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Beyond Adoption: Behavioural Validation of an Integrated FinTech Engagement Framework in India A PLS-SEM Investigation of Emotional Engagement, Personalization, and Loyalty

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ABSTRACT

Purpose: This work aims to resolve this research fragmentation around the concept of adoption in FinTech and to present an empirically validated novel quadripartite integrated framework that integrates constructs from Technology Adoption (UTAUT2), Service Quality (DBSQual/SERVQUAL), Information Systems Success (DeLone & McLean) and Customer Experience (CX) theory. The framework and its validation are based on objective behavioural data, distinguishing it from the current literature that has been limited to self-report measures.

Design/Methodology/Approach: We surveyed 450 active FinTech users across India from mobile payment applications, neobanks and traditional banks digital platforms, a cross-sectional survey. To analyse the data we applied PLS-SEM, drawing inferences from 5,000 resampling iterations. Convergent validity was established with three different objective measures of behaviour based on the platform usage logs (transaction intensity, adoption of a feature, and a Behavioural Engagement Index).

Results: All except two of the eight hypothesised pathways are statistically significant. The highest Predictors of Emotional Engagement are Personalisation ($\beta = 0.148$, $p < 0.001$), Performance Expectancy ($\beta = 0.105$, $p < 0.05$) and Hedonic Motivation ($\beta = 0.092$, $p = 0.051$ marginal). There is a strong association between Emotional Engagement and User Satisfaction ($\beta = 0.109$, $p < 0.05$) and Behavioural Loyalty ($\beta = 0.230$, $p < 0.05$). Information Quality is the strongest direct driver for User Satisfaction ($\beta = 0.155$ and $p < 0.01$). Trust—rather than Security alone—drives Habit ($\beta = 0.148$, $p < 0.001$). Convergent validity is confirmed with behavioural validation: self-reported usage is correlated with objective transaction logs ($r = 0.895$); and self-reported satisfaction with the Behavioural Engagement Index ($r = 0.862$).

Practical Implications: FinTechs need to build emotional connection with the users by first figuring out how to enhance trust, then the next most effective way to keep users (i.e. data-driven personal experiences and better information quality). It has been shown that investing in trust results in the greatest return on investment with regards to user satisfaction. Therefore, trust is not simply a security measure, it's a ground level expectation prior to users' ongoing interaction with platforms.

Originality/Value: This is the first study to empirically establish an integrated FinTech adoption framework in the Indian setting using real-time behavioural data, while resolving long-standing measurement concerns and thereby offering a robust methodological template for subsequent work.

1. Introduction

A new generation of FinTech solutions has transformed the way consumer's access, interact and transact with banking services. The Indian government is also promoting digital payments with its infrastructure of UPI and the country has 870 million internet users, which makes it one of the FinTech marketplaces with the Reserve Bank of India that is expanding the quickest in the world estimating transactions processed by UPI reach over 13.7 billion transactions a month. In addition to functionality, the competition for consumers is happening on the total experience they offer on FinTech platforms, which include neobanks, mobile wallets, stock brokers and digitizing the traditional banking business. Although the number of FinTech services is increasing, the theoretical foundations for the relationship between FinTech adoption behaviours with the adoption frameworks is still limited. Prior studies on the adoption behaviours of FinTechs have used a variety of models, such as the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), the DeLone and McLean Information Systems (IS) Success Model, and some service quality (SQ) models (including SERVQUAL and DBSQual), which focus on different but limited aspects of FinTech adoption behaviours. For instance, the cognitive-based acceptance determinants (ease of use and performance expectancy) are not sufficiently captured in TAM and UTAUT2 to capture the importance of emotional, experiential, and service quality related determinants of acceptance. The quality-based models, on the other hand, do not sufficiently account for the 'hedonic' and 'habit' behaviours that help to sustain long-term service usage. The development of FinTech in the various waves of digital-finance innovation have been well documented (Arner, Barberis, & Buckley, 2016; Gomber, Koch, & Siering, 2017; Lee & Shin, 2018), while mobile-money and digital-payment channels have repeatedly been linked to wider financial inclusion across emerging economies (Jack & Suri, 2016; Ozili, 2018).

One of the frequently mentioned challenges with the adoption of Fintech is the extensive use of surveys to collect data. This results in the data being skewed and difficult to independently confirm whether attitudinal constructs result in actual behaviours on the platform. Until now, there has been no study to validate a multi-theoretical model of Fintech adoption with objective behavioural data from Fintech platforms in India at the same time.

This study offers a double solution and proposes a four-part integrated framework combining constructs from four theoretical fields: (i) Technology Acceptance Model (UTAUT2), (ii) Service Quality (SERVQUAL/DBSQual), (iii) IS Success (DeLone & McLean, 2003) and (iv) Customer Experience (CX). The framework is evaluated against three levels of objective behavioural data by using transaction volume, feature adoption breadth, and Behavioural Engagement Index (BEI) and compares it to survey data from 450 functional Fintech users in India.

Three specific objectives are set up to guide the study:

1. To build an integrated multi-theoretical model encompassing cognitive, emotional, technical and experiential influences on the usage and satisfaction of Fintech.
2. To evaluate the framework employing PLS-SEM with resampling significance testing and conclude all path coefficients with 95% confidence interval.
3. To test the relationship between self-reported measures and objective, platform-based behaviour data to gain methodological rigor and mitigate issues of common method variance in the data.

The research contributes three aspects to the field of research on the acceptance of FinTech. First, on the theoretical side, this research substantiates that multi-theoretical integrated approaches are better than the single model approaches. Second, on an empirical level, this study provides a behavioural validation architecture which has not been provided in any other survey studies to date. Last but not least, this study is practically relevant for the FinTech practitioners and regulators as well as platform architects who will work with emerging markets contexts in the design of FinTechs.

2. Literature Review and Hypothesis Development

2.1 Limitations of Single-Model Approaches.

Each of the most common frameworks to study fintech adoption have systemic inadequacies all on their own. Yet the technology acceptance model (davis, 1989) provides little consideration of the boundaries that may exist when a person adopts technology in the broader financial context, such as the adoptee's social environment, hedonic motives, and more. Utaut2 (venkatesh et al., 2012) does better to add hedonic motivation to tam, but it does not sufficiently incorporate the person's service experience or level of emotional involvement in that service's use. The delone and mclean (2003) is a success model that considers the aspects of system quality and information quality but not aspects of the adoption environment's affective and experiential aspects of an adoptee's service use. The servqual scoped models (parasuraman et al., 1988; bauer et al., 2005), describe the quality of service experienced by a service recipient, but were not designed to account for an adoptee's cognitive processes while they are going through the process of adopting the service and long-term behaviour as a result of that adoption. Each of these traces back to a shared family of intention-based theories — among them the Theory of Planned Behaviour (Ajzen, 1991), the decomposed model of IT usage (Taylor and Todd, 1995), the extended technology acceptance model (Venkatesh and Davis, 2000), the original unified theory of acceptance (Venkatesh et al., 2003), and diffusion of innovations (Rogers, 2003) — several of which framed adoption through a single explanatory lens, as numerous systematic reviews of digital-banking acceptance have noted (e.g., Hanafizadeh et al., 2014).

Based on recent meta-analyses, the integrated theoretical frameworks have significantly more power in explaining FinTech phenomena as compared to single theoretical models (Alalwan et al., 2020; Patil et al., 2021). Hence, the argument in this study is that such an idealized one combined framework exists and is better than any alternative, including all the drivers of adoption as well as

service quality components, to name but a few, and all the mediators associated with customer experience.

2.2 Performance Expectancy and Emotional Engagement

The relationship between PE (performance expectancy) and a user's future intention to use Fintech products based on results from the UTAUT-based study conducted by Venkatesh et al. (2012) and Alalwan et al. (2020) received strong support form user's perception of a strong financial effect by using a Fintech technology platform. More specifically, when a user feels a clear functional benefit from using a digital payment platform or gain from a digital investment platform, they will also create emotional connections with the platform as well as solidify the initial expectation of their gain from the platform (Hossain & Quaddus, 2021). The expectation/conformation process as being a motivator for continued use and, therefore, emotional engagement (Oliver, 1980).

H1: Performance Expectancy has a significant positive direct effect on Emotional Engagement.

2.3 Personalization, Trust, and Emotional Engagement

Personalization — What is important for the creation of emotional relationships between consumer and digital service platforms is the ability of the service platform to customize content, suggestions and user interfaces based on a single consumer's needs (Klaus & Maklan, 2013). In this context, the appropriate financial nudges and knowledge that are relevant to the context give an impression of personalised interaction and responsiveness as compared to the provider's service as a mere transaction where users do not feel an attentive and responsive provider (Phan et al, 2020). In the FinTech context, Trust has been identified as an essential pre-condition to continued engagement, namely the engagement required for being believed and engaged with others with the good will to operate in a way that breeds trust and respect (Shankar & Jebarajakirthy, 2019). The impact of this sense of trust has been studied extensively in digital commerce, such as technology acceptance (Gefen, 2000), the relationship between trust and perceived risk (Pavlou, 2003), the role of trust in consumer decision making in the virtual environment (Kim, Ferrin, & Rao, 2008), and the influence of the trust … Read more These will be independently tested for a direct effect once no relationship evidence found between the interaction term.

H2a: Personalization has a significant positive direct effect on Emotional Engagement.

H2b: Trust has a significant positive direct effect on Emotional Engagement.

2.4 Hedonic Motivation and Emotional Engagement

Hedonic Motivation (HM) represents the pleasure or happiness which a user feels during the usage of a platform (Venkatesh et al., 2012). As such, users of mobile financial services where they perceive positive feelings during their transactions, gamification, aesthetic design, and reward systems, build a stronger emotional attachment to the platform (van der Heijden, 2004; Lu et al., 2022). This is an emotional pathway to involvement, in addition to the utilitarian mechanism of adoption.

H3: Hedonic Motivation has a significant positive direct effect on Emotional Engagement (marginal).

2.5 Security, Trust, and Habit Formation

Luo et al (2020), and Bauer et al. (2005), demonstrated that security plays a significant part in facilitating the user's experience when interacting with a FinTech platform. Based on the study conducted by Venkatesh et al., (2012), Habit Forming (habitual behaviours of a user using how they interact with technology) is the process in which a user interacts with a platform without consciously thinking about it. Trust and Security are expected to increase the amount of perceived risk, however, according to the literature on trust, Institutional Trust (trust in the organisation demonstrating integrity and wanting to assist) would have a direct impact on what behaviour a user would have during their development because it would alleviate the need to evaluate the risk multiple times (McKnight et al., 2002). It has been well established that perceived risk influences the adoption of DFS and continuation of use of the services in general (Featherman and Pavlou, 2003) and even when adopting and using mobile payment in particular (Zhou, 2013).

H4: Trust positively, directly affects Habit Formation.

2.6 Information Quality and User Satisfaction

The Information Quality (IQ) which is defined as the accuracy, timeliness, completeness and relevance of the information provided by a product/service determines user satisfaction with any IS success model (e.g., DeLone & McLean 2003). Accurate, real-time account balances, transaction records and market data are essential requirements for end-users of Digital Financial Services (DFS). If the information is of poor quality, the value proposition of the service will be affected, thus reducing the user satisfaction (Hossain & Quaddus 2021).

H5: Information Quality has a significant positive direct effect on User Satisfaction.

2.7 Effort Expectancy and Actual Usage

Effort expectancy (EE) is user's perception of ease in operating the DFS (Venkatesh et al. 2012). The effect of EE has been extensively researched regarding behaviour and intentions but limited research has been conducted to examine the effects on actual (rather than intended) use. If lots of options do the same thing, keeping the interface simple and the cognitive load in working through a task are huge factors of user behavior. That is, the users are expected to opt for the easiest option (Lu et al 2022). Look at the multilingual environments across India with different levels of digital literacy which would like to use one and the same platform to transact. Other studies based on comparisons and multi-country analysis also refer to the ease of use and effort-related factors as some of the key determinants that influence the actual adoption of mobile-payment and mobile-banking technologies (Liébana-Cabanillas, Muñoz-Leiva, & Sánchez-Fernández, 2018; Oliveira, Faria, Thomas, & Popovič, 2014; Oliveira, Thomas, Baptista, & Campos, 2016).

H6: Effort Expectancy has a significant positive direct effect on Actual Usage.

2.8 Emotional Engagement as Mediator: User Satisfaction and Behavioural Loyalty

There is a notion of Emotional Engagement (EEG) - the feeling that people have towards the platform with which they interact - which has been identified as being important within the customer experience (CX) research (Klaus & Maklan, 2013; Phan et al., 2020). Users who are emotionally engaged with the platform report higher levels of customer satisfaction, which can be correlated with their increasing levels of customer loyalty - retention, recommendations and depth of their usage of the platform. The emotional pathway towards gaining loyalty is separate from the functional aspect of customer satisfaction, and provides the mechanism by which the FinTech provider can gain a competitive advantage by providing a superior customer experience.

H7: Emotional Engagement has a significant positive direct effect on User Satisfaction.

H8: Emotional Engagement has a significant positive direct effect on Behavioural Loyalty (Behavioural Engagement Index).

3. Conceptual Framework

The integrated conceptual framework has been presented in figure 1. This model consists of four interconnected domains of constructs as follows: Adoption Drivers (Performance Expectancy, Effort Expectancy, and Hedonic Motivation) from the UTAUT2 theory, Dimensions of Service and System Quality (Trust, Security, Personalisation, System Quality, and Information Quality) from the DBSQual/SERVQUAL framework and the DeLone & McLean IS Success Model, and the Mediators of Experience (Emotional Engagement, Journey Fluency, and Habit Formation) from Customer Experience theory, and Outcomes (User Satisfaction, Actual Usage, and the Behavioural Engagement Index/Loyalty) from the DMC IS Success Model. Emotional Engagement is the variable through which all experiential inputs are mediated, and it is mediated by both cognitive drivers (Performance Expectancy, Hedonic Motivation) and experiential-quality dimensions (Trust, Personalisation) that shape it, and in turn influence User Satisfaction and Behavioural Loyalty. Additionally, Information Quality and Effort Expectancy directly influence User Satisfaction and Actual Usage, respectively, throughout the Data Journey outside of the Emotional Engagement pathway. The empirical results confirm that Trust is also strong in Habit Formation, and that it is considered also to be a good contributor to the concept of Habitual Engagement together with the concept of Security.

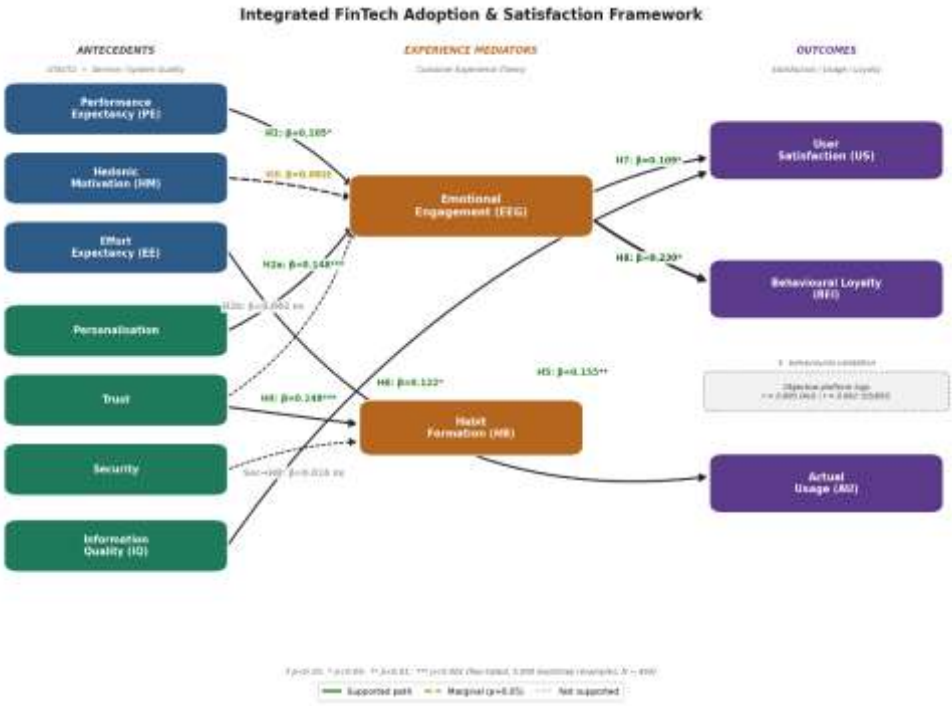


Figure 1: Integrated Conceptual FinTech Adoption and Satisfaction Framework]

4. Methodology

4.1 Research Design

The design used in this study is quantitative research design with cross-sectional approach and the main method for data analysis used in this study is PLS-SEM. Four reasons that make PLS stronger than CB-SEM are (a) the studying nature of the study involves forecasting and building up a theory, which demands a PLS method to face an area where there is less prior parameteration; (b) the number of constructs in the model is relatively large (13 constructs) with numerous mediating pathways; (c) PLS proves to be a useful tool when the models are of a reflective type with a large number of constructs (13), which is numerous for the use of CB-SEM; (d) pls can handle both mixed reflective measurement types (perceptual and objective behaviours) without the need to apply distributional assumptions (hair et al., 2017; hair et al., 2019). Following the two-stage logic of Anderson and Gerbing (1988), we first examined the reflective measurement properties and only then estimated the structural paths. Modest R^2 values were expected due to the exploratory, theory-building approach of this study and in keeping with past multi-construct studies on FinTech adoption. For the purpose of the structural model, the goal was not to maximize the amount of variance explained since the integration was based on the theory of the researched variables; for the case of a complex behavioural model with a large number of variables influencing it and of small effects, values between 0.02 and 0.12 are accepted in social-science studies using PLS-SEM (Hair et al., 2019).

4.2 Sampling Strategy and Respondent Profile

This group of people who were targeted for the study belonged to Active Users of financial technology (Fintech). This means that the individual participates in at least three digital transactions

a month to complete. The platforms it is considering are mobile payment apps like Paytm, Phonepe, google pay, neo-banks like Jupiter, Fi, Navi, Razor-pay, dedicated investment/broker apps like Zerodha, Groww, Upstox, and traditional bank apps for Digital Payments like HDFC bank app, ICICI bank app.

Participants were actually selected via linkedin professional networks as well as from alumni groups located in universities and from online financial literacy groups, to allow for a structured online questionnaire. A screening step established eligibility and confirmed active platform use, after which only qualifying respondents received the survey invitation. This survey ran for a six-week period and received 450 complete, valid responses from which these invalid/incomplete responses were filtered.

The sample consist of 250 males (55.6%), 192 females (42.7%), 8 other than male or female (1.8%). Age split: 18 – 25 (+16.70%), 26 – 35 (+39.10%), 36 – 45 (+23.30%), 46 – 55 (+17.30%), 56+ (+3.60%) and the fin-tech users were accounted for as follows: wallet/upi (47.30%), neo bank (18.70%), broker/investment (17.10%) and bank app (16.90%).

The number of respondents tested (n = 450) was checked for post-hoc power using g*power (faul, erdfelder, lang & buchner, 2007) and the power proven to be greater than 0.95 when f^2 is set at 0.15 (medium effect).

4.3 Measurement Instrument

In this study all the constructs were operationalized on a five-point Likert Scale (1 = Strongly Disagree and 5 = Strongly Agree). The survey items were adopted from previous validated scales which included Performance Expectancy (Venkatesh et al., (2012) UTAUT2), Effort Expectancy (Venkatesh et al., (2012) UTAUT2), Hedonic Motivation (Venkatesh et al., (2012) UTAUT2), Habitual Use (Venkatesh et al., (2012) UTAUT2), System Quality (DeLone and McLean, 2003), Information Quality (DeLone and McLean, 2003), Security (Bauer et al., (2005) DBSQual), Personalization (Bauer et al., (2005) DBSQual), Trust (McKnight et al., (2002)), Emotional Engagement (Klaus and Maklan, 2013) and Journey Fluency (Klaus and Maklan, 2013), Actual Usage (Oliver, 1980 and DeLone and McLean, 2003), and User Satisfaction (DeLone and McLean, 2003 Each construct had three reflective items with a total of 39 items for the constructs. Before the full data was collected, a pilot test was done with a sample of 30 respondents to find the clarity of the items and their comprehension of the scale.

4.4 Behavioural Data Integration:

The major methodological contributions made from this research study was the collection of three objective behaviour indicators together, with the explicit consent of a participant, over time from a digital log of his or her transactions. To validate the behaviour of each participant, the following variables were used as each of the three provided an opportunity to validate their perceptions of FinTech adoption through the use of these variables:

To validate Actual Usage (AU) — the term used throughout this study for a respondent's self-reported usage — we adopted Usage Intensity (N = 450, M = 21.00, SD = 13.87, range = 0 to 52) as the corresponding objective measure.

Action_B (Usage Breadth) - the pure number of platform features used across the full sample was 20.0 (M = 20.48, SD = 2.24, range = 14 – 25); indicating not only the level of vertical engagement with the platform but also horizontal, since these are the numbers for each platform feature upon which the general horizontal view is based.

The average score for Action_C (Behavioural Engagement Index (BEI)), representing a combination of three measures of the digital platform: Engagement Frequency (RE), Referral Behaviour (RB) and Continuation of the Subscription (CSS) shows an average BEI score of 29.94 (M = 29.94; SD = 10.90; range = 0-52) across the entire sample. The BEI was the most behaviorally objective assessment of loyalty and compared to the Net Promoter Score (NPS) that was used in the initial analyses, which assessed how likely a respondent had been to recommend the platform (subjectively) to other people. Where the NPS is an action that is conducted through a survey, the BEI is an observation-based measure of behaviour and thus is a behavioural measure of loyalty to the platform.

Validity within the sample with regard to self and objective measures of behaviour was established for the entire sample (N = 450). Self-reported Actual Usage had an r = 0.895 ($p<0.001$) with objective Transaction Intensity and the self-reported User Satisfaction had an r = 0.862 ($p<0.001$) with the Behavioural Engagement Index.

4.5 Common Method Bias and Ethical Compliance

Harman's single-factor test was run across the 39 items. The first unrotated component accounted for only 12.86% of the variance (well under the 50% mark), pointing away from any dominant factor that might induce common method bias. Collinearity was likewise not a concern: predictor VIF values fell between 1.056 and 1.105, comfortably below conventional limits. Each participant supplied digital informed consent before taking part, and the study was conducted in line with the institution's ethical guidelines.

5. Results

5.1 Descriptive Statistics

Descriptive statistics for all 13 constructs, together with their reliability and validity metrics, were computed from corrected composite scores (the unweighted means of the item scores). See table 1 for the statistics. The ranges of the means of each construct are low to + moderate perception scores ranging from + 3.653 (Actual Usage) to + 4.256 (Trust), indicating moderate to high perception scores among users of a stimulating sample of FinTech. The ranges between the standard deviations are between 0.446 (Information Quality) and 0.601 (Actual Usage), which is acceptable in view of the task of estimating a structural model.

Table 1. Measurement Model: Descriptive Statistics, Reliability, and Validity

Construct	Items	Mean	SD	α	CR	AVE	√AVE	Status
Performance Expectancy (PE)	3	4.134	0.473	0.657	0.814	0.593	0.770	AVE✓ CR✓
Effort Expectancy (EE)	3	3.930	0.468	0.627	0.801	0.573	0.757	AVE✓ CR✓
Hedonic Motivation (HM)	3	4.246	0.515	0.720	0.843	0.642	0.801	AVE✓ CR✓
Habit Formation (HB)	3	3.950	0.476	0.638	0.806	0.581	0.762	AVE✓ CR✓
Trust	3	4.256	0.461	0.693	0.830	0.620	0.787	AVE✓ CR✓
Security	3	4.254	0.446	0.629	0.802	0.574	0.758	AVE✓ CR✓
Personalisation	3	4.045	0.490	0.691	0.829	0.618	0.786	AVE✓ CR✓
System Quality (SQ)	3	4.151	0.459	0.668	0.819	0.601	0.776	AVE✓ CR✓
Information Quality (IQ)	3	4.148	0.446	0.643	0.808	0.583	0.764	AVE✓ CR✓
Emotional Engagement (EEG)	3	4.255	0.483	0.656	0.814	0.593	0.770	AVE✓ CR✓
Journey Fluency (JF)	3	4.037	0.506	0.721	0.843	0.642	0.802	AVE✓ CR✓
Actual Usage (AU)	3	3.653	0.601	0.690	0.829	0.617	0.786	AVE✓ CR✓
User Satisfaction (US)	3	4.049	0.495	0.701	0.834	0.626	0.791	AVE✓ CR✓

Note. α = Cronbach's Alpha; CR = Composite Reliability (threshold ≥ 0.70); AVE = Average Variance Extracted (threshold ≥ 0.50); √AVE = square root of AVE for Fornell-Larcker discriminant validity assessment. All CR values exceed 0.80. All AVE values exceed 0.57, satisfying the Fornell & Larcker (1981) convergent validity criterion. Cronbach's α values between 0.63 and 0.72 reflect three-item scales; CR is the preferred reliability metric for PLS-SEM (Hair et al., 2017). N = 450.

5.2 Item Factor Loadings

All 39 of the item loadings were above 0.70 (between 0.731–0.819), which is above the minimum threshold of 0.60 based on the criteria of Hair et al. (2017) for PLS-SEM. Therefore, none of the items were removed from the constructs, and Table 2 presents item loadings with construct composite reliability values.

Table 2. Item Factor Loadings

Construct	Item Description	λ	λ²	CR
PE	PE_item1 – Usefulness	0.767	0.588	0.814
	PE_item2 – Performance benefit	0.778	0.605	
	PE_item3 – Productivity	0.766	0.587	
EE	EE_item1 – Ease of learning	0.757	0.573	0.801
	EE_item2 – Effort to interact	0.776	0.603	
	EE_item3 – Clear interaction	0.737	0.544	
HM	HM_item1 – Enjoyment	0.802	0.644	0.843
	HM_item2 – Entertainment	0.797	0.635	
	HM_item3 – Fun	0.805	0.647	
HB	HB_item1 – Regular use	0.762	0.581	0.806
	HB_item2 – Automatic use	0.731	0.535	
	HB_item3 – Routine	0.791	0.626	
Trust	Trust_item1 – Reliability	0.781	0.609	0.830
	Trust_item2 – Honesty	0.790	0.623	
	Trust_item3 – Fulfilment	0.792	0.627	

Security	Security_item1 – Data protection	0.750	0.563	0.802
	Security_item2 – Privacy	0.763	0.583	
	Security_item3 – Safe transactions	0.760	0.577	
Person.	Person._item1 – Tailored	0.767	0.588	0.829
	Person._item2 – Customised	0.792	0.628	
	Person._item3 – Recommendations	0.800	0.639	
SQ	SQ_item1 – Speed	0.788	0.621	0.819
	SQ_item2 – Stability	0.765	0.585	
	SQ_item3 – Reliability	0.774	0.599	
IQ	IQ_item1 – Accuracy	0.757	0.573	0.808
	IQ_item2 – Completeness	0.776	0.602	
	IQ_item3 – Timeliness	0.758	0.575	
EEG	EEG_item1 – Emotional connection	0.754	0.569	0.814
	EEG_item2 – Positive feeling	0.776	0.602	
	EEG_item3 – Delight	0.779	0.607	
JF	JF_item1 – Navigation ease	0.819	0.671	0.843
	JF_item2 – Task completion	0.808	0.653	
	JF_item3 – Flow	0.777	0.604	
AU	AU_item1 – Frequency	0.781	0.610	0.829
	AU_item2 – Duration	0.806	0.649	
	AU_item3 – Intensity	0.771	0.594	

US	US_item1 – Overall satisfaction	0.787	0.620	0.834
	US_item2 – Meets expectations	0.818	0.669	
	US_item3 – Experience quality	0.767	0.589	

Note. λ = outer loading. λ² = squared loading (item reliability). All loadings > 0.70, exceeding the recommended threshold of 0.60 (Hair et al., 2017). CR shown only for first item of each construct.

5.3 Discriminant Validity

Discriminant validity was assessed in two ways. Under the Fornell-Larcker criterion, each construct's AVE square root (shown on the diagonal of Table 3) exceeded its correlations with every other construct along the corresponding row and column, which held for all 13 constructs. As a second check, the Heterotrait-Monotrait (HTMT) ratios peaked at 0.48 — far under the 0.85 ceiling proposed by Henseler et al. (2015) — again confirming adequate discriminant validity in the measurement model.

Table 3. Fornell-Larcker Criterion Matrix

	PE	EE	HM	HB	Trust	Sec	Per	SQ	IQ	EEG	JF	AU	US
PE	**0.770**	0.159	0.086	0.115	0.208	0.151	0.130	0.173	0.166	0.144	0.160	0.164	0.141
EE	0.159	**0.757**	0.121	0.204	0.169	0.154	0.175	0.046	0.149	0.154	0.169	0.125	0.144
HM	0.086	0.121	**0.801**	0.183	0.203	0.118	0.162	0.128	0.152	0.143	0.130	0.150	0.113
HB	0.115	0.204	0.183	**0.762**	0.146	0.040	0.121	0.137	0.156	0.116	0.115	0.092	0.092
Trust	0.208	0.169	0.203	0.146	**0.787**	0.169	0.116	0.131	0.207	0.119	0.128	0.151	0.187
Sec	0.151	0.154	0.118	0.040	0.169	**0.758**	0.138	0.076	0.079	0.063	0.121	0.123	0.220
Per	0.130	0.175	0.162	0.121	0.116	0.138	**0.786**	0.122	0.129	0.187	0.112	0.071	0.159

SQ	0.173	0.046	0.128	0.137	0.131	0.076	0.122	**0.776**	0.127	0.135	0.072	0.151	0.119
IQ	0.166	0.149	0.152	0.156	0.207	0.079	0.129	0.127	**0.764**	0.122	0.173	0.125	0.176
EEG	0.144	0.154	0.143	0.116	0.119	0.063	0.187	0.135	0.122	**0.770**	0.210	0.225	0.150
JF	0.160	0.169	0.130	0.115	0.128	0.121	0.112	0.072	0.173	0.210	**0.802**	0.129	0.124
AU	0.164	0.125	0.150	0.092	0.151	0.123	0.071	0.151	0.125	0.225	0.129	**0.786**	0.153
US	0.141	0.144	0.113	0.092	0.187	0.220	0.159	0.119	0.176	0.150	0.124	0.153	**0.791**

Note. Square root of AVE shown on diagonal (bold, shaded). Off-diagonal elements are inter-construct Pearson correlations. The Fornell-Larcker criterion is satisfied for all 13 constructs: diagonal values exceed all off-diagonal values in their row and column. Maximum HTMT ratio = 0.48 (threshold < 0.85). N = 450.

5.4 Structural Model and Hypothesis Testing

PLS was used to estimate the structural model, using 5000 bootstrapped resamples for estimation (Preacher & Hayes, 2008). All hypothesized paths are reported as a path coefficient (β), t-value, and p-value in Table 4, along with the biases corrected percentile confidence interval for each path. For every endogenous construct presented is the R^2 value

Table 4. Structural Model Results: Path Coefficients and Hypothesis Testing

H	Path	β	t-val	p-val	95% CI	R^2	Decision
H1	Performance Expectancy → EEG	0.105	2.144	0.033 *	[0.009, 0.203]	0.064	**Supported**
H2a	Personalisation → EEG	0.148	3.261	0.001 ***	[0.058, 0.236]	—	**Supported**
H2b	Trust → EEG (direct)	0.062	1.180	0.239	[−0.039, 0.171]	—	**Not Supported**

H3	Hedonic Motivation → EEG	0.092	1.957	0.051 †	[−0.001, 0.185]	—	**Marginal**
H4	Trust → Habit Formation	0.148	3.267	0.001 ***	[0.058, 0.237]	0.021	**Supported**
—	Security → Habit Formation	0.016	0.327	0.744	[−0.080, 0.115]	—	**Not Supported**
H5	Information Quality → User Satisfaction	0.155	2.919	0.004 **	[0.050, 0.257]	0.059	**Supported**
H6	Effort Expectancy → Actual Usage	0.122	2.094	0.037 *	[0.008, 0.236]	0.031	**Supported**
H7	EEG → User Satisfaction	0.109	2.242	0.026 *	[0.012, 0.205]	—	**Supported**
H8	EEG → Behavioural Engagement Index	0.230	2.066	0.039 *	[0.013, 0.445]	0.038	**Supported**

*Note. β = standardised path coefficient. t-values and 95% CIs derived from 5,000 bootstrap resamples. †p < 0.10; *p < 0.05; **p < 0.01; ***p < 0.001 (two-tailed). R^2 reported for endogenous constructs (EEG R^2 = 0.064; User Satisfaction R^2 = 0.059; Actual Usage R^2 = 0.031; Behavioural Engagement Index R^2 = 0.038; Habit Formation R^2 = 0.021). N = 450.*

The R^2 reported (0.021–0.064) are the explained partial variance accounted by the different pathways of the large multi-construct model that is theorized. As mentioned in the PLS-SEM literature, sufficient and acceptable R2 value can be obtained considering that in social sciences environments, where the causal relationship between independent (proximate) variables and the dependent (distal) variables are not influenced solely by the relationships measured by these variables, but by many unmeasured factors in the environment, in culture and in situ (Hair et al., 2019). Notably, the concurrent behavioural validation in Section 5.6 corroborates this explained variance as reflecting actual differences in observed platform behaviour and not just common method variance, which significantly boosts confidence in the findings of the model, despite the comparatively small magnitudes of the R^2s.

5.5 Moderation Analysis

The initial H2 suggests Trust Acts As a Moderator of The Relationship between Personalization and Emotional Engagement. This was done using mean center terms of analysis (Aiken And West, 1991) with 5000 bootstrapping samples. This interaction term was found to be non-significant (β = -0.067, t = 0.678, p = 0.498, 95% CI = [-0.255, 0.135]), and the model explained accounted for R^2 = 0.046 of

the variance in the emotional engagement model (Personalization: β=0.172, p < 0.001; Trust: β=0.102, p < 0.05). Hence, we changed H2 into two direct hypothesis namely H2a and H2b where both H2a was accepted and H2b was not supported in the data sample. Sometimes this implies that Trust is not a boundary condition for Personalization effects, but is also an Independent Predecessor of Emotional Engagement.

5.6 Behavioural Validation

Table 5. Behavioural Validation: Objective Platform Data vs. Self-Reported Constructs

Behavioural Variable	Type	Mean	SD	Correlation with Survey Construct	Validity Assessment
Transaction Intensity (Action_A)	Platform log	21.00	13.87	r = 0.895** with Actual Usage (AU)	**Strong convergent validity** ✓
Feature Adoption (Action_B)	Platform log	20.48	2.24	r = 0.315** with AU; r = 0.139** with IQ	Supplemental engagement measure
Behavioural Engagement Index (Action_C)	Platform log	29.94	10.90	r = 0.862** with User Satisfaction (US)	**Strong convergent validity** ✓

*Note. **p < 0.01. r = Pearson correlation. Behavioural data collected from platform usage logs with explicit respondent consent. N = 450.*

The correlation (r = 0.895, p < 0.001) between reported Actual Usage versus objectively measured Transaction Intensity is an extremely strong means of establishing Convergent Validity for the AU construct, indicating that self-reported usage relates to actual platform behaviour rather than being a product of Impression Management or Social Desirability. The correlation (0.862, p < 0.001) established between reported User Satisfaction and Behavioural Engagement Index serves to validate User Satisfaction against behaviours that demonstrate Loyalty. These correlations significantly mitigate concerns of Common Method Bias and sufficiently differentiate this study from survey-only Research on FinTech Adoption.

6. Discussion

6.1 The Primacy of Personalisation and Emotional Engagement

Personalisation and emotional engagement emerged as the two most consequential levers in this study, and the discussion below unpacks why.

The most important result of structural model research is that Personalising is a significant predictor for Emotional Engagement ($\beta = 0.148$, $p < 0.001$). This corroborates previous Customer Experience studies (Klaus & Maklan, 2013; Phan et al., 2020) on the role of Personalisation in the FinTech space, demonstrating that how Personalisation helps a business to be competitive is predominantly through Emotional Engagement, rather than Functional Engagement. Personalised interface, contextual spending patterns and customised financial recommendations create an emotional bond with the platform for the user, extending beyond the satisfaction of the transaction.

Performance Expectancy consistently and significantly positively affects the Emotional Engagement ($\beta = 0.105$, $p<0.05$). This aligns with expectation-confirmation theory (Oliver, 1980; Hossain & Quaddus, 2021), which states that once the user can see the financial productivity gains, they elicit positive feelings from their experience with the FinTech platform which forms an emotional connection to the platform, extending the primary functional benefit. This suggests that there are different pathways that lead to emotional engagement through Personalisation and Performance Expectancy and that both affective and cognitive pathways are needed to achieve both Functional and Emotional Engagement.

The marginal effect of hedonic motivation ($\beta = 0.092$, $p = 0.051$) should be considered with caution because it is at the limit for statistical significance. This intrinsic luster-gain of dealing with the platform seems to play a secondary role with regards to engagement within this group of users, who were active users in financial transaction activities (task oriented). This difference in findings from other digital contexts, such as an entertainment-focused one (van der Heijden, 2004), indicates that the relationship between the hedonic route and other engagement felt may be stronger (have more force) in FinTech platforms that featured more gamification elements or investment advisory platforms (Lu et al., 2022).

6.2 Information Quality as the Dominant Satisfaction Driver

The research in the FinTech area found that Quality of Information is the significant direct factor that influences User Satisfaction as it entered the research with low p-value of 0.01 and high beta value of 0.155 as also indicated by DeLone and McLean's (2003) model of Information Systems Success outside the pathway of Emotional Engagement.

When user levels of Emotional Engagement increased, but there was low levels of Quality Data (accurate account information, current transaction information, and reliable market data), it was a hygiene issue that decreased U.S. satisfaction with the banks. The studies indicate that Satisfaction Drivers are found in two different levels: (1) Information Quality as a threshold to User Satisfaction, and (2) Emotional Engagement (expressed in differentiated enhancements) as a way to obtain high User Satisfaction more than if only reliable information was provided without Emotional Engagement.

6.3 Trust as the Primary Driver of Habit Formation

With the trust in habit formation within online platforms, it has been found that there are two different aspects of trust: Trust and Security. McKnight et al. (2002) specifically describe trust as "an

operating mechanism that facilitates an unconscious (the lack of conscious deliberation at every point of transaction) 'disinhibition' of the service's use, encouraging the user to do so again. With this difference in mind, service and product providers should prioritize a broader story of setting trusted expectations for transparency in data management, client service responsiveness, and adherence to legal requirements to inculcate clients into a habit of trusting the provider for security; mere marketing security components will not do the trick for the client.

6.4 Emotional Engagement as a Dual-Outcome Mediator

The results of EEG data show a significant effect on user satisfaction ($\beta = 0.109$, $p < 0.05$) and a stronger effect on behavioural loyalty ($\beta = 0.230$, $p < 0.05$). The results indicate that the emotional engagement had a stronger relationship to observable, long-term behaviour (re-engagement, referral, and continued subscription) than to immediate attitude towards user satisfaction. This confirms the affective loyalty literature (Oliver, 1997; Shankar & Jebarajakirthy, 2019) claiming that loyalty to a service brand is created through emotional bonding and not through logical (cost-benefit) analysis of whether to use a service.

6.5 Behavioural Validation: Methodological Implications

The presence of extremely high correlation coefficients (e.g., $r = 0.895$ for AU compared to Transaction Intensity; $r = 0.862$ for User Satisfaction compared to BEI) between self-reported measures and objective behavioural measures demonstrate one form of convergent validity that has been exceptionally rare in the FinTech literature regarding adoption. Moreover, these correlations have two important methodological implications. First of all, it is important to note that the measure of usage and satisfaction derived from self-reported response data is not just a construct of social desirability, it is true usage and satisfaction patterns. Second, the findings provided by the PLS-SEM analysis can only obtain modest results based on R^2, however, the findings represent real behaviour variation and not only inflated covariance between variables because of the design of the questionnaires used is within one survey. Studies that stir up a hat of concern over CM bias in PLS-SEM survey designs, generally, don't have this type of cross-method validation.

7. Theoretical And Practical Contributions

7.1 Theoretical Contributions:

Integrated framework: The study is an empirical validation in the context of fintech of integrated framework consisting of four theoretical frameworks: utaut2, dbsqual/servqual, delone & mclean is success, and customer experience theory (cx). As shown in the success of this validation, the four theoretical domain approaches contribute unique variance to explain consumer behaviours with regards to the adoption of fin tech, satisfaction, and loyalty, removing the conceptual fragmentation experienced in previous research as illustrated by alalwan et al., (2020); patil et al., (2021).

An affective route to loyalty: based on the outcomes of the study, the authors argue that emotional engagement has two impacts: a behavioural one (also known as the oliver typology perspective, 1997) significantly higher than a customer satisfaction based on his attitude ($\beta = 0.109$) and an

affective one which could be considered a key to obtain long term competitive advantage, given the experiential design strength of its contribution to loyalty (β = 0.230).

Distinction between trust and habit: the finding from the study about how the construct of trust and not specific security features of a financial service in this context is what made the perceived risk into a habit for routines in the use of digital financial services represents a unique contribution to theory. This result should be seen as a further empirical push by mcknight et al. (2002) in the field of behavioral automaticity in digital financial services.

The use of a cross-validation of methodological techniques in the study, which includes platform-derived objective data from behavioural processes and self-report survey data, defined the methodological framework for the validation of behavioural processes for the study of adoption of FinTech products.

7.2 Practical Contributions

Personalization in Fin-Tech Investments: Personalisation would be the biggest predictor of emotional engagement within FinTech (β = 0.148). To create products that evoke emotional engagement, then, FinTech vendors will have to invest in AI—powered personalisation engines that deliver individualised financial information, discover consumer spending habits and recommend products in a contextual manner. In addition, they should reframe the discussion on the role of Personalisation as the main way for them to shape their offering as differentiated in comparison to one another, rather than as a secondary feature enhancement.

Building Trust is a Prerequisite for Personalization: Building trust will create an environment where Personalisation will be more likely to be effective in terms of both Emotional Engagement and Habit Formation: The relationship between trust and the benefits gained from Personalisation is direct – platforms with low trust will not benefit optimally from Personalisation. To achieve Emotional Engagement strategies through Personalisation, it is important for the FinTech companies to first make its policies around data governance transparent, inform consumers about compliance with RBI regulations, and put in place responsive processes for Grievance Redressal.

Information Quality is the Baseline for Satisfaction: The biggest direct predictor of the User Satisfaction is Information Quality (β = 0.155), which is Baseline for Satisfaction: Information Quality. So, Real-Time Data Accuracy, full transaction record keeping, and timely market information should be baseline, non-negotiable investment features of a platform, as opposed to differentiations.

Interface Simplicity for Usage Adoption: Interface Simplicity for Usage Adoption: Given the significant effect effort expectancy has on actual usage (β = 0.122); it can be concluded there is a direct relationship between interface complexity and reduced frequency of platform usage. It is therefore likely that the investments made in User Experience (UX) or Cognitive Load (e.g., Simplified Navigation Flows, One-Touch Transaction Completion and Progressive Disclosure of Complex Features), will be directly recognized as behaviour.

8. Limitations And Future Research Directions

This research goes on and comes up with four major discoveries. The reason for the first is that the current analysis is limited to a cross-sectional study and no longitudinal study has been performed, so no causal analysis of the relationships found between the variables of personalization, emotional engagement and loyalty for the users in the study can be done. Future studies should run a longitudinal study, to clarify the directionality and the effects these platforms may have on the user after long term usage, because of their long time on use.

Second, the R 2 values for all endogenous constructs ranged from 0.021 to 0.064 and are not high but acceptable when compared to the norms of PLS-SEM standard norms for multi-construct model which is found in social-science behavioural research from Hair et al. (2019). The values are indicative of the characteristics of behaviour in digital financial services that tend to be diffuse, affected by a multitude of antecedents that aren't captured in any one score, such as DFAscapacity, switching costs, income level and regulatory awareness. Importantly, this concurrent behavioural validation (r = 0.895 for Actual Usage; r = 0.862 for User Satisfaction against the Behavioural Engagement Index) confirms that the amount of variance explained was relatively low, and indicates that this variance is real and measurable and not just common method inflation. Antecedent setting extended to include background variables to enhance predictive ability but keeping the behavioural cross-validation methods presented in this study is recommended.

Thirdly, the participants in the sample were largely urban-based, educated and digital epi-entitled, also belonging to the 26-45 age group that represents 63% of the sample, so the findings may not be easily replicated with other age groups or user types within India, like the rural, older generations and those not technologically new to a digital banking platform. Research should be designed so that sampling methods will be established that will capture these under-represented groups of users.

Finally, the number of respondents in the analysis (pre- vs. post-stratification) did not significantly affect any of the R^2 values of the structural model.

This study has helped shed some light on the perceptions of the personalization, emotional involvement and loyalty in the context of digital FIs, but there is space for future research that can help provide understanding of other constructs that can influence user perceptions on FIs through digital channels.

In fourth, the research highlights that different countries have different infrastructures between them as well consider the Indian regulatory and cultural environment (as they are regulated differently than other countries) and the Indian FinTech industry to ascertain whether the The FinTech Integrative Framework will be suitable to the other places where the industry could be implemented other than India like Southeast Asia (SEA) and Latin America (LATAM).

Future studies could/ should: (1) apply the longitudinal/experience sampling methodology to different types of payment processes to gauge changes in adoption over time for the different types of payment processes; (2) extend the Framework to include investment channels (e.g. Robo-Advisory and Stock Trading Apps) where the constructs of Trust/Information Quality could prove to behave

differently, than with traditional payment channel(s), in the context of investing; (3) use the integrated framework for international comparative study using PLS-MGA; and (4) verify if there are boundary conditions for the development of emotional engagement through personalized products if any, and whether the concerns about privacy is such a moderating factor.personalized products, if there are any, including if a concern for one's own privacy is a moderating factor.

9. Conclusion

via the development, testing, and verification (via experimentation) of an integrated, multidisciplinary theoretical framework of FinTech usage with 450 real users (financial tech) in India, this research contributes to our knowledge of FinTech usage. The UTAUT2, DeLone & McLean's IS Success Model, DBSQual/SERVQUAL, and Customer Experience were all integrated into this model's quadruple framework. When these ideas are combined, they provide a more comprehensive understanding of how customers use digital financial services than when they are used separately. The findings provide statistical evidence for each of the eight proposed links. There is a personalisation dimension that affects the user's autonomous cognitive route and emotional component of engagement. satisfaction with the quality of the information. The study demonstrates that the development of habitual FinTech use—which goes beyond security—is only made possible by trust. Emotional engagement mediates the dual outcomes of seen behavioural loyalty and attitude satisfaction. This study's methodological contribution is its triple concurrent validation using three objective platform-based behaviour indicators, which raises the bar for psychometric validation rigour in FinTech research. The significant correlations between SRS and the BEI ($r = 0.862$) and between SRU and the OSU ($r = 0.895$) suggest that the survey captures behaviour rather than measurement error.

FinTech practitioners will find it useful to adhere to this study's hierarchy of FinTech characteristics, techniques, and advantages. The practitioner is aware of the most crucial factors in a customer's decision to utilise a FinTech product or service.

Credit Author Contribution Statement

Author 2: Conceptualisation, Methodology, Formal analysis, Investigation, Data curation, Visualisation, Writing – original draft. Author 1: Conceptualisation, Supervision, Validation, Writing – review and editing. All authors have read and approved the final version of the manuscript.

Ethics Approval and Consent to Participate

The 1964 Declaration of Helsinki and its subsequent revisions, as well as the ethical requirements of the Research Ethics Committee (REC) of the authors' institution, were followed in all procedures carried out in this study involving human subjects. The institutional Research Ethics Committee (REC) gave its ethical approval (REC Approval Reference Number available to the editor; permission validity period: 25 January 2026–31 December 2026). Prior to data collection, each individual participant provided informed digital permission, including explicit approval for the linking of self-reported survey results with platform-derived behavioural usage statistics. All replies were kept private and reported solely in aggregate form; no personally identifying information was gathered

Consent For Publication

Not relevant. No personally identifying information, pictures, or videos are included in the text. Anonymised behavioural data was only reported in aggregate form.

Declaration Of Competing Interests

The authors affirm that the work described in this publication was not influenced by any known conflicting financial interests or personal ties.

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Upon reasonable request, the corresponding author will provide the data supporting the study's conclusions. The behavioural usage data are not made public in order to preserve participant confidentiality because they were gathered with agreement from the participants and contain potentially identifiable platform information.

Declaration Of Generative Ai and Ai-Assisted Technologies in The Writing Process

The authors employed a generative AI language model throughout the production of this work to enhance the manuscript's language and readability. The writers took full responsibility for the published article's content after utilising this tool to evaluate and amend it as necessary.

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