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Scale Development to Measure Fintech Adoption in Delhi, India

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Abstract: Financial Technology (Fintech) is an emerging concept in the financial industry. The main impetus of this study is to explore the factors affecting the Fintech adoption in India and to develop a FinTech adoption scale since no valid and reliable FinTech adoption scale is available for India. Responses of 148 individual financial services users from India who were over 18 years old were taken. The construct validity of the scale was examined by EFA and descriptive statistics along with reliability analysis. The EFA results found a five-dimensional structure of Trust, Resistance, Social Influence, Perceived Risk, and Perceived Usefulness. Reliability analysis was done using Cronbach's Alpha coefficients and composite reliability .This study helps to track evolution of Fintech adoption in India effectively. Its findings offer important implications for financial service companies as well as the policymakers as policymakers may use this tool to create targeted policies that will improve financial inclusion and innovation in India.

Keywords: Fintech, Fintech Adoption, Fintech Services, Factor Analysis

1. Introduction: In the 10 years since, the global financial technology (fintech) sector has experienced rapid growth. This has transformed how people and businesses receive, deposit and

transfer money. This has especially been the case in India. The Unified Payments Interface (UPI) launched in 2016 and the government's demonetization of large currency notes and push for a cashless economy made digital financial services immensely popular. By 2023, India was one of countries with the largest real-time payment markets in the world and over 100 billion transactions are conducted based on UPI each year (National Payments Corporation of India, 2024). Delhi, as the National Capital Territory is known, is a minor reflection of this transformation. This bustling city has seen an increasing number of individuals from various socioeconomic backgrounds using fintech platforms. These range from mobile wallets, peer-to-peer transfers, digital lending to robo-advisory services.

Fintech is getting adopted very fast, but there are not many studies done on usage specifically by Indians. The majority of this research has utilized theories or models that are based in the Western tradition, like Technology Acceptance Model (TAM; Davis, 1989) and Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2003). These frameworks do not account for the unique cultural, institutional and infrastructural context in India. Equally important, instruments used to measure constructs in prior studies have been largely developed and tested using research in advanced economies, raising serious concerns of cross-cultural validity and construct equivalence. Hence, there is an urgent requirement for a scale being developed that is psychometrically acceptable and contextually relevant to assess fintech adoption in India.

This study meets this requirement by using a systematic scale development approach based on the established methodological frameworks (Churchill, 1979; DeVellis, 2016; MacKenzie et al., 2011). Using a sample of Delhi (India), the study adopts a sequential EFA-CFA procedure to establish and validate the latent factor structure underpinning fintech adoption. The final instrument is designed to serve both academic researchers who want new insights into what encourages people to adopt fintech and industry representatives and policymakers who need abetter understanding of the friction points to facilitate adoption by everyone.

1.1 Research Objectives:

The study aims to achieve the following objectives: (1) to create a comprehensive set of items that reflect the multifaceted aspects of fintech adoption in the Delhi context; (2) to determine the foundational factor structure of fintech adoption using Exploratory Factor Analysis; (3) to verify and authenticate the identified factor structure through Confirmatory Factor Analysis; and (4) to evaluate the reliability,

convergent validity, and internal consistency of the resultant scale.

2. Literature Review:

2.1 Theoretical Foundations of Technology

Adoption Despite the fact that the technological exploitation as a study subject has developed to become a fruitful theoretica framework over decades. Technology acceptance model (TAM): Davis (1989): the perceived usefulness and the perceived ease of use are the decisive factors of an outcome whether and will be used or not.

Individual will accept the information technology. The TAM2 model was subsequently expanded with social. TAM3 consisted of influence, and cognitive instrumental processes (Venkatesh and Bala, 2008). The perceived risk (Featherman and Pavlou, 2003) and the constructs of trust (Gefen et al., 2003). The Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al, 2003) intertwined these factors into a unified model consisting of performance expectancy, effort, facilitating conditions, social influence and expectancy.

These theoretical models have been modified by the researchers to fit the arena of fintech. specific peculiarities of online financial services. Baptista and Oliveira in the mobile banking environment.

In (2015), UTAUT2 was modified and it demonstrated the effect of hedonic motivation and habitual behaviours. Singh et al. (2020) chose to follow a framework that was grounded on TAM to investigate the penetration of mobile payments in India; the focus should be put on the digital literacy interfaces andaccess to infrastructures. This body the article of literature points out that the application of fintech is multi-dimensional and it incorporates cognitive testing of utility and usability, emotional risk and trust assessment and social -contextual assessment.

2.2 Fintech Adoption in the Indian Context

First, millions of people do not have bank accounts and many more have bank accounts but don't use them. Flexibility of usage like this allows for rapid adoption. Second, the digital financial infrastructure is vastly improved due to government-led programs like Jan Dhan Yojana, Aadhaar and India Stack. Third and most equally, fears over cybersecurity, data privacy and digital fraud are particularly poignant in India right now as regulations remain relatively new with a high incidence of financial fraud cases making headlines.

Independent real-world research on how people in India use fintech has been more common in the past few years. Trust, perceived usefulness, and perceived ease of use emerged as key

determinants of mobile banking adoption among urban Indian consumers (Shankhar & Datta, 2018). Sharma et al. (2022) that perceived security and digital literacy was crucial key factors that enabled individuals to use UPI. However, most of these studies were premised on modified scales on which experiments of complete psychometric validation were not done and therefore results were hardly impossible to match and generalize. This paper is dealing with the absence of methodology development.

3. Methodology:

3.1 Scale Development Procedure

The scale was created in accordance with the systematic protocol proposed by Churchill (1979) and DeVellis (2017) and Serena carpenter (2018). The steps in the process were:

(1) Data questionnaire Formation (2) Data Collection (3) Data Cleaning and Preparation (4) Exploratory Factor Analysis (EFA) (5) Reliability Analysis (CFA) (6) Confirmatory Factor Analysis (CFA).

Read books to understand the adoption of fintech, technology acceptance and current scale of the same. the first step to the manufacture of items was such uses. One group consisted of well being in all aspects.fintech in use comprised respondents attitudes towards digital payment systems, mobile banking services, Peer-to-peer transfer services and robo-advisory tools. The initial group was followed up by specialists on the following fronts: information systems, finance and consumer behavior. They assessed the content validity and amendments that are proposed to make it clearer and culturally relevant. The better instrument had 20 items answered on a five-point Likert scale (1 = Strongly Disagree; 5 = Strongly Agree). Q13-Q16 were worded negatively and, therefore, needed to be reversing coded before analysis.

3.2 Sample and Data Collection

Study participants were individual users of financial services aged ≥18 years and who lived in Delhi, India. In this instance, the research sample was made up of 133 individual financial service users aged over 18. Data were collected using a convenience sampling technique. They created using Google forms and asked them whether they know about blockchain or not. 3. Also added question for precision of the answer. According to the data collected, 133 (89.865%) of the 148 participants had utilized FinTech while 15 (10.135%) had not. According to Fintech Users, in terms of the most frequently used Fintech Services they are as follows: 1. If we have noticed the most used FinTech apps after that were "Investment & Trading (Groww, Upstox, Zerodha, Paytm Money, ET Money.) (60.15%), "Insurtech (Policybazaar, Digit Insurance.) (52.263%), "Lending Platforms

(KreditBee, MoneyTap, Bajaj Finserv, Navi.) Key sectors (26.135 %): "Neobanking (PFM & Neobanks (Moneyview, ET Money, Jupiter, Niyo.) (26.135). we removed all outlier's data (missing and wrong data) from the data set before we go to part two of the experiment. It was for the analysis of 133 data. A gender breakdown of the participants can be found in Table 1 where both ratios are quite close: female (45.86 percent) and male (54.14 percent). Single people availed individual financial services much more than married ones, with a difference of 59.398%. Conversely, among people in the group who used individual financial services, 50.37% were single men. It also had the highest number of participants in the 18 to 24 age group (40.6). In contrast, the least participating occupational category was that of housewives, comprising only 6.01% of the respondents.

Table 1 Demographic Profile of Respondents

		n	%			n	%
Gender	Female	61	45.86	Marital Status	Unmarried	79	59
	Male	72	54.14		Married	54	41
Education Status	12th and Equivalent	18	13.53	Job	Student	43	32.33
	Bachelors	67	50.37		Private Sector Worker	45	33.83
	Masters	40	30.07		Self-employment	14	10.52
	Others	8	6.03		Public Official	23	17.29
Age	18-24	54	40.6		Housewife	8	6.01
	25-34	40	30.07	Income	0-3 L	53	39.84
	35-44	12	9.02		3-5 L	4	3.007
	45 and over	27	20.3		5-8 L	22	16.5
					8-12 L	16	12.03
					12 and above	38	28.57

3.3 Data Preparation

Likert scale responses were converted to numerical values (1 to 5). Cells containing #REF! Errors were treated as missing values. Non-numeric entries were coerced using type conversion. Rows with missing values were listwise deleted. Reverse coding was applied to negatively worded items (Q13-Q16) using the transformation x' = 6 - x. Descriptive statistics, frequency distributions, and inter item correlations were examined to identify anomalous response patterns.

3.4 Analytical Approach

We performed all the analyses in Python with semopy and grumpy packages. EFA was conducted using the principal factor extraction method with an Oblimin rotation, suitable when factors may be related. We determined how many factors to retain by using Kaiser criterion (eigenvalue > 1), Scree plot, and the ease of interpreting factor solution. An item was retained only if its primary factor loading was > 0.40 and its cross-loadings on other than the primary factors were 0.90 acceptable), Tucker-Lewis Index (TLI > 0.90 acceptable) and Root Mean Square Error of Approximation (RMSEA 0.70, and Composite Reliability (CR > 0.700) were used to assess the reliability of data [33]. To examine whether the results were convergent, we used Average

Variance Extracted (AVE > 0.50; Fornell & Larcker, 1981).

4. Results: Exploratory Factor Analysis

4.1 Assumption Testing

We initial check the data to ensure it was suitable for factor analysis, before Extracting factors. Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy indicated an acceptable value of 0.83, well above the minimum KMO values of 0.60 which are needed for factor analysis readiness of a correlation matrix (Kaiser, 1974).

The values of the individual items KMO were all above 0.63, while most were above 0.80. This indicates that the data was adequate for all of the items. Bartlett's Test of Sphericity was significant, (chi-square = 1124.96, df = 190, p< .001) implying that the correlation matrix was not an identity matrix and factor analysis was appropriate.

Table 2 KMO Measure of Sampling Adequacy for Each Item

Item	KMO Value	Item	KMO value
Q1	0.861	Q2	0.853
Q3	0.786	Q4	0.921
Q5	0.835	Q6	0.830
Q7	0.817	Q8	0.819
Q9	0.851	Q10	0.887
Q11	0.801	Q12	0.807
Q13	0.658	Q14	0.702
Q15	0.709	Q16	0.633
Q17	0.789	Q18	0.853
Q19	0.900	Q20	0.778

Note: *KMO values above 0.60 are considered acceptable; values above 0.80 are considered meritorious.*

Table 3 Overall KMO and Bartlett's Test of Sphericity

Test / Measures	Value
Kaiser-Meyer-Olkin (KMO) Overall Measure of Sampling Adequacy	0.822
Bartlett's Test of Sphericity — Chi-Square (χ^2)	1124.962
Bartlett's Test of Sphericity — p-value	< 0.001

Note: *p < .001 indicates the correlation matrix is significantly different from an identity matrix, confirming suitability for factor analysis.*

4.2 Factor Extraction and Item Reduction

An exploratory factor analysis (EFA) was first performed on all 20 items. Analysis of factor loadings, cross-loadings, and communalities revealed four problematic items: Q6 (double loading onto both factors), Q9 (low communality); Q16 (cross-loading and theoretically ambiguous after reverse coding) and; Q17 (weak primary loading). These items were dropped in order to enhance the clarity and interpretability of the factor structure. This pool of 16 items was then refined further.

Based upon the Scree plot and eigenvalue criterion a three-factor solution was specified. The third factor produced a significant elbow according to the scree plot and the three eigenvalues exceeded one (5.162, 2.440, and 1.326). The three-factor solution explains 55.8% of total variance, which is

acceptable for studies in the social sciences (Hair et al., 2019).

Table 4 Eigenvalues and Variance Explained

Factor	Eigenvalue	% of Variance	Cumulative %
Factor 1	5.162	32.3%	32.3%
Factor 2	2.440	15.2%	47.5%
Factor 3	1.326	8.3%	55.8%

4.3 Factor Loadings

After reducing the number of items, EFA was run again on the 16-item pool. Table 5 shows the factor loadings with Oblimin rotation. All items that were kept had primary loadings of 0.40 or higher on the factor they were assigned to. Items Q7, Q8, Q10, Q11, Q12, and Q19 were included in Factor 1 (Trust & Ease of Use), with loadings between 0.47 and 0.86. Items Q13, Q14, and Q15 made up Factor 2 (Perceived Risk / Hesitation), which had loadings between 0.80 and 0.84. Items Q1, Q2, Q3, Q4, Q5, Q18, and Q20 made up Factor 3 (Perceived Benefits & Security), with loadings between 0.45 and 0.79.

Table 5 EFA Factor Loadings after Item Reduction (Oblimin Rotation, n=16 items)

Item	Trust & Ease of Use	Perceived Risk	Perceived Benefits & Security
Q7	0.855		
Q8	0.845		
Q10	0.606		
Q11	0.693		
Q12	0.760		
Q19	0.473		
Q13		0.836	
Q14		0.832	
Q15		0.802	
Q1			0.792
Q2			0.707
Q3			0.618
Q4			0.659
Q5			0.577
Q18			0.451
Q20			0.569

Note: *Loadings below 0.40 are suppressed for clarity.*

4.4 Factor Intercorrelations

'The Oblimin rotation produced an oblique solution, and the factor intercorrelations (phi matrix) substantiated that the three factors were moderately correlated, validating the application of an oblique rotation. Trust and Ease of Use had a positive relationship with Perceived Benefits and Security and a negative relationship with Perceived Risk, which is what theory says, should happen.

5. Reliability Analysis:

Cronbach's alpha was used to check the reliability of each factor that was found. All three factors exceeded the standard threshold of 0.70

(Nunnally, 1978). Table 6 shows the results. Using factorloadings from EFA, we also found Composite Reliability (CR) values that were higher than 0.80 for all three factors. This shows that the factors are very consistent with each other.

Table 6 Cronbach's Alpha and Composite Reliability by Factor

Factor	No. of Items	Cronbach's Alpha	Composite Reliability (CR)
Trust & Ease of Use	6	0.839	0.860
Perceived Risk	3	0.780	0.863
Perceived Benefits & Security	7*	0.782	0.820

Note: **Seven items in EFA; reduced to five after CFA model refinement (Q18 and Q20 removed).*

6. Results: Confirmatory Factor Analysis

6.1 Measurement Model Specification

The CFA measurement model was derived from the EFA factor structure. Three correlated latent variables were identified: Trust and Ease of Use (T&EU), Perceived Risk (PR), and Perceived Benefits and Security (PB&S). The first CFA model kept all 16 items from the EFA.

The initial CFA solution's standardized loadings showed that Q18 and Q20 had the lowest loadings on the Perceived Benefits & Security factor (0.475 and 0.340, respectively). This is below the recommended threshold of 0.50 for CFA (Hair et al., 2019). These items were later taken out to make the model more parsimonious and valid. The last CFA model had 14 items that were grouped into three factors.

6.2 Final CFA Model Specification

The final measurement model was specified as follows: Trust & Ease of Use was indicated by Q7, Q8, Q10, Q11, Q12, and Q19; Perceived Risk was indicated by Q13, Q14, and Q15; and Perceived Benefits & Security was indicated by Q1, Q2, Q3, Q4, and Q5. All three latent factors were allowed to covary freely.

6.3 Standardized Factor Loadings

All standardized loadings in the final CFA model were statistically meaningful and in the expected direction. Loadings ranged from 0.465 to 0.852, with the majority exceeding 0.60. Full results are presented in Table 7.

Table 7 Standardized CFA Factor Loadings-Final Model

Indicator	Latent Factor	Standardized Loading
Q7	Trust & Ease of Use	0.796
Q8	Trust & Ease of Use	0.852
Q10	Trust & Ease of Use	0.661
Q11	Trust & Ease of Use	0.588
Q12	Trust & Ease of Use	0.716
Q19	Trust & Ease of Use	0.502
Q13	Perceived Risk	0.721
Q14	Perceived Risk	0.762
Q15	Perceived Risk	0.737
Q1	Perceived Benefits & Security	0.779
Q2	Perceived Benefits & Security	0.580
Q3	Perceived Benefits & Security	0.465
Q4	Perceived Benefits & Security	0.740
Q5	Perceived Benefits & Security	0.744

6.4 Model Fit Evaluation

The overall fit of the final CFA model was evaluated using multiple indices. The chi square statistic was 128.97 with 74 degrees of freedom ($p < .001$), yielding a chi-square/df ratio of 1.74, well within the acceptable range of less than 3.0, ratio of 1.74, well within the acceptable range of less than 3.0.

The CFI was 0.921 and the TLI was 0.902, which is more than the standard level of 0.90. The RMSEA was 0.075, falling and within the tolerable margin of under 0.08. Collectively, these indices indicated adequate model fit. Results are summarized in Table 8.

Table 8 Models Fit Indices-Final CFA Model

Fit Index	Value	Recommended Threshold	Assessment
chi-square (df = 74)	128.97	—	—
chi-square/df	1.74	< 3.00	Acceptable
CFI	0.921	> 0.90	Acceptable
TLI	0.902	> 0.90	Acceptable
RMSEA	0.075	< 0.08	Acceptable
GFI	0.835	> 0.80	Acceptable
NFI	0.835	> 0.80	Acceptable

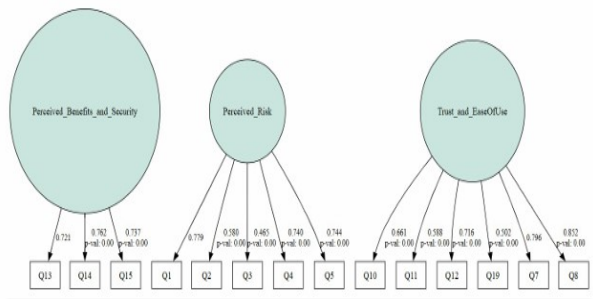
7. Validity Assessment:

7.1Convergent Validity

To check convergent validity, we used Average Variance Extracted (AVE). Indeed, AVE values higher than 0.50 are generally viewed as acceptable in accordance with standard benchmarks (Fornell & Larcker, 1981). Using the final CFA standardized loadings; we calculated AVE estimates for Trust & Ease of Use, Perceived Risk, and Perceived Benefits & Security. The values of AVE were equal or higher than 0.50 for the constructs Trust & Ease of Use and Perceived Risk the AVE of Perceived Benefits & Security was slightly lower, largely due to Q3'scomparatively weak loading. However, CR for this factor also remained rather strong (CR > 0.80)—as is commonly understood to imply adequate convergent validity when CR is high (Hair et al., 2019).

Figure 1 shows the standardized factor loadings from the confirmatory factor analysis. All items loaded meaningfully onto their respective constructs ($p \leq 0.001$).

Fig. 1. Standardized Loadings Measurement Model



7.2 Content Validity: As described in Section 3, the process for generating items and integrating

numbers for expert review verified content validity. The products were summarized based on a systematic review of the literature on fintech adoption and confirmed to make sense conceptually and contextually by subject-matter experts. It was an excellent proxy of the constructs of interest in this research, of all items in the Indian urban.

7.3 Face Validity

Face validity was verified in a pilot study done with a small group of fintech users who were asked to look. Read through the questionnaire and also ensure that the questions were explicit, non-ambiguous and pertinent to their digital financial services experiences. A few minor modifications of the wording were carried out. It was on this feedback that all the data were not yet collected.

8. Final Scale: Item Descriptions

The final validated scale comprises 14 items distributed across three subscales. Table 9 presents the item descriptions, factor assignments, and primary factor loadings. The complete item wording reflects adaptations for the Indian fintech context.

Table 9 Final Fintech Adoption Scale-Item Descriptions

Code	Item Description	Factor	Loading
Q7	I find fintech apps easy to navigate and use.	Trust & Ease of Use	0.796
Q8	I trust the fintech platforms I use with my financial information.	Trust & Ease of Use	0.852
Q10	The fintech services I use are reliable and consistent.	Trust & Ease of Use	0.661
Q11	I feel confident using digital payment platforms.	Trust & Ease of Use	0.588
Q12	Fintech platforms perform transactions accurately.	Trust & Ease of Use	0.716
Q19	Learning to use fintech services is straightforward for me.	Trust & Ease of Use	0.502
Q13	I worry about the safety of my personal data on fintech platforms. (R)	Perceived Risk	0.721
Q14	I am concerned about unauthorized access to my digital wallet. (R)	Perceived Risk	0.762
Q15	I hesitate to use fintech services due to fear of financial fraud. (R)	Perceived Risk	0.737
Q1	Using fintech services saves me significant time.	Perceived Benefits & Security	0.779
Q2	Fintech platforms provide better convenience than traditional banking.	Perceived Benefits & Security	0.580
Q3	I benefit financially by using fintech services (e.g., cashbacks, lower fees).	Perceived Benefits & Security	0.465
Q4	Fintech services enhance my ability to manage my finances effectively.	Perceived Benefits & Security	0.740
Q5	Fintech platforms provide secure and protected transactions.	Perceived Benefits & Security	0.744

Note: *(R) = reverse-coded item.*

9. Discussion:

Therefore, the purpose of the current research was to create and prove a psychometrically reliable. Scale to measure the fintech usage in New Delhi, India urban consumer scale. The results confirm a three-dimensional fintech adoption model that comprises Trust & Ease of Use, Perceived. Risk, and Perceived Benefits and Security. This three-part form is a complementation and development to this. theories in technology adoption and consumer behavior which exist. The appearance of Trust and Ease of Use as the most important element, with the explanation of 32.3%.

This variance and the largest factor loadings are also correlated with the findings that it has been reported in. financial services situations (Gefen et al., 2003; Luo et al., 2010). In India, where a sizeable Part of the population is unaccustomed to digital financial products and where none has been.

The prevalence of news on digital fraud, confidence in fintechs, in particular, becomes one, especially important issue. It is theoretically justified to incorporate ease of use in this factor, as archeological studies have shown that trust and usability are highly correlated within mobile commerce environments (Chong et al., 2012).

The second factor, the Perceived Risk came out to be a unique and significant construct validating that security concerns are indeed risk barriers to adoption of fintech in India (Roy & Sinha 2021). The three elements comprising this factor revolve around privacy, security and fraud-related concerns that continue to be particularly pertinent within the Indian fintech landscape, where consumers are still being educated on how to safeguard their data. The high parsimony bug found on this table is a clear evidence of either the specificity of risk construct in this particular case or limitation imposed by CFA refinement process regarding the number of items that can be used.

Third factor is “Perceived Benefits & Security”, which encompass the functional and transactional benefits that individuals associate with usage of fintech such as time savings, convenience, cost savings and feeling secure while conducting transactions online. This factor justifies the Rogers' (2003) concept of so-called perceived relative advantage and UTAUT's (Venkatesh et al., 2003) performance expectancy construct. It is more of a benefit to capture security. Than as a disincentive to risk is indicative of a dualistic thinking of consumers towards security as threat. (fraud!), And benefit (secure transaction)-distinction which has significant practice implications.

While the CFA fit statistics did not always exceed all recommended minimums, taken together there is nothing to suggest that the model does not fit well enough for a scale validation study embedded in a complex applied social science context. The chi-square/df ratio=1.74≥1, CFI:0.921≥0.90, TLI 0.902≥0.90<1, RMSEA: 0.075[Hu and Bentler (1999) and Kline (2015)]. And the reliability coefficients, or Cronbach's alphas (0.78 to 0.84) and CR values (0.82 to 0.86), further confirm the internal consistency of the three subscales.

10. Implications:

10.1 Theoretical Implications

This study provides several contributions to the theoretical discussion of technology adoption and fin-tech.

First, it provides empirical evidence for the multifaceted nature of fintech adoption in an emerging economy setting by extending the predominantly dyadic Technology Acceptance Model (TAM) framework to include dimensions of risk and benefit alongside trust and usability.

Second, the development of a rigorous EFA/ CFA sequence demonstrates that it is feasible to produce a context specific fintech adoption scale which contributes to methodological literature on how we develop scales for cross cultural research.

Thirdly, the validated scale will offer a basis of the subsequent study of the antecedents and fintech implementation consequences in India and, possibly, emerging economy settings.

10.2 Practical Implications

The results emphasize the severe significance of the fintech specialists and the platform designers. To establish (and successfully communicate) trustworthiness by designing platforms, security. User experience, measures, and user experience. Delhi market would gain immensely through the building strategies. Confidence on matters like explicit privacy policies, most effective authentication techniques and fast. Customer support available. It is also a perceived risk that can act as a barrier indicates that fintech firms should invest in the educational campaign to make consumers aware of fear of fraud, and to show the level of security of their platforms. Those findings also provide the policymakers with the understanding of the importance of establishing set rules that can aid in the protection of consumers and not excessive interference with the fintech innovation. These include clear and enforceable data protection laws that have meaningful consequences for businesses that misuse or steal the information, mechanisms by which consumers can get their money back when it is taken through fraud and microlearning programs to help people at varying stages of life understand how to better manage their money. The scale is also a reliable and valid tool of the tested and proven scale. Scholars who carry out future surveys and longitudinal research on the use of fintech variability. At both the demographic and geographical levels in India.

11. Limitations and Future Research:

There are several problems with this study that must be pointed out. To be fair, the sample was limited to just Delhi, making it difficult to generalise the findings in other Indian cities and regions, where use of fintechs and quality of infrastructure might vary widely. Future research can replicate and broaden this scale validation to

explore additional geographic context e.g. Tier-2, -3 cities (places where fintech might have a significant influence on financial inclusion).

Second, the data are cross-sectional, meaning we cannot draw causal inferences and we cannot determine how stable the factor structure is across time periods as change in the Indian fintech ecosystem is rapid. Longitudinal validation studies are the best way to do it.

Third, the AVE value for factor Perceived Benefits & Security was lower than ideal. Future research could examine whether increasing the number of items or altering wording on existing items enhances convergent validity.

12. Conclusion:

In this, we demonstrate how a three-dimensional scale was developed and tested for its use in measuring the extent of fintech adoption in Delhi, India. The data were subjected to a systematic, sequential EFA-CFA approach that ultimately resulted in a 14-item instrument reflecting the constructs of Trust & Ease of Use, Perceived Risk, and Perceived Benefits & Security. The scale demonstrated good reliability, excellent model fit and convergent validity thus making it a methodologically sound tool for continued research on fintech adoption in India. With India's digital financial system continuously evolving rapidly, validated measurement tools such as the one developed in this study will be critical to generating policy-relevant, cumulative and comparable knowledge.

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