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What Drives Fintech Use? Modelling and Predicting Usage Behaviour

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Abstract

Fintech disrupts traditional financial services in terms of its mode of delivery and the magnitude of its operations. Moreover, the growing practitioner and academic interest in Fintech has added to the humongous perspectives of Fintech research. The term "financial technology" (Fintech) refers to a digital business model that serves the financial needs of people all over the world and has grown to be an integral part of the financial services industry. Although widespread, the Fintech boom is mostly uncontrolled, necessitating a cautious approach to its applications and advantages. The paper proposes a model to estimate Fintech usage by customers and tries to assess the model's predictive ability through PLS-SEM. The current research addresses the theoretical gap in Fintech usage behaviour and highlights the managerial implications of assessing and predicting Fintech use. The research endeavour aims to contribute to existing scholarly discussions but also lay the groundwork for further investigation into the intricacies of Fintech usage behaviour.

Keywords: Financial Technology, Usage Behaviour, PLS-SEM

JEL: D91, C52

Introduction

Financial Technology (Fintech) is a necessity-driven innovation has garnered the interest of scholars as a self-serviced technology (Gai et al., 2018; Goldstein et al., 2019; Leong, 2018; Liu et al., 2020; Ramesh, 2019; Rupeika-Apoga & Wendt, 2021; Utami et al., 2021; Schueffel, 2016). Recent works have examined the Fintech phenomenon through marketing-centric arguments, especially consumer based decision-making (Barbu et al., 2021; Ramesh, 2019) ; customer adoption (Nawayseh, 2020; Nayak Kini & Basri, 2022; Tripathy & Jain, 2020); customer intention (Afandi, 2020; Andrew et al., 2021; Ayoungman et al., 2021; Peong et al., 2020) as a determinant of Fintech adoption. The research trajectory also visits customer privacy and security risks in the growing body of Fintech literature (Bhatt et al., 2023; Dorfleitner et al., 2023; Lai et al., 2019; Stewart & Jurjens, 2018). The results of the study showed that Fintech has an impact on financial services by increasing their effectiveness (Baporikar, 2023). Despite a variety of works, core theoretical frameworks for consumer behaviour on Fintech are scant. The present study has put forth a conceptual model to investigate the strength of the inter-relationships through PLS-SEM using Smart –PLS4.

Literature Review

Our study while building from recent literature has attempted to investigate the behavioural approach from the viewpoint of four variables viz., consumer adoption, consumer intention, customer privacy, and usage behaviour of Fintech customers. Contextualising the same in literature we present arguments that build our conceptual model and hypothetical frame of analysis.

Customer Adoption

Customer adoption is a core construct in our hypnotised model. Customer adoption as a sentiment drives the customer to demonstrate continued usage of the Fintech. However, adoption behaviour does not guarantee sustained

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used of products and services. Recent literature for Fintech assigns an important role to adoption behaviour as a retention strategy (Tripathy & Jain, 2020; Utami et al., 2021; Joshi, 2022); as a technological prerogative (Alwi, Salleh et al., 2019; Chuang et al., 2016; Fu & Mishra, 2022; Jünger & Mietzner, 2020; Singh et al., 2023; Sunardi et al., 2022) , in multiple cross-cultural contexts (Alwi et al., 2019; Das, 2020; Ernst & Young, 2019; Y. K. Lee, 2021; Tapanainen, 2020; Yoshino et al., 2020).

Customer Intention

Intentions indicate how hard the consumer will try to adopt Fintech. The literature on customer intention on Fintech seems relatively scarce, analogous works with related self-serviced technology platforms argue about the multidimensionality of customer intention (Athapaththu & Kulathunga, 2018; Hajli, 2015; Lin, 2007; Millson, 2017) and highlights customer intention as a causal variable that influences the adoption behaviour of Fintech customers (Le, 2021; Liébana-Cabanillas et al., 2020, 2021; Bhardwaj et al., 2022; Srivastava & Singh, 2022).

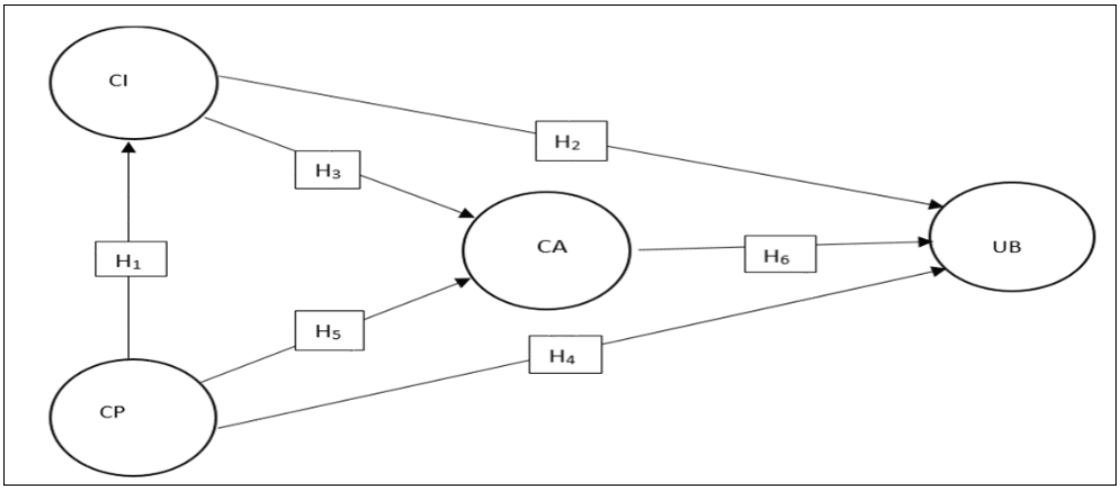
Customer Privacy

Privacy concerns between consumers and service providers of data-driven technological products and services are a vigorous area of research. Literature has capitalised on the fact that customer privacy and long-term Fintech sustainability are interdependent (Dewi & Gola, 2021; Dorfleitner et al., 2021; Gai et al., 2017; Liao et al., 2020; Li et al., 2019). Works argue that privacy and security concerns need to be addressed to protect financial misdemeanours (Dorfleitner & Hornuf, 2019b; Herdinata, 2020; Hussain et al., 2021; Venkatesan, et al., 2022; Lee & Ahn, 2016).

Usage Behaviour

Usage behaviour is a self-reported metric on purchase activity that highlights frequency and summary of purchases. The authors collude with existing researchers that have been for designating usage behaviour of technology-based services as a pre-purchase intention and also as a post-purchase reaction (Gerlach & Lutz, 2019; Karjaluoto et al., 2020; Kirana & Havidz, 2020; Oertzen & Odekerken-Schröder, 2019; Sengodan, 2021; Talukder et al., 2014). Building upon scant works the study places usage behaviour as a target outcome of the adoption process of Fintech users.

Based on the body of work our study has built a conceptual model (Fig. 1) and formulated hypotheses to support our arguments.



Source: Authors.

Note: CP=Customer Privacy, CI=Customer Intention, UB=Usage Behaviour, and CA=Customer Adoption.

Fig. 1: Theoretical Model and Hypothetical Framework

Thus, borrowing from theory and related literature, our conceptual model presents the following hypotheses:

H_1: Customer privacy has a significant effect on customer intention.

H_2: Customer intention has a significant effect on usage behaviour.

H_3: Customer intention has a significant effect on customer adoption.

H_4: Customer privacy has a significant effect on usage behaviour.

H_5: Customer privacy has a significant effect on customer adoption.

H_6: Customer adoption has a significant effect on usage behaviour.

Methodology

The following section evaluates the conceptual framework for the established statistical frame of analysis. The model has been assessed, measured, and evaluated based on guidelines provided for PLS-SEM, Predictive analysis, Effect size analysis, and Priority analysis.

Design of the Study

For the purpose of the study, a cross-sectional simple random sample was drawn from Fintech users residing in Arunachal Pradesh in India during the months of August 2022 to October 2022. A self-designed questionnaire cum schedule (Annexure I) with a mix of descriptive as well as Likert type questions keeping in context the research objectives of the study. The process yielded a total of 403 respondents. To test the sample adequacy, the G*power software was used. A post-hoc test with an effect size f^2=0.15 with a sample size of 403 was conducted which reported an achieved power of 99 percent. Thus, the sample adequacy was met. The descriptive statistics are present for the study in Table 1.

Table 1: Descriptive Statistics of the Study (N=403)

Sex			
			%
	Male	198	60.74
	Female	128	39.26
Marital status			
	Single	237	72.69
	Married	89	27.30
Age			
	Gen Z	147	45
	Millennials	134	41.10
	Gen X	41	12.57
	Baby Boomer	4	1.22
Educational Qualification			
	Upto 12th Standard	34	10.4
	Upto Graduate	160	49.07
	Post Graduate and Above	133	40.79

Occupation			
	Student	52	15.95
	Government Employee	82	25.15
	Private Employee	37	11.34
	Unemployed	119	36.50
	Business	28	8.58
	Homemaker	8	2.45
Monthly Family Income			
	Upto 10000	169	51.84
	10001 to 50000	110	33.74
	50000 and Above	47	14.41
Approximate Number of FT Transactions Per Month			
	Upto 5	40	12.26
	More than 5	288	88.34

Source: Authors.

Assessment of the Measurement Models

An assessment of the structural model for the four latent variables, viz., Customer Adoption [CA], Customer Intention [CI], Customer Privacy [CP], and Usage behaviour [UB] were measured through 19 Likert-type questions (including 4 Global items) with 5 anchor points strongly disagree (1) to strongly agree (5). The results show that all construct measures are reliable and valid and collinearity values within acceptable thresholds (Table 2). When small sample sizes are employed or complex models with numerous indicators and model links are estimated—both of which are common in the social sciences—PLS-SEM offers comprehensive benefits over CB-SEM. PLS-SEM should be used in circumstances where there is a lack of theoretical knowledge and excessive complexity; because the current study uses a hierarchical component model of the reflective-formative variety, it has model complexity. With the intricacy of the current study project, the PLS-SEM technique becomes more suitable than the CB-SEM strategy (Wold, 1980). Moreover, PLS-SEM is used in demanding sectors of research, producing superior results and earning more acclaim from academics. (2013) Hair, Ringle, and Sarstedt. One of the best methods for examining predictive models in the early phases of theory building is PLS-SEM (Hairet al., 2012b; Henseler et al., 2009; Richter et al., 2016; Sarstedt et al., 2014; Wold, 1980). Our study includes Customer intention (CI), Customer privacy (CP), Customer adoption (CA), and Usage behaviour (UB). Therefore, it is a suitable technique for our data analysis.

Table 2: Assessment of the Measurement Models

Constructs	*Variable Items*	*Loadings*	*Cronbach's Alpha>0.6*	*Composite Reliability (Rho_a)>0.6*	*Composite Reliability (Rho_c)> 0.6*	*Average variance extracted (AVE)>0.5*	*Variance Inflation Factor (VIF)*
Customer Adoption	CA1	0.787	0.854	0.863	0.891	0.577	2.009
	CA13	0.792					1.832
	CA4	0.769					1.82
	CA5	0.783				0.568	1.937
	CA7	0.715					1.647
	CA8	0.707					1.648

Constructs	*Variable Items*	*Loadings*	*Cronbach's Alpha>0.6*	*Composite Reliability (Rho_a)>0.6*	*Composite Relibility (rho_c)> 0.6*	*Average variance extracted (AVE)>0.5*	*Variance Inflation Factor (VIF)*
Customer Intention	CI10	0.803	0.633	0.64	0.802	0.575	1.301
	CI16	0.755					1.204
	CI8	0.715					1.246
Customer Privacy	CP2	0.68	0.767	0.777	0.842	0.517	1.268
	CP4	0.705					1.732
	CP5	0.795					1.812
	CP6	0.729					1.701
	CP8	0.679					1.606
Usage Behaviour	UB12	0.726	0.81	0.814	0.868	0.575	1.40
	UB4	0.703					1.613
	UB7	0.79					1.895
	UB8	0.792					1.831
	UB9	0.756					1.716

Source: Authors.

Note: CP=Customer Privacy, CI=Customer Intention, UB=Usage Behaviour, and CA=Customer Adoption.

Table 3 shows the discriminant validity assessment, through the HTMT values, are lower than 0.85.

Table 3: Discriminant Validity Analysis of All Predictors

Predictors	*CA*	*CI*	*CP*
CA	xx	xx	xx
CI	0.387	xx	xx
CP	0.367	0.24	xx
UB	0.763	0.622	0.371

Source: Authors.

Note: CP=Customer Privacy, CI=Customer Intention, UB=Usage Behaviour, and CA=Customer Adoption.

Assessment of the Explanatory Power

The explanatory power of our model has been evaluated for its quality criteria, by the coefficient of determination given by R^2. Table 4 shows the R^2 values and the adjusted R^2 of our target construct, i.e., Usage behaviour (UB). We consider the adjusted R^2 as the predictors that have been accommodated for our particular model. Thus, the values for Usage Behaviour (UB) are 0.5, Customer Intention (CI) is 0.025, and Customer Adoption (CA) is 0.157. Thus, the explanatory power of the model is moderate for Usage behaviour and weak for Customer intention and Customer Adoption (Chin, 1998).

Table 4: R Square Values

Variables	*R-Square*	*R-Square Adjusted*	*Inference for Explanatory Power*
CA	0.161	0.157	Weak explanatory power
CI	0.027	0.025	Weak explanatory power
UB	0.504	0.5	Moderate explanatory power

Source: Authors.

Note: CP=Customer Privacy, CI=Customer Intention, UB=Usage Behaviour, and CA=Customer Adoption.

Mediation Analysis

In line with our research objectives, we examine the mediating effects of CA, CI on UB. Mediation analysis demonstrates the power of one or more intervening variables on the outcome variable. In our study, in predicting UB (outcome), our intervening variables are CI and CA. Following literature, we use the function of bootstrapping to assess first the direct relationships. The direct path coefficients, the significance, and the relative strengths of each path give an inference of the significance of the direct paths (Table 5).

Table 5: Path Relationships and Significance

Hypothesis	*Path*	*Original Sample (O)*	*P Values*	*Bias*	*LLCI 2.50%*	*ULCI 97.50%*	*Inference if the Relation is Significant at p<0.05*
H_1	CP -> CI	0.165	0.0	0.007	0.068	0.243	Yes
H_2	CI -> UB	0.273	0.0	-0.001	0.198	0.349	Yes
H_3	CI -> CA	0.256	0.0	0.002	0.154	0.348	Yes
H_4	CP -> UB	0.072	0.1	-0.001	-0.015	0.155	**No**
H_5	CP -> CA	0.27	0.0	0.005	0.186	0.348	Yes
H_6	CA -> UB	0.55	0.0	0.001	0.464	0.626	Yes

Source: Authors.

Note: LLCI =Lower limit confidence Interval, ULCI=Upper limit confidence Interval.

From Table 5, it is seen that the paths between CA -> UB, CI -> CA, CI -> UB, CP -> CA and CP -> CI are statistically significant. However, CP -> UB is not significant at 5% significance level for T values and P values and also straddles a 0 between the upper limit and lower limits of the Confidence Intervals. We find that the strongest effect is CA -> UB and it is also significant. The path CP -> UB is the weakest and is not significant. The indirect effect involves a series of exogenous variables, one or more intervening variable (mediator) and the outcome variable. The test for the presence of mediation is done through the mediation analysis of specific indirect effects and is presented in Table 6. The paths CI -> CA -> UB, CP -> CA -> UB, CP -> CI -> UB, and CP -> CI -> CA demonstrate partial mediation as all the β values are significant and the direct paths are also significant. The only exception is the path CP -> CI -> CA -> UB, which shows an inference of being fully mediated as the direct path was not significant. This allows us to conclude that UB is mediated by the explanatory variables CA and CI in our model.

Table 6: Mediation Analysis (Specific Indirect Effects)

Path Relations	*Original Sample (O)*	*T Statistics (|O/STDEV|)*	*β Values*	*Bias*	*LLCI 2.50%*	*ULCI 97.50%*	*Significance at p<0.05 and Inference*
CI -> CA -> UB	0.141	4.959	0.0	0.001	0.085	0.197	Yes, Partial mediation
CP -> CA -> UB	0.148	5.784	0.0	0.003	0.099	0.198	Yes, Partial mediation
CP -> CI -> UB	0.045	2.868	0.004	0.002	0.018	0.078	Yes, Partial mediation
CP -> CI -> CA	0.042	2.855	0.004	0.002	0.017	0.073	Yes, Partial mediation
CP -> CI -> CA -> UB	0.023	2.896	0.004	0.001	0.009	0.04	Yes, Full mediation

Note: CP=Customer Privacy, CI=Customer Intention, UB=Usage Behaviour, CA=Customer Adoption LLCI =Lower limit confidence Interval, and ULCI=Upper limit confidence Interval.

Source: Authors.

Predictive Analysis

To bridge the gap between explanatory power and the predictive power of the PLS-SEM model (Hair et al., 2017), as found in the extant literature, the authors have attempted the predictive power assessment for Usage Behaviour. For the Prediction analysis, we run the PLS predict and calculate the values of Q^2, RMSE and MAE.

This has been presented in Table 7. The positive Stone Geisser -Q^2 values of PLS-SEM-based predictions for UB reflect a high predictive relevance of our model (Shmueli et al., 2019). Our next evaluation is for the error criteria, which calls for an examination of the Root Mean Square Error (RMSE) and Mean Absolute error (MAE) of the PLS_SEM model and the Linear model (LM). The choice between the RMSE values and the MAE values depends upon whether the distribution is symmetrical or not. A symmetrical distribution works well with RMSE while a non-symmetrical distribution works best with the MAE errors. Upon observation of the kurtosis, skewness and pictorial histograms of the indicators of UB shows that the values are not symmetrically distributed, and hence we are to consider MAE values only. Literature concedes if the PLS model has fewer errors than the LM, the overall model has high prediction and can be used for unseen samples. The five Usage Behaviour indicators in the PLS-SEM analysis give smaller prediction errors compared to the LM. This confirms the high predictive power of the model and point to the robustness of the model for unseen samples.

Table 7: Results of the Predictive Analysis

Target Construct Indicators	*Q^2 Predict*	*PLS-SEM_ MAE*	*LM_MAE*	*Whether the Prediction Error of PLS-SEM < LM?*	*Inference*
UB12	0.035	0.451	0.46	Yes (-0.009)	Presence of predictive power with less error in PSL SEM
UB4	0.05	0.541	0.56	Yes (-0.033)	Presence of predictive power with less error in PSL SEM
UB7	0.061	0.479	0.495	Yes (-0.013)	Presence of predictive power with less error in PSL SEM
UB8	0.008	0.578	0.579	Yes (-0.019)	Presence of predictive power with less error in PSL SEM
UB9	0.052	0.053	0.054	Yes (-0.001)	Presence of predictive power with less error in PSL SEM

Source: Authors.

Evaluation of the Total Effects of Constructs

In order to assess the importance of the individual variables affecting the outcome of UB, we run an importance performance analysis. For this, we examine the total effects and the performance parameters of all the variables. The total effects give the importance criteria while the performance index demonstrates the rescaled, unstandardised latent scores of the constructs. Table 8 presents an analysis of the importance and performance of the variables in explaining our model.

Table 8: Importance and Performance of the Variables on UB

Predictors	*Importance (Total Effects)*	*Performance*	*Inference*	*Suggested Management Priority*
CA	0.55	78.236	High importance- high performance	High
CI	0.414	69.534	Medium importance-medium performance	Moderate
CP	0.289	76.735	Low importance –high performance	Low

Source: Authors.

Note: CP=Customer Privacy, CI=Customer Intention, UB=Usage Behaviour, and CA=Customer Adoption.

The examination of the total effects gives an inference about how well the variables perform in the model. An analysis of the same leads us to believe that the variable CA (0.55) has the most importance and its performance (78.236) is the highest among the rest of the variables. Next in importance is CI (0.414), while its performance in the model is at least at 69.534. The variable CP has the least effect on the variable UB at 0.289 but ranks second in terms of performance among all variables. As CP has small importance management will be misguided if they

invest more effort in the variable. It is also to be noted that the direct path is not significant, leading the authors to contest that privacy as a management priority will be misguided if they invest more effort in the variable.

Furthermore, Fig. 2 depicts the priority map for the predictor constructs.

Results and Discussion

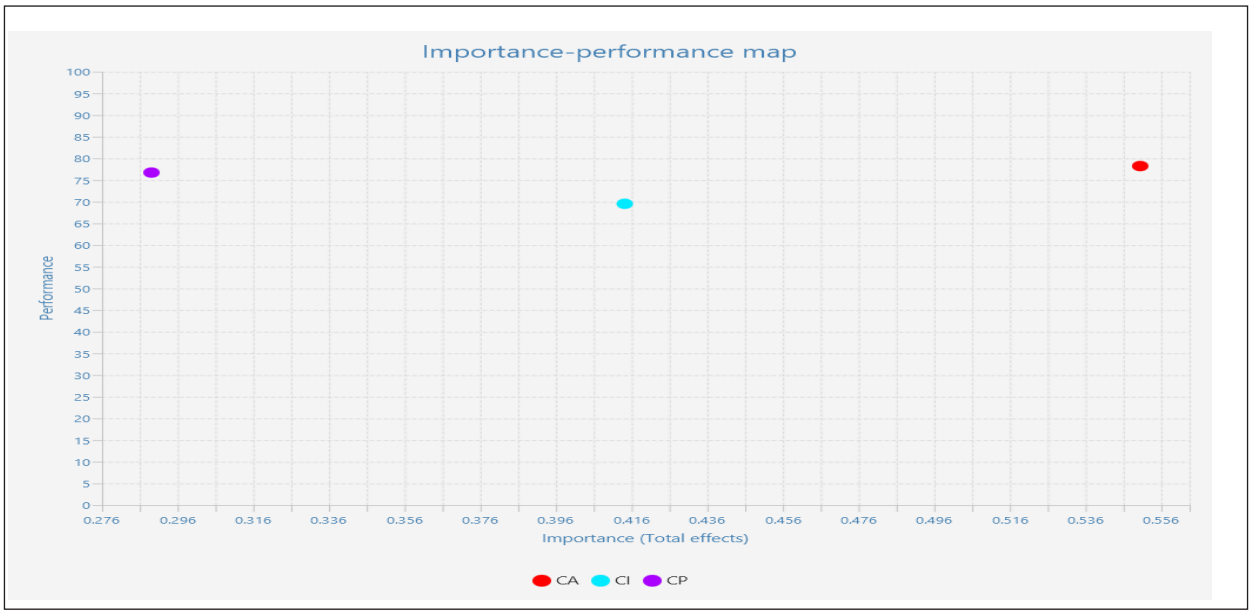
The study was undertaken to bring about the factors that lead to usage behaviour in Fintech. Cogent literature highlights that exogenous variables like customer intention, customer privacy, and customer adoption are precursors to usage behaviour. Building a conceptual model on the basis of theoretical constructs, the authors thus examined the relationships through SMART-PLS4 software using 403 sample respondents from Arunachal Pradesh, the easternmost state of India. The model was evaluated along its measurement criteria, importance criteria, mediation analysis, and predictive power which forms a special focus of our model. The robustness of the conceptual model and the hypothetical model has been argued for, considering the parameters of quality which the measurement model has met viz., Cronbach alpha, Rho, AVE, HTMT, R^2 and addressed collinearity values through VIF, in line with the literature. The hypotheses (H_1, H_2, H_3, H_5, and H_6) of the model point towards the significant relationships among the select constructs with the sole exception of H_4 i.e., the significance of the relationship between customer privacy to usage behaviour. Further, the mediation analysis has revealed paths CI -> CA -> UB, CP -> CA -> UB, CP -> CI -> UB, and CP -> CI -> CA are partially mediated, whereas the path CP -> CI -> CA -> UB is fully mediated as the direct path was not significant. This allows us to conclude that UB is mediated by more than one explanatory variable, viz., CA and CI, in our proposed model.

The predictive power of the conceptual model is a key contribution of our current study. By considering the Stone Geisser statistics and resulting predictive errors of the PLS-SEM and linear models, the five Usage Behaviour indicators in the PLS-SEM analysis have given rise to smaller prediction errors compared to the LM. In line with the literature, therefore, we confirm the high predictive power of the model. Having situated this, we add a priority analysis to chart out the constructs which hold more importance (total effect) and performance (on a scale of 1 to 100). We find that Customer Adoption has the most importance (highest total effect, 0.55) and its performance (78.236) is the highest among the rest of the variables (Fig. 2). The managerial implication of this finding is to continue the focus given to adoption behaviour, as not only is the construct high performing and important, but its path is also significant, which means customer usage depends to a considerable extent on customer adoption tactics by management. An interesting finding is also the priority of customer privacy which is an insignificant path but ranks as a high performer. Management is advised to restrict expending much focus on this variable as the efforts may not see commensurate returns in the long run. A caution needs to be inserted at this juncture. The coming future could likely see customer privacy issues being consolidated by a regulatory framework by appropriate institutions. The trump card in the model, however, is customer intention, underperforming in the current study but considering its significant path, management may place reasonable attention to this as it has the potential to grow in importance and improve its performance.

Conclusion and Way Forward

The objective of our study was to propose a model for the usage behaviour of Fintech services. In doing so, we have observed that customer privacy, customer intention, and customer adoption behaviour can predict the usage behaviour of Fintech users. We do owe up to certain limitations: first, being confined to the population of a remote Indian state; second, the choice of only three predictors of usage behaviour, making the model a simplistic one; and third, that it has been confined to only select Fintech services. Nevertheless, the contribution of the work is significant as it establishes a robust predictive model that can be used to chart future research agendas. To name a few the model can be applied to unseen populations, be expanded to the Fintech services not addressed in current work, and incorporate newer variables to explain Fintech usage behaviour. The managerial implications of paying renewed vigour to the customer adoption process, improvement in customer intention tactics and keeping a lookout for security issues (which could soon take the form of a regulatory framework) have been acknowledged. Fintech use may have been a forced choice in India, demonetisation and subsequently due to

the touchless landscape of COVID-19. Fintech remains a disruptive self-serviced technology paving the way for a normed behaviour in how financial transactions are being experienced. Usage behaviour will no longer be delimited to the frequency of use and number of units purchased. Usage behaviour could be defined in the context of Fintech as a complex phenomenon that evolves as quickly and as disruptively as the Fintech trajectory.



Source: Authors.

Fig. 2: Priority Analysis through IPMA

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ANNEXURE I

Questionnaire Cum Schedule (Anchor Points 5 = Strongly Agree to 1 = Strongly Disagree)

Latent Variables	*Question Code*	*Statements*
Customer Adoption	CA1	I can easily use Fintech.
	CA4	I am confident that Fintech provides service convenience.
	CA5	I like to adopt Fintech due to its informative features.
	CA7	I use my Fintech due to its attractive interface.
	CA8	I use Fintech due to range of services.
	CA13	I believe that Fintech provide Compatibility with daily operation.
Consumer Privacy	CP2	I am confident that OTP are secure for transaction.
	CP4	I am aware Fintech rely on open surface and are prone to malicious attack.
	CP5	I am confident that OTP are secure for transaction.
	CP6	I am confident that Bio-Metric Authentications are secure for transaction.
	CP8	I am aware that Fintech put risk on data security.
		I believe SMS based confidentiality can enhance security.
Customer Intention	CI8	I will do more business with this Fintech service provider in the next few years.
	CI10	I will continue using Fintech as I enjoy the Fintech experience.
	CI16	I will continue using it.
Usage Behaviour	UB4	It is easier to find information I need on the Fintech than in a bank.
	UB7	The FinTech gives me access to information that I cannot find elsewhere.
	UB8	The FinTech is prompt in responding to my queries.
	UB9	The FinTech understand the needs of their customers.
	UB12	In terms of system quality, I would rate the FinTech highly.