

Understanding Fintech Adoption Among Urban Households in Ernakulam Kerala Using an Extended Technology Acceptance Model

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Abstract

FinTech has changed the provision of financial services because of its effectiveness, efficiency, and convenience. However, problems regarding privacy risks, financial risks, and performance risks have influenced the user's decision-making process. The current study aims to examine the variables that affect the usage of FinTech with regard to the households in Ernakulam district, Kerala. Quantitative cross-sectional survey research design was chosen in which the primary data collection involved collecting the information from 200 FinTech users in the study area through the use of a structured questionnaire. The Technology Acceptance Model (TAM) framework with extension includes PU, PEOU, PR, FR, and PER as determinants of BI. Descriptive statistics, reliability test, factor loading test, and Pearson correlation test were performed in order to analyze the collected data. It was found that the reliability test indicated good internal consistency in which all of the variables provided alpha and composite reliability values above 0.88. PU has a mean value of 4.00 while PEOU has a mean value of 4.13 indicating positive attitudes towards FinTech products among urban households. Results for the correlation analysis indicated extremely high positive correlation between PU and BI ($r = 0.959, p < 0.01$) and between PEOU and BI ($r = 0.885, p < 0.01$). On the other hand, Privacy Risk ($r = -0.980, p < 0.01$), Financial Risk ($r = -0.964, p < 0.01$), and Performance Risk ($r = -0.976, p < 0.01$) indicate an extremely high negative association with behavioral intentions. This suggests that the risks associated with FinTech are a major barrier to the adoption of the technology because it affects consumer decision making concerning FinTech products negatively. From the findings above, it is apparent that the perceived benefits as well as the perceived risks significantly influence the adoption of FinTech by urban households. Making the technology more user-friendly coupled with increased security measures against risks such as privacy threats, financial risk, and performance risk, will make people feel confident about using FinTech.

Keywords: FinTech Adoption, Technology Acceptance Model, Perceived Risk, Behavioral Intention, Urban Households, Digital Financial Services, Financial Inclusion.

Introduction

The financial environment has changed considerably over the decades, owing to technological development, affecting how consumers obtain and benefit from financial products. In urban locations, the use of technology and FinTech innovations has facilitated changes pertaining to transactional activities involving the receipt or loaning of digital currency needed by consumers. Fintech has brought about digital improvements in terms of service delivery through the adoption of not just digital networks (blockchain), but also artificial intelligence (AI). As far as urban families go, the adoption of financial technology can be very convenient for them, with the barriers of access to capital becoming considerably lowered (Nymana & Usun, 2023). Nevertheless, the level of willingness of consumers to adopt technology-oriented financial products depends greatly on their perception of benefits and risks associated with it. The second objective of the research was to consider how differences between consumer willingness to accept new technology impacted the acceptance of technology in urban Bangladeshi families.

The Technology Acceptance Model (TAM) is a model which is used to measure FinTech adoption behavior by considering PEOU and PU as two basic antecedents of BI in FinTech adoption (Filfilan & Alattas, 2025). Regarding PU and PEOU, scholars emphasize on both variables as a positive effect on the intentional acceptance of technology-based financial products especially among users having intermediate exposure to the technology in urban areas (Huarng & Yu, 2022). Moreover, in case the variable risk is considered alongside PU and PEOU, TAM is better at explaining the concept of BI as the risk is an important variable affecting user acceptance of digital financial services. Risk, which includes privacy, financial and performance risk, hinders FinTech adoption. Similarly, just like PEOU and PU, privacy risk which involves data breaches and financial risk which involves monetary losses affect users of digital products having digital exposure in urban areas. Performance risk involves the reliability or lack of it of the system which may deter the users from adopting digital financial products (Arner et al., 2015).

In this study, the focus is on understanding the impact that PEOU, PU, and perceived risks have in the adoption of FinTechs by urban households through correlation analysis based on the TAM framework. Some of the contributions of the paper include the examination of risk as a multidimensional construct in the TAM framework, identifying the specific adoption pattern of FinTechs by urban users, and providing practical guidance for FinTech providers to reduce the risks involved. This research is focused on studying the correlation between PU, PEOU, and perceived risks in the adoption of FinTechs by urban households. Contributions of the paper include the examination of risk as a multidimensional construct in the TAM framework and understanding adoption patterns in urban settings.

This research is important since it analyzes the role of factors affecting FinTech adoption among urban households in Ernakulam, a state of Kerala, India, which is currently experiencing technological innovation and adoption of digital finance products. The contribution of this research will be towards providing a wider perspective about the impact of both motivating and demotivating factors (usefulness, ease of use, and risk factors), such as privacy risk, financial risk, and performance risk, influencing the adoption intention of FinTech service by extending the TAM framework with risk perspectives. The findings of the research will assist stakeholders, such as FinTech service providers, financial institutions, and policymakers, in developing strategies for facilitating FinTech services adoption and dealing with concerns raised by users regarding the safety and trustworthiness of using digital financial products. This study brings insights into the Indian Urban context since there is little empirical research on FinTech adoption.

The key contribution of the study follows,

- Builds upon TAM and incorporates additional determinants such as privacy, monetary, and performance risk factors for FinTech adoption.
- Fills the knowledge gap in relation to FinTech adoption in urban India through empirical evidence collected in the city of Ernakulam in the state of Kerala.
- Takes into account the problematic aspects associated with benefits and risks and explains how perceived benefits facilitate adoption, whereas perceived risks impede it.
- Suggests measures for FinTech service providers and policymakers that could facilitate faster adoption through better interface design and security.

Research Hypothesis

- H1: PU has a positive correlation with BI in adopting FinTech services.
- H2: PEOU has a significant positive correlation with BI.
- H3: Privacy risk has a significant negative correlation with BI.

- H4: Financial risk has a significant negative correlation with BI.
- H5: Performance risk has a significant negative correlation with BI.

This paper is organized into five sections. Section II reviews relevant literature and develops the study hypotheses based on the extended Technology Acceptance Model (TAM). Section III describes the research methodology, data collection, and analytical procedures. Section IV presents and discusses the empirical findings, while Section V concludes the study with future research directions.

Literature Review and Hypothesis

FinTech can be defined as a groundbreaking trend within the financial services sector involving integration of digital technologies into the traditional finance operations. The implementation of different FinTech innovations such as mobile banking, e-wallets, peer-to-peer lending, online payments, and others has significantly enhanced access to financial services and their usability (Banna et al., 2022; Basole & Patel, 2018). Research has been recently conducted about the significance of FinTech as a means for advancing digital financial inclusion and transformation (Banna et al., 2022; Basole & Patel, 2018). According to the findings of this study, the usage of FinTech technologies has been identified as an extremely effective approach towards advancing financial inclusion through enhancing access and user engagement (Aloulou et al., 2024; Dawood et al., 2022). Similarly, another study revealed that the collaborative efforts related to the introduction of FinTech innovations help achieve the objectives of sustainability through ensuring financial inclusion and accessibility (Danladi et al., 2023). In addition, one more study found out that technological convenience and accessibility were the key factors influencing consumers' behavior in FinTech (Choi et al., 2024). Consumer perspectives appeared to be particularly important in FinTech adoption in this context (Chen et al., 2019).

Undoubtedly, the Technology Acceptance Model (TAM) is considered one of the most popular models in terms of theorizing about service adoption through technology. According to TAM theory, adoption of technology depends on the level of utility and ease of use of that technology. Recent research supports the relevance of TAM theory application in cases relating to FinTech. Hence, recent studies found that perceptions of usefulness and ease of use are critical variables in determining user intentions of using FinTech applications in banking (Raza & Tursoy, 2025). In addition, in a separate study, technology acceptance factors were identified as crucial predictors of user intentions related to adopting FinTech applications (Bajunaied et al., 2023). Moreover, similar findings were found in case of Vietnamese youth, where perceptions of usefulness and ease of use influenced their intentions of utilizing FinTech platforms (Mha, 2015; Khuong et al., 2022). Thus, TAM theory will be used in this research since it contains relevant concepts for predicting FinTech adoption.

However, despite the benefits offered by FinTech services, the privacy, security, and technical issues play a significant role in hindering their adoption process. Perceived risk theory holds that consumer beliefs about possible risks before adopting a new technology are an essential element (Mehrotra, 2019). Within a similar setting, this paper found that perceived risk is a vital variable influencing the adoption intention of FinTech services concerning privacy and security (Zhao & Khaliq, 2024). Another paper has revealed that perceived value can be useful in promoting adoption but, on the other hand, risks prevent consumers from using mobile FinTech services (Lee & Shin, 2018; Wei et al., 2025). Security risks, mistrust, and uncertainties were considered major constraints to FinTech service adoption in developing countries (Breidbach et al., 2020; Nalluri & Chen, 2024). Moreover, another paper noted that trust serves as a mediating variable between perceived risk and adoption intention (Chawla et al., 2023). Therefore, it becomes evident that privacy risk, financial risk, and performance risk are some of the crucial variables to consider within the current research.

From the literature review, it can be understood that some of the most important factors influencing the adoption of FinTech applications include perceived usefulness, perceived ease of use, trust, and perceived risk. While a number of contemporary studies have been devoted to understanding the determinants of FinTech technology adoption by undertaking extensive analysis in various geographical locations and socio-demographic groups, the availability of literature on adopting FinTech technology among the urban households in the state of Kerala is extremely limited. Moreover, while the existing research places much emphasis on identifying the benefits associated with technology adoption, it has paid insufficient attention to studying the effects of privacy risk, financial risk, and performance risk together. The present study tries to address these two gaps in the literature using the Technology Acceptance Model, which takes into consideration both benefits and risks.

Research Methodology

Study Area

This research was conducted in the Ernakulam District of Kerala, India, which is among the most urbanized and digitized parts of the State. This area has been known to be one of the most significant business districts of Kerala in terms of commercial activities and financial operations. Hence, there is a large number of banking establishments as well as various other technologies used in the region. The Ernakulam District has recently been experiencing the rapid growth of various innovative digital financial solutions, including mobile banking, UPI payments, digital wallets, and online investments. Therefore, it can be stated that the chosen location would be an ideal choice for investigating the determinants of FinTech adoption by urban households.

Research Design

A quantitative cross-sectional research methodology was employed to determine the connection between Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Privacy Risk (PR), Financial Risk (FR), Performance Risk (PER), and Behavioral Intention (BI) to adopt FinTech. In this study, the Technology Acceptance Model (TAM) is the theoretical framework where perceived risks were considered the external variable influencing the adoption intention.

Target Population and Sampling Frame

Target population consisted of members of urban households residing in the Ernakulam district, under municipal corporations and urban localities that had already utilized at least one kind of FinTech solution (mobile banking, digital wallets, UPI apps, or finance portals).

Sampling frame consisted of the following methods:

- RWAs (resident welfare associations)
- Professional networking sites
- Education centers
- Social media community groups

Groups of users of digital banking and FinTech in Ernakulam

In order to qualify as an individual to be a part of this study, one should have been older than 18 and have availed themselves of the FinTech facilities in the previous six months period.

Sampling Technique and Sample Size

For the selection of respondents for the study, the purposive sampling technique was employed, and the respondents chosen were the ones who had used the FinTech services previously. This ensured that the respondents were experienced enough to answer the questions asked.

In total, there were 20 questions posed to the respondents in six constructs. According to the recommendations of other recent studies, it was necessary to have 5-10 respondents for each question; thus, a total of 200 respondents were chosen for the study.

Data Collection Procedure

Data collection was carried out from January to March 2025 through the administration of a structured questionnaire posted online using the Google Forms tool. The survey questions were carefully crafted after examining previously established measurement instruments used in earlier research focusing on TAM model and Fintech adoption, thus guaranteeing that the questions were not only content-relevant and valid for measurement of key variables in the current study. To start with, the questionnaire was tested by scholars specializing in digital finance and consumer behavior before main data collection process took place. In addition, a pilot test was undertaken on 20 respondents whose goal was to measure the reliability and comprehensibility of the questions used in the survey. After making the required changes to the survey tool on the basis of the results obtained during the pilot test, the final form of the questionnaire was distributed to potential respondents through email, WhatsApp groups, professional networks, and social media platforms. All the responses were carefully analyzed to make sure that it had come from respondents who qualified to take part in the research.

The conceptual framework that is going to be used for this research can be seen in fig. 1. The above framework represents an expansion of TAM by integrating the following three types of risks: privacy risk, financial risk, and performance risk. Perceived usefulness (PU) and perceived ease of use (PEOU) are supposed to have a positive

influence on the behavioral intention (BI) of FinTech acceptance, whereas privacy risk (PR), financial risk (FR), and performance risk (PER) are supposed to negatively impact B.

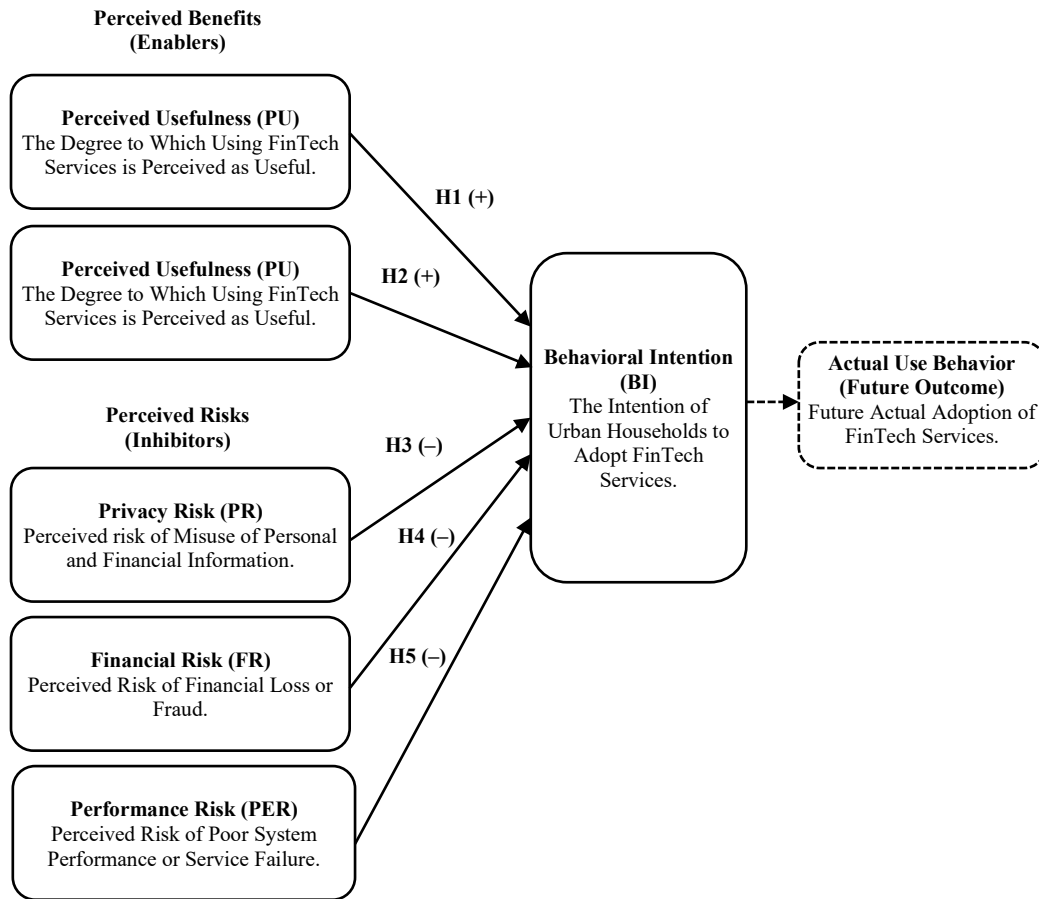


Fig. 1: Conceptual Framework for FinTech Adoption Among Urban Households Based on the Extended Technology Acceptance Model (TAM)

Measurement of Variables

All constructs were measured using a five-point Likert scale ranging from: 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree.

Table 1: Measurement Constructs and Number of Questionnaire Items

Construct	Number of Items
Perceived Usefulness (PU)	4
Perceived Ease of Use (PEOU)	4
Privacy Risk (PR)	3
Financial Risk (FR)	3
Performance Risk (PER)	3
Behavioral Intention (BI)	3

In table 1 indicates the measurement constructs which were used in the research along with the number of items for each measurement construct.

Analytical Model

Relationship between research variables was tested using descriptive statistics, reliability analysis, factor loading, and Pearson correlation.

The formula for the analytical model is depicted in equation 1:

$$BI = f(PU, PEOU, PR, FR, PER) \quad (1)$$

Mathematical Description

Pearson's Correlation Coefficient was used in order to determine the degree of relationship between variables, as shown in equation 2.

$$r = \frac{\sum(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum(X_i - \bar{X})^2 \sum(Y_i - \bar{Y})^2}} \quad (2)$$

Interpretation:

- $r > 0$: Positive relationship
- $r < 0$: Negative relationship
- $|r| \rightarrow 1$: Strong relationship
- $r = 0$: No relationship

Additionally, reliability was assessed using Cronbach's Alpha are demonstrated in equation 3:

$$\alpha = \frac{k}{k-1} \left(1 - \frac{\sum \sigma_i^2}{\sigma_T^2} \right) \quad (3)$$

Values above 0.70 indicate acceptable internal consistency.

Results and Data Analysis

Data Analysis was done using IBM SPSS Statistics Software version 26.0 while data preparation and coding was done using Microsoft Excel. The dataset comprised of 200 valid data samples collected from a survey done on urban families from Ernakulam, Kerala using online questionnaire provided in the medium of Google Forms. Data collection was done based on six constructs namely Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Privacy Risk (PR), Financial Risk (FR), Performance Risk (PER), and Behavioral Intention (BI) where information was collected using 20 questions rated on five-point Likert scale responses ranging from 1 to 5 (Strongly Disagree to Strongly Agree). Initial data processing included data cleansing to detect any errors such as missing data, duplicates and inconsistent values in the data. Different data analyses done included Descriptive statistics, Reliability analysis, Factor loading analysis and Pearson correlation analysis. With respect to Parameter Initialization, $\alpha = 0.05$ at 95% Confidence Interval, Cronbach's Alpha > 0.70 , and Factor Loadings > 0.60 were set as the minimum required parameters respectively.

Descriptive Statistics

In table 2 displays the result of descriptive statistics of the constructs studied based on the sample size of 200 respondents. This table provides insights into the central tendency of each construct under analysis.

Table 2: Descriptive Statistics of the Study Constructs

Construct	N	Mean	Std. Deviation	Skewness	Kurtosis
Perceived Usefulness (PU)	200	4	0.65	-0.29	-1.47
Perceived Ease of Use (PEOU)	200	4.13	0.6	-0.40	-1.46
Privacy Risk (PR)	200	2.28	0.98	0.47	-1.30
Financial Risk (FR)	200	2.41	0.93	0.32	-1.60
Performance Risk (PER)	200	2.33	0.85	0.4	-1.44
Behavioural Intention (INT)	200	3.93	0.93	-0.47	-1.21

These results demonstrate that individuals from urban areas have demonstrated a high level of optimism concerning the usefulness (mean = 4.00) and ease of use (mean = 4.13) of the FinTech service, thus demonstrating their high level of comfort using these kinds of services. As for the risk perception, it is considered to be quite moderate with the privacy risk (mean = 2.28) being slightly lower than both the financial risk (mean = 2.41) and the performance risk (mean = 2.33). Furthermore, the willingness of residents from urban areas to adopt FinTech services is rather high as well (mean = 3.93), which is associated with the high behavioral intention to adopt this kind of service.

Reliability Analysis

In table 3 indicates the results of reliability and convergent validity of the research concepts. Reliability was calculated by the help of Cronbach's Alpha and Scale Composite Reliability (SCR), while the evaluation of the convergent validity was carried out through Mean Extracted Variance (MEV). The research concepts achieved Cronbach's Alpha values above 0.80, SCR values exceeding 0.88, and MEV values above 0.65.

Table 3: Reliability and Convergent Validity Assessment of the Measurement Constructs

Construct	No of Items	Cronbach's α Coefficient	Scale Composite Reliability (SCR)	Mean Extracted Variance (MEV)
Perceived Usefulness (PU)	4	0.888	0.925	0.758
Perceived Ease of Use (PEOU)	4	0.82	0.883	0.659
Privacy Risk (PR)	3	0.918	0.942	0.843
Financial Risk a(FR)	3	0.904	0.941	0.843
Performance Risk (PER)	3	0.87	0.924	0.803
Behavioural Intention (INT)	3	0.944	0.966	0.905

Factor Loading

Table 4: Factor Loadings of Measurement Items for the Study Constructs

Construct	Item	Loading
PU-Perceived Usefulness	PU01	0.972
	PU02	0.768
	PU03	0.909
	PU04	0.819
PEOU-Perceived Ease of Use	PEOU01	0.961
	PEO02	0.656
	PEO03	0.863
	PEOU04	0.733
PR-Privacy Risk	PR1	0.979
	PR2	0.893
	PR3	0.87
FR-Financial Risk	FR1	0.919
	FR2	0.823
	FR3	0.915
PR-Performance Risk	PER1	0.944
	PER2	0.811
	PER3	0.927
BI-Behavioural Intention	INT1	0.979
	INT2	0.914
	INT3	0.959

Factor loadings for the measurement indicators for each construct to be used in the research were provided in table 4. The use of factor loadings was taken into consideration when assessing the strength of relationship between the indicators and corresponding latent constructs. Factor loadings ranged from 0.656 to 0.979, which is above the cut-off point value of 0.60. Therefore, it could be said that the reliability of indicators was quite high whereas the validity of constructs was adequate. All indicators seemed to be valid measures of their constructs, namely Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Privacy Risk (PR), Financial Risk (FR), Performance Risk (PER), and Behavioral Intention (BI).

Correlation Matrix (Pearson r)

Table 5: Pearson Correlation Matrix Among FinTech Adoption Constructs

Variable	INT	PU	PEOU	PR	FR	PER
INT	1	0.959**	0.885**	-0.980**	-0.964**	-0.976**
PU	0.959**	1	0.917**	-0.970**	-0.968**	-0.967**
PEOU	0.885**	0.917**	1	-0.885**	-0.928**	-0.915**
PR	-0.980**	-0.970**	-0.885**	1	0.973**	0.972**
FR	-0.964**	-0.968**	-0.928**	0.973**	1	0.977**
PER	-0.976**	-0.967**	-0.915**	0.972**	0.977**	1

Correlation coefficients among the variables considered are shown in table 5, where INT is Behavioral Intention, PU is Perceived Usefulness, PEOU is Perceived Ease of Use, PR is Privacy Risk, FR is Financial Risk, and PER is Performance Risk. According to table 5, there exist strong positive relationships between perceived usefulness and

behavioral intention ($r = 0.959, p < 0.01$) and between perceived ease of use and behavioral intention ($r = 0.885, p < 0.01$). Therefore, perceived advantages play an important role in shaping behavioral intention towards using FinTech solutions. In addition, privacy risk, financial risk, and performance risk are negatively related to behavioral intention.

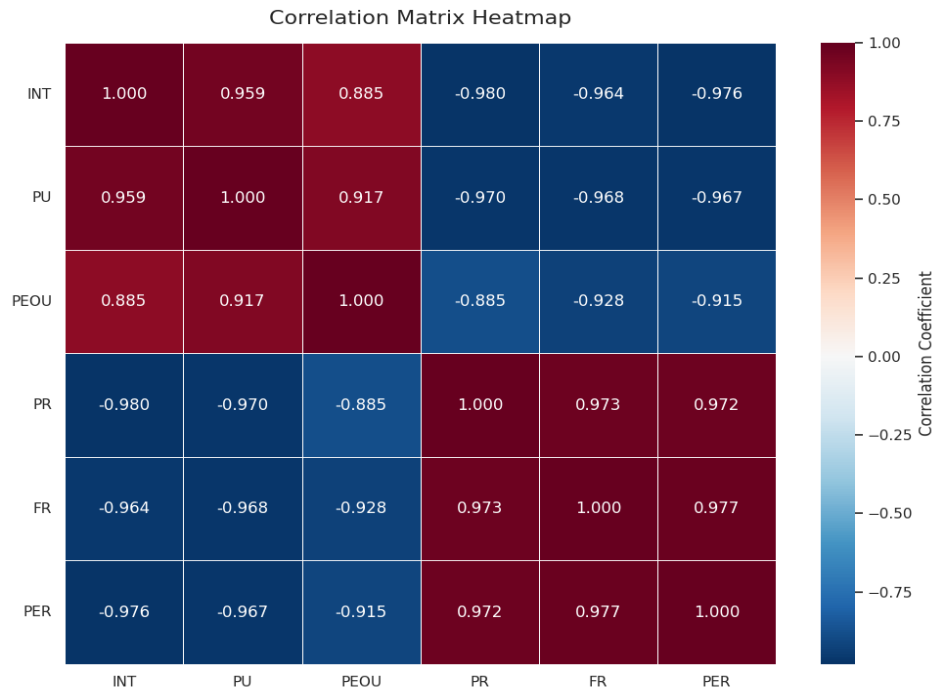


Fig. 2: Correlation Matrix Heatmap of FinTech Adoption Constructs

In fig. 2, the heat map on the correlation matrix which is employed to show the correlations between INT, PU, PEOU, PR, FR, and PER. Reddish colors denote strong positive correlation while blue color denotes strong negative correlation. The behavioral intention is found to exhibit a strong positive correlation with perceived usefulness ($r = 0.959$) and perceived ease of use ($r = 0.885$) implying that higher perceived advantages contribute to the increased acceptance of FinTech among users. Conversely, privacy risk ($r = -0.980$), financial risk ($r = -0.964$), and performance risk ($r = -0.976$) exhibit a strong negative correlation with behavioral intention.

Mean Scores by Risk Dimension

Table 6: Mean Scores and Interpretation of Perceived Risk Dimensions in FinTech Adoption

Risk Dimension	Mean	Interpretation
Privacy Risk	2.28	Respondents express relative assurance regarding data security.
Financial Risk	2.41	A moderate level of concern about potential financial losses is evident.
Performance Risk	2.33	Moderate apprehension exists concerning system reliability and functionality.

In table 6 summarizes the mean ratings of three dimensions associated with FinTech adoption as well as the appropriate meaning of each dimension in this context. On the level of perceived risks for all dimensions, the participants indicated moderate to low perceived risk levels. On the privacy risk dimension, the mean rating was found to be lowest (2.28). This is because there exists some trust from users regarding the level of security associated with their data. On the other hand, the financial risk dimension has a comparatively highest rating of mean score of 2.41. This shows that users have concerns regarding the risk of financial loss when adopting FinTech technology. The same applies to the performance risk dimension of 2.33.

The level of urban household adoption of FinTech services is moderate; privacy risk is slightly lower compared to financial risk and performance risk.

Hypothesis Testing and Objective-Based Analysis

This research paper is meant to investigate the relationships between PU, PEOU, privacy risks, financial risks, performance risks, and BI with regard to FinTech innovation among families living in urban areas of Ernakulam,

Kerala. All the hypotheses have been tested using Pearson Correlation test method, and the results can be observed from table 7.

Table 7: Hypothesis Testing Results

Hypothesis	Relationship	Correlation (r)	p-value	Result
H1	PU → BI	0.959	<0.01	Supported
H2	PEOU → BI	0.885	<0.01	Supported
H3	PR → BI	-0.980	<0.01	Supported
H4	FR → BI	-0.964	<0.01	Supported
H5	PER → BI	-0.976	<0.01	Supported

The results of the hypothesis test through Pearson Correlation Analysis are presented in table 7. The observation can be made that the perceived usefulness is significantly positively related to behavioral intention ($r = 0.959, p < 0.01$). Thus, hypothesis H1 gets proven: people will be more motivated to use FinTech services if it expect the services to be useful for them. Likewise, it was identified that there is a significantly positive correlation between perceived ease of use and behavioral intention ($r = 0.885, p < 0.01$). Thus, people are more motivated to use FinTech products if it sees them as user-friendly.

Furthermore, the results show that there is a significantly negative relationship between perceived risks and behavioral intention. There are three aspects related to perceptions of risks that affect people's willingness to adopt FinTech products: privacy risks ($r = -0.980, p < 0.01$), financial risks ($r = -0.964, p < 0.01$), and performance risks ($r = -0.976, p < 0.01$). Therefore, H3, H4, and H5 get proven: people tend not to adopt the FinTech services due to their fear of privacy and financial issues.

Conclusion

This study investigated the factors that influence the use of FinTech services among urban householders in Ernakulam, Kerala, based on TAM with some changes by including PU, PEOU, PR, FR, and PER variables. Findings revealed that both the benefits and risks are crucial when influencing the intention of the respondents to adopt FinTech services. Based on descriptive statistics, PU and PEOU have very high values ($M = 4.00$; $M = 4.13$) which implies that FinTech services are beneficial and easy to use by the consumers. In contrast, PR, FR, and PER have moderate means ($M = 2.28$; $M = 2.41$; $M = 2.33$). All of the hypotheses tested in this study received strong support from the findings obtained from the correlation analysis. The variables perceived usefulness ($r = 0.959, p < 0.01$) and perceived ease of use ($r = 0.885, p < 0.01$) correlated positively with behavioral intention and indicated that there is a relationship between a high level of usefulness/ease of use and increased FinTech use. On the other hand, variables of privacy risk ($r = -0.980, p < 0.01$), financial risk ($r = -0.964, p < 0.01$), and performance risk ($r = -0.976, p < 0.01$) correlated negatively with behavioral intention and showed that a high perception of risk among users influences their behavior related to using FinTech applications. These findings can contribute to the existing body of knowledge in the field of fintech and can be useful for practitioners seeking to understand why certain individuals choose not to utilize fintech products. For future research, one might consider employing larger samples that include people from both urban and rural settings, adding more independent variables to the study, using a longitudinal design or even a structural equation model.

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