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Article

Effect of Endogenous and Exogenous variables on Customer behavioural intention in Adoption of Digital Banking Services - A Technology Acceptance Model Study in the State of Telangana

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Abstract

Technological Innovations and advancements in information and communication technology have shown massive growth across industries, including banking. With the internet of things, the stringent and traditional methods of banking have seen a complete metamorphosis from time to time. This has facilitated the customer to have all their banking services at their fingertips without visiting physical banking outlets with their mobile gadgets. It reduces transaction costs and customers' fatigue from standing in long queues, saving time. The mere advancement of technology cannot transform the entire process. There are other factors like extraneous variables or other behavioural-related factors which drive the customers towards the adoption of digital technology. Moreover, the technologies which are vulnerable while dealing with financial-related activities. Hence, the present study is an attempt to examine the endogenous and exogenous variables and their influence on perceived usefulness and perceived ease of use which will influence behavioural intention to drive towards actual usage of digital technologies in banking. The present study examines the opinion of 686 respondents across the Telangana state using E-TAM introduced by Venkatesh and Bala.

Keywords: *Digital Banking, Behavioural Intention, E-TAM Model, Adoption and Digital Technologies*

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Introduction:

The banks need to re-engineer and redesign their platforms to build channels through digital technologies. Customers expect increased dynamism at the front end. The existing banking systems are centralized in their operations and traditional in nature, leading to potential delays in implementing the changes in the banking system. The banks should focus on decoupling their existing monolithic approach to compete with the core concept of the digital-only banking approach (***Newman, Sam-2015).*** Banks should alter their processes through financial re-engineering through technologies.

The existing data policies in banking are rigid and have no access to the third party until now. Banks did not require any data to share with their competitors or other service providers in banking collaborations. Some banks used their data to improve their product and services. However, the digitalization of the banking sector requires sharing the database with third parties to provide better digital banking services to its customers. The European banks experienced the same in data sharing with the consent of the Customers ***(O'Flaherty, K. W., et al.)***.

Technology-driven banking sector requires a "one size fits all" approach by facilitating varied options and recommending diversified products to the customers on a bigger scale, the financial diffusion and reduced interactions by using data to provide a personalized customer experience in banking services ***(Allen, F., Gu, X., & Jagtiani, J.)***. Service providers analyze by integrating various sets of recorded data pertinent to customer like demographic, transaction, interaction, behaviour and application usage etc. Banks can provide and create unique experience to its customers. At the same time customers also expect the privacy, security, trust, perceived advantage, perceived use and cared interactions while dealing with digital channels.

Digital infrastructure, the internet of things, digital awareness and a model of the digital framework are prerequisites for the digitalization of banking services. The government policy should also facilitate promoting digital services to its customers. The services providers of digital banking products should address risk management and provide trust and other security-related matters to their customers to adopt digital banking services.

Objectives of the study:

The present study focus to examine

1. To study the Endogenous and Exogenous Variables that influence Perceived Ease of Use and Perceived Usefulness.
2. To study the Behavioural Intention of the customers in adopting Digital Technologies in Banking Sector.

Hypotheses:

H_{01}: Endogenous and Exogenous variables have a positive impact on PU and PEU.

H_{02}: PU and PEU has a positive influence on Behavioral Intention.

H_{03}: Behavioral Intention has a positive influence on Actual Digital Usage in Banking.

Preparation of data screening for the analysis:

The researchers collected data by employing a questionnaire and survey method. The data sets are to be screened prior to the analysis to find if there are any missing values in the data sets, outliers, find data rage if there is any deviation from the prescribed range, checking data for normality and conduct of Multi-Collinearity to make statistical analysis effective (Garson, 2015)[1].

Analysis of missing data and conduct of imputation:

The researcher employed SPSS software to find the missing values in the Data set. The Univariate Statistics is performed for the quantitative variables and categorical variables in the analysis to identify missing values. The analysis revealed that the data has a very less percentage of missing values which is less than 1% for the item.

The total number of items which has missing data is only nine in the data set under the study. The little's MCAR test is conducted to find whether the values are missing completely at random (Little, R.

J., & Rubin, D. B. 1989)[2]. The test has shown that the Chi-square value is 873.144, df - 824 and significance value =.114 for 686 sample data. Since the test significance value is greater than 0.05, which means that the data missing is completely at random. In order to replace missing values, the researcher has used a widely prevailing and accepted method that is multiple imputation analysis (Van Buuren, S. 2012)[3] .

While conducting multiple imputation analysis, the bootstrapping value is taken as 5 for the simulation and automatic method, i.e., Markov Chain Monte Carlo (MCMC) simulation methods, to predict and replace the missing values for the analysis (Garson, G. D. 2015)[4]. The missing values for the Items SN1, SN2, SN3, IUE5, TRU1, TRU2, TRU3, BK1 and BK2 are assigned.

Testing data for Outliers:

The researcher has used the Mahalanobis Distance method to identify the values which are farthest from the Centroid value from the data by finding the Mahalanobis D-square value. The multivariate outliers are identified by considering the P_1 and P_2 values, which are up to less than 0.05. However, the criteria for the deletion of those outliers permitted less than 10% of the total sample collected (Yuan, K.-H., & Zhong, X. 2013)[5]. The study under consideration has values as per criteria to fit the model. Since data has multivariate outliers, it is very difficult for the researcher to delete all the outliers. Whenever the outliers are removed, additionally new outliers will be identified in case of data having multivariate outliers. In this case, the researchers used the Mahalanobis method (Jarrell, M. G. 1994)[6] .

Conduct of Normality Test:

There are two main statistical tests to measure the normality, i.e. skewness and kurtosis are to be tested whether, the data is normal or not. To find whether the data is symmetric or asymmetric, the statistical measure of skewness is used. The tool kurtosis is used to find the weather data that measures heavy-tailed or light-tailed relative to the normality of distribution. The measurement criteria for the normality to fit the model, the skewness value is determined to be less than three, and the kurtosis is less than three times of the standard error preferred (Sposito et al., 1983)[7]. The above which these values are considered to be not a good fit for model (Stevens, J. P. 2009)[89]. The annexure is attached to show the values of skewness and kurtosis of the present study.

Test for Validity and Reliability:

The researcher has conducted convergent validity and discriminant validity to ensure validity while conducting CFA for SEM analysis. The study employed a master validity test by using AMOS plugin to obtain the CR, AVE, MSV and correlation table values developed by James Gaskin[10]. This ensures that the factors under the study demonstrate adequate reliability and validity for testing the SEM model.

Composite Reliability Test:

In order to test the internal scale consistency, the researcher has used a composite reliability test for the SEM analysis model. Composite reliability, sometimes referred to as construct reliability, measures the internal consistency of the scale used for CFA. It is similar to Cronbach's alpha which tests in the case of Exploratory Factor analysis (Netemeyer, 2003)[11]. It explains the variance between the total amount of true score variance compared to the total scale score Variance (Brunner & Süß, 2005)[12]. Otherwise, it is the indicator which explains the shared variance between the Observed variables employed as an Indicator of a latent construct (Fornell & Larcker, 1981)[13].

The threshold for testing composite reliability for CFA is 0.70, said to be good reliability with 0.50 AVE, values anywhere from 0.60 to above are also considered to be reasonable. It is also debatable as different authors have suggested different values for the same. However, it is considered that the smaller the value, the lower will be the reliability level and the larger the composite reliability value, the higher reliability. The values above 0.95 are also considered to be not necessarily good as it is an indication of redundancy of the scale (Hulin, Netemeyer, and Cudeck, 2001)[14].

The following table is the measure of Composite Reliability used for testing thresholds for evaluating the internal consistency of the scale employed for the SEM analysis.

CONSTRUCT	COMPOSITE RELIABILITY(CR) VALUE
Perceived Usefulness	0.900
Perceived Ease of Use	0.895
Accessibility	0.834
Behavioural Intention	0.836
Risk	0.823
Compatibility	0.894
Trialibility	0.831
Availability	0.712
Trust	0.881
Internet Usage Efficacy	0.905
Social Norms	0.849
Govt. Initiatives	0.913
Bank Promotion	0.875
Actual Digital Usage	0.851
Awareness	0.861

The table above shows the Composite reliability values for the constructs used in the analysis. As per the thresholds prescribed, the CR values are greater than 0.70 for all the constructs, which is considered to be a good reliability for the internal consistency of the scale for the study.

Convergent Validity

The Average Variance Extracted (AVE) is used to test convergent validity. The convergent validity is a sub-part of the construct validity, where construct validity measures the construct to ensure whether the construct is actually measuring the same purpose or not. The Convergent validity takes two measures and ensures that the construct measures are related. The AVE is greater than 0.5 for all the constructs under the study. The AVE is considered to be a strict measurement which explains the convergent validity. According to Malhotra and Dash (2011), "AVE is a more conservative measure than CR. On the basis of CR alone, the researcher may conclude that the convergent validity of the construct is adequate, even though more than 50% of the variance is due to error." (Malhotra and Dash, 2011, p.702)[15].

CONSTRUCT	AVERAGE VARIANCE EXPLAINED(AVE)
Perceived Usefulness	0.600
Perceived Ease of Use	0.681
Accessibility	0.558
Behavioural Intention	0.562
Risk	0.699
Compatibility	0.585
Trialibility	0.552
Availability	0.553
Trust	0.653
Internet Usage Efficacy	0.615
Social Norms	0.653
Govt. Initiatives	0.779
Bank Promotion	0.700
Actual Digital Usage	0.741
Awareness	0.756

From the above table, it is evident that all the values are above 0.50 for the construct under the study, and as per the thresholds, the study has fulfilled convergent validity to proceed for CFA.

Discriminant Validity:

Discriminant validity is a measure which tests the uncorrelated or how distinct is the factors under the study. The discriminant validity is tested by using maximum shared variance, which is supposed to be less than the AVE for testing validity analysis. Discriminant Validity is achieved if the MSV or Average shared squared variance(ASV) is less than the Average Variance Extracted. In general, the AVE is considered to be a strict measurement which explains the convergent validity, it is stated that “AVE is a more conservative measure than CR. On the basis of CR alone, the researcher may conclude that the convergent validity of the construct is adequate, even though more than 50% of the variance is due to error.” (Malhotra and Dash, 2011, p.702)[16]. To assess the discriminant validity Fornell and Larckers approach is used where AVE of each construct is supposed to be higher than the squared correlation between the construct and any other construct (Fornell and Larcker, 1981)[17]. The table also shows the MaxR(H), which is the maximum reliability indicator. The acceptable threshold of MaxR(H) is >0.70. It is also called as McDonald's construct reliability. "It shows the H coefficient, which describes the relation between latent construct and the measured indicator. It is unaffected by the sign which an indicator carries in loadings, also draws information from all indicators in such a way that commensurate with their ability to reflect the construct"(Hancock and Mueller, 2001)[18] .

Table: Maximum Shared Variance and Maximum reliability indicators for Discriminant Validity.

CONSTRUCT	MSV	MaxR(H)
Perceived Usefulness	0.593	0.901
Perceived Ease of Use	0.616	0.896
Accessibility	0.548	0.842
Behavioural Intention	0.503	0.846
Risk	0.096	0.823
Compatibility	0.596	0.901
Trialability	0.541	0.832
Availability	0.524	0.712
Trust	0.607	0.900
Internet Usage Efficacy	0.539	0.914
Social Norms	0.398	0.864
Govt. Initiatives	0.442	0.914
Bank Promotion	0.645	0.877
Actual Digital Usage	0.485	0.852
Awareness	0.510	0.866

From the above table, it is ensured that the MSV and MaxR(H) thresholds are fulfilled for the study to proceed with the analysis. The MaxR(H) coefficient indicators are above 0.70 as per the prescribed thresholds. And the MSV is less than the AVE.

Table: Correlation among constructs, AVE and Squared Inter-Construct Correlation matrix.

	PU	PEU	ACC	BI	RSK	COMP	TRL	AVAI	TRU	IUE	SN	GI	BP	ADU	AWR
PU	**0.775**														
PEU	0.679	**0.825**													
ACC	0.674	0.772	**0.747**												
BI	0.678	0.839	0.712	**0.749**											
RSK	0.132	0.167	0.163	0.213	**0.836**										
COM	0.701	0.703	0.804	0.702	0.094	**0.765**									
TRL	0.662	0.662	0.676	0.722	0.310	0.699	**0.743**								
AVAI	0.695	0.686	0.715	0.665	0.244	0.735	0.638	**0.743**							
TRU	0.726	0.779	0.680	0.655	0.000	0.713	0.529	0.581	**0.808**						
IUE	0.763	0.799	0.687	0.702	0.184	0.772	0.644	0.635	0.711	**0.785**					
SN	0.572	0.593	0.563	0.579	0.239	0.567	0.521	0.469	0.524	0.595	**0.808**				
GI	0.586	0.665	0.556	0.562	0.210	0.584	0.524	0.526	0.619	0.615	0.631	**0.882**			
BP	0.741	0.803	0.625	0.742	0.216	0.758	0.606	0.577	0.646	0.679	0.561	0.626	**0.837**		
ADU	0.658	0.697	0.619	0.689	0.113	0.692	0.614	0.581	0.604	0.658	0.492	0.530	0.623	**0.861**	
AWR	0.635	0.714	0.591	0.686	0.169	0.652	0.584	0.545	0.639	0.623	0.536	0.585	0.679	0.602	**0.870**

The table above shows the values corresponding to the AVE that are being highlighted in block letters. The values in the diagonal indicate correlations of the construct, and the corresponding values are square pf correlations between the correlations obtained using the master validity plugins from Gaskins from AMOS software (Gaskin J., & Lim[19]It is stated that if AVE is higher than the square of the inter-construct correlation for each construct, then it is considered that the discriminant validity is supported(Farrell, A. M.[20]. In the above-mentioned model, the master validity table shows that the discriminant validity is established for the model.

Testing of Model fit Indices for Confirmatory Factor Analysis for SEM:

The model fit indices for the goodness of fit for CFA model measures are stated as per the determinants calculated, and the threshold is given below (Hu and Bentler 1999).[21] The detailed thresholds with contextualized guidelines are stated in Hair et al[22]. The standardized measures and their threshold i.e., Chi-Square/df (cmin/df) is < 3 good; < 5is sometimes permissible. The p-value for the model should be >0.05. CFI values > 0.95 is considered to be great, >0.90 traditional; and >0.80 is sometimes permissible as the constructs under the study are large. GFI value is considered to be >0.95 while AGFI is >0.80 as per the base line model (Kaplan, 2000)[23]. However, this is not the same for all circumstances to have the goodness of fit indices greater than the baseline model. As the sample size varies and the number of constructs in the model increase, the prescribed indices change for goodness of fit (Hu & Bentler, 1995, p. 95)[24]. The threshold values for the badness of fit SRMR <0.09 and RMSEA <0.05 is considered to be good,0 .05 to 0.10 is moderate and >.10 is considered to be a bad fit. The incremental fit indices IFI>0 .9 and TLI > 0.9. Indices described above of the model change when the model has complexity and a sample of more than 250 sizes, and the achievement of the goodness of fit varies with CFI (Hair et al., 2010)[25].

The Measurement Model fit Indices for testing Conceptual TAM Under the Study (Initial Untrimmed model):

The study employed maximum likelihood estimation for assessing CFA for the model test. The ML method estimation, standardized estimates and modification indices were used to calculate model parameters to assess the CFA model fit. The estimated values of the base model under the study are given below.

The Model has χ^2 =4753.010, df = 1627, p = .000 and the CMIN/df i.e. χ^2/df= 2.921, The model tested RMR value as 0.056, GFI = 0.802, AGFI=0.770. The baseline comparisons of the model IFI = 0.894, TLI= 0.880, CFI= 0.893 and RMSEA 0.054, PCLOS=0.000. The Untrimmed model has some of the goodness of the fit indices below the prescribed level of measurement. Hence, the researcher has gone for redefining and model trimming to fit the model better.

Refinement of Model trimming for improving Measurement Indices:

The study focused on improving the model by calculating modification indices. The study has identified regression weights less than 0.7 and factor loading, which is less than 0.5, identified and deleted from the model to get model fit indices to improve. The constructs like RK3, INT1, INT2, UE1, and UE2 are removed from the model to improve model fit indices.

The study also used 'connecting of error' terms to improve the model fit. The following are the values of the trimmed model. The trimmed model has χ^2 =3635.125, df = 1319, p = .000 and the CMIN/df i.e. χ^2/df= 2.756. The model tested RMR value as 0.044, GFI = 0.898, AGFI=0.880. The baseline comparisons of the model IFI = 0.914, TLI= 0.903, CFI= 0.914 and RMSEA 0.051. PCLOSE= 0.021. The Untrimmed model has most of the goodness of the fit indices below the values. Hence, the researcher has gone for redefining and model trimming to better fit the model.

The model above has fulfilled the criterion for the goodness of fit for CFA to proceed for the structural equation model to fit ETAM model for the analysis.

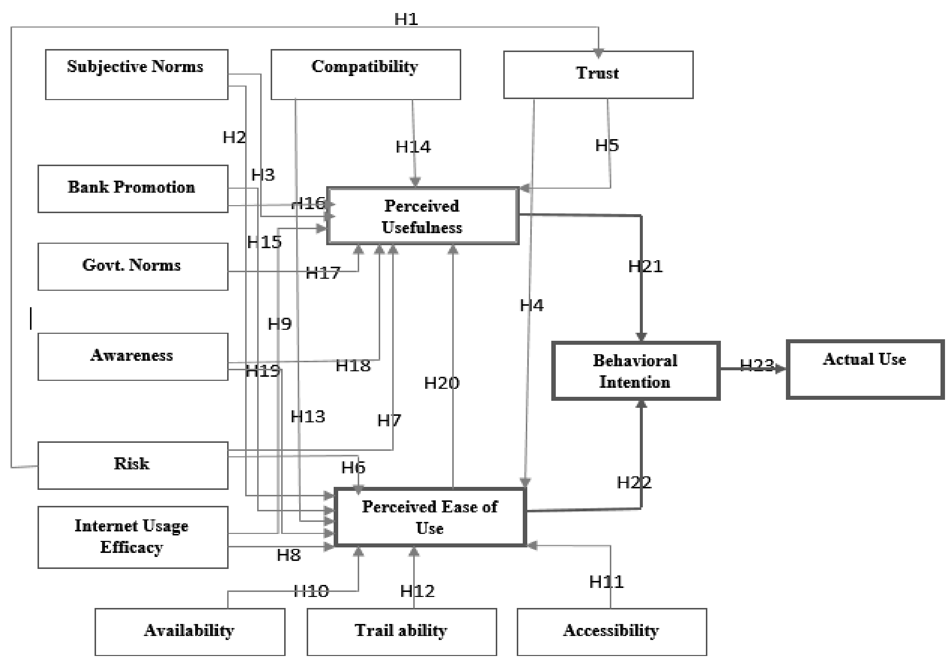
Testing Hypothesized Causal relationship of Structural Model for Conceptual TAM Path analysis:

The figure below shows the testing of the conceptual model developed based on TAM3, TAM-3 is an integrated model which explains the individual level acceptance of Technology adoption and its use. Venkatesh and Bala develop this model by considering their own construct of TAM2 (Venkatesh & Davis)[26], combining it with the actor determinant perceived ease of use and perceived usefulness on customers behavioural intention(Venkatesh)[27]This model includes independent variables and dependent variables and measures the impact of those variables influencing the Behavioural Intention of the Individuals in adopting digital technologies in the banking sector(FinTech).

The present model has taken the variables, i.e., risk, trust, government initiatives, bankers promotion, awareness, social influence and internet usage efficacy, on the variables perceived usefulness and perceived ease of use which will reflect on the behavioural intention of the individuals to drive towards actual usage of the system. On the other hand, the study also focused on testing variables like compatibility of technologies, availability, trialability, and accessibility influence the perceived ease of use, which will reflect on the behavioural intention to use digital technologies.

The figure below shows the path analysis of the Conceptual model developed based on the integrated TAM3 model developed by Venkatesh and Bala.

Conceptual Frame Work of TAM for Digital Technologies Acceptance in the Banking Sector:



The figure above is the conceptual model Developed by taking the Venkatesh and Bala E-TAM model to study the present Technology acceptance level in Banking Sector. The model incorporates the other variables, like availability, accessibility, awareness and trialibilty etc., into the model to study the influence of exogenous variables on the acceptance model. It considers the basic TAM with extended variables for the analysis under the study.

The standard regression weights calculated for the variables to test relation using E-TAM Model.

Path analysis relation			Estimate	SE.	CR.	P-Value	Decision
TRU	<---	RK	.043	.052	.818	.413	Not Supported
PEU	<---	SN	.018	.018	1.000	.317	Not Supported
PU	<---	SN	.048	.021	2.280	.023	Supported
PEU	<---	TRU	.202	.026	7.662	***	Supported
PU	<---	TRU	.121	.033	3.701	***	Supported
PEU	<---	RK	.063	.028	2.285	.022	Supported
PU	<---	RK	.015	.032	.452	.651	Not Supported
PEU	<---	IUE	.138	.021	6.684	***	Supported
PU	<---	IUE	.109	.026	4.192	***	Supported
PEU	<---	AVL	-.001	.022	-.068	.946	Not Supported

Path analysis relation			Estimate	SE.	CR.	P-Value	Decision
PEU	<---	ACC	.101	.020	5.116	***	Supported
PEU	<---	TRL	.012	.026	.464	.643	Not Supported
PEU	<---	COM	.379	.030	12.791	***	Supported
PU	<---	COM	.412	.046	8.951	***	Supported
PEU	<---	BKP	.154	.019	7.940	***	Supported
PU	<---	BKP	.083	.025	3.343	***	Supported
PU	<---	GVT.P	.002	.018	.122	.903	Not Supported
PEU	<---	AWR	.113	.020	5.590	***	Supported
PU	<---	AWR	-.024	.024	-.972	.331	Not Supported
PU	<---	PEU	.298	.084	3.565	***	Supported
BI	<---	PU	.215	.061	3.541	***	Supported
BI	<---	PEU	.656	.083	7.871	***	Supported
ADU	<---	BI	.916	.082	11.242	***	Supported

Estimates of the R Square Coefficient Value for the Dependent Variables:

The table below shows the R^2 coefficient value for the dependent variables perceived ease of use, perceived usefulness, behavioural intention and actual system usage for the conceptual model under the study. The R^2 value indicates the variance caused by the independent variable on the dependent variable under the study. The R^2 value indicates that high or low in accordance with the use and context with which the regression model is developed.

Dependent Variables	R Square Value
Perceived Ease of Use	.907
Perceived Usefulness	.888
Behavioural Intention	.747
Actual Digital System Usage	.528

Summary of Hypotheses testing using Path analysis:

The path model established above shows the causal relationship between the constructs and the study adopted to test the hypotheses.

	Hypotheses Statement	Decision
H_1	Perceived risk positively influences the trust of the individuals in adopting digital technologies in the banking sector(Fintech).	Not Supported
H_2	Social Norms positively influence perceived ease of use in adopting digital technologies in the banking sector(Fintech).	Not Supported
H_3	Social Norms positively influence perceived usefulness in adopting digital technologies in the banking sector(Fintech).	Supported
H_4	Trust positively influence perceived usefulness in adopting digital technologies in the banking sector(Fintech).	Supported
H_5	Trust positively influence perceived usefulness in adopting digital technologies in the banking sector(Fintech).	Supported
H_6	Perceived risk negatively influences perceived usefulness in adopting digital technologies in the banking sector(Fintech).	Supported
H_7	Perceived risk negatively influences perceived usefulness in adopting digital technologies in the banking sector(Fintech).	Not Supported

H_8	Internet Usage efficacy positively influences perceived usefulness in adopting digital technologies in the banking sector(Fintech).	Supported
H_9	Internet Usage efficacy positively influences perceived usefulness in adopting digital technologies in the banking sector(Fintech).	Supported
H_{10}	The availability factor positively influences the PEU in adopting digital technologies in the banking sector(Fintech).	Not Supported
H_{11}	Accessibility factor positively influences PEU's adoption of digital technologies in the banking sector(Fintech).	Supported
H_{12}	The trial ability factor positively influences the PEU in adopting digital technologies in the banking sector(Fintech).	Not Supported
H_{13}	The compatibility factor positively influences the PEU in adopting digital technologies in the banking sector(Fintech).	Supported
H_{14}	Compatibility factor positively influences the PU in adopting digital technologies in the banking sector(Fintech).	Supported
H_{15}	Banks promotions positively influence PEU in adopting digital technologies in the banking sector(Fintech).	Supported
H_{16}	Banks promotions positively influence PU in adopting digital technologies in the banking sector(Fintech).	Supported
H_{17}	Govt. initiatives positively influence PU in adopting digital technologies in the banking sector(Fintech).	Not Supported
H_{18}	Awareness positively influences PU in adopting the Digital Technologies in the banking sector(Fintech)	Supported
H_{19}	Awareness positively influences PEU in adopting digital technologies in the banking sector(Fintech).	Not Supported
H_{20}	Perceived Ease of Use positively influences perceived usefulness in adopting digital technologies in the banking sector(Fintech).	Supported
H_{21}	Perceived usefulness positively influences individuals' behavioural intention in adopting digital technologies in the banking sector(Fintech).	Supported
H_{22}	Perceived Ease of Use positively influences individuals' behavioural intention in adopting digital technologies in the banking sector(Fintech).	Supported
H_{23}	Behavioural intention positively influences the actual digital usage of individuals in adopting digital technologies in the banking sector(Fintech).	Supported

Discussion and conclusion:

From the above data, it is evident that the factors influencing the adoption of digital technologies have a significant impact on the dependent variables like perceived ease of use and perceived usefulness. It, in turn, had resulted in the actual digital usage of technologies in the banking sector. The basic TAM Model, which includes only PU and PEU on behavioural intention, has shown that the model proposed by Davis (1986) is significant, and it can be accepted from the model that the respondents are willing to accept the technologies in banking. However, the study also attempted to understand the other exogenous and endogenous variables that influence perceived ease of use and perceived usefulness of the technologies, which reflects and impacts the behavioural intention of the respondents in using the technologies. When different variables were tested, the factors of social norms, the availability of technologies, and the trialability factor had no positive impact on the perceived ease of use. The factors like risk, government support and awareness have not influenced the perceived usefulness of the technologies in banking. The study compared the R^2 value to measure how well the Regression model is fit for the study made based on the Beta Values. The R^2 value for the dependant variable perceived usefulness is .888 (88.8%), which is considered a good indicator that the variables strongly impact the construct. The R^2 value for the dependant variable perceived ease of use is .907 (90.7%). It strongly explains the variance caused by Independent variables on the perceived ease of use. For the construct behavioural intention, the R^2 value is .747, which indicates that the PU and PEU cause 74.7% of the variance, and the actual digital usage is .528. When compared to other variables for the construct, the actual digital use is significant, but it is moderate, where 52.8% only results in actual digital system usage of technologies in the banking sector.

Finally, the study concludes that the respondents under the study have a positive opinion which indicates that the usage of technologies has an advantage. It is a good sign from the respondents, which shows a high level of variance that caused perceived usefulness and perceived ease of use of technologies that drive the behavioural intention of the respondents. However, the final adoption of the technologies is not in the same accordance with the positive opinion of the respondents. There is a need to address certain issues restraining the respondents in resulting in actual usage.

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