The Untold Story of FinTech Customers' Experience

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Understanding user experience is crucial for advancing FinTech innovations and shaping customer-centric policies. This study analyses 5.69 million FinTech app reviews using machine learning techniques to uncover sentiments and key concerns in India's FinTech ecosystem. Results reveal a generally positive user experience, with emotions like trust and joy dominating across sectors. Topic modelling identifies customer support, technical and app functionality, and loan-related concerns. Empirical findings from the fractional probit model highlight the positive, albeit diminishing, impact of market share on favourable review sentiment, while data privacy and app updates emerge as significant drivers.

Introduction

FinTechs have become pivotal in reshaping key financial segments, including payments, credit and investment, thus, transforming the financial service delivery across nations. The extant literature notes that high transaction speed, personalisation, security and transparency are driving customer preferences for FinTech innovations (Feyen *et al.*, 2023). India, the world's third-largest and fastest-growing FinTech ecosystem, is emerging as a global leader in digital finance (RBI, 2024). With over 10,000 FinTech startups—the country ranks as the second-largest app market globally, recording 26.4 billion downloads

in 2023 (Tracxn, 2024; Statista, 2024). Finance apps alone account for 481 million downloads, led by digital wallet and payment apps (100 million), personal loan apps (93 million), and investment apps (64 million) in Q4 2023 (Statista, 2024). Over the past decade, FinTech funding has grown at a robust 21 per cent compound annual growth rate (CAGR), driven by global liquidity post-pandemic, with payments and alternative lending segments dominating fundraising (Tracxn, 2024; Saroy *et al.*, 2023). Adoption is particularly high among younger users, with 52 per cent being under 25 years and 51 per cent coming from semi-urban and rural areas (TransUnion CIBIL, 2023). To foster responsible innovation, the Reserve Bank has launched initiatives like the Regulatory Sandbox, the RBI Innovation Hub, and digital lending norms and SRO framework for FinTechs, balancing consumer protection and systemic stability. Looking ahead, India's FinTech market is projected to grow from $110 billion to $420 billion over the next five years, with a CAGR of 31 per cent (Chaudhary, 2024).

The thriving FinTech ecosystem, while promising, often masks the underlying challenges faced by customers as diverse users onboard and FinTech business models rapidly evolve to meet their varied needs. A customer-centric approach—grounded in understanding customer needs, safeguarding their interests and building trust—requires embedding continuous feedback mechanisms into business strategies (Das, 2023). Traditional methods to address these issues, including usability testing (Nielsen, 1993), surveys, and focus groups (Morgan, 1993) are limited by scalability, high cost, time lags and potential user or surveyor bias. A novel method, which is superior to formal surveys, is analysing online reviews for eliciting near real-time customer feedback. With mobile applications (or apps) as

primary interfaces, users increasingly share feedback through ratings and reviews (Huebner *et al.*, 2018), influencing app adoption and purchase decisions (Burgers *et al.*, 2016). However, the sheer volume, unstructured formats, spelling errors, emoticons, and multilingual content—often mixing English with regional languages—pose significant methodological challenges.

Understanding user experience is crucial for advancing FinTech innovations and shaping customer-centric policies. This study analyses 5.69 million FinTech app reviews using advanced machine learning techniques such as Distilled Bidirectional Encoder Representations from Transformers (DistilBERT) and BERTopic to uncover sentiments and key concerns in India's FinTech ecosystem. Results reveal a generally positive user experience, with emotions like trust and joy dominating across sectors. Topic modelling of negative reviews identifies customer support, technical and app functionality, and loan-related concerns. Empirical findings from the fractional probit model (FPM) highlight the positive, *albeit* diminishing, impact of market share on favourable review sentiment, while data privacy and app updates emerge as significant drivers. When interpreting the study's results, it is important to note that negative app reviews may have prompted remedial actions by corresponding FinTechs, though customers may not have updated their reviews. Nonetheless, recurring issues across apps highlight their prevalence and warrant attention from FinTechs, SROs and policymakers.

The study is organised as follows: Section II reviews the relevant literature. Section III details the data and methodology, while Section IV presents the major findings. Section V concludes with some policy perspectives.

II. Literature review

The proliferation of social networks, online consumers and user-friendly application interfaces has significantly increased the volume of data, creating new opportunities for text-based research (Zhao *et al.*, 2020). App reviews have emerged as a valuable crowd-sourced indicator of user satisfaction (Vasa *et al.*, 2012). Despite the diverse insights these reviews offer regarding user expectations and app usage, the systematic and timely analysis of the growing volume of reviews across numerous apps remains a significant challenge (Huebner *et al.*, 2018).

Machine learning techniques have become essential for extracting nuanced insights from large sets of unstructured data (Pang and Lee, 2008). Evidence suggests that applying sentiment analysis to identify customer emotions such as trust, joy, fear, and anger (Omotosho, 2021) enhances understanding of user feedback regarding bank responsiveness, app functionality and operational failures (Balcıoğlu, 2024). Topic modelling techniques have also been extensively used to extract valuable insights into app quality and sales (Khalid *et al.*, 2014; Liang *et al.*, 2015). Factors driving app satisfaction include the number of downloads, app category (Pagano and Maalej, 2013), app functionalities (Luiz *et al.*, 2018), and benefits like delivery efficiency and customer support (Kumar *et al.*, 2023). Factors such as ease of use, perceived usefulness, perceived value, performance expectancy, user experience, and perceived quality have also been identified for FinTech mobile apps using a set of relevant words (Perea-Khalifi *et al.*, 2024). Policy makers worldwide are increasingly leveraging data analytics tools to analyse user-generated content, such as social media posts, to inform decision-making and policy development (Driss *et al.*, 2019). Furthermore, app review data can serve as an early-warning system for predicting fraud and default rates (Pranata *et al.*, 2019).

In the Indian context, while studies have applied machine learning to extract insights from short-text social media data (Trivedi and Singh, 2021), research on user experiences in FinTech apps using online reviews remains limited. A study on a peer-to-peer (P2P) lending app revealed that users were generally satisfied with loan processing times, with less emphasis on ease of use, cost and risk (Gupta and Mahajan, 2023). Another study demonstrated the positive impact of the Reserve Bank of India's 2017 P2P lending guidelines on user sentiments, as assessed by the Valence Aware Dictionary and Sentiment Reasoner (VADER) model (RBI, 2024).

Against this backdrop, the paper seeks to offer a thorough assessment of user adoption and satisfaction of Fintech applications. Unlike previous studies, this research utilises a larger sample size and explores a wider range of factors, including app attributes, functionalities, company funding stages, FinTech categories, privacy issues, and regulatory affiliations.

III. Data and Methodology

III.1 Sample Selection

This study analyses a sample of 107 business-to-consumer (B2C) FinTechs in India, comprising 61 alternative lending apps, 25 payments apps and 21 banking tech app.[1] These FinTechs were identified using Tracxn database[2] and subsequently mapped to the Google Play Store. The final selection of associated apps was based on four criteria: (a) FinTech follows a B2C business model; (b) FinTechs which have primary business line as either payment or lending or banking; (c) FinTechs which have crossed the threshold average deadpool age of three years (*i.e.,* launched in or before 2022)[3]; and (d) apps having minimum of 50 reviews.

III.2 Data Collection

The open-access Python package *google-play-scraper* (JoMingyu, 2019) was used to extract app reviews. Over 5.69 million reviews, spanning April 2022 to August 2024, were collected, along with app-specific data like unique installations, review counts and major app updates. Two factors guided the selection of the study period: first, exclusion of potential distortions from the COVID-19 pandemic on user sentiments and second, relevance from a policy perspective. Analysing outdated reviews may not reveal current challenges in Indian FinTech ecosystem, which require timely corrective measures.

Privacy and data safety policies for each app were also compiled, covering aspects like permissions requested. Privacy data include an overview of more than 13 types of permissions that applications may request from users, such as identity, contacts, location, SMS, phone details, photo/media/files, storage, camera, microphone, WiFi connection, device and call information and others. FinTech-specific data, including year of incorporation, funding raised, founder backgrounds, funding stage and annual revenue, were sourced from the Tracxn database.[4] Major app updates were extracted from the respective app pages on the Google Play Store. All the non-categorical variables were aggregated (averaged) at the app level for the subsequent cross-sectional analysis.

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[1] Alternative lending, payments and banking tech apps are apps that have lending, payments and banking as their primary business lines, respectively. It is possible that FinTech categories may overlap, thus, the primary business model is taken for classification into these categories.

[2] FinTechs in the domains of payments, alternative lending and banking technology, were shortlisted from Tracxn, a market intelligence platform, and verified through their respective official websites, yielding 376 valid firms. These account for about 60 per cent of total funding raised by B2C FinTechs in India, with an even higher share for app-based firms. After excluding acquired entities without standalone financials, 107 FinTechs with 5.69 million reviews were retained, forming a robust and representative sample for analysing customer concerns.

[3] The average deadpool age is computed from 429 deadpooled B2C FinTechs in banking tech, payments, and lending identified from Tracxn, where 'deadpool' denotes firms that cease to exist. To ensure meaningful sentiment analysis and relevance for policy making, the study focuses only on operational FinTechs older than three years, with defunct or very new apps excluded. Any selection bias is minimal, and FinTech age is controlled for in the empirical analysis.

[4] Accessed as on September 26, 2024.

III.3 Sentiment Analysis

Sentiment analysis is performed to identify review sentiments such as positive, negative, or neutral in line with extant literature (Omotosho, 2021; Mishev *et al.*, 2020). In the FinTech sector, sentiment analysis and deep learning models have been applied to assess user satisfaction and identify customer concerns in FinTech applications (Masturoh and Pohan, 2021; Al Ryan *et al.*, 2023; Huebner *et al.*, 2018). Natural Language Processing (NLP) tasks involving pre-trained language models typically employ either feature-based or fine-tuning approaches.[5] In the Indian context, where digital texts often mix regional languages such as Hindi with English, fine-tuned models like BERT have shown superior performance (Wadhawan and Aggarwal, 2021). Accordingly, this study employs a fine-tuned DistilBERT, a faster and smaller transformer-based model (Sanh, 2019).

For training the data, a random sample of 4000 observations[6] was drawn from the dataset. Each review in the sample was manually labelled into three sentiments, *viz.*, positive, negative, and neutral. This pre-trained DistilBERT-based uncased model was fine-tuned on the labelled data to classify each review into the aforementioned three sentiment categories. In terms of performance of the trained data, DistilBERT model showed higher accuracy than VADER (Table 1).[7] Moreover, the training data was fairly balanced between positive and negative reviews in DistilBERT, making it the preferred model.[8]

Table 1: Accuracy Scores of Review Sentiment Classifiers

(in per cent)

Model	Training Set	Test Set
VADER	81.5	81.6
DistilBERT	97.46	96.1

Source: Authors' calculations.

III.4 Emotion Classification

The National Research Council (NRC) - Canada emotion classifier, a rule-based approach, is used to ascertain the eight types of emotions associated with user adoption of FinTech apps, *viz.*, 'trust', 'anticipation', 'joy', 'surprise', 'sadness', 'fear', 'anger', and 'disgust' (Mohammad and Turney, 2013). However, the emotion 'surprise' is excluded from this study due to ambiguity regarding its positive or negative connotation.

III.5 Topic Modelling

To uncover customer concerns in FinTech applications, topic modelling on labelled negative reviews is employed. Traditional methods like Latent Dirichlet Allocation (LDA) and Non-negative Matrix Factorisation (NMF) can yield homogenous or overly broad topics, as their efficacy decreases with short, unstructured, and complex text (Egger and Yu, 2022). In contrast, BERTopic, a neural network model, provides more meaningful and consistent insights (Grootendorst, 2022; Krishnan, 2023). Thus, a semi-supervised BERTopic with Term Frequency-Inverse Document Frequency (TF-IDF) is applied to negative reviews across FinTech app segments. A topic model, one for each category of app, was trained on a sample of reviews.[9] The trained models were then used

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[5] The feature-based approach relies on predefined word features to assign sentiment scores, as seen in VADER. VADER, a lexicon and rule-based sentiment analysis model, is particularly effective among machine-learning-oriented techniques (Hutto and Gilbert, 2014). In contrast, the fine-tuning approach involves adjusting pre-trained models like BERT (Devlin *et al.*, 2018) to classify text into sentiment categories.

[6] The size of the labelled dataset is sufficient as the difference in accuracy score in train and test data predictions is one per cent, indicative of no overfitting or underfitting.

[7] Accuracy is the proportion of all classifications that were correct, whether positive or negative. It is computed as: (True Positive + True Negative)/ (True Positive + True Negative + False Positive + False Negative).

[8] With neutral reviews at ~1 per cent, excluding them simplifies the analysis to focus on the imbalance between positive and negative reviews, making it a binary classification problem.

[9] To construct a robust and well-generalised BERTopic models, diverse and representative samples of reviews were extracted for training from reviews spanning April 2022 to August 2024. The models were trained on a smaller sample due to computing constraints, with each iteration using a random subset of 30,000–40,000 reviews, resulting in category-wise sample shares of 10, 20 and 30 per cent alternative lending, payments and banking tech apps, respectively. These trained models were then used to predict topics on a more recent set of reviews (April 2023 – August 2024), ensuring robust classification across evolving trends in customer reviews.

to classify the remaining reviews into identified topics.[10] Only reviews exceeding 30 characters were analysed, resulting in 5,37,611 reviews; comprising 2,77,003 reviews for Alternative Lending, 1,90,594 for Payments, and 70,014 for Banking Tech. From the topic model output, only coherent and specific clusters were considered for analysis, thereby retaining 26.3 per cent of reviews in Alternative Lending, 25.4 per cent in Payments, and 33.7 per cent in Banking Tech in the final analysis. For brevity and better comprehension, topics were later manually clubbed in 11 broad themes.
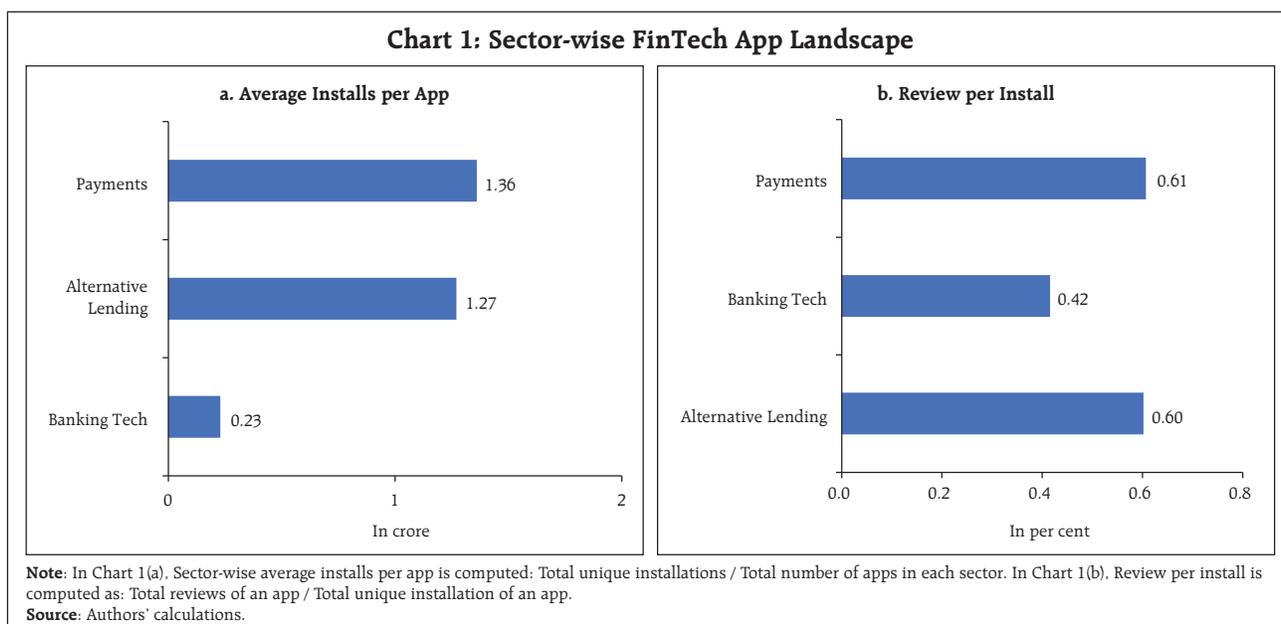
IV. Empirical Results

IV.1 Stylised Findings

Among the three sectors under study, *viz.*, payment, lending and banking,[11] apps with payment or lending as their primary business are more likely to get installed than banking (Chart 1a). The likelihood of receiving a review per unique FinTech
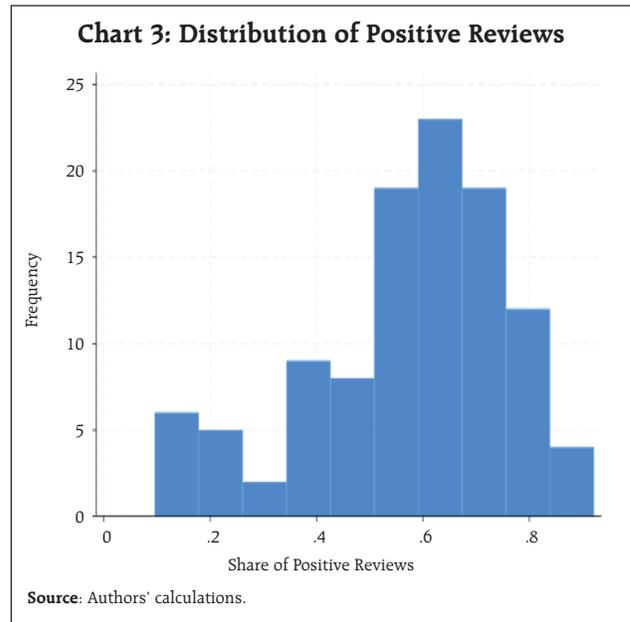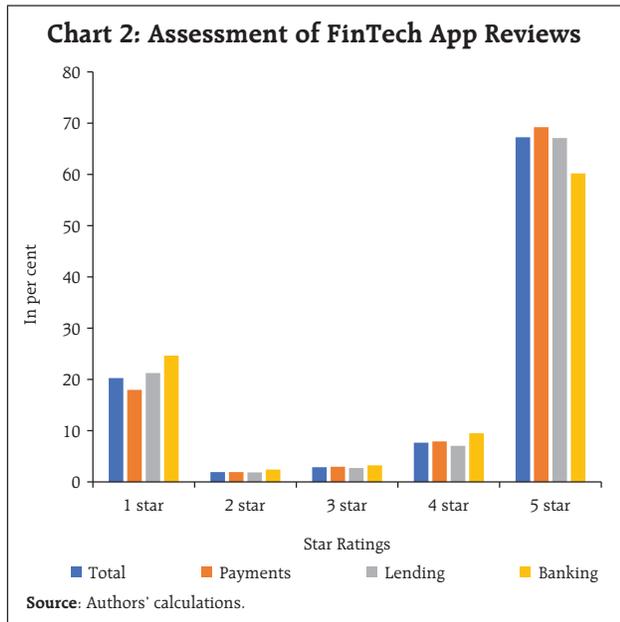
app installation is 0.54 per cent, marginally higher for payment and lending apps (0.6 per cent) compared to banking technology apps (Chart 1b). *Albeit*, the apps under study have received around six million reviews during the last two years, providing ample opportunities to understand the major customer concerns.

FinTech reviews are polarised in India, with around 20 per cent of total reviews belonging to one star and 67 per cent of total reviews belonging to five stars (Chart 2). Thus, these extreme reviews account for almost 87 per cent of total reviews in the FinTech ecosystem. In terms of sentiment analysis, the numbers may vary. The divergence in sentiments between ratings and reviews can be attributed to the underlying metrics; while ratings reflect the overall number of responses, including those without written feedback, sentiment analysis is confined to the sub-sample of worded reviews, suggesting that consumers with extreme experiences are more likely to leave a

Chart 1: Sector-wise FinTech App Landscape

a. Average Installs per App

Payments	1.36
Alternative Lending	1.27
Banking Tech	0.23

In crore

b. Review per Install

Payments	0.61
Banking Tech	0.42
Alternative Lending	0.60

In per cent

Note: In Chart 1(a), Sector-wise average installs per app is computed: Total unique installations / Total number of apps in each sector. In Chart 1(b), Review per install is computed as: Total reviews of an app / Total unique installation of an app.
Source: Authors' calculations.

[10] Since the BERTopic identifies reviews with dominant topic, reviews were classified into 295, 191, and 185 topics for alternative lending, payments and banking tech, respectively. Similar topics were clubbed into 11 broad themes (reported later in Table 3); while vague and incoherent topics were dropped.

[11] Four outlier apps in terms of total installs (two payment apps and two banking apps) are excluded while calculating the average installs per app for each of these sectors.

Chart 2: Assessment of FinTech App Reviews

Source: Authors' calculations.

Chart 3: Distribution of Positive Reviews

Source: Authors' calculations.

worded review as compared to others (Schoenmueller *et al.*, 2020; Hu *et al.*, 2017). Further, there also exists a positive imbalance in FinTech reviews, which means that the share of positive reviews received by most of the apps is higher than the share of negative reviews.

Notably, 61.7 per cent of all FinTech apps studied received a share of positive reviews in the 50 to 80 per cent range. A smaller share of apps (7 per cent) received less than 20 per cent positive reviews. Thus, the distribution of mean positive reviews is slightly negatively skewed in the Indian FinTech ecosystem (Chart 3). Among the FinTech apps that were below the overall positive average, 58 per cent belong to payments sector, 22 per cent belong to alternative lending and 20 per cent belong to the banking tech sector.
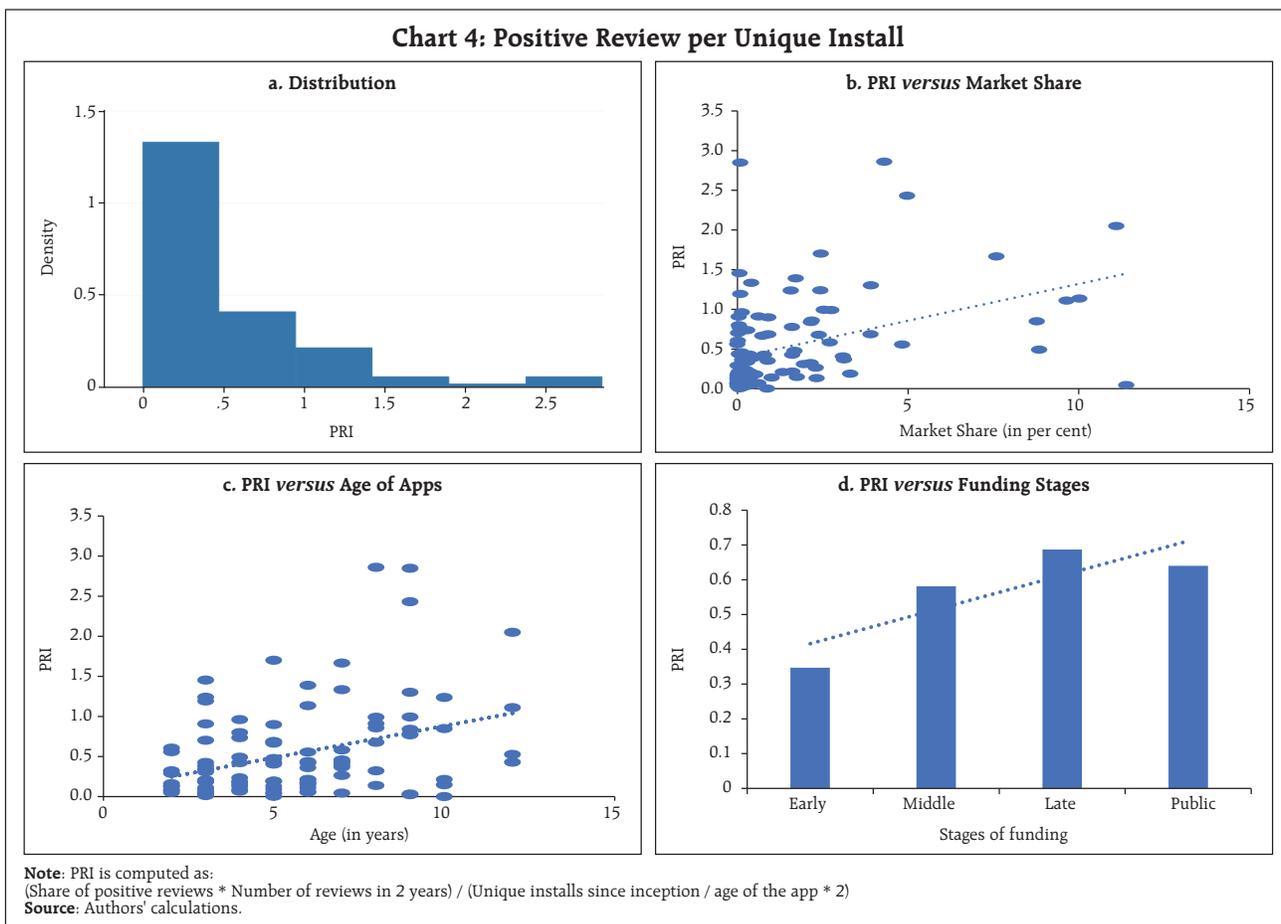
Positive reviews per unique installation (PRI) of the app may be more relevant since majority of customers do not leave a review. PRI is positively skewed with majority of the apps having PRI below 1 (Chart 4a). PRI varies according to characteristics of FinTech apps. PRI increases with the segment-wise market share of the apps in terms of installs (Chart 4b).

The PRI also increases with age as the FinTechs cross the average age of being deadpooled (*i.e.*, 3 years) [Chart 4c]. Similar relationship is observed with the funding stages of FinTechs, with an initial increase from early stage to late stage followed by a mild decline for public FinTechs (Chart 4d).

IV.2 Analysis of Emotions in Reviews

Emotional expressions in the customer reviews provide more insights regarding the satisfaction or dissatisfaction of customers. Following standard literature, this study examines three positive emotions (trust, anticipation of better outcomes and joy) and four negative emotions (disgust, sadness, fear and anger) [Omotosho, 2021].

The most positive emotion associated with the Indian FinTech ecosystem is trust across all sectors, followed by anticipation of a good outcome and joy. Across sectors, around 50 per cent of customers have expressed trust with the FinTech ecosystem. Among the negative emotions, the most expressed emotion is anger, followed by sadness, fear and disgust. Anger is expressed by 14 per cent of customers.

Chart 4: Positive Review per Unique Install

a. Distribution

b. PRI *versus* Market Share

c. PRI *versus* Age of Apps

d. PRI *versus* Funding Stages

Note: PRI is computed as:
(Share of positive reviews * Number of reviews in 2 years) / (Unique installs since inception / age of the app * 2)
Source: Authors' calculations.

Overall, positive emotions dominate in all sectors, reflecting a generally favourable sentiment, but negative emotions warrant attention for targeted improvements (Table 2).

Table 2 : Sector-wise Emotion Classification

(in per cent)

Emotions	Alternative Lending	Banking Tech	Payments	Total
Positive Emotions				
Trust	47.63	53.31	48.62	48.98
Anticipation	43.50	44.21	43.90	43.73
Joy	40.69	42.05	43.25	41.55
Negative Emotions				
Anger	13.68	15.35	14.99	14.31
Sadness	13.10	12.86	13.10	13.05
Fear	11.11	10.86	11.27	11.10
Disgust	10.26	8.28	8.50	9.46

Note: Presence of emotions is scaled to total reviews in the sample period, providing an overview regarding the percentage of customers that expressed an emotion.
Source: Authors' calculations.

IV.3 Topic Modelling of Negative Reviews

Negative reviews can function as an effective feedback mechanism from customers to FinTechs, and can also provide macro-level insights to policy makers. Employing topic modelling on negative reviews based on their embedded key messages represents an innovative approach to understanding the overarching challenges faced by customers. Major issues highlighted by the sector-wise analysis of negative reviews using topic modelling are provided in Table 3.

A major concern identified across sectors is customer support and service (CSS), which emerges as the most significant concern for banking technology customers, and the second-largest for payment tech and alternative lending tech users. Within this

Table 3: Major Concerns of FinTech Customers

(in per cent)

Broad Concerns	Alternative Lending	Payments	Banking Tech
Credit/Loan related	52.02	15.64	4.66
Customer support and service	11.19	20.52	35.90
Technical issues and app functionality	7.39	23.74	35.27
High interest rates and hidden charges	6.78	10.93	0.31
Payment Processing and Settlement Related Issues	7.18	7.96	9.93
Account related	6.54	6.02	3.99
Cashback/Rewards	3.21	7.83	0.99
Harassment and unethical practices	1.38	0.21	0.93
KYC and verification related issues	1.77	6.41	3.96
Promotional messages and misleading advertisements	0.87	0.58	0.52
User data and privacy	1.68	0.16	3.54

Note: Figures indicate per cent of reviews in the total number of final reviews in each category.
Source: Authors' calculations.

category, key issues include unresponsive customer support such as delayed or no responses to emails, calls, or chat queries; lack of effective escalation mechanisms and inadequate resolution for critical or urgent issues or difficulties in reaching out to a human agent; rude or unprofessional behaviour from customer support staff; poor handling of technical issues, loan repayment problems, or account-related queries; automated and generic responses without actionable solutions to user complaints; frustration with limited or unavailable support channels such as missing customer care numbers; and lack of effective resolution despite multiple communication and grievance escalation.

Another major concern is technical issues and app functionality, which is the most prominent issue for payment tech apps, the second-largest for banking tech, and the third-largest for alternative lending tech. Specific issues include frequent app crashes, freezing and loading failures, inability to login, and email, employment status and one-time

password (OTP) verification issues. Customers also face slow app performance, server downtimes, and update delays, alongside persistent bugs, glitches, and compatibility issues. Errors in essential features such as payment processing, Know Your Customer (KYC), and data synchronisation are prevalent, as are issues following app updates, including functionality disruptions and forced reinstallation. Other issues include missing basic features such as scan-and-pay and problems with available features like biometric authentication, unified payments interface setup, password resets and repeated malware warnings.

For alternative lending tech app users, loan and credit-related issues account for over 50 per cent of complaints. Specific issues under this broad concern can be categorised into three sub-topics, *viz.*, loan application and approval issues, credit limit related issues and data discrepancy issues. Loan application related issues include delayed processing of loan applications or applications remaining under review for extended periods, approved loans not being disbursed, and loan and offer rejections without clear reasons or transparency. Credit limit issues include issues with loan eligibility after repayment, including repeated rejections despite good credit scores or payment history, low initial credit limits or credit limit reductions (after application) without justification, and inability to increase credit limits despite timely repayments. Customers have also pointed out data discrepancy issues such as errors in sanctioned *versus* disbursed loan amounts, inaccurate or delayed updates to credit rating agencies and negative impacts on credit scores due to errors in reporting or hidden penalties. Additionally, the topic modelling analysis did not bring out prevalence of fraudulent apps in the ecosystem. This is because of the removal of fraudulent lending apps from the Play Store by the Reserve Bank of India and Self-Regulatory Organisations (SROs), in an effort to reduce digital lending frauds.

IV.4 Determinants of FinTech Apps' User Experience – An Econometric Analysis

Customers are expressing their sentiments in reviews as presented in the previous sections. In this section, the determinants of positive review sentiments are analysed using FPM, since the dependent variable - share of positive reviews of apps - lies between zero and one.

Three variants of the FPM, *viz.*, the full sample (Model 1), the full sample excluding outliers (Model 2) and a trimmed sample by excluding observations beyond ±1.78 standard deviations from the mean of the dependent variable (Model 3)[12] are presented (Table 4; Average Marginal Effects are reported in Annex - Table 1). The preferred model is Model 2, which provides estimation on the full sample by excluding outliers. As alluded to earlier, since not all FinTech app users leave reviews and reviews are often polarised, the regression controls for review per install (RPI) and review polarity[13].

The model indicates that the share of positive reviews flattens after reaching a certain age threshold. Further, apps with a larger market share exhibit a significantly higher proportion of positive reviews. This relationship, however, diminishes over time. Age, reflecting the survival dynamics of apps, and market share, representing business expansion strategies of apps, collectively highlight the alignment of positive reviews with the performance of individual apps within the FinTech ecosystem.

Two additional app-specific characteristics that significantly influence the share of positive app reviews are data privacy and major app updates.

Table 4: Drivers of FinTech Apps' User Experience Summarised Fractional Probit Regression Outputs

Dependent Variable: Share of Positive Reviews	(1)	(2)	(3)
Variables	Baseline	Baseline Excluding Outliers	Trimmed Sample- 1.78 SD
Age @	0.114*	0.103	0.115**
	(0.068)	(0.065)	(0.058)
Age^2	-0.011**	-0.011*	-0.010**
	(0.006)	(0.005)	(0.005)
Log of total funding	0.020	0.022	0.003
	(0.023)	(0.025)	(0.023)
Medium data collection #	0.860***	0.597**	0.118
	(0.297)	(0.244)	(0.073)
High data collection #	0.662**	0.360	-0.030
	(0.316)	(0.265)	(0.083)
Segment market share $	0.057***	0.046**	0.045**
	(0.018)	(0.021)	(0.018)
Segment market share^2	-0.0008***	-0.0006**	-0.0006**
	(0.0003)	(0.0003)	(0.0003)
App's major update !	0.292**	0.367**	0.190
	(0.156)	(0.163)	(0.168)
Update * Review per install	0.460**	0.545**	0.451*
	(0.207)	(0.234)	(0.238)
Review per install $	0.265***	0.256*	0.277**
	(0.078)	(0.139)	(0.134)
Polarity	-2.425**	-3.95***	-2.732***
	(1.171)	(0.949)	(0.899)
Constant	0.568	2.153**	1.881**
	(1.128)	(0.924)	(0.864)
Observations	91	88	84
Log pseudolikelihood	-58.80	-56.86	-55.00
Prob > ch^2	0.00	0.00	0.00
Pseudo R^2	0.047	0.047	0.027

Notes:
1. Parentheses indicate robust standard errors. *, **, *** represent 10 per cent, 5 per cent and 1 per cent level of significance.
2. The sample size reduces from 107 to 91 owing to missing observations in log of total funding.
3. In Model 2, three outlier apps in variables like review per install (> 2 per cent); polarity (< 0.7) and app's major updates (> 8) are excluded (one app each).
4. In Model 3, sample is trimmed by removing the apps that lie on extreme ends of the dependent variable (*i.e.*, the share of positive reviews in total reviews) by 1.78 standard deviation.
5. @ includes age of the app and not of the FinTech.
6. # Relative to apps with low data collection (that seek least number of permission between 0-4). Data collection variable is constructed as a simple aggregation of the 13 types of permissions sought by FinTech apps. The value between 10 to 13 permissions is labelled 1 (high data collection); between 5 to 9 is labelled 2 (medium data collection); between 0 to 4 is labelled 3 (low data collection). High data collection results in lower privacy levels, while low data collection ensures higher privacy
7. $ These variables are in percentage terms.
8. ! Any major update to the app since the first review (post April 1, 2022). It is a dummy variable, if there is a major update, it is equal to 1 and 0, otherwise.
Source: Authors' calculations.

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[12] The upper bound, corresponding to the maximum value of the share of positive reviews (dependent variable), is 0.921049. To exclude a proportionate number of apps with lower shares of positive reviews, 1.78 standard deviation from the mean was selected.

[13] Polarity is computed as the sum of number of 1 and 5 star rated reviews as a share of total reviews.

Compared to apps collecting minimal information (zero to four permissions), apps requiring a moderate level of user data (five to nine permissions) exhibit a notably higher share of positive reviews. However, the model indicates that further increases in data collection (exceeding ten data points) do not significantly affect the share of positive reviews, except in baseline model 1. This finding is consistent with insights from the topic modelling analysis, which suggest that excessive data collection without commensurate service improvements can lead to customer dissatisfaction, suggesting an inverse U-shaped relationship between permissions requested and user satisfaction.

Updates are an important feature of apps, that are generally aimed at improving app functionality. Consistent with this, the share of positive reviews is significantly higher for apps that received major updates during the study period compared to those without such updates. This aligns with the findings from the topic modelling exercise, where many customers highlighted concerns about app functionality. Thus, major updates appear to address these issues, improving app performance and leading to greater customer satisfaction (Perea-Khalifi *et al.*, 2024). In the presence of major updates, the share of positive reviews rises with increasing RPI, indicating that updates enhance functionality and encourage more users to share positive experiences.

The main findings remain consistent across the full sample, including when outliers are retained (Model 1). For additional robustness checks, a third model is estimated using a trimmed sample that includes only observations within ± 1.78 standard deviations of the dependent variable. The results remain broadly consistent, affirming their robustness.

V. Policy Implications and Conclusion

Consumer online reviews play a pivotal role in technology adoption by offering near real-time insights into user experiences. Using a large dataset of 5.69 million user-generated reviews, this study applies advanced machine learning techniques to analyse sentiments and extract key user concerns, offering insights for policymakers and industry stakeholders to enhance user satisfaction in the FinTech ecosystem.

Indian FinTech apps, overall, deliver a positive user experience. Among the three sectors under study—payment, alternative lending, and banking tech—apps in the payment and lending sectors are more likely to be installed and receive a review per install. Sectoral analysis reveals that positive emotions, including trust, anticipation of a better outcome and joy, are prevalent across all sectors, indicating a generally favourable sentiment. However, prevalence of negative emotions such as anger, fear and sadness underscore areas for targeted improvements. Topic modelling results highlight customer support and service as a major concern across sectors, with issues like unresponsive support, inadequate grievance resolution and limited customer care contact channels. Technical issues and app functionality, including app crashes, login failures, and server downtimes, are the most significant for payment tech and banking tech apps. For alternative lending apps, over half of the complaints relate to loan and credit issues, such as processing delays, credit limit concerns and data discrepancies.

Empirical analysis indicates that market share has a positive, *albeit* diminishing, impact on user experience, highlighting the importance of a competitive FinTech ecosystem to sustain innovation. Key app characteristics, such as data privacy and

major updates, are also significant drivers of positive reviews. Major updates enhance app functionality, leading to increased positive reviews and greater user engagement. Privacy, in turn, follows an inverse U-shape association with user satisfaction, indicating the importance of improving service delivery in proportion to data collection. The growing importance of customer-centric financial innovations emphasises the need for robust regulatory strategies, supported by advanced data analytics and AI-assisted tools, to address evolving user concerns and inform forward-looking policies.

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Annex

Table 1: Drivers of FinTech Apps' User Experience - Summarised Fractional Probit Average Marginal Effects (AMEs)

Dependent Variable: Share of Positive Reviews	(1)	(2)	(3)
Variables	Baseline	Baseline Excluding Outliers	Trimmed Sample-1.78 SD
Age @	0.002	-0.003	0.004
	(0.006)	(0.006)	(0.006)
Log of total funding	0.007	0.008	0.014
	(0.008)	(0.010)	(0.009)
Medium data collection #	0.322***	0.225**	0.043
	(0.102)	(0.091)	(0.028)
High data collection #	0.247***	0.137	-0.011
	(0.109)	(0.096)	(0.031)
Segment market share $	0.02***	0.016**	0.016***
	(0.007)	(0.007)	(0.006)
App's major update !	0.110*	0.136**	0.071
	(0.057)	(0.060)	(0.006)
Update * Review per install	0.170***	0.202**	0.177**
	(0.076)	(0.086)	(0.088)
Review per install $	0.098***	0.095**	0.103**
	(0.028)	(0.051)	(0.050)
Polarity	-0.897**	-1.463***	-1.018**
	(0.431)	(0.345)	(0.333)
Observations	91	87	83

Notes:

1. Parentheses indicate robust standard errors. *, **, *** represent 10 per cent, 5 per cent and 1 per cent level of significance.
2. AMEs measure the average change in the dependent variable resulting from a one-unit change in an independent variable, holding all other variables constant.
3. The sample size reduces from 107 to 91 owing to missing observations in log of total funding.
4. In Model 2, four outlier apps in variables like customer support concerns (>15 per cent of total negative concerns); review per install (> 2 per cent); polarity (< 0.7) and app's major updates (> 8) are excluded (one app each).
5. In Model 3, sample is trimmed by removing the apps that lie on extreme ends of the dependent variable (*i.e.,* the share of positive reviews in total reviews) by 1.78 standard deviation.
6. @ includes age of the app and not of the FinTech.
7. # Relative to apps with low data collection (that seek least number of permissions between 0-4). Data collection variable is constructed as a simple aggregation of the 13 types of permissions sought by FinTech apps. The value between 10 to 13 permissions is labelled 1 (high data collection); between 5 to 9 is labelled 2 (medium data collection); between 0 to 4 is labelled 3 (low data collection). High data collection results in lower privacy levels, while low data collection ensures higher privacy
8. $ These variables are in percentage terms.
9. ! Any major update to the app since the first review (post April 1, 2022). It is a dummy variable, if there is a major update, it is equal to 1 and 0, otherwise.

Source: Authors' calculations.