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Predicting the Impact of Socio-Demographic Factors on Fintech Usage and Adoption

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Abstract

Financial technology (FT) has played a crucial role in the delivery of financial services in India, especially in the more digitally advanced areas, such as Thrissur district, Kerala. Although the fintech adoption proliferated quickly, there remains inequality in the adoption of such technologies among socio-demographic classes. The current study examines how sociodemographic traits affect fintech adoption and uptake using the Technology Acceptance Model (TAM). The study design employed was descriptive-analytical. Using Google Forms, a structured questionnaire was distributed to a sample of 312 fintech users in the Thrissur district in order to collect primary data. In order to determine the associations and relationships between sociodemographic variables, perceived usefulness, perceived ease of use, fintech adoption, and usage, the statistical data were analyzed using a spreadsheet program with SPSS, including percentages, chi-square tests, and correlation analysis. The results demonstrate that age, gender, and education do not significantly correlate with the data; nevertheless, occupation ($\chi^2 = 123.463$, $p < 0.000$) and income ($\chi^2 = 15.750$, $p < 0.015$) are significantly correlated with fintech adoption and usage. The correlation research indicates that the use of fintechs has a strong positive correlation with adoption ($r = 0.739$) and perceived usefulness and ease of use a ($r = 0.725$). Moderately positive associations were perceived usefulness and financial usage ($r = 0.591$) and perceived usefulness ($r = 0.566$). According to the study, the large impact on the fintech uptake has been on the usability evaluation and social economic stability. The findings can be used to promote fair digital financial inclusion by policymakers and fintech firms.

Keywords: Fintech Adoption, Fintech Usage, Socio-Demographic Factors, Technology Acceptance Model, Perceived Ease of Use, Financial Inclusion.

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Introduction

FT has entirely changed the world of financial services by making banking, payments and investments opportunities more convenient, fast and economical (Liébana-Cabanillas et al., 2014). The growing number of smart phones, internet penetration and internet payment systems in the world have made fintech uptake very fast, particularly in the emerging market economies. Non-physical wallets, mobile banking, peer-to-peer lenders, and artificial advisory services have transformed the traditional system of financing by making it more convenient and low cost in terms of transactions (Arasuraja, 2025). However, this still remains inhibited by the current obstacles, such as the deficiency in digital literacy and related cybersecurity threats, distrust in technology, absence of data safety, and access discrepancies to technological infrastructure that continue to influence user interaction and constrain its use across the world.

The adoption rate of fintech in India has been rapid, through the efforts in the field of digital payments, Unified Payments Interface (UPI), and mobile banking (Lee & Shin, 2018). Digital financial ecosystem has further evolved because of several government initiatives such as Digital India, financial inclusion, etc. The state of Kerala is becoming a digitally progressive state, in particular, thanks to the high literacy rate, a well-developed communication system, and the policy of technology friendliness. One of the primary centers for fintech adoption in the area is Thrissur, the state's first digital district. Despite the favourable conditions, differences in the use and acceptance of fintech also exist across socio-demographic segments and depend on various factors such as Income, occupation, education, and availability of digital resources (Venkatesh et al., 2012).

Objectives

1. To conduct research into how sociodemographic factors affect the uptake and use of fintech.
2. To examine the association between the perceived ease of use and the perceived usefulness.
3. To determine how fintech uptake is impacted by perceived ease of use.
4. To determine how the use of fintech is influenced by perceived utility.
5. To establish the relationship between the utilization of financial technologies and the adoption of fintechs.

The structure of the paper is as follows. The literature review is presented in Section II. The conceptual framework and research technique are explained in Section III. Results and data analysis are presented in Section IV. Section V discuss the results. Section VI presents the conclusion and future scope.

Review of literature

The relevance of sociodemographic and behavioural aspects in affecting user acceptance and adoption is highlighted by earlier research on fintech uptake (Ryu, 2018). The use of the literature gives the research a significant theoretical basis for the nature of the interactions of individuals with digital financial services. Numerous academics have examined how age affects fintech adoption, but their conclusions have been conflicting. The study mentions that age is not a major factor in predicting the usage of fintech, which means that individuals of all ages become more open to digital financial services. However, other scholars indicate that the latter tend to be more open to using fintech due to their exposure to digital technologies (Lin et al., 2017; Marikyan et al., 2023), whilst other users (older) tend to be hindered by their digital literacy, privacy, and security fears (Ozili, 2018).

The differences in the use of fintech between the sexes are also the subject of research. The author observed that women do not perceive fintech services as safe as men, and this fact could reduce the level of adoption. Social norms and cultural expectations also influence gender-based behavior (Gupta et al., 2019). On the other hand, they found that the amount of difference between the males and females in terms of fintech utilization is minimal, meaning that even gender disparities are gradually being evened out (Gomber et al., 2017; Slade et al., 2015).

Another factor that significantly affects the uptake of fintech is education. The studies indicate that tertiary education might be used to enhance digital literacy and awareness, thus causing a rise in the use of fintech services (Venkatesh et al., 2003; Gai et al., 2018). However, education level has not been discovered by other practitioners to have an influential effect on adoption since digital platforms are increasingly becoming more convenient and reachable (Slade et al., 2015; Singh & Srivastava, 2018). This is why financial and digital literacy programs are relevant to less educated customers.

The definitions of fintech adopted are critical in terms of earnings and occupation. The survey found that because they have access to digital assets, those with greater economic standing are more inclined to use fintech (Arner et al., 2015). Conversely, the poor still cannot access technology (Poudel et al., 2023; Hu et al., 2019). According to (Bhatnagar et al., 2024), young people are also early adopters, being younger, more educated, and financially stable, in general.

In fintech research, the TAM Model has gained popularity. According to Davis, perceived utility and perceived usability are important indicators of technology adoption (Kang, 2018; Koul & Eydgahi, 2018).

Later studies determined that user-friendly interface and helpful features are significant contributors to the usage of fintech (Oliveira et al., 2016; Alalwan et al., 2016). Extended TAM models, which consider trust, risk, and security, have gone ahead to augment explanatory power (Shaikh & Karjaluoto, 2015).

However, there is extremely little research that is done at the district level in Kerala, even though it is widely researched. There has not been a study conducted to study the combination of the socio-demographic variables and TAM constructs within the region. The proposed research is useful in filling this gap because it analyses fintech adoption behaviour in the Thrissur district and provides insight that is useful to the population of this city.

Empirical research carried out as recently as 2021 to 2024 also contributes to the application of the TAM Model as used in the fintech setting. Modern research lays greater emphasis on the emergence of digital trust, awareness, and the availability of cybersecurity in fintech adoption patterns. Research Studies in emerging and developing economies indicate that the socio-economic stability and digital literacy moderately influence the TAM constructs, the perceived usefulness, and actual usage behavior, particularly (Schorr, 2023). These observations also confirm the argument for local, district-level studies of fintech adoption practices to understand contextual dynamics of fintech adoption better.

Although earlier studies of fintech adoption have examined it using the TAM Model and socio-demographic variables, most have been based on national or global contexts (Singla et al., 2025). Even though Thrissur is a digital district, there aren't many empirical research conducted at the district level in Kerala. Also, there is a minimal combination of behavioural factors or demographic characteristics that are frequently analysed in the literature. Though previous investigations of fintech adoption have analysed it through the TAM Model and socio-demographic factors, most have focused on the national or global context. Little empirical research has been conducted at the district level in Kerala, particularly in Thrissur, even though Thrissur is a digital district. Additionally, the literature often analyses behavioural factors or demographic characteristics separately, with little combination. Moreover, little research provides comprehensive statistical data on the interaction between socio-economic variables and TAM constructs in semi-urban and developing regional settings. This deprives both the applicability of the generalized findings to local policy-making and the business strategies of region-specific insights.

By integrating the sociodemographic factors into TAM constructs in a district-level analysis, the research aims to close these gaps. It provides useful data about Thrissur's fintech adoption behavior and highlights the combined impact of income, occupation, perceived utility, and usability. The study is valuable in that it provides locally applicable knowledge that can be used to develop specific fintech projects and financial inclusion programs.

Hypothesis Development

According to the theories of the TAM Model and the empirical results from previous studies, the following hypotheses are made.

H01: The use of fintech and age do not significantly correlate.

H11: The use of fintech and age are significantly correlated.

H02: There is no significant relationship between gender and the use of fintech.

H12: There is a significant relationship between gender and the use of fintech.

H03: The use of fintech and education do not significantly correlate.

H13: There is a significant relationship between education and the use of fintech.

H04: The use of fintech and occupation do not significantly correlate.

H14: The use of fintech and occupation are significantly correlated.

H05: Income and the use of fintech do not significantly correlate.

H15: The use of fintech and income are significantly correlated.

H06: Fintech adoption and sociodemographic factors do not significantly correlate.

H16: Fintech adoption and sociodemographic factors are significantly correlated.

H07: Perceived usefulness and ease of usage are positively correlated.

H08: Fintech usage and perceived ease of use are positively correlated.

H09: Fintech usage and perceived utility are positively correlated.

H10: Fintech adoption and usage are positively correlated.

Research Methodology

In order to investigate fintech adoption behaviour, the study used a descriptive-analytical research approach. Convenience sampling was used to select 312 fintech users in Thrissur district, Kerala. Data was gathered using Google Forms and a standardized questionnaire.

Journals, reports, and online publications were among the secondary data that supported the original data. The SPSS was used for statistical analysis because to its dependability, the content of its statistical tools, and its general applicability to research in the social sciences.

Reliability Analysis

The internal consistency of the measuring scales was evaluated using Cronbach's Alpha. The constructs included fintech usage, adoption, perceived utility, and perceived ease of use. Multiple Likert-scale items were used to measure each construct. According to the reliability results, all constructs had alpha values above the suggested cut-off value of 0.70, which indicates that the measuring instruments' internal consistency and reliability are adequate.

The respondents' sociodemographic traits were examined using percentages. To look for correlations between categorical variables, the Chi-square test was employed, as long as the observations were independent and the expected number of observations in each cell was adequate. Correlation analysis was used to ascertain the direction and strength of the relationship between continuous variables under the assumptions of linearity and normality.

Table 1: Reliability Analysis of Constructs

Construct	Number of Items	Cronbach's Alpha (α)
Perceived Ease of Use (PEOU)	4	0.821
Perceived Usefulness (PU)	4	0.846
Fintech Usage	3	0.793
Fintech Adoption	3	0.801

As shown in table 1, the findings verify that every construct has adequate reliability and is appropriate for additional statistical examination.

Based on the TAM Model, the proposed research methodology will include sociodemographic variables, perceived utility, perceived usability, and fintech acceptance and use. Fig. 1 displays the conceptual framework for the investigation.

Technology Acceptance Model (TAM)

In many respects, the most popular theoretical framework for studying information systems and technology adoption is the TAM. Davis created the TAM hypothesis in the 1980s to explain user behavior in terms of perceived utility and ease of use (Davis, 1989). The study emphasized that these constructs can affect the actual fintech usage behavior. Also highlighted the contributions of trust, perceived risk, and social influence to user acceptance. On the same note, the study indicated that personal and environmental factors, as well as TAM variables, interact to influence adoption behavior. The degree to which consumers believe the fintech will increase their financial efficacy is known as perceived usefulness. On the other hand, perceived ease of use refers to how simple the technology is to use. All these aspects influence the actual fintech usage behavior of users. In this analysis, TAM provides a systematic model to analyze fintech adoption, taking into account the socio-demographic variables, in order to provide effective predictions about the direction of adoption and also formulate specific strategies.

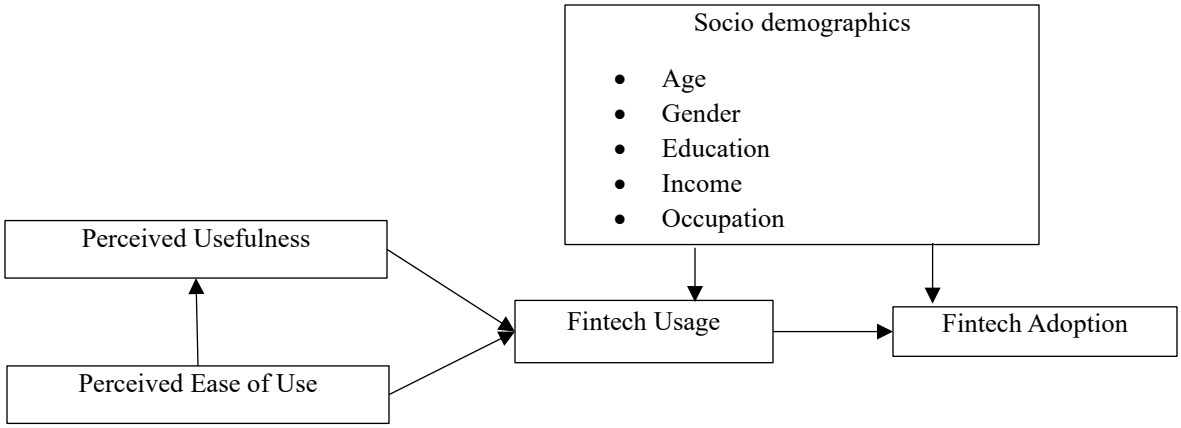


Fig. 1: TAM Model

Data Analysis and Interpretation

Data analysis refers to the methodical search for information to find trends, patterns, and information. The next step in making meaning out of these results is interpretation, which often involves distilling down complex data to make meaning. Together, they are an important process of informed decision-making in a wide range of areas. This research provides different methods of analysis, such as regression, correlation, and percentage analysis.

Percentage Analysis

Table 2: The analysis of the respondents' Socioeconomic Profile by Using Percentages

	Category	Number of respondents	Percentage Of Respondents
Age	18-30 years	84	26.92
	31- 40 Years	48	15.38
	41 - 50Years	83	26.60
	51 - 60 Years	54	17.31
	Above 60 Years	43	13.78
	Total	**312**	**100.00**
Gender	Men	185	59.29
	Women	127	40.71
	Total	**312**	**100.00**
Education	School Level	46	14.74
	Graduates	93	29.81
	Post Graduates	64	20.51
	Professionals	56	17.95
	Others	53	16.99
	Total	**312**	**100.00**
Income	Below two lakhs	89	28.53
	2-5 lakhs	127	40.71
	5-8 lakhs	68	21.79
	8 lakhs and more	28	8.97
	Total	**312**	**100.00**
Occupation	Private employees	189	60.58
	Government employees	56	17.95
	Self employed	18	5.77
	Retired	25	8.01
	Unemployed	24	7.69
	Total	**312**	**100.00**

(Source: Primary data)

Table 2 indicates that most of the participants are in the age ranges of 18-30 and 41-50 years. The study involves both male and female respondents with different educational levels. Most participants have an income of 2-5 lakhs, and a significant majority work in the private sector.

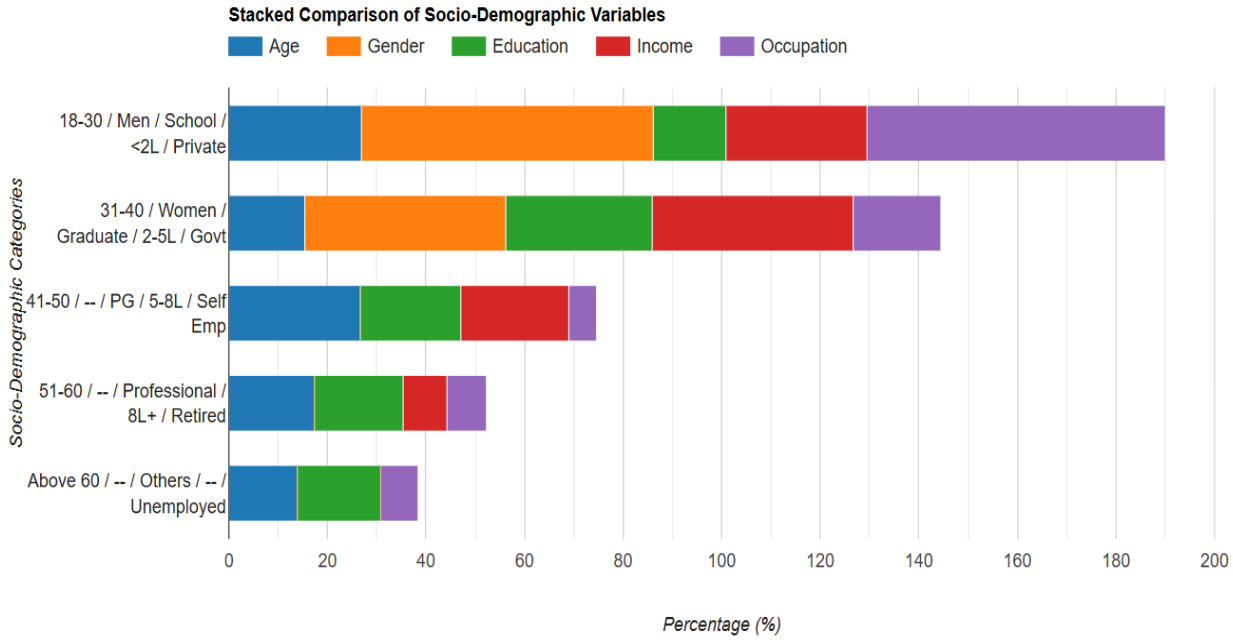


Fig. 2: Clustered comparison of socio-demographic distribution of respondents based on percentage analysis (N = 312)

Fig. 2 presents a clustered comparison of the socio-demographic characteristics of fintech users in the Thrissur district.

Chi-Square Analysis

Chi-square analysis compares observed and expected frequencies to assess the relationship between categorical variables. It is applied in fields such as the social sciences, health, and market research because it is commonly used in research to determine whether a significant relationship or difference exists among groups. Specifically, this statistical test is helpful for analyzing data with ordinal or nominal variables. In this study, the association between several demographic characteristics and fintech use is evaluated using the chi-square test.

Table 3: Chi-square Analysis: H_0: There is no association between socio-demographics and level of Fintech Usage

Socio Demographics	Hypothesis	Chi-square value (χ^2)	P value	Result
Age	There is no association between Age and Fintech usage	10.961	0.204	Accepted Hypothesis
Gender	There is no association between Gender and Fintech usage	1.512	0.470	Accepted Hypothesis
Education	There is no association between Education and Fintech usage	10.487	0.106	Accepted Hypothesis
Occupation	There is no association between Occupation and Fintech usage	123.463	0.000**	Rejected Hypothesis
Income	There is no association between Income and Fintech usage	15.750	0.015*	Rejected Hypothesis

The null hypothesis is not rejected at the 5% level because table 3 shows that the P-values for education, age, and gender are greater than 0.05. Hence, age, gender, or education level does not influence the Level of fintech usage. Age and fintech usage are not significantly correlated since various people use these online financial services for different purposes. The lack of a relationship between gender and the extent to which people actually use fintech services may be due to the gender-neutral design of online banking sites, which aim to be easily accessible to all users. Education has a lesser effect on the likelihood that an individual will use neo banks, because people, regardless of education, are becoming familiar with digital platforms and adopting new technology. The null hypothesis is rejected since the P-value is less than 0.01 at the 1% significance level, suggesting a relationship between occupation and fintech usage.

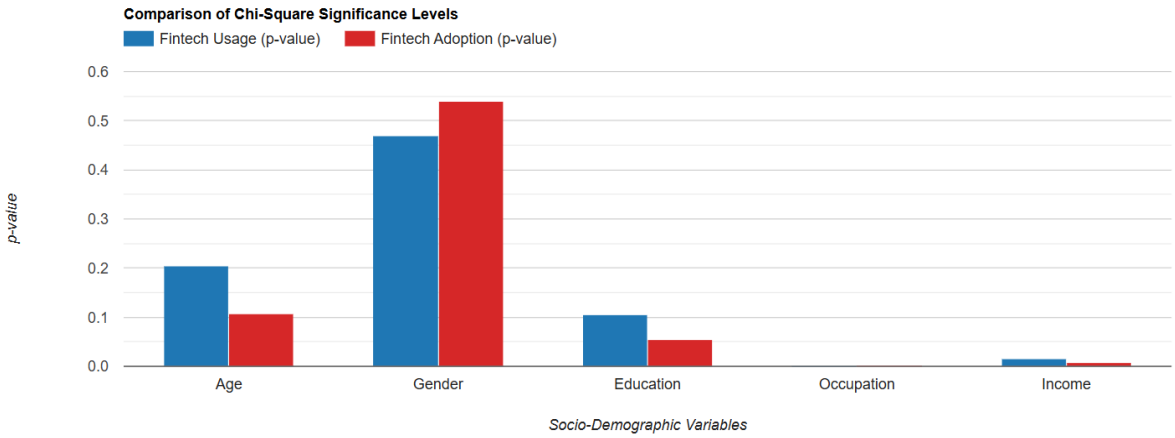


Fig. 3: Clustered Comparison of Chi-square Significance Levels (p-values) for Socio-Demographic Variables Influencing Fintech Usage and Adoption

Fig. 3 provides a comparative visualization of the significance levels of socio-demographic variables affecting fintech usage and adoption. Neo banks stand a better chance of being embraced by industries that require digital financial management and regular financial transactions because they are easier and more effective. Since the P-value is less than 0.05, the null hypothesis is rejected at the 5% significance level. Consequently, it can be said that the degree of fintech usage and income are related. Upper-income groups might opt for such platforms due to their new-age features and investment opportunities. Also, wealthy individuals generally lack financial services that enhance their standard of living and are more convenient-a service that neo banks could provide.

Table 4: Chi-square Analysis: H_0: There is no Association Between Socio-demographics and Level of Fintech Adoption

Socio Demographics	Hypothesis	Chi-square value (χ^2)	P value	Result
Age	There is no association between Age and Fintech Adoption	3.157	0.107	Accepted Hypothesis
Gender	There is no association between Gender and Fintech Adoption	1.234	0.539	Accepted Hypothesis
Education	There is no association between Education and Fintech Adoption	12.333	0.055	Accepted Hypothesis
Occupation	There is no association between Occupation and Fintech Adoption	29.047	0.001**	Rejected Hypothesis
Income	There is no association between Income and Fintech Adoption	17.826	0.007**	Rejected Hypothesis

From table 4, it is evident that age, gender, and education do not correlate with the level of actual fintech adoption, as digital banking services are universally appealing across age, gender, and education levels due to accessibility, convenience, and financial needs, among other factors. Income and occupation are related to the use of fintech. People employed in jobs relating to technology or those who commonly deal with money transfer are most likely to become early adopters since they are used to interacting with online interfaces and money control needs. People with greater income may be more willing to adopt these platforms because of their innovativeness and investment possibilities. Apart from this, wealthy individuals often seek out complementary financial services that provide them with a more convenient lifestyle—a service that neo banks can offer.

Correlation Analysis

Correlation analysis examines the strength and direction of correlations between two or more variables. By calculating the degree to which changes in one are linked to changes in the other, it offers information on the linear relationship between two variables. Correlation analysis is a widely applied research tool across a range of fields that enables pattern identification, forecasting, and decision-making. This study examines the relationships between perceived usefulness and perceived ease of use, perceived usefulness and fintech usage, perceived ease of use and fintech usage, and fintech usage and adoption.

Table 5: Correlation Analysis

Sl. No.	Hypotheses	Coefficient of correlation	Interpretation
1	Perceived usefulness and perceived ease of use are positively correlated.	0.725	High positive correlation
2	Fintech usage and perceived ease of use are positively correlated.	0.566	Moderate positive correlation
3	Fintech usage and perceived usefulness are positively correlated.	0.591	Moderate positive correlation
4	Fintech usage and adoption are positively correlated.	0.739	High positive correlation

(source: Primary data)

Table 5 demonstrates a moderately good correlation between Fintech usage and perceived utility (0.591) and ease of use (0.566). Fintech usage and uptake (0.739) and perceived utility and ease of use (0.725) are highly positively correlated. Also, the confidence interval of correlation coefficients (e.g., r = 0.725, CI [0.68, 0.76]) were calculated, which showed statistical strength.

Regression Analysis

Multiple regression analysis was used to further investigate the predictive impact of TAM factors on fintech utilization.

Table 6: Multiple Regression Analysis – Impact on Fintech Usage

Variable	Unstandardized Coefficient (B)	Standardized Coefficient (β)	t-value	p-value	Result
Constant	0.812	—	3.214	0.001	—
Perceived Ease of Use (PEOU)	0.421	0.438	6.287	0.000**	Significant
Perceived Usefulness (PU)	0.367	0.392	5.914	0.000**	Significant

Table 7: Model Summary

R	R^2	Adjusted R^2	F-value	Significance
0.684	0.468	0.465	135.72	0.000**

As indicated in table 6, multiple regression analysis was used to investigate the impact of perceived utility and simplicity of use on fintech usage. According to table 7, the whole model explains about 46.8% of the variance in fintech usage (R2 = 0.468) and is statistically significant ($F = 135.72$, $p < 0.01$). Fintech usage is significantly positively impacted by perceived usefulness ($\beta = 0.392$, $p < 0.01$) and perceived simplicity of use ($\beta = 0.438$, $p < 0.01$). Among the predictors, perceived ease of use exerts a slightly stronger influence. These results demonstrate that users are more inclined to embrace fintech when they believe the platforms are user-friendly and advantageous. Thus, hypotheses H08 and H09 are supported.

Performance Comparison

A comparative analysis of fintech uptake and use by income and occupational group reveals some general performance disparities. Increased adoption and use are found in the higher income category as well as in professional occupations. The unemployed and impoverished populations are relatively engaged in comparison to the overall population. Additionally, the current study demonstrates that there is a greater acceptance of technology use in Thrissur due to the higher correlation between perceived ease of use and perceived usefulness (r=0.725) and usage and adoption (r=0.739) when compared to earlier national studies. This implies that the performance of fintech is positively impacted by regional digital infrastructure and awareness campaigns. The results show a positive correlation between socio-economic stability and digital financial participation, and show stable growth in fintech.

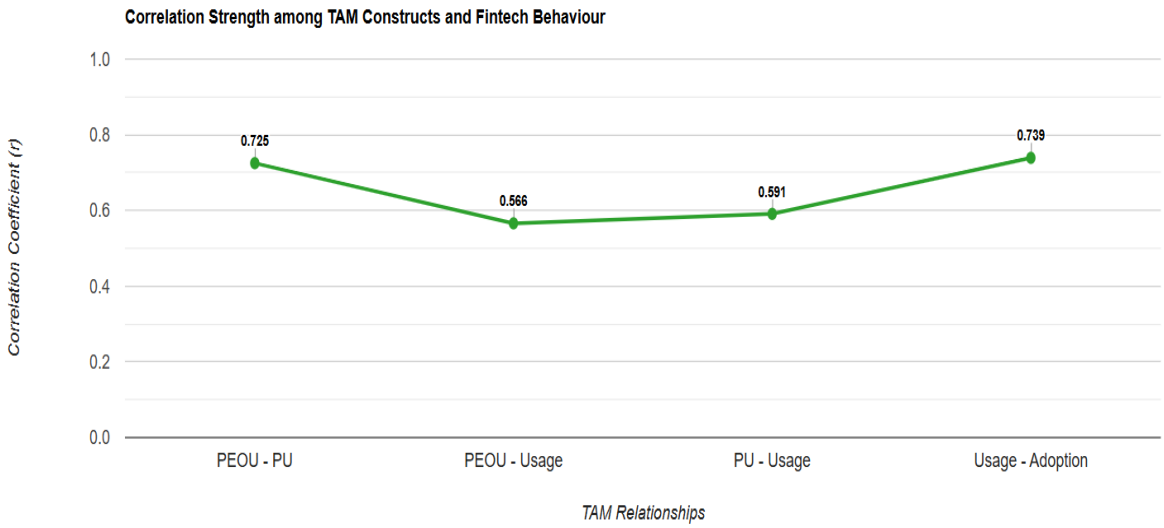


Fig. 4: Correlation coefficients among TAM Model constructs and fintech behavioral variables

Fig. 4 graphically presents the magnitude of correlation coefficients among the TAM constructs and fintech behavioral variables.

Discussions

The study's findings provide empirical evidence for a few of the theories put forth. The chi-square analysis shows that the H01, H02, and H03 testing the association of age, gender, and education with the use of fintech are accepted, as no statistically significant relationships were found in the data ($p>0.05$). These findings imply that demographic variables like age, gender, and educational attainment do not significantly influence the use of fintech in the Thrissur district. This implies that fintech platforms have succeeded in terms of inclusiveness among demographic groups.

However, H14 and H15, which stated significant associations between occupation, Income, and fintech usage, are supported by the findings. The use of fintech is statistically significantly correlated with occupation ($p < 0.01$) and income ($p < 0.05$). Similarly, the variables of socio-economics have significant effects on the fintech adoption as well, thus supporting H16. These results confirm that economic stability and employment status play an important role in influencing digital financial participation. People in professional fields and with higher Income earn more are likely to use fintech services as a result of more financial capabilities and exposure to digital services.

The correlation analysis is further used to validate the TAM Model constructs. H07 is supported by the strong positive correlation ($r = 0.725$) between perceived ease of use and perceived utility, indicating that consumers who think fintech systems are easy to use are more likely to think they are valuable. H08 and H09 are supported by somewhat favorable correlations between perceived usefulness and fintech usage ($r = 0.591$) and perceived ease of use and fintech usage ($r = 0.566$). Furthermore, the strong correlation between fintech usage and adoption ($r = 0.739$), supporting H10, which shows that higher usage behaviour leads to continued adoption.

In general, the results confirm the idea that socioeconomic stability and TAM characteristics are significant predictors of fintech participation, although demographic factors such as age, gender, and education levels did not show a significant effect. The results confirm the ability of the TAM Model to describe the behavior of fintech adoption at the district level. The results are of extreme significance to the fintech companies and the policymakers. To attract various groups of users, service providers should try to make the user interface more straightforward and enhance the perceived benefits. Tailored financial products and sensitization programs should be directed towards reducing the incomes of people employed in informal sector. Adoption can also be facilitated through training programmers which are focused on digital literacy. Such experiences may help the policy makers develop inclusive digital finance policies and infrastructure investments. Segmentation-based marketing strategies will also enable fintech companies to maximize customer acquisition and retention.

Theoretical Contribution

This work makes some contributions to the current body of knowledge in a number of ways. One, it extrapolates the application of TAM Model by incorporating the socio-demographic variables in addition to the central constructs of TAM in a district level environment. While previous studies have mostly shown national or cross-country analysis, this study covers empirical evidence localized at the Thrissur district level and therefore adds context-specific richness to the fintech adoption literature. Second, the findings demonstrate that while demographic factors like age, gender, and education have no statistically significant impact on fintech use, socioeconomic stability, particularly occupation and income, has significant effects on fintech usage and adoption. The understanding of the moderating impact of structural economic considerations in technology adoption behavior is expanded upon by this difference. Third, TAM's explanatory robustness for developing digital finance ecosystems is confirmed by the strong relationships between perceived usefulness, adoption, usage, and ease of use. The study increases the study's theoretical generalizability and external applicability in the context of FT adoption by validating TAM in a semi-urban regional setting.

Practical Implications

The outcomes are of high significance to the policy makers and fintech companies. To attract various groups of users, service providers should try to make user interfaces simpler and enhance the perceived benefits. Lower-income workers in the informal sector should get customised financial products and awareness campaigns.

Adoption can also be improved through training programmes with a focus on digital literacy. Such lessons can guide policymakers to come up with inclusive digital finance policies and infrastructure investments. Marketing strategy based on segmentation will also help fintech companies maximise customer reach and retention.

Conclusion and Future Scope

In this study, effects of occupation and Income have been found to have significant effects on occupancies and adoption of fintech, with no statistically significant effects of age, gender, and education. The chi square results ($p < 0.05$) reveal a robust correlation between socioeconomic position and fintech engagement. Strong positive correlations between perceived usefulness and ease of use ($r = 0.725$) and usage and adoption ($r = 0.739$) can be seen using the correlation analysis results. The results highlight the fact that the top factors in fintech adoption are usability and functional value. Digital financial inclusion is achievable faster by enhancing the user experience and perceived benefits. The experiment also affirms the fact that there is a positive feedback loop of usage and adoption. To explore motivational forces behind behaviour and regulatory factors, longitudinal designs, comparative studies of regions, and qualitative studies can be taken up by future studies. These researches may focus on understanding the influence of socioeconomic factors on fintech adoption in different scenarios. They might also examine the impact of user trust, security issues and privacy concerns on fintech adoption in greater detail. Furthermore, studying regulatory factors may assist in determining essential policies to engage more people and integrations into the digital financial ecosystem.

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