the factors influencing the adoption of financial technology services. The research found that customers were less likely to adopt FinTech services if they had higher concerns about security, information secrecy, limited government control,

and service intuitiveness obstacles. These concerns were more prominent behind FinTech adoption rather than demographic variables.

Ashoer *et al.* (2024) aimed at identifying the influence of digital financial literacy on perceived usefulness of mobile applications in Indonesia. A moderating effect of gender was found, which showed that men played a major role than women in enhancing financial technology use and digital financial inclusion.

Choi *et al.* (2024) explored the factors influencing adoption of FinTech services by analysing South Korean panel data (N = 3465, 2019–2020). It was concluded that the 50 to 64 years age group and those living with younger generations are more inclined towards FinTech, and enjoyment of digital media and engagement with youth drives their involvement.

Cahyadi *et al.* (2024) indicated that demographic factors such as age and gender had minimal impact on the perceived usefulness of FinTech services in Indonesia. However, education level played a significant role, particularly for individuals with advanced degrees, as it strengthens the link between perceived usefulness and the intention to use FinTech services.

Gupta (2024) analysed the demographic dynamics influencing FinTech adoption, emphasizing the perceived usefulness of mobile applications. The paper identified that younger individuals and those with higher education levels perceived mobile FinTech applications as more useful. The reason might be that they are more comfortable with technology. Additionally, income levels also had a significant effect.

Kumar and Rani (2025), by comparing awareness levels between male and female users, examined the factors affecting the adoption of financial technology among Indians. A sample of 411 male and 473 female respondents was used by including two cross-sectional surveys. It was attained that awareness was significantly influenced by attitude and personal innovativeness; however, no impact was noted for technology anxiety.

Sharma and Munjal (2024) studied FinTech adoption in India in the light of the 'Technology Acceptance Model, Unified Theory of Acceptance and Use of Technology, and Theory of Planned Behaviour'. Data were collected from 500 FinTech adopters using a five-point Likert scale. Analysis was completed through SmartPLS and age was taken as a moderating variable. Results highlighted the role of user-friendliness and convenience in adopting financial technology.

Wu and Peng (2024) found that perceived usefulness, perceived ease of use, innovation, and financial awareness had a positive impact on the intention to adopt FinTech applications among rural residents. Findings indicated that

perceived usefulness acted as a mediator between perceived ease of use and behavioural intention. Also, it came out that demographic factors play an important role in technology acceptance.

Bhat *et al.* (2025) found that demographic characteristics, including age and education level, significantly influenced the perceived usefulness of mobile applications in FinTech, and younger users had higher digital literacy. High digital literacy also correlated with a higher appreciation for the convenience offered by financial technology solutions. Additionally, the research indicated that demography has a significant influence on trust in FinTech platforms, which ultimately affects perception of usefulness.

Mittal *et al.* (2025) highlighted that for adopting financial technology and consumer innovativeness, demographic factors such as gender, age, education, and income play an important role. Further analysis revealed significant differences in adoption of financial technology between genders, although no significant differences were observed across age, education, and income groups.

Pradhan *et al.* (2025) explored how digital financial technology can promote financial inclusion. The study was conducted in Madhya Pradesh (India). Results revealed that adoption of digital financial technology varied according to age, caste, gender, education, income, and occupation. Educational attainment was observed as a significant determinant. Age showed a non-linear relationship and female users were found to be fewer. It was also attained that individuals with diverse demographic and socio-economic backgrounds face challenges in adopting major digital transaction modes such as credit/debit cards, wallet-to-wallet, and SMS-based methods.

Singla *et al.* (2025) studied demographic factors and adoption of financial technology in emerging economies, specifically by analysing data from fifteen countries. It was shown through analysis that economically stronger nations obtained higher FinTech scores. Also, it was found that variations in adoption were influenced by regulatory policies, cultural attitudes, and changes in consumer behaviours.

Setyanti *et al.* (2025) analysed the factors which influence adoption of financial technology among Indonesian households. Findings revealed savings ownership as the most significant predictor, and only a few households utilized digital financial services. Educational level, ICT (information-communication-technology) experience, and formal employment were also found as significant predictors. Geographic disparities were also observed. Further, formal employment and land ownership were found to be more impactful in rural regions, and participation in government assistance programs negatively correlated with FinTech use.

2.2. Research Gap and Questions

Nonetheless, even though the literature on the adoption of FinTech continues to expand, there are noticeable gaps. First, the majority of previous research considers demographic factors as control factors, but not as the major ones that influence perceived usefulness. It restricts the knowledge of the active role of demographic features in determining the cognitive judgments of users of FinTech services as opposed to determining the outcome of adoption. Second, while the majority of studies focus on variables like age, gender, living place, education, and income (Solarz & Swacha-Lech, 2021; Krupa & Buszko, 2023; Cahyadi *et al.*, 2024; Mittal *et al.*, 2025), minimal research papers use occupation as a determinant (Pradhan *et al.*, 2025). Accordingly, to append to the literature, this research adds marital status, academic field, family type, tax-paying status, and occupation as noteworthy factors which are found either missing or least studied earlier.

Third, empirical or theoretical support is lacking on the reasons for demographic differences in perceived usefulness. Fourth, research is mainly focused on developed economies, with few studies being done in emerging and developing markets. Due to differences in financial literacy, digital infrastructure, socio-economic inequality, and regulatory conditions, the effects of demographic determinants of perceived usefulness might be different in different settings. Last but not least, the analysis of the demographic factors behind perceived usefulness in an Indian environment is of specific significance due to India being a rapidly digitizing country and characterized by high demographic diversity. Further, the adoption of digital financial services has been helped in India by the popularity of applications like UPI-based payment systems and by government programs like Digital India and Financial Inclusion.

The role of demographic factors in perceived usefulness in India can thus offer important insights into the design of inclusive financial technologies, alleviating digital divides, and facilitating equal financial participation. Besides, empirical evidence obtained in the Indian setting can be used to apply technology acceptance models in emerging economies. Hence, a thorough study is necessary that places demographic factors at the center stage in determining the perception of usefulness of financial technology among consumers. This backdrop sets the agenda for conducting this research, and the paper specifically aims at answering two research questions.

RQ 1: Which demographic determinants are significant for their impact on perceived usefulness of financial technology?
RQ 2: How do demographic differences influence perceived usefulness of financial technology?

Now, the next part details the research methodology.

3. Research Methodology

The methodology applied for answering the research questions is presented in the form of a flowchart and expressed in sub-sections.

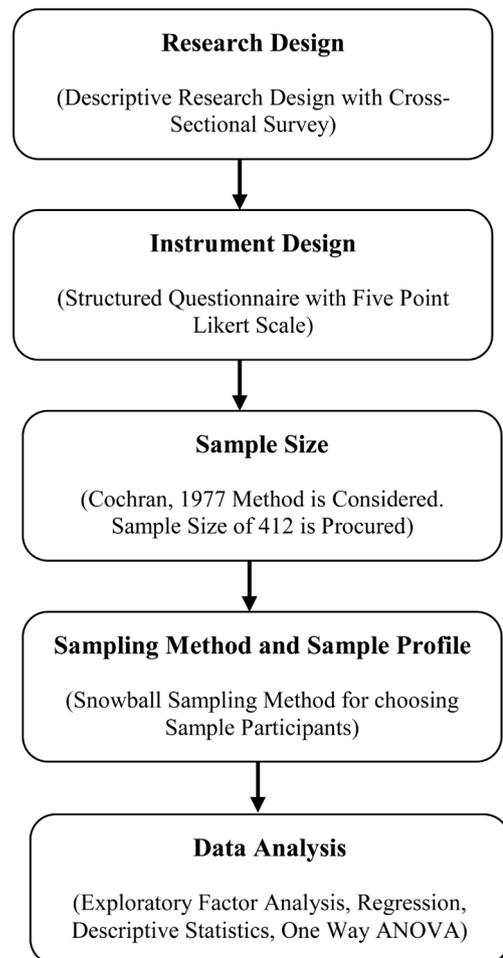


Figure 1: Flowchart Showing Research Methodology

3.1. Research Design

The design of this research is a cross-sectional descriptive research design, as people's perceptions according to their demographic profile are described and a cross-sectional sample is used.

3.2. Instrument Design

A structured online questionnaire containing questions on demographic characteristics (refer Table 1) and twelve statements measuring Perceived Usefulness (PU) was constructed. The statements on PU are integrated from the literature in the questionnaire. The language of the statements was modified to ensure uniformity and validity. The concise

statements used are shown in Table 3. A five-point Likert scale ranging from 1 = Strongly Disagree to 5 = Strongly Agree is used.

3.3. Sample Size

Data from 430 respondents were received. After editing and deleting outliers, data for 412 respondents were found sufficient for further analysis (Mundfrom *et al.*, 2005; Hair *et al.*, 2019). For deciding the appropriate sample size, the method propounded by Cochran (1977) is applied because of its suitability for large populations. According to Cochran's (1977) formula, sample size may be estimated as:

$$n = z^2 pq / e^2$$

where n = required sample size, z = z-score based on a 95 percent confidence interval which is equal to 1.96, p = estimated proportion of measured attribute in a population (usually taken as 50% or 0.5), q = estimated proportion of absence of measured attribute in a population ($q = 1 - p$), e = margin of error (acceptable precision is 5 per cent, i.e., 0.05). With all these values, $n = (1.96)^2 (0.5) (0.5) / (0.05)^2 = 384.16$. To that extent, a minimum sample size of 384 would be required to cover all possible analyses. In accordance with this, a sample size of 412 is justified for this study.

3.4. Sampling Method and Sample Profile

Primary data are collected via the constructed questionnaire, which was administered through Google Forms. The Snowball Sampling Method is used for the same. In this method, initial participants are located and requested to recommend new participants; then other participants are also asked to send the questionnaire within their networks. Although this is a non-probability method, it is very much applicable in instances where there is no or little possibility of having a sampling frame. It is also highly cost-effective, time-efficient, allows for rapid conscription, and builds trust through referrals (Ting *et al.*, 2025). Accordingly, the given approach is believed to be the most appropriate when it comes to conducting the survey, as it is far more challenging to get exhaustive, precise, and current enumeration of all the persons utilizing financial technology services. However, prior to filling out the questionnaire, a section was given for instructions and it was specified that those who are already using any kind of FinTech service (examples were given in the questionnaire), have at least completed their senior secondary education, and are residents of the State of Haryana (India) can fill out the questionnaire. Further, the Purposive Sampling Method is used in the selection of the

State of Haryana. Haryana is selected as it is a progressive state, possesses a wide socio-cultural and demographic setting, is characterized by the presence of fast urbanization and digitalization, and it borders the National Capital, New Delhi (Department of Economic and Statistical Affairs, Haryana, 2025). Out of the twenty-three districts, fourteen districts in Haryana are under the National Capital Region (NCR) (National Capital Region Planning Board, 2018). In this manner, it can be stated that respondents in Haryana are appropriate and suitable for this research purpose. Next, the demographic profile of respondents is included in Table 1.

Table 1: Demographic Profile of Respondents

Demographic Variable	Categories	Frequency	Percentage (%)
Age	Average of Age	26.12	
	Range of Age	18 to 79	
Gender	Male	182	44.2
	Female	230	55.8
Place of Living	Urban	210	51.0
	Semi-Urban	43	10.4
	Rural	159	38.6
Marital Status	Married	117	28.4
	Unmarried	289	70.1
	Separated	06	1.5
Educational Qualifications	Senior Secondary	119	28.9
	Graduation	141	34.2
	Post-Graduation and Higher	152	36.9
Academic Field	Arts and Humanities	85	20.6
	Commerce and Management	234	56.8
	Science and Technical	93	22.6
Tax-paying Status	Taxpayer	160	38.8
	Not a Taxpayer	252	61.2
Type of Family	Joint	189	45.9
	Nuclear	223	54.1
Family Income (Monthly)	Upto Rs.20000 (Lower)	128	31.1
	Rs.20000 to Rs.50000 (Lower-Middle)	66	16.0
	Rs.50000 to Rs.80000 (Middle)	79	19.2
	Above Rs.80000 (Upper)	139	33.7

Occupation/ Profession	Business/ Professional/Self- Occupation	34	8.2
	Bank and Corporate Employees	72	17.5
	School, College, University Teachers	82	19.9
	Students	207	50.2
	Retired/Currently Not Working	05	1.2
	Home Makers	06	1.5
	Agriculture or Horticulture	06	1.5

Source: Primary Data Collection through Questionnaire Survey

Table 1 presents the demographic characteristics of the respondents and reveals a diverse sample composition. The average age of the sample participants is 26.12 years, ranging from 18 to 79 years. In terms of gender, 55.8 percent are females and 44.2 percent are males, showing predominance of female respondents. Regarding the place of residence, the majority of respondents (51%) belonged to urban areas, followed by 38.6 percent from rural areas and 10.4 percent from semi-urban localities. With respect to marital status, 70.1 percent are unmarried, while 28.4 percent are married and a small proportion (1.5%) are separated. In terms of educational background, 36.9 percent had post-graduation or higher qualifications, 34.2 percent had graduation, and 28.9 percent had completed senior secondary education. The academic field of respondents showed that 56.8 percent were from Commerce and Management, 22.6 percent from Science and Technical, and 20.6 percent from Arts and Humanities disciplines. Considering tax-paying status, 38.8 percent are identified as taxpayers, whereas 61.2 percent are non-taxpayers. In terms of family structure, 54.1 percent of respondents belonged to nuclear families, while 45.9 percent were from joint families. The distribution of monthly family income revealed that 33.7 percent of the respondents belonged to the upper-income group, followed by 31.1 percent in the lower-income group, 19.2 percent in the middle-income group, and 16 percent in the lower-middle-income group. With regard to occupation, the majority (50.2%) are students, emphasizing the earlier view of average age and young sample participants. Nearly all major professions are covered in the sample.

3.5. Analysis Tools

Collected data are coded and analysed using the Statistical Package for the Social Sciences (SPSS). Exploratory

Factor Analysis, regression, descriptive statistics, and one-way ANOVA are the techniques used for data analysis. Exploratory factor analysis is used to test the dimensionality of the construct. In this study, Perceived Usefulness (PU) is the dependent variable, and all demographic characteristics are independent variables. To obtain the variable PU, the responses of twelve statements measuring Perceived Usefulness are averaged into a single variable by using the Compute option in the Transform tab in the SPSS file. This is done after analysing the dimensionality of the construct (analysed in Section 4.1). In this way, the variable PU is a metric variable for analysis. Among demographic variables, age is measured on a ratio scale, and other demographic variables are taken as non-metric. So, for the variable age, regression analysis is performed, as both the dependent and independent variables are metric. For other variables, one-way ANOVA is applied for assessing significant differences between means, because the dependent variable in these cases is metric, but the independent variables are non-metric in nature. Analyses have been presented in suitable tables, and the source of each table is analysis of collected data by the authors.

Now, the next section is devoted to analysis of data in the light of research questions.

4. Analyses and Results

4.1. Dimensionality of Construct of Perceived Usefulness

First of all, to test the dimensionality of the twelve statements that measure Perceived Usefulness (PU), exploratory factor analysis with the maximum likelihood method is adopted. Factor analysis is applied because the statements in the questionnaire were incorporated from the literature, and the literature presents many conclusions stating that PU may be a single construct or it may be multi-dimensional (Ambalov, 2021). So, testing the dimensionality of the construct of PU becomes inevitable. Table 2 presents the results of factor analysis. The KMO value assesses sampling adequacy. A value of 0.962 means that factor analysis is highly appropriate for the dataset. Bartlett's test checks whether the correlation matrix is an identity matrix. A significant result ($p < 0.001$) indicates that correlations are sufficient for factor analysis, and the variables share common variance. A significant value of chi-square also supports proceeding with factor analysis. Further, only one Eigenvalue comes out as greater than 1 (9.568), explaining 79.735 percent of variance. Hence, the analysis suggests a one-factor solution, and unidimensionality can be interpreted for the construct of PU.

Table 2: Results of Exploratory Factor Analysis

Factors	Total	% of Variance	Cumulative %
1	9.568	79.735	79.735
2	0.515	4.290	84.026
3	0.463	3.855	87.881
4	0.255	2.123	90.004
5	0.222	1.854	91.858
6	0.200	1.671	93.529
7	0.169	1.411	94.940
8	0.160	1.329	96.269
9	0.141	1.174	97.443
10	0.121	1.008	98.451
11	0.111	0.926	99.377
12	0.075	0.623	100.000
Kaiser-Meyer-Olkin Measure of Sampling Adequacy			0.962
Bartlett's Test of Sphericity	Chi-Square	6550.659	
	df	66	
Sig.		0.000	
Goodness-of-fit Test	Chi-Square	583.265	
	df	54	
Sig.		0.000	

Table 3 presents the descriptive statistics and factor loadings for the items measuring Perceived Usefulness. The mean values of the items range from 3.21 to 3.67, indicating that respondents generally agreed moderately with the statements reflecting the usefulness of mobile applications. The standard deviation values lie between 1.275 and 1.356, suggesting a moderate level of variation in responses across items. Among the items, PU8 recorded the highest mean score (Mean = 3.67), reflecting that respondents particularly valued the convenience and constant accessibility of digital payment platforms. This was followed by PU9 (Mean = 3.58) and PU7 (Mean = 3.56), emphasizing the efficiency and comfort associated with digital transactions. In contrast, the item PU10 (Mean = 3.21) had the lowest mean, indicating relatively less agreement regarding the perceived benefit.

The factor loadings for all items ranged from 0.810 to 0.930, exceeding the minimum recommended threshold of 0.70 (Hair *et al.*, 2019); thereby confirming the high convergent validity and strong internal consistency of the construct. The highest loading was observed for PU9 (0.930), while the lowest was for PU10 (0.810). The square of the factor loading indicates the proportion of variance in a variable that is explained by a specific factor. The coefficient of Cronbach's Alpha ($\alpha = 0.977$) for reliability is good (Hair *et al.*, 2019), and split-half reliability also came out as respectable. So, it can be interpreted that all the items reliably contribute to the measurement of Perceived Usefulness.

Table 3: Descriptive Statistics and Factor Loadings

Items	Measurements	Mean	Std. Deviation	Factor Loading	(Factor Loading) ²	Reliability
PU1	Negligible Human Interaction	3.37	1.307	0.878	0.771	Cronbach Alpha: 0.977 Split-Half Reliability Cronbach Alpha (PU1 to PU6): 0.959 Cronbach Alpha (PU7 to PU12): 0.957
PU2	Discounts / Offers / Schemes / Cash Back	3.33	1.280	0.812	0.659	
PU3	Reliable / Trustworthy	3.41	1.275	0.905	0.819	
PU4	More Transparent (one can receive instant details about all transactions)	3.41	1.280	0.890	0.792	
PU5	Leads to Growth of Economy and Nation	3.43	1.289	0.904	0.817	
PU6	No need to carry cash	3.52	1.317	0.906	0.821	
PU7	No/less need to physically visit a banking institution	3.56	1.317	0.904	0.817	
PU8	Anytime / Anywhere availability (24x7x365)	3.67	1.356	0.917	0.841	
PU9	Efficient Record Keeping and Tracking	3.58	1.303	0.930	0.865	
PU10	Purchase Now, Pay Later	3.21	1.332	0.810	0.656	
PU11	No Need to Remember Due Dates for Regular Payments	3.37	1.318	0.865	0.748	
PU12	Convenient and Time Saving	3.30	1.312	0.853	0.728	

4.2. Perceived Usefulness and Demographic Influencers

For finding answers to research questions, the statements of perceived usefulness are averaged to get the dependent

Table 4: Regression Results for Age and Perceived Usefulness

R	R Square	Adjusted R Square	Std. Error of the Estimate	F (sig.)	Independent Variables	Unstandardized Coefficients		Standardized Coefficients	t (sig.)
						B	Std. Error	Beta	
0.228	0.052	0.050	1.138	22.427 (0.000)	Constant	2.766	0.151	----	18.260 (0.000)
					Age	0.026	0.005	0.228	4.736 (0.000)

Table 4 defines a weak positive relationship between age and perceived usefulness as 0.228. Value of R^2 shows that about 5.2 percent of variance in perceived usefulness is explained by age. Adjusted R^2 depicts that after adjusting for sample size and predictors, the explained variance remains almost the same (5.0%), confirming a small but consistent effect. The value for Std. Error is acceptable. Also, F-value highlights that the model is significant for prediction. Further, regression analysis indicates that age significantly predicts perceived usefulness. The unstandardized coefficient suggests that for every one-year increase in age, the perceived usefulness score increases by 0.026 units. Although the relationship is statistically significant, the effect size is modest, implying that while older individuals tend to perceive financial technology as slightly more useful, other factors likely have a stronger influence. Solarz and Swacha-Lech (2021) and Krupa and Buszko (2023) is disagreed here for favouring young people. Mittal *et al.* (2025) also go against with their finding of no-significant influence of age. But, Choi *et al.* (2024) is supported as they said that older age group are more inclined towards FinTech.

• Perceived Usefulness across Gender

Table 5: Gender Differences and Perceived Usefulness

Gender	Mean	N	Std. Deviation	F	Sig.
Male	3.522	182	1.159	1.961	0.162
Female	3.361	230	1.170		

The analysis explored whether there are any significant differences in perceived usefulness of financial technology across gender groups. Results indicate that male respondents (Mean = 3.52, SD = 1.16) reported slightly higher perceived usefulness compared to female respondents

variable, and all the demographic variables are taken as independent variables, as already mentioned earlier. Separate analysis is presented for each variable.

• Perceived Usefulness across Age

(Mean = 3.36, SD = 1.17). Although the mean score for males is marginally higher, yet this difference is relatively small. To test whether this observed difference is statistically meaningful, an F-test is conducted. The results (F = 1.961, $p = 0.162$) show that the difference between male and female respondents is not statistically significant. This means that any variation in perceived usefulness between genders is likely due to random chance rather than a genuine gender-based difference. Ashoer *et al.* (2024) is against to the present result as they said men play a significant role in FinTech usage. Mittal *et al.* (2025) also go against by finding significant difference between genders. However, Cahyadi *et al.* (2024) is favoured for mentioning minimal impact of gender.

• Perceived Usefulness across Place of Living

Table 6: Place of Living and Perceived Usefulness

Area	Mean	N	Std. Deviation	F	Sig.
Urban	3.646	210	1.125	11.847	0.000
Semi-Urban	3.657	43	1.051		
Rural	3.088	159	1.174		

The results of the analysis in table 6 reveal a clear and statistically significant difference in the perceived usefulness of financial technology across places of living (F = 11.847, $p < 0.001$). Respondents from urban (Mean = 3.65, SD = 1.13) and semi-urban (Mean = 3.66, SD = 1.05) areas reported higher perceived usefulness compared to those from rural areas (Mean = 3.09, SD = 1.17). This suggests that individuals living in urban and semi-urban settings tend to find financial technologies more useful than rural area users. Wu and Peng (2024) result go against as they found impact from the side of rural residents.

• Perceived Usefulness across Marital Status

Table 7: Marital Status and Perceived Usefulness

Marital Status	Mean	N	Std. Deviation	F	Sig.
Married	3.884	117	1.022	13.059	0.000
Unmarried	3.249	289	1.176		
Separated	3.444	6	1.148		

Table 7 demonstrates a statistically significant difference in the perceived usefulness of financial technology across marital status ($F = 13.059$, $p < 0.001$). Married respondents (Mean = 3.88, SD = 1.02) reported the highest level of perceived usefulness, followed by separated respondents (Mean = 3.44, SD = 1.15), while unmarried respondents (Mean = 3.25, SD = 1.18) reported the lowest perceptions. This points up that usefulness perceptions may be shaped by marital responsibilities.

- **Perceived Usefulness across Educational Qualifications**

Table 8: Educational Qualifications and Perceived Usefulness

Educational Qualifications	Mean	N	Std. Deviation	F	Sig.
Senior Secondary	3.036	119	1.074	28.677	0.000
Graduation	3.197	141	1.200		
Post-Graduation and Higher	3.960	152	1.008		

One-way ANOVA in table 8 divulges a statistically significant difference ($F = 28.677$, $p < 0.001$). Respondents with post-graduation or higher education (Mean = 3.96, SD = 1.01) reported the highest perceived usefulness, followed by those with graduation (Mean = 3.20, SD = 1.20), while respondents with only senior secondary education (Mean = 3.04, SD = 1.07) showed the lowest perceived usefulness. These findings indicate that individuals with higher education tend to have greater exposure to digital tools, stronger technological literacy, and more familiarity with financial systems which likely contribute to their higher appreciation of FinTech's utility. Conversely, those with lower educational attainment may encounter greater challenges in understanding or accessing digital financial platforms, leading to lower perceived usefulness. The studies by Alshari and Lokhande (2022), Cahyadi *et al.* (2024), Gupta (2024), and Pradhan *et al.* (2025) are supported for mentioning positive influence of education. But, Mittal *et al.* (2025) found no significant result for education; thus, not supported.

- **Perceived Usefulness across Academic Field**

Table 9: Academic Field and Perceived Usefulness

Academic Field	Mean	N	Std. Deviation	F	Sig.
Arts and Humanities	3.236	85	1.099	2.043	0.131
Commerce and Management	3.441	234	1.216		
Science and Technical	3.588	93	1.084		

Table 9 displays no statistically significant differences in perceived usefulness among respondents from different academic fields ($F = 2.043$, $p = 0.131$). Although mean scores were somewhat higher among participants from science and technical backgrounds (Mean = 3.59) compared to its counterparts, these variations were not large enough to indicate a notable difference.

- **Perceived Usefulness across Tax-paying Status**

Table 10: Tax-paying Status and Perceived Usefulness

Taxpayer	Mean	N	Std. Deviation	F	Sig.
Yes	3.828	160	1.120	32.448	0.000
No	3.181	252	1.127		

The ANOVA results in table 10 disclose a significant difference in perceived usefulness of financial technology based on tax-paying status ($F = 32.448$, $p < 0.001$). Respondents who reported paying taxes (Mean = 3.83, SD = 1.12) have high mean score compared to those who do not pay taxes (Mean = 3.18, SD = 1.13). This suggests that individuals who are formally integrated into the financial system are more likely to recognize and appreciate the benefits of digital financial services.

- **Perceived Usefulness across Type of Family**

Table 11: Type of Family and Perceived Usefulness

Type of Family	Mean	N	Std. Deviation	F	Sig.
Joint	3.391	189	1.185	0.439	0.508
Nuclear	3.467	223	1.153		

The analysis for type of family (table 11) found no significant difference in perceived usefulness of financial technology between respondents from joint families (Mean = 3.39, SD = 1.19) and nuclear families (Mean = 3.47, SD = 1.15); though mean of respondents from nuclear families are somewhat higher. Likely, Krupa and Buszko (2023) is contradicted for finding impact from the side of larger households. This result suggests that regardless of whether people live in joint or nuclear family settings, they tend to view financial technology as similarly beneficial.

- **Perceived Usefulness across Family Status**

Table 12: Family Status and Perceived Usefulness

Family Status	Mean	N	Std. Deviation	F	Sig.
Lower	2.958	128	1.159	18.450	0.000
Lower-Middle	3.468	66	0.860		
Middle	3.273	79	1.237		
Upper	3.941	139	1.059		

Results in table 12 highlight a statistically significant difference across income groups ($F = 18.450$, $p < 0.001$). Respondents in the upper-income group (Mean = 3.94, SD = 1.06) reported the highest perceived usefulness, while those in the lower-income group (Mean = 2.96, SD = 1.16) reported the lowest. The lower-middle (Mean = 3.47) and middle (Mean = 3.27) groups fall between these extremes. The finding stipulates that family income has a substantial effect on how useful people perceive financial technology to be. Alshari and Lokhande (2022) and Pradhan *et al.* (2025) are supported for mentioning that income positively influences perceived benefits. But, Mittal *et al.* (2025) found contradictory result with no significant impact of income.

- **Perceived Usefulness across Occupation**

Table 13: Occupation and Perceived Usefulness

Profession/ Occupation	Mean	N	Std. Deviation	F	Sig.
Business/ Professional/ Self-Occupation	3.833	34	1.050	8.036	0.000
Bank and Corporate Employees	3.961	72	1.067		
School, College, University Teachers	3.702	82	1.113		
Students	3.117	207	1.145		
Retired/ Currently Not Working	2.800	05	0.570		
Home Makers	3.472	06	1.055		
Agriculture or Horticulture	2.486	06	1.058		

Table 13 is visible with demographic features of respondents as per occupation. The results of one-way ANOVA indicate a significant difference ($F = 8.036$, $p < 0.001$), reflecting that occupation plays an important role in shaping individuals' perceptions. Bank and corporate employees reported the highest mean score (Mean = 3.96), followed by business professionals and self-employed individuals (Mean = 3.83), which may be

due to their professional exposure and financial literacy. Teachers (Mean = 3.70) and homemakers (Mean = 3.47) display moderate perception levels, whereas students (Mean = 3.12) demonstrate lower engagement, potentially reflecting limited income or practical financial needs. The lowest mean is found among those engaged in agriculture or horticulture (Mean = 2.49) and retired or currently not working individuals (Mean = 2.80), reflecting relatively low FinTech awareness or accessibility in these groups. The significant result is consistent with Pradhan *et al.* (2025).

The next section concludes the findings with overall discussion.

5. Conclusion and Discussion

All in all, the findings specify Perceived Usefulness (PU) as a unidimensional construct, and the mean scores suggest that respondents moderately agree regarding the usefulness of financial technology. As an answer to the first research question, it can be concluded that demographic characteristics play a crucial role in shaping the perceived usefulness of financial technology. While gender, academic field, and family type do not significantly influence perceived usefulness, age, living area, marital status, education, tax-paying status, family income, and occupation have a statistically significant influence. Attempting to answer the second research question, the finding for age suggests life-stage experiences, with growing age potentially leading to a greater appreciation of FinTech tools. Both male and female respondents generally view financial technology as moderately useful; this finding suggests that gender does not play a decisive role in shaping users' evaluations of how useful financial technology is.

People from urban and semi-urban areas have higher perceptions than those from rural areas. This may be attributed to their greater exposure to digital financial services, better internet connectivity, and easier access to banking and mobile infrastructure. Conversely, respondents from rural areas may encounter limited access and lower digital literacy. Married and separated individuals (however, due to their sample size, results should be generalized cautiously) find FinTech applications more useful. It may be because they are often responsible for household financial management and family-related financial planning, which might increase their dependence on and appreciation for digital financial services. In contrast, unmarried individuals may have simpler financial needs and may not use financial technology as extensively, leading to relatively lower perceptions.

Regarding educational level, it is observed that education strongly determines perceived usefulness of financial technology. Highly educated individuals perceive

financial technology as more relevant and practical. However, the slightly higher mean among science and technical students may point to greater technological familiarity or comfort with digital systems, while those who studied arts and humanities fields may require more exposure to technology-driven financial tools. Further, the findings demonstrate that individuals who participate in the formal financial and taxation system are more receptive to usefulness. It may be attributed to the reason that taxpayers may have greater familiarity with digital payments, e-filing, and online banking systems. Conversely, non-taxpayers may have limited exposure to or engagement with formal financial channels, resulting in lower perceived usefulness.

Next, the result of no significant difference between joint and nuclear families represents the increased individualization of financial decision-making and the accessibility of financial technology to everyone. As digital payments become personal and device-based, family structure contributes little to the development of perceptions of usefulness. Family type outcomes can also indicate a cultural shift where family members stop making decisions collectively and instead embrace financial independence. Besides, the family income analysis bestows the fact that higher-income groups support usefulness perceptions. On the other hand, those from lower-income households might face obstacles which include less access to smartphones, poor connectivity, reduced digital literacy, or distrust of digital systems and thus have weaker perceptions. This trend also causes an income-based digital and financial divide. The results also prove that professional background is another contributor to perception, with those who are financially active demonstrating higher usefulness.

In the next two sections, implications and further research directions are discussed.

6. Implications and Directions

Based on the results, it is implicated that 24/7 access, safe record management, and time-efficient transactions are critical to improve the perceptions of financial technology. To create a sense of confidence among the population, it might be necessary to emphasize economic gains and the national growth characteristics of FinTech tools. In addition to this, awareness can be enhanced through training programs targeting the young generation. Gender differences denote that policymakers need not draw distinctions in functionality between genders when encouraging financial technology. Nonetheless, the difference in awareness depends considerably on geographical location, and thus specific attention should be paid to rural regions, in which digital infrastructure and internet connectivity have a vital role. The observation that married people find

financial technology more helpful indicates that developers should also consider specific features and communication approaches tailored to different life-cycle phases. Further, as education level enhances perceived usefulness, government agencies and financial institutions are in a position to develop specific training for people with lower education levels. Developers ought to make user interfaces simple and offer visual instructions to those who do not have advanced skills. Communication approaches should be diversified; more educated users can be offered more complex abilities with a focus on advanced aspects, whereas less educated users should be offered messages emphasizing simplified convenience, security, and time-saving benefits. One can also say that the cross-disciplinary nature of financial technology is applicable to various academic backgrounds.

Further, the paper implicates that awareness will play a significant role in motivating positive perceptions among taxpayers with regard to digital financial platforms. It implies that non-taxpayers are frequently from low-income and lower education backgrounds and may benefit from incentives, training, and streamlined procedures. Financial institutions are advised to market services uniformly regardless of family type since perceptions seem to be individually motivated. The result on income and perceived usefulness suggests there is a demand to intervene among lower-income groups to enhance awareness and accessibility. Also, specialized educational courses are suggested for agricultural workers, retirees, and students to improve financial literacy, whereas easier banking services should be created for the rural population, and financial management applications should be developed for students in order to familiarize them with financial services early in their lives.

7. Future Scope

Through this paper, different probable research directions are proposed as potentially promising for the future. The main points of discussion may include generational differences, especially between Gen Z and Millennials, and how perceptions change over time as well as with personal experience. Research in cross-cultural studies may also focus on whether the gender aspect or gender-neutrality in perceived usefulness is applicable across various socio-economic and cultural conditions. Secondly, researchers may concentrate on rural-based infrastructure and connectivity problems and examine whether programs like awareness campaigns or rural banking can enhance perceived usefulness. Another direction is to measure the effect of major life events, such as marriage or parenthood, as possible sources of perception changes. The impact of educational factors such as financial literacy, technology training, and exposure to online platforms should be

researched to determine how these aspects mediate the relationship between education and perceived usefulness. It is also possible to study the impact of exposure to digital finance in curricula and the use of e-government services, particularly among non-taxpayers.

It is also suggested that demographic variables can be incorporated into a structural model to assess the joint impact of these variables. In addition, comparisons across countries or regions should be conducted to determine whether the observed trends are particular to that context or general. The mediating or moderating relationships between demographics and usefulness through digital literacy, trust, and perceived risk are also worth deeper investigation. Finally, qualitative methods such as interviews or focus groups may provide more insight into the obstacles faced by people with low perceived usefulness.

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Authorship Contribution

Rajesh Gupta: Contributed to the development of the introduction and literature review, laying a strong conceptual foundation for the study. Actively participated in refining the final version of the manuscript by offering thoughtful and constructive feedback, strengthened the analysis, and enhanced the overall quality and coherence of the work.

Karnika Gupta: Conceptualized and initiated the idea for the paper, shaping its central theme and direction. Led the development of the research methodology and carried out the data analysis with rigour and precision. Also contributed significantly to refining and finalizing the discussion and implications sections, ensuring the findings were clearly interpreted and meaningfully connected to theory and practice.

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Ethical Approval

This research collected data from human participants through a voluntary online survey designed to ensure

anonymity. No personally identifiable information such as names, addresses, or phone numbers was collected. Participants were clearly informed that all responses would be used solely for academic and research purposes.

Declaration

The author hereby declares that this research paper is an original work conducted by the author. All sources and references have been properly acknowledged, and the work has not been submitted or published elsewhere.

Conflict of Interest

The author declares that they have no conflict of interest regarding the publication of this paper.

Data Availability Statement

Authors declare that the data supporting the conclusions of this study can be obtained upon request from the corresponding author, K.G.

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