ADOPTION OF FINTECH SERVICES IN UTTAR PRADESH: USING EXTENDED TAM

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Abstract

Rapid progression in technology has resulted in the tremendous growth & development of FinTechs, which significantly transformed the framework of the Indian Financial System. So, the present research aims at contributing to the literature by employing extended TAM to examine Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Government Influence (GI) & Security (S) as the factor influencing users' Intention to Adopt (ITA) FinTech Services in India. Our findings revealed that PEOU, PU & GI significantly impact the usage of Financial Technological Services while Security has an insignificant influence on users' intentions. Moreover, it was found that PU mediates the association of PEOU with ITA. Therefore, the present research contributes to the literature concerned with factors affecting users' ITA FinTech Services and validating Technology Acceptance Model (TAM) in anticipating users' ITA FinTech Services by adding Security & Government Influence as additional constructs.

Key Words

Behavioural intention; financial technology; FinTech services; perceived usefulness, TAM.

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INTRODUCTION

The global recession, of 2008 was the catalyst of the growth & development of FinTechs that become users' favorites in no time (Capgemini Research Institute, 2021) because they turned the limitations of conventional financial institutions into their strength. It is one of the rapidly emerging fields in the financial ecosystem, and also the confluence of financial services with expanding technologies is crucial in building a vigorous digital nation that would lead India toward digital transformation (Deloitte, 2017). FinTech services are the digitalized & technology-enabled financial products & services that are provided by FinTech companies & financial institutions (Osman et al., 2021). Such services are altering the way users think while accessing, investing, managing, and spending their savings, in order to achieve their demand of availing financial services at an affordable cost (Shah et al., 2019). The inefficiency of conventional financial services like labor-dependent financial services, paper-based and manually done procedures, etc. offers a great chance for FinTechs to acquire and retain users at low cost, and that would lead to greater adoption of financial services (Deloitte, 2017). The FinTech sector of Asia region is highly dominated by two developing nations namely, India & China (KPMG, 2018). According to Goyal et al. (2021), India has experienced a tremendous rise in FinTech companies as there are more than 2,100 FinTech companies, out of which around 67 percent of them have come into existence in the past five years. Also, the worldwide FinTech industry is anticipated to expand at a CAGR of 23.58 percent from 2021-2025, and with the predicted market opportunity of $1.3 trillion by 2025 and more than 4200 active FinTech firms, India is quickly emerging as the global center for the FinTech industry (EY, 2022). It is because of the initiatives taken by the government & regulatory bodies for the digital nation, with the help of more internet and smartphone usage which led to greater utilization of technology-enabled services (Deloitte, 2017). According to Invest India (2023), "India has the highest FinTech Adoption rate globally of 87 percent which is significantly higher than the Global average rate of 64 percent". And it has one of the fastest budding FinTech ecosystems globally having a FinTech industry market size of $50 Billion which is projected to be ~$150 billion by 2025 and also it documented the highest absolute number of real-time transactions globally crossing around 48 billion that is around 6.5 times of the collective volume of world's leading nations like U.S, Canada, U.K., France & Germany in 2021 (Invest India, 2023).

The usage rate of Fintech services has enormously increased after the COVID-19 outbreak indicating greater financial inclusion (Gupta and Agrawal, 2021). The main reason behind the greater adoption rate of FinTech services is that FinTech companies are mostly aiming at tech-friendly users resulting in reduced budgetary & resource exploitation in convincing uninterested users also these companies deliver financial products & services to the financially underserved & unserved section of the society that is high in masses in developing nations (Slazus and Bick, 2022; EY, 2016). Users with less financial literacy can also use FinTech services, so it has the potential to serve the unbanked population that has low financial literacy (Setiawan et al., 2021). The growth & development of FinTech Services has greatly influenced individuals' day-to-day life as services like online mobile payment, e-wallets, InsurTech, TradeTech, cryptocurrencies, etc. have made financial transactions, effortless & scalable for them (Osman et al., 2021).

FinTech offers a wide range of benefits to its users, still, it is an alien term for a large section of the nation even if they know then also, they restrain to use and it is because of various factors that affect users' behavioral intention while adopting technology-enabled financial Services (Singh et al., 2021).

According to Indian Ambassador Taranjit Sandhu, "Uttar Pradesh is destined to become a powerhouse of India, with a population of 240 million it is the most populous state". Also, over the past four years, Noida and Greater Noida (districts in Uttar Pradesh) have become preferred locations for establishing Uttar Pradesh financial technology (FinTech) companies (Express News Service, 2022). UP government has also signed a MoU with a US-based fintech firm for investing 500 crores for setting up its operations in Lucknow and Noida.

Therefore, the present research aims at contributing to the literature by employing extended TAM to examine PU, PEOU, GI & S as the factor influencing users' intention to use FinTech Services in Uttar Pradesh. However, there are past studies that have addressed the adoption of a particular type of FinTech Services like Mobile payments, Online Banking, etc. but there is very fewer literature as per our knowledge that is conducted in India and addressed FinTech Services adoption as a whole. And absolutely no research that is conducted in Uttar Pradesh and attempted to assess the users' intent towards FinTech services usage.

Since "Uttar Pradesh favored destination for Fintech companies" (News Desk, 2022) and also there is an excessive rise in the number of FinTech users in Uttar Pradesh so there is a need to explore more on this topic as it will enable FinTech service providers & system developers to better understand the users' attitudes & perceptions towards using such services so that they can propose solutions and design services to retain users' and also attract potential consumers. Therefore, this study attempts to bridge the gap by tackling this issue.

Hence, the rest of the paper is presented in various sections, where Section 2 outlines the prior works of literature that were reviewed based on FinTech services, TAM constructs (PU & PEOU), Security & GI as additional constructs, Intention to use FinTech services and accordingly conceptual research model and hypothesis were developed & framed. Section 3 explains the methodology used in the study involving questionnaire preparation, data collection & scale reliability are explained. In section 4, the result of the study is presented and section 5 comprises findings & discussions. Section 6 concludes the research work while sections 7 and 8 contain the implications, limitations & future research scope.

BACKGROUND & HYPOTHESIS FRAMING

FinTech Services

FinTech is the portmanteau of Financial Technology, which refers to an organization or a firm that delivers financial services & products with the employment of technology and their main goal is to grab the attention of consumers by offering convenient products, easily accessible & efficient services as compared to traditional financial services (Susilo et al., 2019). As per Financial Stability Board (FSB), "FinTech is technologically enabled financial innovation that could result in new business models, applications, processes, or products with an associated material effect on financial markets and institutions and the provision of financial services". Basically, it refers to a financial processing unit that facilitates the nation's financial sector in providing efficient customer care and assistance by using technologically-equipped methods (Gupta and Agrawal, 2021).

Theoretical Background

For assessing users' adoption intention and behavior towards a technology, prior studies have adopted several theories like TRA, UTAUT, TPB, etc. but among all TAM is most widely adopted by researchers to understand consumers' adoption & usage intent towards a technology or system. Theory of Reasoned Action (TRA) is the base model of TAM, which was originally designed for examining IBM employees' acceptance of word processor technology (Patel and J. Patel, 2017).

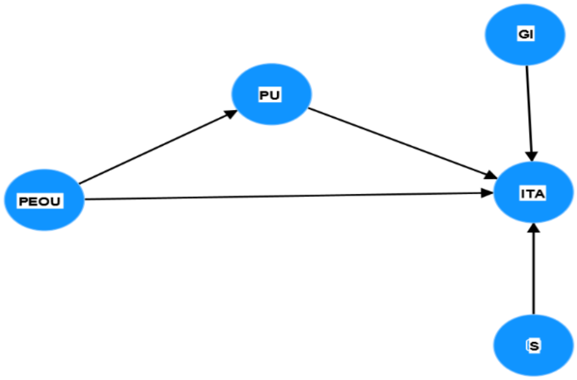
Previous works of literature have correlated FinTech services adoption with various theories but TAM is extensively used by past studies (Susilo et al., 2019; Slazus and Bick, 2022; Chong et al., 2010, Cheng et al., 2006) while conducting research that is concerned with the adoption of FinTech Services and its related fields. Therefore, since TAM has been enormously backed by empirical findings so the present study has used TAM as the base model to examine the factors that affect the users' intention to adopt FinTech Services in India with special reference to selected districts of Uttar Pradesh.

Framing hypothesis for the proposed model

As TAM has enormous empirical and pragmatic support from prior studies so in this study TAM is used as our foundation model. However, in the initial model of the Technology Acceptance Model Davis (1989), only PU & PEOU were used as the predictor variable and Behavioural Intention (BI) was the outcome variable but in the present research, we have used TAM as the base model and augmented it by adding two more independent variables namely, Government Influence (GI) & Security (S). Also in the original model, the attitude was included as it mediates the relationship of PU & PEOU with behavioral intention but recent works of literature have excluded it since it does not mediate the relation of PU & PEOU with behavioral intention (Patel and J. Patel, 2017). So, in this study, attitude is not included in the model.

Therefore, we have utilized the original constructs of TAM which are PU & PEOU but also added GI & S, considering that they are crucial for users' intention to adopt FinTech Services in India. So, we assume that the present study will be a literature contribution to the augmented Technology Acceptance Model by using GI & S along with the actual constructs of TAM for examining whether PU, PEOU, GI & S influence users' intention while adopting FinTech Services. Table 1 presents the prior studies that administered the same association. Figure 1 shows the conceptual model of the study.

Figure 1: Conceptual Research Model



Government Influence (GI) & Intention to Adopt (ITA) Financial Technological Services

The government of any nation plays an important role in developing its FinTech Sector, as it frames laws & regulations that help the FinTech sector to grow & develop (Setiawan et al., 2021), facilitate users with the proper infrastructure needed, and also promote it among its citizens by making them aware about the benefits of such services. The government efforts would encourage individuals. So, government influence is an important factor that affects users' intention to use Technology-enabled Services as studied by prior researchers (Chong et al., 2010; Hu et al., 2019; Osman et al., 2021) while Setiawan et al. (2021) found that there is the insignificant influence of GI on users' intention. The present study hypothesizes that:

H1: GI positively influences users' ITA FinTech Services.

Perceived Ease of Use (PEOU), Perceived Usefulness (PU), and Intention to Adopt (ITA) FinTech Services

As per Liébana-Cabanillas et al. (2014), the Perceived Ease of Use refers to users' perception that adopting a particular technology requires no or very less effort. Users are expected to use FinTech services if they believe them to be user-friendly, easy to use, & less complicated (Patel & and J. Patel, 2017). While Perceived Usefulness (PU) is the degree to which a user's subjective probability that adopting a certain technology will result in his/her improved job performance (Venkatesh and Bala, 2008). And Intention to use refers to the user's intent to adopt, in contrast to their actual use of FinTech services (Cheng et al., 2006). PU & PEOU are considered the prime constructs that are capable to influence users' intention to use any technology (Davis, 1989). Therefore, in the present study, we examined the association of PEOU with users of ITA FinTech Services with PU as a mediating variable, as PU is a crucial factor in technological usage (Setiawan et al., 2021). Hu et al. (2019) found that PEOU has a significant impact on PU while Patel and J. Patel (2017) concluded that PEOU has a significant impact on Users' intentions. On the contrary, Setiawan et al. (2021) & Chong et al. (2010) found that PEOU had an insignificant influence on users' intentions. Cheng et al. (2006) & Setiawan et al. (2021) revealed that the relationship between PEOU and Users' intentions is mediated by PU. So, based on prior literature, the hypothesis was framed as:

H2: PEOU has a significant positive impact on users' ITA FinTech Services.

H3: PEOU is positively related to PU.

H4: The relationship between PEOU and users' ITA FinTech Services is mediated by PU.

Perceived Usefulness (PU) and Intention to Adopt (ITA) FinTech Services

PU is the users' perception to adopt or not to adopt certain technology to the extent that it will facilitate them to enhance their job performance (Davis, 1989). It is expected that users mostly prefer to use FinTech services if they find them to be more useful as compared to conventional financial services (Patel and J. Patel, 2017). Prior studies found that there is a positive correlation between PU and users' ITA FinTech services (Setiawan et al., 2021; Chong et al., 2010; Cheng et al., 2006; Patel and J. Patel, 2017). So, the hypothesis was developed as:

H5: PU has a significant positive impact on users' ITA FinTech Services.

Security (S) and Intention to Adopt (ITA) FinTech Services

Security & privacy is considered vital factor to make sure that the users' information is unavailable to suspicious or unauthorized consumers who can misuse the data (Ismail et al., 2018). Security issues like personal & financial data leakage, cyber threat, identity threat, etc. are the major issues that may negatively affect users' intention to use FinTech services (Osman et al., 2021). The study by Cheng et al. (2006) & Patel and J. Patel (2017) revealed that there is a strong impact of security on users' intentions contradicting this Chau & Ngai (2010) found that security is not a significant factor that influences young users' intention to adopt fintech services. So, we hypothesize that:

H6: S positively influences users' ITA FinTech Services.

Table 1: Effects of the Proposed Relationships

ASSOCIATION	PRIOR LITERATURE
S→ITA	(Cheng et al., 2006), (Ismail et al., 2018), (Alwi et al., 2019), (Osman et al., 2021), (Patel and J. Patel, 2017)
GI→ITA	(Setiawan et al., 2021), (Chong et al., 2010), (Hu et al., 2019), (Osman et al., 2021)
PEOU→ITA	(Liébana-Cabanillas et al., 2014), (Daragmeh et al., 2021), (Setiawan et al., 2021), (Chong et al., 2010), (Patel and J. Patel, 2017)
PU→ITA	(Liébana-Cabanillas et al., 2014), (Daragmeh et al., 2021), (Setiawan et al., 2021), (Chong et al., 2010), (Cheng et al., 2006), (Patel and J. Patel, 2017)
PEUO→PU	(Daragmeh et al., 2021), (Hu et al., 2019)
PEOU→PU→ITA	(Daragmeh et al., 2021), (Setiawan et al., 2021), (Cheng et al., 2006)

METHODOLOGY

Data Collection

In the present study, we attempt to ascertain empirically whether constructs (namely, Government Influence, Perceived Usefulness, Perceived Ease of Use, & Security) influence users' intention to adopt FinTech Services. Further, we test the mediation effect of Perceived Usefulness between Perceived Ease of Use & Users' Intention to use FinTech Services. So, we constructed a research instrument consisting of five constructs, which are GI, PU, PEOU, S & ITA. All constructs excluding demographic variables were measured on a 5-point Likert scale (5 = strongly agree and 1 = strongly disagree) as used by Singh et al. (2021); Upadhyay and Jahanyan (2016) & Daragmeh et al. (2021) to assess users' intention towards technology-abled services. There were 22 items for 5 variables in the research questionnaire that were taken from past literature and further amended as per the need of our study. Before sharing the research instrument, a pilot study was conducted with 40 FinTech Users, to check the reliability of the statements of the questionnaire, and accordingly, modifications were made.

Further, the sample size of the study in case the population is unknown is the minimum number of indicators multiplied by 5 (Hair et al., 2014), there were 21 indicators in this study so the minimum sample size required is 105 respondents. So, we distributed questionnaires to 280 respondents and received 220 responses in total. After filtering invalid questionnaires consisting of missing & incomplete questionnaires, there were 209 valid responses, which is above the minimum required sample size. Overall, we achieved a response rate of 75 percent, which is adequate & acceptable for the analysis. The data was collected through hybrid (online & offline) mode using a combination of convenience & snowball sampling and the target population of the study was FinTech Service users residing in four cities of India namely, Prayagraj, Noida, Lucknow & Varanasi. Microsoft Excel & SmartPLS 4 were employed for data analysis. Table 2 depicts the demographic profile of the respondents, in which 43.5 percent of the respondents were male while 56.5 percent were female. 18.2 percent of the respondents were below 25 years, 27.8 percent were between 25-40 years, 28.2 percent were between 41-55 years and 25.8 percent were above 55 years of age. Educational qualifications show that the majority of the respondents were graduated (34.4 percent) and post-graduated 49.3 percent) while 10.5 percent had intermediate degrees, 1.6 percent held Ph.D. degrees & above and 3.8 percent had any Diploma/ Professional Degree.

Table 2: Demographic Profile

GENDER	FREQUENCY	PERCENT (%)
Male	91	43.5
Female	118	56.5
Total	209	100.0
AGE		
Below 25 years	38	18.2
25-40 years	58	27.8
41-55 years	59	28.2
Above 55 years	54	25.8
Total	209	100.0
EDUCATION		
Intermediate	22	10.5
Graduation	72	34.4
Post-Graduation	103	49.3
Ph.D. & above	4	1.9
Any Diploma/ Professional Degree	8	3.8
Total	209	100.0

Source: Own survey.

Common Method Bias (CMB)

CMB, which is also known as common method variance or just method bias. Common method variance (CMV) is the systematic amount of fictitious covariation shared between various variables due to a similar method employed for the collection of data (Buckley, Cote, & Comstock, 1990). Since, all variables in the present study are measured using a common survey questionnaire so there might be chances of the presence of covariance among them (Malhotra et al., 2016). So, to address common method variance-related issues authors have used Harman’s single factor test, which is a broadly employed method used for assessing CMB in a single-method research design (Podsakoff et al., 2003). Basically, in this test

Exploratory Factor Analysis (EFA) is done on all the items, and CMB is present if a single factor comes from unrotated factor solutions or a first factor ascertains that there are many variations in the variables (Podsakoff and Organ, 1986). It is widely accepted that if the result of a single-factor test is less than 50 percent of the variance, there are fewer chances of CMV (Daragmeh et al., 2021). The result of Harman's single factor of the study was within the acceptable range. Therefore, there is an absence of CMV in the study.

RESULTS

For testing the research hypothesis, SEM is applied in the study. It's a multivariate technique, that is the amalgamation of factor analysis and multiple regression. It facilitates the researcher to assess a string of interrelated dependence associations among the measured variables as well as the latent constructs and also between various latent constructs, all at the same time (Hair et al., 2015). Further, for estimating the parameters Partial Least Square SEM was employed. In the present study, SmartPLS 4 software is used for validating the research hypothesis. Data was examined in two steps, firstly measurement model was analyzed by assessing the construct validity & reliability of each construct and then the structural model was studied. The structural model also known as an inner model in PLS-SEM depicts the constructs and shows an association among the constructs while measurement models of the constructs also known as the outer model in PLS-SEM show the association among the constructs and the indicator variables (Hair et al., 2017).

Measurement model of the study

Firstly, we measured the reliability & validity of the research data. A reliable measuring instrument provides consistent and stable results (Kothari, 2004). As per Hair et al. (2019), indicator loadings of items more than 0.70 are regarded as within the acceptable range. Table 3 shows that every item of the data is within the acceptable limit. Moreover, Cronbach alpha and Composite reliability were measured for determining the internal reliability of the data. According to Daragmeh et al. (2021) & Fornell and Larcker (1981), Convergent reliability is more than 0.70 while Cronbach's alpha of more than 0.80 is the indicator of good internal consistency. And since the present variables have convergent reliability & Cronbach alpha above 0.70 & 0.80, so the data has good internal consistency.

Table 3: Construct reliability and validity

Constructs	Item Loadings	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)

Government Influence (GI)		0.923	0.929	0.939	0.687
GI1	0.775				
GI2	0.885				
GI3	0.904				
GI4	0.777				
GI5	0.862				
GI6	0.705				
GI7	0.875				
Intention to Adopt (ITA)		0.920	0.923	0.943	0.806
ITA1	0.863				
ITA2	0.892				
ITA3	0.915				
ITA4	0.921				
Perceived Ease of Use (PEOU)		0.878	0.879	0.916	0.733
PEOU1	0.838				
PEOU2	0.845				
PEOU3	0.869				
PEOU4	0.873				
Perceived Usefulness (PU)		0.895	0.897	0.934	0.826
PU1	0.922				
PU2	0.904				
PU3	0.901				
Security (S)		0.911	0.925	0.944	0.849
S1	0.944				
S2	0.914				
S3	0.905				

Source: SmartPLS 4 (v.4.0.8.6).

Validity is the extent to which a measuring instrument exactly and accurately depicts what it is needed to do (Hair et al., 2015). For assessing the validity of the present study, convergent and discriminant validity is used. The average variance extracted (AVE) is used to determine convergent validity. AVE above 0.50 or higher indicates that the construct describes 50 percent of variance and it is the acceptable range of AVE, and in Table 3 it can be seen that the AVE of all constructs is above 0.50. Further, discriminant validity is calculated to ensure that a constructed measure is unique and has no relation with other measures (Henseler et al., 2015). Firstly, discriminant validity was calculated as per Fornell and Larcker (1981), in which the AVE of each construct should be more than its correlation with other constructs.

Table 4: Fornell-Larcker criterion

	GI	ITA	PEOU	PU	S
GI	0.829				
ITA	0.627	0.898			
PEOU	0.503	0.698	0.856		
PU	0.469	0.716	0.747	0.909	
S	0.269	0.410	0.491	0.517	0.921

Source: SmartPLS 4 (v.4.0.8.6).

In Table 4, it can be seen that all constructs satisfy the condition, so DV is acceptable. Further, DV was calculated by using the Heterotrait-monotrait ratio (HTMT), which was suggested by Henseler et al. (2015) as they were against the Fornell-Larcker criterion. The threshold value required for structural models with similar constructs is 0.90 while for distinct constructs is 0.85 (Henseler et al., 2015). In Table 5, it can be seen that the values of all constructs are within the threshold range.

Table 5: Heterotrait-monotrait ratio (HTMT)

	GI	ITA	PEOU	PU	S
GI					
ITA	0.673				
PEOU	0.558	0.775			
PU	0.510	0.787	0.842		
S	0.287	0.443	0.545	0.566	

Source: SmartPLS 4 (v.4.0.8.6).

Structural equation modelling

SEM is a process used for assessing a sequence of interrelationships between a set of constructs expressed by various measured variables and merged into an integrated model (Malhotra and Dash, 2022). For evaluating the structural model of the study, the collinearity of the formative indicators was calculated using the Variance Inflation Factor, and VIF values of more than 5 suggest that there are major collinearity issues between the indicators of formatively calculated constructs (Hair et al., 2019).

Table 6: Collinearity statistics (VIF)

Constructs	VIF
Government Influence (GI)	
GI1	2.129
GI2	3.973
GI3	4.751
GI4	2.109
GI5	3.185
GI6	1.928
GI7	3.323
Intention to Adopt (ITA)	
ITA1	2.831
ITA2	3.161
ITA3	4.682
ITA4	4.839
Perceived Ease of Use (PEOU)	
PEOU1	2.088
PEOU2	2.140
PEOU3	2.672
PEOU4	2.686

Perceived Usefulness (PU)	
PU1	2.928
PU2	2.605
PU3	2.609
Security (S)	
S1	4.737
S2	4.004
S3	2.395

Source: SmartPLS 4 (v.4.0.8.6).

Table 6 shows that all VIF values are below the threshold limit so there are no collinearity issues. Further, for determining the explanatory power of the structural model, the value of R^2 i.e., coefficient of determination is calculated. R^2 shows the variance that is explained in each of the endogenous constructs and R^2 values range between 0 to 1 indicating a high explanatory power (Hair et al., 2019). Table 7, it is observed that exogenous constructs can interpret 64.8 percent of the variance of the dependent variable i.e., intention to adopt, which is within the range and has moderate explanatory power.

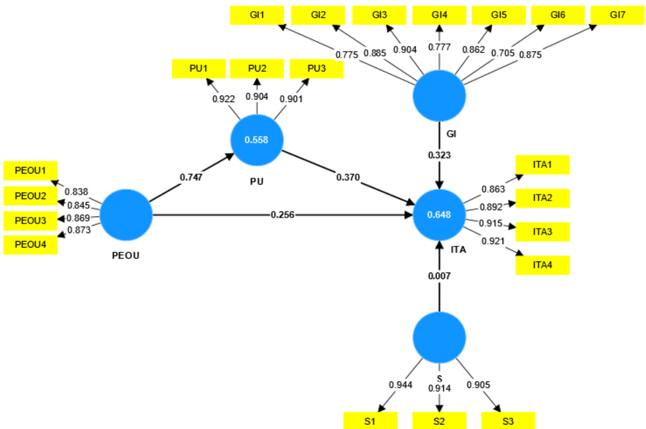
Table 7: Values of R-square

	R-square	R-square adjusted
ITA	0.648	0.641
PU	0.558	0.556

Source: SmartPLS 4 (v.4.0.8.6).

After examining the explanatory power of the model, the next step bootstrapping process was carried out with 5,000 samples for testing the framed hypothesis of the study. In Figure 2, the results of the structural model are explained.

Figure 2: Structural results of the research model



Source: SmartPLS 4 (v.4.0.8.6).

Table 8 shows the results of the hypothesis testing. In hypothesis 1, the effect of Government Influence (GI) on Intention to Adopt (ITA) is examined. Government Influence (GI) has a significant positive association with ITA ($\beta = 0.323$ & $p < 0.05$). Hence, hypothesis 1 is supported.

Hypothesis 2 studies the effect of PEOU on ITA while hypothesis 3 examines the effect of PU on PEOU. The result shows that PEOU has a direct significant positive association with ITA and PU ($\beta = 0.256$, $p < 0.05$ & $\beta = 0.747$, $p < 0.05$). So, hypotheses 2 & 3 are also supported.

Hypothesis 4 determines the effect of PU on ITA and PU has a significant positive association with ITA since $\beta = 0.370$ & $p < 0.05$. Therefore, hypothesis 4 is supported.

Hypothesis 5 examines the impact of Security (S) on ITA and results reveal that Security (S) has an insignificant positive association with ITA since $\beta = 0.007$ & $p > 0.05$. So, hypothesis 5 is rejected.

Hypothesis 6 assesses the association between PEOU and ITA Fintech Services as mediated by Perceived Usefulness (PU). It was found that PEOU has a positive indirect association with ITA mediated by PU with $\beta = 0.276$ & $p < 0.05$. Hence, hypothesis 6 is also supported.

Table 8: Hypothesis results

Relationship		Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
	Direct Effect					
GI -> ITA		0.323	0.321	0.058	5.556	0.000
PEOU -> ITA		0.256	0.256	0.072	3.534	0.000
PEOU -> PU		0.747	0.749	0.049	15.191	0.000
PU -> ITA		0.370	0.371	0.066	5.560	0.000
S -> ITA		0.007	0.003	0.053	0.126	0.900
	Indirect Effect					
PEOU -> PU -> ITA		0.276	0.278	0.056	4.969	0.000

Source: SmartPLS 4 (v.4.0.8.6).

FINDINGS AND DISCUSSIONS

Our study aims at examining the factors that affect users' ITA FinTech Services by validating extended TAM for understanding the users' intent toward FinTech Services. Each hypothesis concerned with the association among the variables is framed and validated through reliability testing and Structural Equation Modelling. The outcome of the research revealed that there is a significant positive influence of PU, PEOU & GI on users' ITA FinTech Services while S has an insignificant influence on the adoption intention of users. It was also found that PU mediates the relationship between PEOU & users' ITA FinTech Services which means that PEOU indirectly influences users' intentions via PU. So, Hypotheses: 1, 2, 3, 4 & 6 are accepted while H5 is rejected.

The survey outcome of the research reveals that GI has a significant association with users' ITA FinTech services as previously concluded by

Chong et al. (2010); Hu et al. (2019) & Osman et al. (2021). In the last decade, the Indian Government has been very active in promoting FinTech services among its citizens and also encouraged them to use FinTech services. Therefore, the government should implement proper laws concerning FinTech services, provide required infrastructures and ensure security & privacy to its citizens to protect them from cybercrimes & frauds.

Further, it was found that PEOU has a direct significant association with users' intentions and it is validated by the study of Patel and J. Patel (2017) but Setiawan et al. (2021); Chong et al. (2010) & Cheng et al. (2006) contradict our results as they found out that PEOU does not have a direct influence on users intention. However, the results of the initial Technology Acceptance Model also support our results. Since the FinTech service is a quite new concept for Indian users especially the users above 41 years of age who prefer to adopt those services that are easy to use, therefore the FinTech companies should offer user-friendly services that are easy to learn & use.

Similar to the results of Hu et al. (2019) & Daragmeh et al. (2021), our study has also identified that PEOU significantly influences PU. While PU mediates the relationship of PEOU with users' ITA FinTech services, our results are consistent with the results of past studies (Daragmeh et al., 2021; Setiawan et al., 2021; Cheng et al., 2006). It means that users find those services useful that are easy to use and hence, prefer to use them. Hence, there is an indirect relation between PEOU & users' intention that is mediated via PU, it implies that users want to put less effort into learning & using FinTech services.

Our results show that PU has a strong association with users' intention to use FinTech Services. Past studies (Setiawan et al., 2021; Chong et al., 2010; Cheng et al., 2006) validate our results. Since PU is a significant factor in determining users' intention to FinTech Services, service providers should let their users know about the various benefits offered by FinTech services in comparison with conventional financial services. Also, fintech companies should focus on promoting and enhancing their features and offer their users with latest innovative services so that they find them useful in their day-to-day life.

Our study found that there is an insignificant influence of security on users' intention to use FinTech Services. Chau and Ngai (2010) validate our finding as they concluded that security isn't a significant factor that influences young users' ITA mobile banking. While Ismail et al. (2018); Alwi et al. (2019) & Osman et al. (2021) contradict our result as they concluded that security & privacy positively affect users' intention to use technology-abled services. This contradiction may be because users find FinTech services more secure than conventional financial services. However, the FinTech service providers need to enhance the security & privacy issues and create awareness about it among their users to protect them from cyber fraud and ensure greater adoption of FinTech services.

CONCLUSIONS

The objective of the present study was to investigate the factors affecting users' intention to adopt FinTech services in India with special reference to four districts of Uttar Pradesh namely Noida, Prayagraj, Lucknow, & Varanasi. We attempted to investigate the direct & indirect impact of PEOU, PU, S & GI on users' ITA FinTech services. Statistical results of our research show that PEOU, PU, & GI have a strong positive impact on users' intentions while security has an insignificant influence on users' intentions. Moreover, the PU was found to be a mediator for the indirect influence of PEOU on Users' intentions. The augmentation of TAM by adding GI & S as an additional variable shows the theoretical input to the literature of factors affecting users' ITA FinTech Services & validating the Technology Acceptance Model (TAM) in anticipating users' ITA FinTech Services.

IMPLICATIONS OF THE STUDY

The present study has theoretical implications as the model framed in this research is an augmented form of TAM by affixing Government Influence & Security as additional constructs. Augmented TAM will facilitate researchers & academicians in better understanding & explaining factors affecting users' intent to adopt FinTech Services like mobile payment apps, digital lending services, etc. Also, the outcome of the research will facilitate FinTech service providers & system developers to design & deliver services that are as per the preference of the consumers, easy to use, secure, and can also consider various factors that influence users' intention towards FinTech services.

The present research validates that Government Influence is a significant determinant that influences users' intent towards FinTech services in Uttar Pradesh, this suggests that Indian Government should frame effective laws and regulations concerning FinTech services to protect the interest of FinTech adopters. Also, Government should provide the proper infrastructure like proper internet services, smartphones, etc., and organize FinTech literacy and awareness programs so that more and more individuals can adopt it.

Further, PEOU & PU are also significant predictors while examining users' intent toward FinTech services so FinTech system developers & service providers should provide users' websites & applications interfaces that can be easily operated, adaptable & convenient for users. They should also provide proper steps or videos on how financial transactions can be carried out on FinTech apps & websites. Also, FinTech service providers should upgrade & enhance their services by considering the feedback given by users so that users' needs & requirements can be catered to successfully.

This research found that security has an insignificant impact on users' intent towards FinTech services and this is because of the reason that users in Uttar Pradesh prefer to use FinTech services like mobile payment apps, digital lending apps, etc. over conventional financial services as they find them more secure and safe. But since prior studies show that security is the key determinant of users' intent to adopt technology-abled services so FinTech service providers must ensure the security and privacy of their users against cyber frauds.

LIMITATIONS AND FUTURE DIRECTIONS

Our research has certain limitations the study was conducted only from the viewpoint of Indian users from several districts of Uttar Pradesh but the model used in our study can be applied by future studies for assessing users' intention to adopt technology-enabled services by other developing nations. We have used only Government Influence (GI) & Security (S) as an additional construct to Technology Acceptance Model (TAM) for evaluating users' intention to adopt FinTech services. Future studies can employ Perceived Risk, Subjective Norm, Quality of service, etc. as additional for assessing users' behavioral intention toward FinTech services. Also, they can use Age, Gender, etc. as moderating variables for studying their influence on users' behavioral intentions.

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