Are Fintech Loan Apps Harmful? Evidence from Users' Experience of Loan Apps in India

ABSTRACT

Existing evidence suggests that fintech has led to better access to finance, especially for the unbanked. However, there is a growing concern among regulators as fintech firms, that provide financial access, mushrooming across the world due to lower regulatory hurdles and higher ease of penetration. Given that there are no stringent disclosure norms, the only way to understand whether these lending apps are harmful is to examine explicit reviews of the users. Using user experience from 2.19 million reviews for Indian fintech loan apps registered in Google Play store, we analyze whether fintech loan firms exploit or help borrowers, especially when they are more vulnerable. We use COVID Lockdown period as a proxy for borrowers' vulnerability. Our results indicate that around 20 percentage of the negative reviews are associated with fraud and scams. Based on text analytics models, namely, LDA and LIWC, we find that fintech firms that emerged during the COVID crisis as more fraudulent and scamsters and also charge higher rates of interest compared to pre-COVID Fintech firms that offer the same service during the COVID crisis period. The results are robust to psychological profiling of user reviews. Using Government declared data on banning some of fraud apps, we find that user reviews are a good predictors of fraudulent apps and our results are robust for possible data manipulation by the loan app creators. Our study suggests that lower entry barriers can lead to exploitation when borrowers are more vulnerable and regulators should be wary of rapidly growing fintech firms.

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1. Introduction

Financial technology, popularly known as fintech has a huge potential to enhance financial service accessibility by lowering costs, enabling more transparency, and reducing information asymmetries in the credit market (Gabor & Brooks, 2017). Lending services, one of the essential elements of financial services, have undergone a transformation due to fintech innovations. Fintech helps loan providers to offer hassle-free and instant credit options to borrowers. The total global estimate of alternative credit through fintech and big techs[1] in 2019 is estimated at 795 billion USD, in which fintech accounted for roughly 223 billion USD and big tech for around 572 billion USD, respectively. It is more established in countries where the ease of doing business is substantial, investor protection disclosure is advanced, and the legal system is efficient (Cornelli et al., 2020).

Fintech plays a crucial role in improving credit access and household resilience to adverse shocks and thus households are less likely to defer expenses due to financial distress (Suri et al., 2021). It effectively reduces the disparity in borrowing exclusion from the traditional credit market (Zhong & Jiang, 2020). Fintech can also help to reduce inefficiencies in the consumer credit market and generate information spillovers to traditional credit intermediaries like banks (Balyuk Sergei Davydenko et al., 2019). The world witnessed a mass adoption of fintech-driven lending services during the outbreak of the COVID-19 pandemic (Bao & Huang, 2021). The fintech industry has seen a global pandemic for the first time since the revolution of mobile application-based lending and platform-based lending. Governments implemented country-wide lockdown measures to

[1] Big tech refers to large technology firms offering fintech services like Google, Amazon and Apple, to name a few.

prevent the spread but pushed people into financial distress and insolvency (Bartik et al., 2020; Humphries et al., 2020) risk. The risk is significantly higher for borrowers with poor credit scores and countries with low fintech adoption (Nigmonov & Shams, 2021). This implies that, during such challenging times, digital technology assisted the financial sector in driving the economy by dealing with pandemic shocks.

In contrast to the positive side to fintech innovations, the fast pace of adoption and lagging regulatory measures have unearthed the negative side of digital lending. Digital lending model adoption has led to uncertain and unpredictable impacts on the financial sector. In developing countries, a significant increase in suspicious lending applications was found, presumably due to consumers having severe financial constraints and being pushed out of the traditional lending sector during the crisis (Fu & Mishra, 2022). It indicates that predatory lenders exploit loopholes in the digital finance regulatory environment to engage in unethical actions. They target vulnerable potential borrowers by exploiting weaknesses and blind spots in the existing legislation. In India, debt traps and severe loan recovery practices have been ruining the lives of borrowers[2]. The Indian central bank, Reserve Bank of India (RBI), appointed a working committee on digital lending in the year 2021 and discovered that out of 1100 loan applications, that were active in 81 app stores available to Indian Android users, 600 are fake[3]. They predict that this trend will intensify as the number of lending applications grow because as users downloading an app will not know for sure whether or not the app is authentic. This incident highlights the necessity for active regulatory action to address the increasing consumer protection risk in the digital lending market.

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[2] A detailed new article investigation link is provided in the Appendix 1.

[3]https://rbidocs.rbi.org.in/rdocs/PublicationReport/Pdfs/DIGITALLENDINGF6A90CA76A9B4B3E84AA0EBD24B307F1.PDF

In summary, existing fintech literature finds both positive and negative aspects based on fintech lending statistics (eg; Bao & Huang, 2021; Cornelli et al., 2020; Yue et al., 2021). On the positive side, fintech firms outperformed traditional lenders in terms of the amount lent to borrowers and the number of new customers onboarding. This indicates that fintech was able to provide better financial access during crisis times than traditional banking. However, on the negative side, fintech firms experienced more delinquency than traditional bank lending with similar borrower profile (Bao & Huang, 2021). This indicates that either borrowers take fintech firms for a ride due to lower hurdle rules for borrowing or fintech firms, with their lower hurdle rate, create a loan trap for borrowers leading to strategic delinquency for more long term exploitation with penalties or higher rates. It is not clear whether fintech are helpful or harmful for borrowers, especially those who are more vulnerable.

Our paper tries to disentangle this issue by studying borrowers' experience with digital lending applications. Given that the only explicit way to know the benefits of a given digital lending platform is through post usage experience of the borrowers, we find that such data provides a rich setting to investigate whether users perceive fintech lending really helpful in providing financial access, especially during crisis time. Besides, there is no other explicit channel to capture fintech firms transactional or related data due to not having strong disclosure norms. First, we compare user reviews of digital loan applications posted before and during the pandemic period. Second, we examine the differences between the mobile lending applications released before (pre-COVID applications) and during the pandemic (COVID period applications) by assessing borrowers' experiences based on their reviews and application features. To evaluate the reviews, we develop Latent Dirichlet Allocation (LDA) Natural Language Processing (NLP) models on 2.19 million reviews in the sample of 110 digital lending applications sourced from the Google Play store.

We find that there was a significant increase in the loan apps creation during COVID period. On average, when we consider all loan apps in the market, loan apps improvised their efficiency in providing timely lending during COVID time. However, when we compare pre-COVID and COVID period issued loan apps, our LDA analysis-based regression models find that borrowers experience higher interest rates and more fraudulent behavior by the lender with loan apps that came during the COVID time. We find that users give 19.7 percent of negative reviews because of the fraudulent behavior of the digital lender. Our results based on the tones and emotions of the users by using Linguistic Inquiry and Word Count (LIWC) software broadly confirm with the LDA analysis, that users used more negative tones and emotions while using loan applications introduced during the COVID time and they are highly correlated with the fraudulent behavior identified through the LDA analysis. We ran a probit model using banned applications as proxy, which showed that LDA and LIWC variables are good predictors of fake/fraud applications.

Our results provide first-hand evidence on the user experience of digital loan applications by using a comprehensive sample. The main implication of our findings is that fintech lending, with lower hurdle rules and ease of borrowing, not necessarily help borrowers with better access to finance and economic upliftment. On the contrary, it can exploit borrowers who are most vulnerable and are easily accessible through technology advancements. Hence, regulators should be wary about the rapid growth in fintech lending market.

The paper is divided into five sections. We review related literature on traditional lenders and fintech in Section 2. The dataset and proposed methodology for this study is provided in Section 3. In Section 4, we present empirical results and a discussion. The paper concludes in Section 5.

2. Related literature

Despite the remarkable progress made in financial inclusion over recent years, the Global Findex database by the World Bank in 2017 revealed that 1.7 billion adults worldwide still do not have access to formal financial services[4]. The reason behind these high levels of financial exclusion include challenges in fulfilling documentation requirements, higher service costs, and distance to the nearest financial institution (Demirgüç-Kunt et al., 2018). According to extant theories, financial market imperfections, including information asymmetries and transaction costs, restrict traditional financial services accessible to poor people, which hinders their ability to escape from financial vulnerabilities (Banerjee & Newman 1993; Galor & Zeira 1993). Philippon (2014) assessed that the unit cost of financial intermediation in the United States has been stable at around two percent for the last 130 years.

Financial innovation theory suggests that information asymmetries, existence of market imperfections and transaction costs gave rise to innovative financial products and services (Fabozzi & Modigliani, 2003). Fintech is considered as an important catalyst for financial inclusion, with mobile financial services – in the form of Fintech having the highest potential in bringing the unbanked into the mainstream financial system. Empirical evidence from Kenya has ascertained that the use of mobile money has increased per capita consumption levels and alleviated two percent of households from poverty (Suri & Jack, 2016). Fintech firms play the role of aggregators as well as innovators by taking advantage of existing infrastructure and adopting competitive strategies for addressing financial inclusion. (Senyo & Karanasios, 2020). Furthermore, Fintech indirectly reduces income inequality through its effects on financial

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[4] https://www.worldbank.org/en/publication/globalfindex

inclusion (Demir et al.,2022). Thus, fintech is the most promising innovation by overcoming traditional finance limitations and reducing consumer vulnerabilities.

Prior studies point out the limitations of traditional banking in reaching out and providing financial access to the most vulnerable during crisis times. Çolak & Öztekin (2021) investigated the global impact of the COVID shock on bank lending. Based on a sample of banks from 125 countries, they demonstrated that bank lending is weaker in countries more affected by the pandemic. Furthermore, Gong et al. (2021) analyzed the effect of the H1N1 pandemic on bank loans in 2009-2010. They found that the pandemic raises the cost of bank loans and reduces the volume of bank lending.

Bao & Huang (2021) investigated the performance of traditional banks and fintech lenders during COVID. They found that fintech lenders outperformed the traditional banks in providing credit accessibility to financially constrained people during the pandemic. The number of new customers increased for fintech companies but decreased for banks after the pandemic. In addition, Fu & Mishra (2022) studied the impact of the pandemic on digital banking and the adoption of fintech. They found a tremendous rise in the number of finance app downloads due to COVID's widespread and subsequent lockdown imposed by the government. These findings suggest that fintech providers eventually surpassed traditional banks' fintech adoption over time. This indicates that borrowers are more inclined towards fintech apps due to their ease of processing loans and corresponding lower hurdle rules for sanctioning loans.

Ease of credit market access has a downside as noted by Yue et.al., (2021). They found that more accessibility leads to higher household consumption and thus succumbing to debt traps. This is evident in a higher delinquency rate compared to traditional banks (Bao & Huang, 2021). It suggests that higher financial accessibility does not imply that it is beneficial for the borrowers. Di

Maggio & Yao (2021) found that fintech borrowers are more likely to default than traditional bank borrowers with similar characteristics. The borrowers experienced only a short-term reduction in terms of credit cost from fintech as their indebtedness increases more than traditional borrowers after taking a loan. Borrowers' outcomes worsen in the month following a fintech loan compared to similar people borrowing from banks. Fintech borrowers enter into a debt trap by remaining loyal to the loan apps as they end up taking multiple loans in the process of repaying older loans generated from a different loan app.

The extant literature is not clear on whether fintech apps exploit borrowers with lower hurdle rules or borrowers exploit the loan apps due to multiple options available to them. We extend this emerging literature by examining how fintech loan apps behave when there is an exogenous shock to credit access. By using newly introduced loan apps during COVID crisis as our treatment sample, we can check how borrowers perceive them compared to the pre-crisis period loan apps.

3. Data and Methodology

3.1. Data collection

We use Google Play Scraper tool in Python to mine user reviews and loan features of digital loan applications from the Google Play store. Google play store is a popular digital distribution service provider for smartphone applications. Users can give feedback for downloaded applications in star ratings and text reviews on app stores. Recent studies found that this feedback provides valuable information about user requirements, ideas for improvements, user sentiments about specific features, and descriptions of experiences with these features (Al-Hawari et al., 2021; Puspaningrum et al., 2018). Considering the popularity of the google play store and the availability of the Google Play Scraper Package in Python, we selected it as an appropriate platform to scrape relevant user reviews of digital loan applications.

We searched for lending applications in the google play store using the terms personal loan, instant loan, need money, and urgent cash. Using Google Play Scraper, we scraped 110 digital loan app descriptions and 21,90,760 user reviews between the year 2019 to 2021, including 45 loan applications released before the pandemic and the remaining 65 applications released during the pandemic. The name, released date, and URL of digital loan applications are listed in Appendix 2. In addition, the process chart of applying for a loan is shown in Appendix 3. It starts with the user locating the loan app from the application store and registering with personal details. Then they can apply for the loan, and the lender will verify the user's identity and approve the loan. We classified reviews with a score of one, two, and three as below satisfaction level or negative reviews, while the rest were classified as above satisfaction level or positive reviews. An example of each score review is given in Appendix 4. We manually collected loan features data from each application's description, including loan tenure, loan amount, and annual percentage rate charged to borrowers.

Figure 1

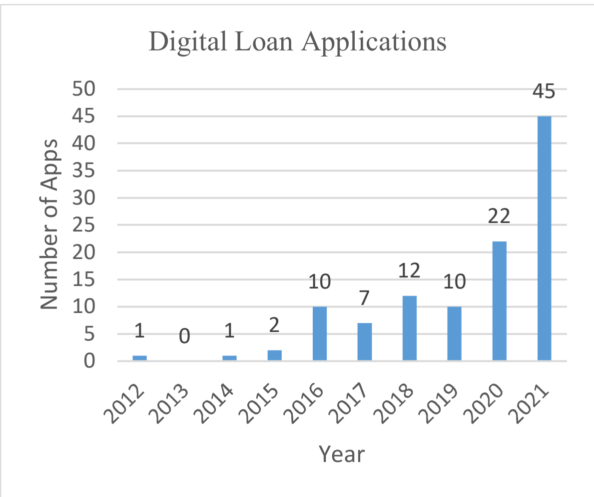


Figure 2

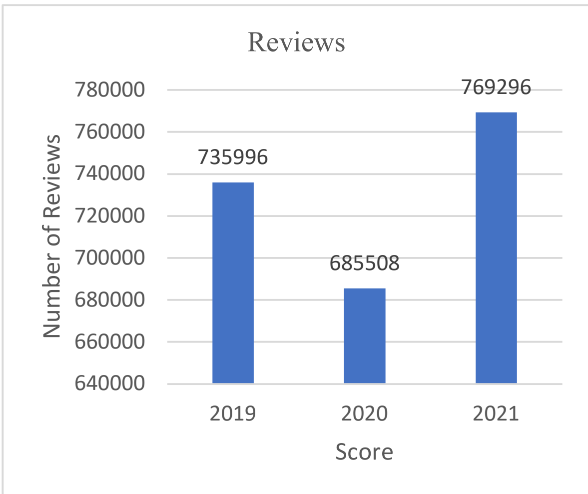


Figure 3

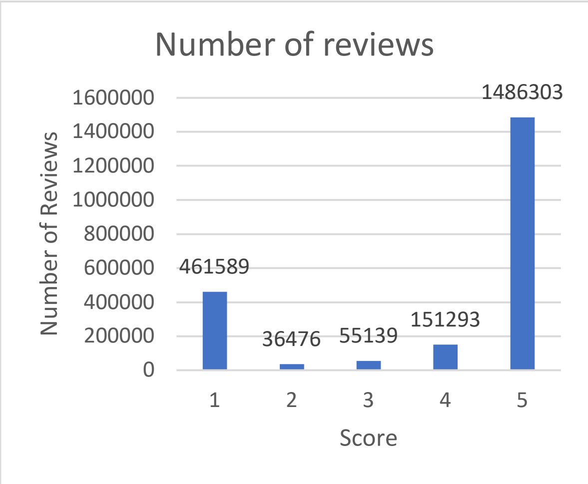
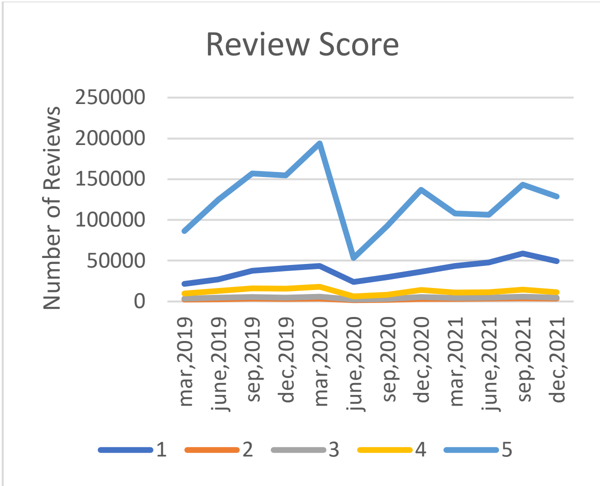


Figure 4



In 2021, the number of applications released and the number of user reviews appear to be high in our sample (Figures 1 and 2). The number of reviews with a 5-star rating comes first, followed by reviews with a 1-star rating (Figure 3). This indicates that the users take more extreme ratings while sharing their user experience. On March 11, 2020, the World Health Organization (WHO) declared the novel coronavirus outbreak a global pandemic. We classified apps and reviews based on this date by considering COVID as a natural experiment. Indian government implemented a country-wide lockdown due to the widespread COVID-19 on 25th March 2020. We can see that the number of 5-star reviews dropped drastically in the second quarter of 2020 but gradually recovered in subsequent quarters (Figure 4). This provides a preliminary evidence that users are not that happy with loan apps during the COVID crisis period.

3.2. Sentiment Analysis

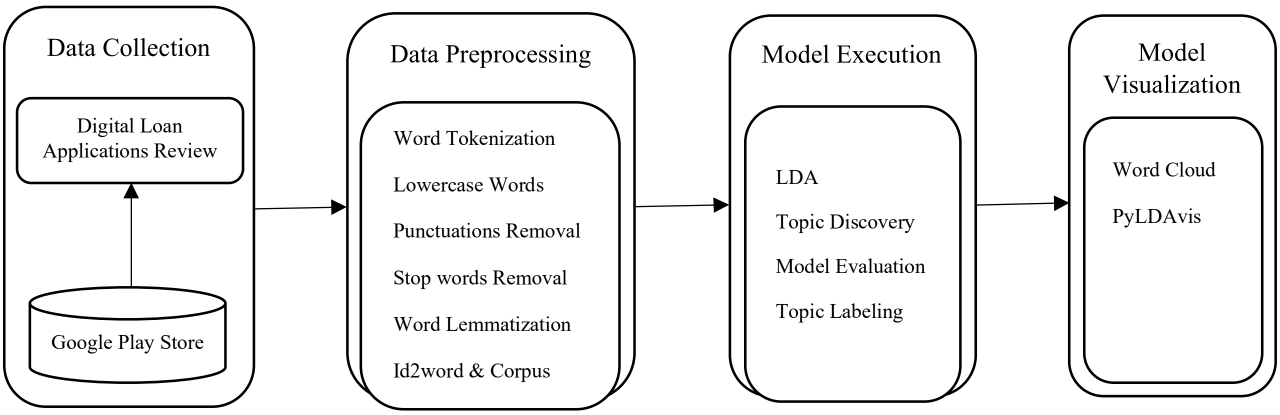
Due to the extensive usage of internet applications, enormous data exists in the form of short texts on social media containing opinions and user-generated reviews on products and services. Thus, mining or extracting such user-generated content and understanding their sentiments have become a trending research area. This is also known as sentiment analysis, which is done at various levels. Sentiment analysis highly relies on language, hence has close relation with Natural Language Processing (NLP). NLP is a branch of computer science, more precisely machine learning, which gives computers the ability to cognize spoken language and texts in the same way as human beings. It is a combination of computational linguistics that enables computers to process voice or text data to understand its entire meaning or user's sentiment. Such user-generated data often exists in an unorganized manner. Thus, for topic discovery and semantic mining from such unorganized content, topic modeling methods prove to be an effective technique widely used in NLP.

3.3. Topic Modelling

Topic modeling is commonly used to explore customer feedback and discover the attributes that affect customer satisfaction (Sutherland & Kiatkawsin, 2020). Users mostly write about their unusual experiences with products or services and will not share opinions that seem irrelevant. Machine Learning constitutes topic modeling, where a programmed model creates word clusters by analyzing text data from multiple documents or a dataset. This automated model reveals the topics that are latent from the given documents' collection. It finds out the topics and unearths viable patterns derived from the available text. This is done by counting and grouping identical word patterns that describe themes within the data. Based on the frequency of the words, i.e., the number of words that often appear in the same document, it finds out the patterns which can be grouped. Several algorithms are in use to perform topic modeling. One such popular model is Latent Dirichlet Allocation (LDA).

LDA is a widely used topic modeling technique under NLP. It structures every text corpus in multiple topics. Each topic has similar terms correlated with a certain probability (Guzman & Maalej, 2014). The topics or themes discovered by the model facilitate the illustration of topics relevant to users. LDA has been used in different industries in previous studies. In the tourism industry, Song et al. (2020) attempted to understand the perceptions and experiences of citizens of an urban park in New York City, whereas Yan et al. (2020) used topic modeling to identify issues related to post-disaster tourism in Lombok and Bali. Bahng & Lee (2020) looked at patients' concerns about hearing loss in the health and safety industry, whereas Min et al. (2020) looked into workplace accident issues. Figure 5 shows the LDA model process flow from data collection to model visualization.

Figure 5 – LDA model process chart



3.4. Data Pre-processing

Figure 5 describes the data processing in the LDA model. We run two LDA models for positive and negative reviews separately. The first model runs with 16,37,596 positive reviews and the second model with 5,53,164 negative reviews. The review data has to be pre-processed for further analysis. Text mining techniques in python by utilizing the platform of Natural Language Toolkit (NLTK) were used for pre-processing the user review data. As described in Figure 5, the tokenization process splits each sentence, paragraph, or text into tokens by using the word tokenize package in NLTK. To minimize redundant terms, every review text was converted to lowercase characters. All punctuation marks were eliminated from the text because they were unnecessary. Stop words were also eliminated from the text using the English stop words corpus included in the NLTK package. Finally, the Text blob package was used to apply word lemmatization. To make it easier to analyze the text, lemmatization converts the words in the sentence into root words.

3.5. Model Execution

The LDA model tool from the Genism package in topic modelling was used to extract the topics behind the reviews. The dictionary(id2word) and the corpus, which generates a unique id for each word in the document and its frequency, are the two key inputs to the LDA topic model. In addition, the model will be provided with a number of topics. The model with the highest accuracy will be chosen for our study once it has been run. Topic coherence measures were used to assess the model accuracy. Topic coherence assesses a single topic by determining the degree of semantic similarity between the topic's high-scoring words. Topics with high topic coherence scores will be generated by a good model.

Table 1 shows the LDA topic with positive and negative reviews of digital loan applications. The chosen LDA model with positive reviews was three topics with the highest coherence score of 0.491, and the chosen LDA model with negative reviews was five topics with the highest coherence score of 0. 5401. All observed words were analyzed and interpreted based on the terms in each group, and a topic label was assigned. In addition, we employed a word cloud to find the most frequently used words in each topic. The Word cloud of positive and negative topics are shown in Figure 6 and 7.

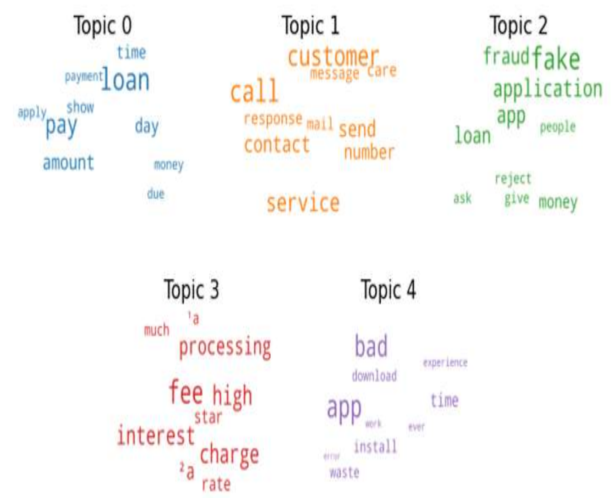
Table 1

Topic No.	Keywords	Topic Label
LDA model with positive user reviews		
0	loan, app, instant, personal, process, recommend, excellent, amazing, useful	Recommend the loan app
1	money, time, help, borrow, credit, amount, work, give, emergency, pay	Timely help
2	application, fast, really, service, great, much, helpful, love, quick, platform	Fast and efficient platform
LDA model with negative user reviews		
0	loan, pay, amount, day, time, show, money, apply, due, payment	Loan processing issue
1	call, customer, service, contact, send, number, care, response, message, mail	Poor customer service
2	fake, application, app, fraud, loan, money, reject, give, ask, people	Fraudulent behavior
3	fee, high, charge, interest, processing, rate, much	High interest and charges

4	app, bad, time, install, waste, download, experience, ever, work, error	Technical errors

Figure 6 – Positive LDA

Figure 7 – Negative LDA



We used the Python package PyLDAvis for visualizing LDA models. It helps in the analysis and creation of highly interactive visualizations of LDA clusters. Figure 8 represents the LDA output with positive reviews and Figure 9 represents the LDA output with negative reviews. In PyLDAvis each topic is represented by a bubble. The larger the bubble, the greater the proportion of reviews in the corpus addressing that topic. So, we can find the proposition of each topic in the negative and positive LDA model.

We assess each LDA topic's contribution to the total positive and negative review of digital loan applications using PyLDAvis (Table 2). In the case of positive reviews, 41.3 percentage users expressed satisfaction with the loan application's prompt assistance, and 35.1 percent recommend the loan applications. Regarding negative reviews, loan processing issues contribute the most (31.3 percent), whereas high interest and charges contribute the least (9.7 percent). Fraudulent behavior contributes 19.7 percent of negative reviews reason. The total frequency of each term in the corpus is represented by blue bars. If no topic is chosen, the most commonly used terms will be displayed in blue bars. The difference in topics is indicated by the distance between the bubbles. The more significant the gap between the topics, the more dissimilar they are.

Figure 8 - Positive review LDA model

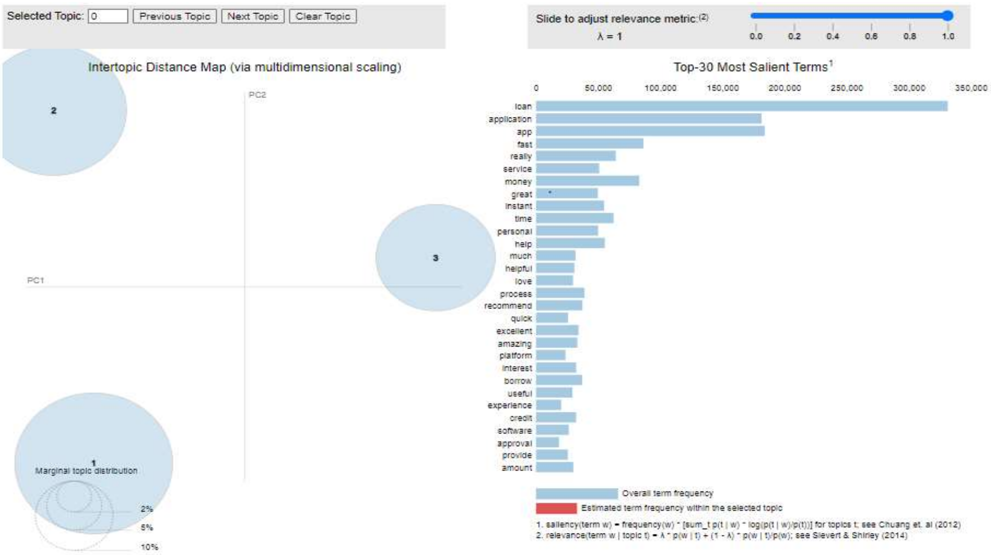


Figure 9 – Negative review LDA model

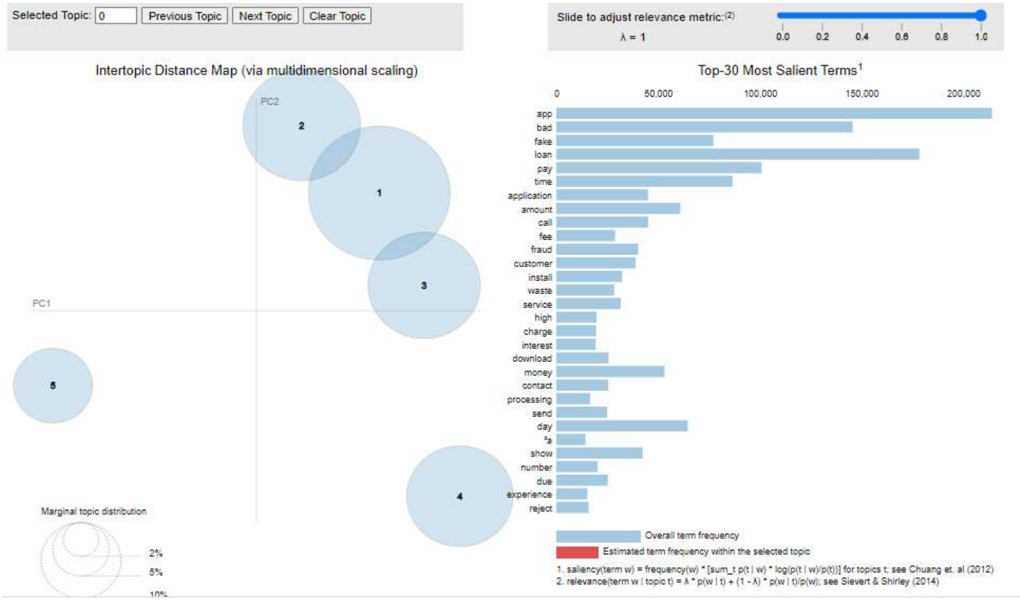


Table 2

LDA Topics	**Percentage of contribution**
Positive reviews	
Timely help	41.3
Recommend the loan app	35.1
Fast and efficient platform	23.6
Negative reviews	
Loan processing issues	31.3
Poor customer service	21.5
Fraudulent behavior	19.7

Technical errors	17.7
High interest & charges	9.7

3.6. Linguistic Inquiry and Word Count (LIWC)

Using LDA, we identified the factors influencing the borrower's behavior. We use the LIWC software system, which was developed by researchers at the University of Texas in Austin, to analyze user reviews with psychological dimensions. "LIWC is a transparent text analysis program that counts words in psychologically meaningful categories," and contains a built-in dictionary with more than 80 psychologically significant dimensions (Tausczik & Pennebaker, 2010). It is based on the psychological concept that use of words in a language is a reflection of one's cognitive or emotional states which results in varied word choices.

LIWC tool facilitates a deep understanding of individuals' communication which is reflected through their choice of words. It serves as a data processing system as well. This system is capable of processing almost any type of text. It begins by reading each word in the content and compares it with existing words in the dictionary. The software then estimates the percentage of words in the textual content and matches it with dictionary categories. We employed LIWC analysis with all the digital loan application reviews. We used the psychological factors associated with user reviews, such as tone positive, tone negative, emotion positive, emotion negative, and sadness from the output. Furthermore, the risk factor was used to determine the risk-related words in the user reviews. The description of each factor is included in Appendix 5.

4. Results

4.1 Comparison of user reviews during Pre-COVID and COVID Periods

The differences between the user reviews of digital loan applications during pre-COVID and COVID periods are measured by using the mean difference test (Table 3 and 4). The result shows that the mean values of all the LDA variables are significantly different between pre-and COVID-period reviews. In the case of positive reviews, we discovered that loan applications provided fast, more efficient, and timely assistance to the borrowers during the COVID period than in the pre-COVID period. However, the recommendations from borrowers have significantly come down in the COVID period. In the case of negative reviews, user complaints about poor customer service, fraudulent behavior, and technical errors have significantly reduced in the COVID period. While the borrowers' criticism of loan processing issues and high interest and charges have increased considerably in the COVID period. The considerable decrease in the recommendation of loan applications could be the result of an increase in loan processing issues during the COVID period because both of these topics account for a large proportion of user reviews.

Table 3 – LDA mean difference test

	Pre-COVID reviews		COVID Period reviews		Two-sample t-test			
	N	Mean	N	Mean	Mean diff	Std Err	t value	p-value
Positive Variables								
Recommend the loan app	752066	0.349	885530	.343	.006	.001	22	0
Timely help	752066	0.343	885530	.344	-.001	.001	-2.85	.005
Fast and efficient platform	752066	0.304	885530	.31	-.005	.001	-22.3	0
Negative Variables								
Loan processing issues	199945	0.239	353219	.256	-.017	.001	-25.8	0

Poor customer services	199945	0.185	353219	.18	.005	.001	8.95	0
Fraudulent Behavior	199945	0.205	353219	.199	.005	.001	9.75	0
Technical errors	199945	0.252	353219	.234	.018	.001	26.45	0
High interest and charges	199945	0.121	353219	.132	-.011	.001	-25.4	0

According to LIWC results, the positive psychological factors associated with user reviews, such as positive tone and positive emotions, have significantly decreased during the COVID. However, negative factors such as negative tone, negative emotion, and sadness of the user have increased significantly during the COVID period, whereas risk factors also have increased.

Table 4 – LIWC mean difference test

	Pre-COVID reviews		COVID period reviews		Two-sample t-test			
	N	Mean	N	Mean	Mean diff	StdErr	t value	p-value
Positive tone	952871	33.426	1237889	27.062	6.363	.05	126.8	0
Negative tone	952871	2.066	1237889	2.547	-.481	.014	-34.55	0
Positive emotion	952871	18.966	1237889	15.926	3.041	.044	68.35	0
Negative emotion	952871	0.731	1237889	.832	-.102	.009	-12.15	0
Sadness	952871	0.025	1237889	.032	-.007	.001	-5.05	0
Risk	952871	0.086	1237889	.111	-.025	.002	-12.4	0

4.2 Comparison of digital loan applications released during Pre-COVID and COVID-Period.

The loan applications released during the pre-COVID and COVID periods are compared to check whether there is a significant difference exist at the mean level (Table 5 and 6). The result indicates that the mean values of all the LDA variables are significantly different. Despite the COVID period applications providing fast, more efficient, and timely assistance to the borrowers than pre-COVID applications, the recommendation by borrowers is higher for pre-COVID released applications. Whereas, in the case of negative reviews, the lending applications released in the COVID period are associated with higher fraudulent behavior and exorbitant interest and charges than apps released pre-COVID. On the other hand, borrowers of pre-COVID applications experienced a higher rate of loan processing issues, poor customer support, and technical errors.

Table 5 – LDA mean difference test

	Pre-COVID Applications		COVID Period Applications		Two-sample t-test			
	N	Mean	N	Mean	Mean diff	StdErr	t value	p-value
Positive Variables								
Recommend the loan app	1510403	0.347	127193	.332	.015	.001	30.95	0
Timely help	1510403	0.344	127193	.345	-.002	.001	-2.5	.013
Fast and efficient platform	1510403	0.306	127193	.32	-.014	.001	-27.95	0
Negative Variables								

Loan processing issues	501164	0.251	52000	.239	.012	.001	10.75	0
Poor customer services	501164	0.186	52000	.144	.042	.001	59.9	0
Fraudulent Behavior	501164	0.195	52000	.258	-.063	.001	-58.7	0
Technical errors	501164	0.242	52000	.217	.026	.001	25.8	0
High interest and charges	501164	0.127	52000	.144	-.017	.001	-23.5	0

In comparison to COVID period released applications, the tone and emotion of user reviews are more positive in Pre-COVID released applications (Table 6). Pre-COVID application has a lower negative tone. In contrast, it has a higher level of negative emotion and sadness among users. The risk factor is higher for the COVID period released applications.

Table 6– LIWC mean difference test

	Pre-COVID Applications		COVID Period Applications		Two-sample t-test			
	N	Mean	N	Mean	Mean diff	StdErr	t value	p-value
Positive tone	2011575	30.145	179185	26.298	3.847	.085	45.15	0
Negative tone	2011575	2.313	179185	2.619	-.307	.026	-11.65	0
Positive emotion	2011575	17.449	179185	14.993	2.456	.074	33.2	0
Negative emotion	2011575	0.802	179185	.628	.175	.013	13.35	0
Sadness	2011575	0.029	179185	.022	.007	.002	3.65	.001

Risk	2011575	0.096	179185	.141	-.045	.004	-11.35	0

In terms of loan features (Table 7), COVID period released applications offer a shorter loan tenure than pre-COVID applications, whereas the Annual Percentage Rate (APR) of pre-COVID applications was higher than that of post-COVID applications. It was noted that most pre-COVID applications have a website, but only a few COVID period applications do and the number of reviews, and the number of reviews per month is higher in pre-COVID apps.

Table 7 - Digital loan application features mean difference test

	Pre-COVID Applications		COVID Period Applications		Two-sample t-test			
	N	Mean	N	Mean	Mean diff	StdErr	t value	p-value
Minimum loan tenure	45	5.245	65	3.908	1.337	.652	2.05	.044
Maximum loan tenure	45	33.378	65	22.83	10.547	4.083	2.6	.012
APR[5]	45	32.211	65	28.27	3.941	1.401	2.8	.006

[5] APR means Annual Percentage Rate, which includes the interest rate, processing charge, tax, and all other charges related to the loan.

website	45	0.756	65	.185	.571	.081	7.05	0
Review by month	45	365.64	65	99.33	266.311	92.966	2.85	.006

The positive LDA model depicts that pre-COVID applications have slightly higher chances of getting recommended by users (Figure 10) than COVID-period applications despite having higher recommendations in the initial phase. In the early COVID period, i.e., March to June 2020, Pre-COVID applications provided timely help to its borrowers but reduced significantly in the subsequent month. During the first two quarters of 2020, there was an increase in the timely assistance given; however, this attribute decreased drastically in the case of both pre-and post-COVID applications in the initial quarters of 2021. Later, both the attributes improved in late 2021. (Figure 11). On the fast and efficiency dimension, pre-COVID applications had invariable scores, while post-COVID applications were observed to be more efficient (Figure 12).

Figure 10

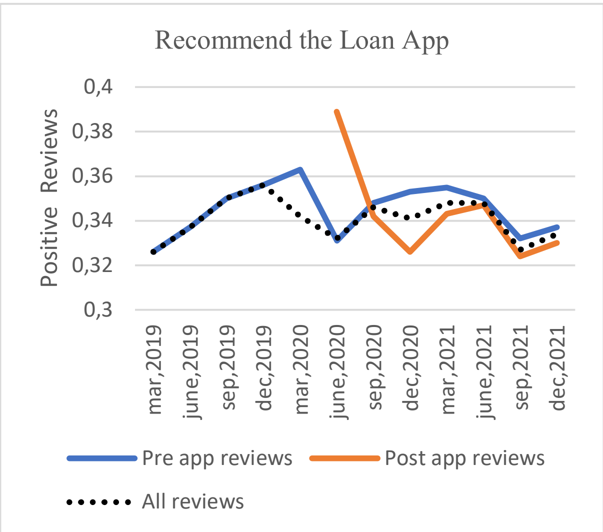


Figure 11

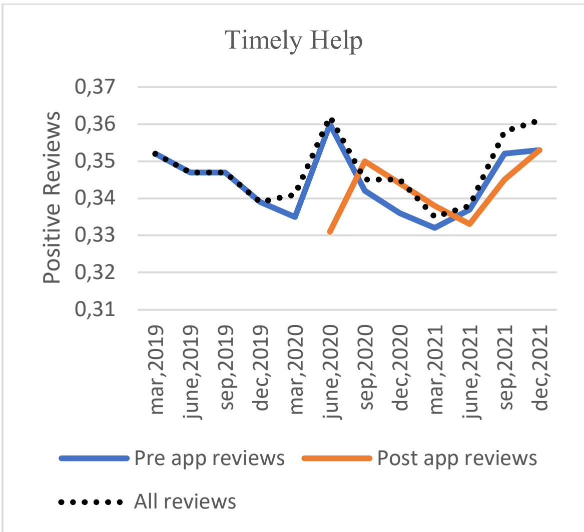
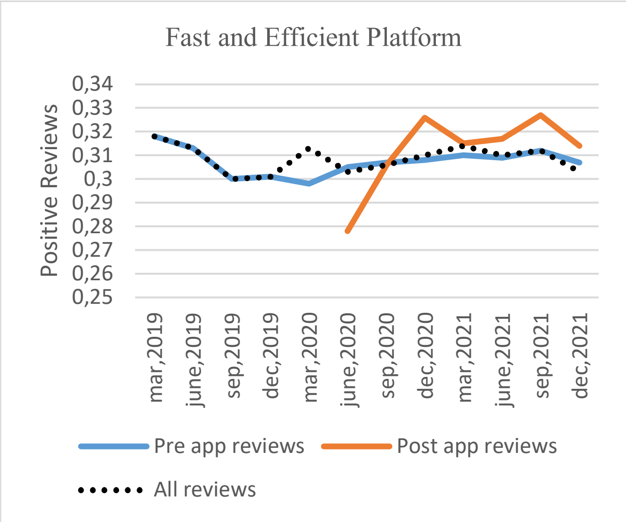
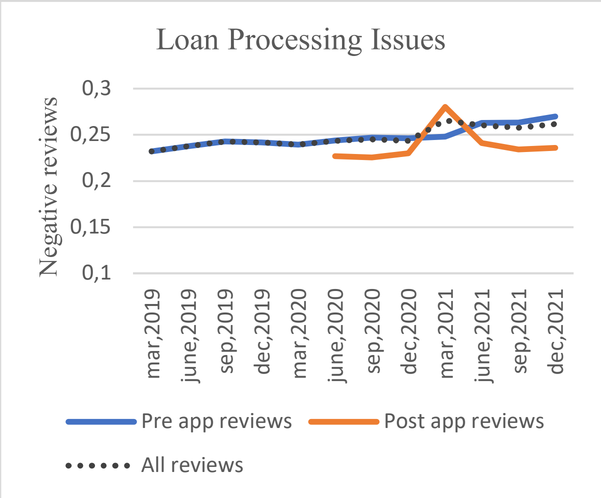


Figure 12



The negative LDA model shows that users of COVID applications complained more about fraudulent behavior and high interest and charges than pre-COVID applications during the pandemic (Figures 13 and 14). There is a minor increase in the loan processing issue in COVID applications during the first quarter of 2021. However, it was reduced in the second quarter (Figure 13). Meanwhile, pre-COVID application's loan processing issues increased marginally during the COVID period (Figure 15). While in case of poor customer service and technical errors, users complain more about pre-COVID applications (Figures 16 and 17).

Figure 13 Figure 14



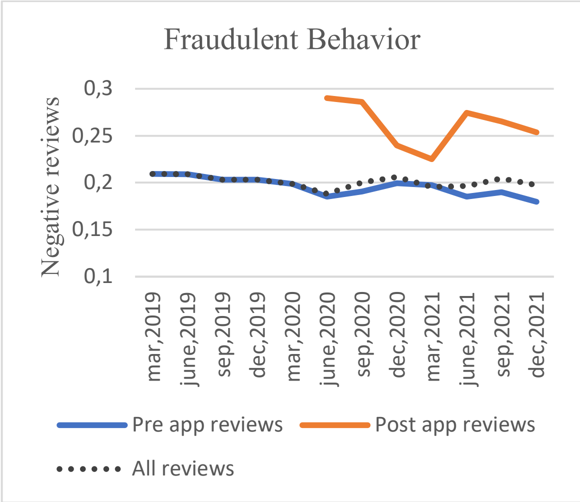
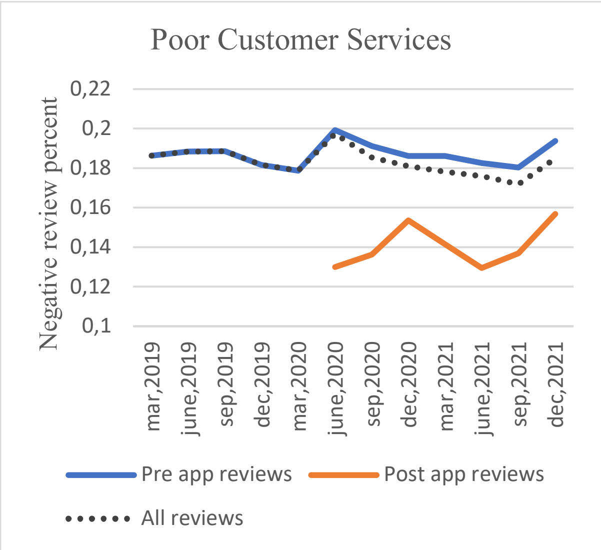


Figure 15

Figure 16



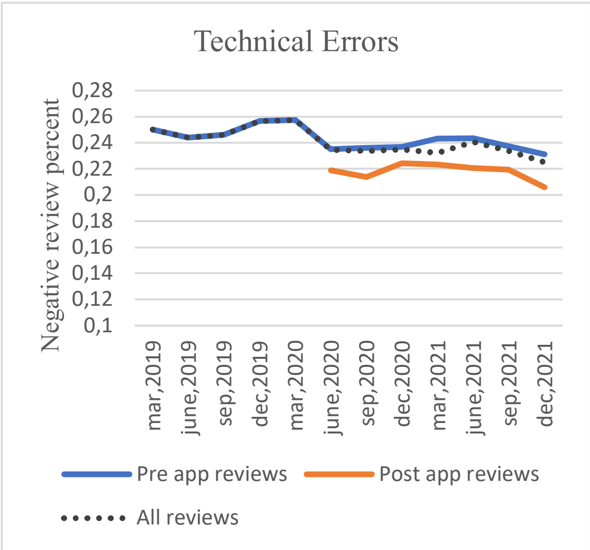
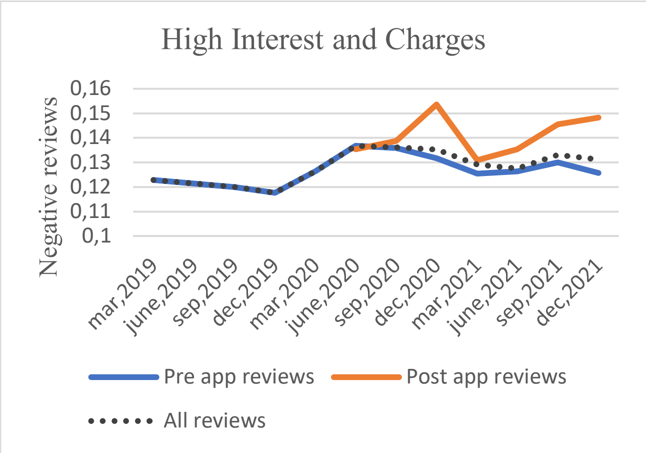


Figure 17



4.3 Regression results

The regression models results are shown in Table 8, with LDA variables as the dependent variables and loan features as the independent variables. COVID is a dummy variable equal to one if the app is released during the pandemic. Website is a dummy variable that takes value one if the app has a separate website. In addition, we use the "reviews by month" variable, from the released date of each app, to reduce review imbalances numbers' effect on the results. We find that COVID does not significantly influence any positive LDA variables. While, except for loan processing issues, the variable COVID has a significant impact on all negative LDA variables. In the COVID applications, there is a significant level of fraudulent behavior by digital lenders, and borrowers have complained about exorbitant interest rates and charges. At the same time, pre-COVID app borrowers experienced a higher rate of poor customer support and technical errors.

The regression models with LIWC variables as the dependent variable and the same independent and control variables are shown in Table 9. COVID has a significant impact on dependent variables including positive tone, positive emotion, and risk. Positive tone and emotion are prominent in pre-COVID applications. In contrast, the risk factor in the application released during the COVID period is high.

Table 8 – LDA Regression results

Variables	Positive Variables			Negative Variables				
	Model 1 Recommend the loan app	Model 2 Timely help	Model 3 Fast and efficient platform	Model 4 Loan Processing Issues	Model 5 Poor Customer Service	Model 6 Fraudulent Behavior	Model 7 Technical Errors	Model 8 High Interest & Charges
COVID	0.0103	-0.0006	-0.0082	-0.0063	0.0405***	0.0665***	0.0372***	0.0174***
	(0.0106)	(0.0134)	(0.0069)	(0.0083)	(0.0067)	(0.0104)	(0.0096)	(0.0042)
Minimum tenure	-0.0015	0.0041	-0.0025	-0.0026**	0.0006	0.0018	-0.0002	0.0003
	(0.0017)	(0.0022)	(0.0015)	(0.0013)	(0.0009)	(0.0017)	(0.0020)	(0.0006)
Maximum tenure	0.0006**	0.0010***	0.0004	0.0001	0.0000	-0.0002	0.0000	0.0000
	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0001)	(0.0002)	(0.0003)	(0.0001)
APR	-0.0011	0.0016	-0.0005	0.0011**	0.0002	-0.0005	0.0008	0.0006**
	(0.0006)	(0.0009)	(0.0005)	(0.0005)	(0.0003)	(0.0006)	(0.0006)	(0.0003)
Website	0.0163	-0.0104	-0.0054	-0.0060	0.0056	0.0077	0.0031	0.0109**
	(0.0113)	(0.0145)	(0.0073)	(0.0090)	(0.0059)	(0.0106)	(0.0107)	(0.0045)
Review by month	0.0000	-0.0000	0.0000	0.0000***	-0.0000	0.0000**	-0.0000	0.0000**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Constant	0.3525***	0.3168***	0.3274***	0.2617***	0.1722***	0.2345***	0.2334***	0.0988***
	(0.0221)	(0.0303)	(0.0186)	(0.0195)	(0.0143)	(0.0195)	(0.0196)	(0.0103)
Observations	110	110	110	110	110	110	110	110
Adjusted R-squared	0.066	0.065	0.001	0.123	0.396	0.410	0.158	0.218

Robust standard errors in parentheses.

*** p<0.01, ** p<0.05

Table 9 – LIWC Regression results

VARIABLES	Model 1 Tone Positive	Model 2 Tone Negative	Model 3 Emotion Positive	Model 4 Emotion Negative	Model 5 Emotion Sadness	Model 6 Risk
COVID	10.9895***	0.6840	7.1334***	-0.0967	-0.0034	0.1452***
	(2.5776)	(0.3755)	(1.6280)	(0.0966)	(0.0080)	(0.0384)
Minimum tenure	0.1625	0.0621	0.1648	0.0129	0.0005	0.0226**
	(0.3316)	(0.0551)	(0.2135)	(0.0154)	(0.0025)	(0.0087)
Maximum tenure	0.0011	-0.0115	0.0078	0.0014	0.0002	-0.0019
	(0.0486)	(0.0094)	(0.0307)	(0.0026)	(0.0003)	(0.0011)
APR (Annual Percentage Rate)	0.2379**	0.0525	0.1407**	0.0212***	-0.0003	0.0001
	(0.1097)	(0.0287)	(0.0674)	(0.0063)	(0.0007)	(0.0029)
Website	-1.6441	0.0521	-0.8988	-0.0795	-0.0036	-0.0067
	(2.4570)	(0.4152)	(1.5466)	(0.1081)	(0.0091)	(0.0417)
Review by month	0.0068	0.0016**	0.0040	-0.0002**	-0.0000	-0.0000
	(0.0042)	(0.0006)	(0.0026)	(0.0001)	(0.0000)	(0.0000)
Constant	16.3205***	2.3207**	8.9283***	0.3071	0.0383**	0.0672
	(4.5651)	(1.0504)	(2.8462)	(0.2339)	(0.0184)	(0.0701)
Observations	110	110	110	110	110	110
Adjusted R-squared	0.330	0.137	0.339	0.079	-0.034	0.120

Robust standard errors in parentheses.

*** p<0.01, ** p<0.0

Robustness Check

There is a possibility that user reviews can be fake or the Fintech Loan Apps creators may delete the negative reviews. We check this possibility by using data released by the Indian Government in year 2022[6]. The Indian Government came out with a list of banned Fintech Loan Apps that were considered fraud/ scam apps after a thorough investigation. Our conjecture is that, if the reviews are fake or there is negative news are under-represented then the reviews' based features should not predict the fraud apps declared by the Government. We ran a probit model with declared fraud apps in our dataset (38) as 1 and the rest as 0. LDA and LIWC based variables are used as the predictors. The results are reported in Table 10. The results show that both LDA and LIWC variables are significant predictors of the fraud Loan Apps. LDA based fraudulent behavior feature is positive and significant and LIWC based positive tone variable is negative and significant. These results suggest that the user reviewers are good predictors of Loan App fraud.

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[6] https://www.the420.in/274-fake-loan-apps-come-under-scanner-for-major-violations-check-full-list-here
https://www.business-standard.com/article/current-affairs/odisha-eow-asks-google-to-remove-45-illegal-loan-apps-from-play-store
https://www.india-p2p.com/india-list-of-banned-loan-apps.html

Table 10 – Probit Model results

Variables	Model 1 LDA Negative	Model 2 LIWC Variables
COVID	1.9688***	2.1604***
	(0.0068)	(0.0034)
Loan processing issues	1.1545***	
	(0.4105)	
Poor customer services	0.5987	
	(0.4111)	
Fraudulent behavior	0.9264**	
	(0.4101)	
High interest & charges	0.7098	
	(0.4097)	
Technical errors	1.0397**	
	(0.4083)	
Tone positive		-0.0013***
		(0.0001)
Tone negative		-0.0001
		(0.0002)
Emotion positive		-0.0005***
		(0.0001)
Emotion negative		-0.0005
		(0.0003)
Emotion sadness		0.0007
		(0.0014)
Risk		-0.0063***
		(0.0012)
Constant	-2.6628***	-1.7490***
	(0.4099)	(0.0020)
Observations	538,164	2,190,760

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$

5. Conclusion

Fintech revolution has provided higher penetration of financial access in the world. Studies have shown that fintech interventions provided better access of finance to the unbanked. However, most of the existing studies do not examine users' perspectives to understand the benefits of Fintech. In this paper, we explore users' experience of Fintech loan applications by collecting 2.19 million user reviews in India. We used text analytics, in particular, Latent Dirichlet Allocation (LDA) model for topic modeling user reviews. We use COVID as a natural experiment to understand how Fintech loan providers are perceived by the borrowers when they are in a vulnerable position. Our hypothesis is that, if fintech benefits people with lower access to finance, it should be more accessible when borrowers have limited or no access and are in financial distress. We find that fintech loan providers that came during the COVID period are perceived as more fraudulent and charged high rates of interest compared to the fintech loan providers who were operating before COVID. The results are robust for possible fake reviewers of negative review deletions by the Loan App creators.

Our evidence indicates that Fintech loan applications for providing loans exploit users when they are highly vulnerable and when other channels of financial access are very limited. Our results suggests that regulators should be vary about the growing fintech providers and regulatory lax in the fintech ecosystem.

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Appendix

1. Case Study

https://timesofindia.indiatimes.com/city/visakhapatnam/loan-app-harassment-case-hyderabad-man-held-in-vizag/articleshow/93886286.cms

2. Digital Loan Applications

No.	Digital Loan Application	Released	App URL
1	Bajaj Finserv-Loan,UPI,Payment	9/18/2012	https://play.google.com/store/apps/details?id=org.altruist.BajajExperia&hl=en_IN&gl=IN
2	LazyPay- Pay Later | Credit Score | Credit via UPI	2/19/2014	https://play.google.com/store/apps/details?id=com.citrus.citruspay&hl=en_IN&gl=IN
3	Instant Personal Loan Online App: LoanAdda	7/24/2015	https://play.google.com/store/apps/details?id=com.addventure.loanadda&hl=en_IN&gl=IN
4	Instant EMI Shopping, Personal Loan app - Kissht	8/14/2015	https://play.google.com/store/apps/details?id=com.fastbanking&hl=en_IN&gl=IN

5	PaySense: Personal Loan App	2/11/2016	https://play.google.com/store/apps/details?id=com.gopaysense.android.boost&hl=en_IN&gl=IN
6	Personal Loan & Salary Advance App - EarlySalary	2/22/2016	https://play.google.com/store/apps/details?id=com.earlysalary.android&hl=en_IN&gl=IN
7	CASHe Personal Loan App	2/25/2016	https://play.google.com/store/apps/details?id=co.tslc.cashe.android&hl=en_IN&gl=IN
8	Instant Approval Personal Loan	3/2/2016	https://play.google.com/store/apps/details?id=com.indialends.android&hl=en_IN&gl=IN
9	Salary Advance | Personal Loan App, QuickCredit	3/4/2016	https://play.google.com/store/apps/details?id=com.quickcredit.mobile&hl=en_IN&gl=IN
10	IDFC FIRST Bank - Loans Online	5/17/2016	https://play.google.com/store/apps/details?id=com.capitalfirst&hl=en_IN&gl=IN
11	Instant Personal Loan App - SmartCoin	6/15/2016	https://play.google.com/store/apps/details?id=in.rebase.app&hl=en_IN&gl=IN
12	InstaLoan:Personal Loan App	7/8/2016	https://play.google.com/store/apps/details?id=com.fullerton.instaloan&hl=en_IN&gl=IN
13	MoneyTap - Credit Line & Personal Loan App Online	7/12/2016	https://play.google.com/store/apps/details?id=com.mycash.moneytap.app&hl=en_IN&gl=IN
14	mPokket: Personal Loan & Instant Student Loan App	12/7/2016	https://play.google.com/store/apps/details?id=com.mpokket.app&hl=en_IN&gl=IN

15	Quick Loan, Instant Loan At Low Interest & Low EMI	3/22/2017	https://play.google.com/store/apps/details?id=com.goupwards&hl=en_IN&gl=IN
16	Instant Personal Loans - Online Loans | OYE Loans	4/7/2017	https://play.google.com/store/apps/details?id=com.globalanalytics.oyeloanindia&hl=en_IN&gl=IN
17	HomeCreditâ€“Personal Loan, Ujjwal Card EMI Solution	4/10/2017	https://play.google.com/store/apps/details?id=com.portal.hcin&hl=en_IN&gl=IN
18	Money View: Personal Loan App	6/20/2017	https://play.google.com/store/apps/details?id=com.whizdm.moneyview.loans&hl=en_IN&gl=IN
19	FlexSalary Instant Loan App	8/7/2017	https://play.google.com/store/apps/details?id=com.flexsalary&hl=en_IN&gl=IN
20	StashFin - Credit Line & Loan	10/17/2017	https://play.google.com/store/apps/details?id=com.stashfin.android&hl=en_IN&gl=IN
21	Finnable Instant Personal Loan	11/27/2017	https://play.google.com/store/apps/details?id=com.finnable.customer&hl=en_IN&gl=IN
22	Personal Loan App, Home Loan, Credit Card	1/1/2018	https://play.google.com/store/apps/details?id=in.apps.myloancare&hl=en_IN&gl=IN
23	Loan App for Instant Personal Loan Online - NIRA	4/23/2018	https://play.google.com/store/apps/details?id=com.nirafinance.customer&hl=en_IN&gl=IN
24	KreditBee: Instant Loan App	5/10/2018	https://play.google.com/store/apps/details?id=com.kreditbee.android&hl=en_IN&gl=IN

25	InstaMoney Personal Loan App	6/4/2018	https://play.google.com/store/apps/details?id=com.innofinsolutions.instamoney&hl=en_IN&gl=IN
26	Instant and Easy Personal Loan from i2iFunding	7/9/2018	https://play.google.com/store/apps/details?id=com.i2iborrower&hl=en_IN&gl=IN
27	Instant Loan & Personal Loan & Advance Salary App	7/17/2018	https://play.google.com/store/apps/details?id=com.phocket&hl=en_IN&gl=IN
28	Mystro: Simple, Quick & Instant Personal Loan app	7/21/2018	https://play.google.com/store/apps/details?id=in.mystro&hl=en_IN&gl=IN
29	Personal Loan, Instant & Online Loan - OfferMeLoan	9/12/2018	https://play.google.com/store/apps/details?id=com.offermeloan.app.offermeloan&hl=en_IN&gl=IN
30	Instant Personal Loan, Payday Loan - Instant Mudra	10/11/2018	https://play.google.com/store/apps/details?id=com.loaneasy&hl=en_IN&gl=IN
31	Personal Loan App Instant Online Loan - RapidRupee	12/4/2018	https://play.google.com/store/apps/details?id=co.afg.rupie&hl=en_IN&gl=IN
32	PhoneParLoan-Personal, Travel, Medical online Loan	12/13/2018	https://play.google.com/store/apps/details?id=com.phoneparloanin&hl=en_IN&gl=IN
33	Tata Capital - Personal Loan	12/31/2018	https://play.google.com/store/apps/details?id=com.snapwork.tcl&hl=en_IN&gl=IN
34	Personal Loan App & Instant Cash Loan - SimplyCash	1/31/2019	https://play.google.com/store/apps/details?id=com.herofincorp.simplycash&hl=en_IN&gl=IN
35	LoanFront - Quick Personal Loan EMIs	3/3/2019	https://play.google.com/store/apps/details?id=in.loanfront.android&hl=en_IN&gl=IN

36	Salary Advance | Personal Loan App - LoanIt	3/7/2019	https://play.google.com/store/apps/details?id=com.loanit.app&hl=en_IN&gl=IN
37	LoanTap - Personal Loan App	3/10/2019	https://play.google.com/store/apps/details?id=in.loantap.app&hl=en_IN&gl=IN
38	Manappuram Personal Loan	5/27/2019	https://play.google.com/store/apps/details?id=com.interstellarz.personalloanapp&hl=en_IN&gl=IN
39	Kosh - Microfinance Loan App Personal	8/22/2019	https://play.google.com/store/apps/details?id=com.kosh&hl=en_IN&gl=IN
40	Finserv MARKETS: Loan,Card,UPI	10/9/2019	https://play.google.com/store/apps/details?id=in.bajajfinservmarkets.app&hl=en_IN&gl=IN
41	Kreditzy Personal Loan App Online Loan	10/29/2019	https://play.google.com/store/apps/details?id=com.kreditzy.android&hl=en_IN&gl=IN
42	Online instant Loan App Personal Loan - instaCash7	11/27/2019	https://play.google.com/store/apps/details?id=com.instacash7&hl=en_IN&gl=IN
43	Instant Personal Loan App - CashTM Cash Thru Mobile	12/29/2019	https://play.google.com/store/apps/details?id=com.cashtm.andriod&hl=en_IN&gl=IN
44	CashNow - Personal Loan App	1/11/2020	https://play.google.com/store/apps/details?id=com.inpaway.kredit&hl=en_IN&gl=IN
45	Prefr Credit - Get instant loan under a minute	2/18/2020	https://play.google.com/store/apps/details?id=com.prefr.credit&hl=en_IN&gl=IN

46	Instant Personal Loan App online loan - Loan Guide	3/16/2020	https://play.google.com/store/apps/details?id=com.instantpersonalloan.developingpanda&hl=en_IN&gl=IN
47	CashKey - Online Personal Loan App	3/19/2020	https://play.google.com/store/apps/details?id=com.fintopia.INcashKey.google&hl=en_IN&gl=IN
48	iCashNow - Personal Fast Online Loan	4/22/2020	https://play.google.com/store/apps/details?id=com.hztec.icashnow&hl=en_IN&gl=IN
49	Instant Personal Loan - CPay	5/4/2020	https://play.google.com/store/apps/details?id=com.personalcpay.app&hl=en_IN&gl=IN
50	Rupee Wallet-Personal Loan App Online Loan	5/4/2020	https://play.google.com/store/apps/details?id=com.flashwallet&hl=en_IN&gl=IN
51	5paisa Loans - Online Personal Loan, Instant Loan	5/5/2020	https://play.google.com/store/apps/details?id=com.fivepaisaloans.p2p.prod&hl=en_IN&gl=IN
52	Cash Credit Loan - Instant Personal Cash Loan App	6/14/2020	https://play.google.com/store/apps/details?id=com.cashcredit.loan&hl=en_IN&gl=IN
53	Instant Credit and Small Business Loan App: Rufilo	6/26/2020	https://play.google.com/store/apps/details?id=com.rufilo.user&hl=en_IN&gl=IN
54	eCredit Point Personal Loan	7/30/2020	https://play.google.com/store/apps/details?id=com.ecreditpoint.app&hl=en_IN&gl=IN
55	Cash Loans	8/12/2020	https://play.google.com/store/apps/details?id=com.loans.cash.cal&hl=en_IN&gl=IN

56	RupeeMenu - Personal Loan Online	8/26/2020	https://play.google.com/store/apps/details?id=com.fintech.rupeemenu&hl=en_IN&gl=IN
57	Rupiyabus - quickest Instant Personal Loan App.	9/4/2020	https://play.google.com/store/apps/details?id=com.id.rupiyabus&hl=en_IN&gl=IN
58	Suvidha Personal	9/13/2020	https://play.google.com/store/apps/details?id=com.suvidha.finance&hl=en_IN&gl=IN
59	Magna â€“ Personal Loan	9/15/2020	https://play.google.com/store/apps/details?id=com.in.magnaloan&hl=en_IN&gl=IN
60	MobiCred - Personal Loan	9/21/2020	https://play.google.com/store/apps/details?id=com.oricred.mobicred&hl=en_IN&gl=IN
61	LoanEZ-Personal Online Loan App	10/16/2020	https://play.google.com/store/apps/details?id=com.treasure.loanez&hl=en_IN&gl=IN
62	Easy Loan â€“ Online Loan Instant Personal Loan	11/7/2020	https://play.google.com/store/apps/details?id=com.easy.loan.instant.jsd&hl=en_IN&gl=IN
63	Use Money-finance online loan app	11/21/2020	https://play.google.com/store/apps/details?id=com.use.money.finance.loan&hl=en_IN&gl=IN
64	Instant Personal Loan App Online Loan -Kredit Loan	11/30/2020	https://play.google.com/store/apps/details?id=india.kredit.loan.cash.app&hl=en_IN&gl=IN
65	RapidPaisa - Instant Personal Loan Online Apply	12/4/2020	https://play.google.com/store/apps/details?id=com.rapidpaisa.instant.loan.app&hl=en_IN&gl=IN

66	Unnati - Quick Personal Loan Online Upto Rs 3 Lakh	2/5/2021	https://play.google.com/store/apps/details?id=com.upwards.unnati&hl=en_IN&gl=IN
67	Rupeloan-online personal loan app in India	2/5/2021	https://play.google.com/store/apps/details?id=com.rupeloan.cash.loan&hl=en_IN&gl=IN
68	CashExpress - Personal Loans Online	2/25/2021	https://play.google.com/store/apps/details?id=com.cashexpress.large&hl=en_IN&gl=IN
69	Cash Me - Personal Loan	3/12/2021	https://play.google.com/store/apps/details?id=com.freshnatural.fourleafgrass.fntflg&hl=en_IN&gl=IN
70	Low interest loan-RupeeKing	3/16/2021	https://play.google.com/store/apps/details?id=com.ruepk.ntyn&hl=en_IN&gl=IN
71	Get Loan - Get Online Easy and Fast Loan	3/19/2021	https://play.google.com/store/apps/details?id=com.gettloannn.loanapppp&hl=en_IN&gl=IN
72	Loan Link â€" Personal loan in India	3/22/2021	https://play.google.com/store/apps/details?id=com.local.library.link&hl=en_IN&gl=IN
73	Fmoney-Personal Loan,Cash Loan,Online Loan	4/2/2021	https://play.google.com/store/apps/details?id=com.fmoney.app.win&hl=en_IN&gl=IN
74	Real Credit-Instant Personal Loan app	4/8/2021	https://play.google.com/store/apps/details?id=com.realcredit.customer&hl=en_IN&gl=IN
75	OK Loan-Instant Personal Cash Loan App	4/15/2021	https://play.google.com/store/apps/details?id=com.tiddler.rupee&hl=en_IN&gl=IN

76	MayaCash - Personal Loan App	4/27/2021	https://play.google.com/store/apps/details?id=com.in.maya.cash&hl=en_IN&gl=IN
77	Kredit-E - Personal loan at 0% Processing Fee	4/29/2021	https://play.google.com/store/apps/details?id=app.kredite2.com&hl=en_IN&gl=IN
78	India Money Instant Personal Loan App	5/1/2021	https://play.google.com/store/apps/details?id=com.arun.rpnm&hl=en_IN&gl=IN
79	Cash-e-Desk - Instant Personal Loan No hidden fees	5/5/2021	https://play.google.com/store/apps/details?id=com.cashedesk.app&hl=en_IN&gl=IN
80	Personal Cash Credit Online Loan - Ants Loan	5/12/2021	https://play.google.com/store/apps/details?id=com.indianaci.antsloan&hl=en_IN&gl=IN
81	ShineLoan-personal loan app	5/28/2021	https://play.google.com/store/apps/details?id=com.shineloan.android&hl=en_IN&gl=IN
82	ClickCash	6/5/2021	https://play.google.com/store/apps/details?id=com.gpfincorp.clickcash&hl=en_IN&gl=IN
83	Cash Pay - Instant Personal Loan by NBFCs/Banks	6/8/2021	https://play.google.com/store/apps/details?id=com.loanapp.loancreditcashapp&hl=en_IN&gl=IN
84	CreditZee - Personal loan app	6/14/2021	https://play.google.com/store/apps/details?id=com.arinfosoft.vishal&hl=en_IN&gl=IN
85	Instant Personal Loan App - Mobile Money	6/16/2021	https://play.google.com/store/apps/details?id=com.mobile.money.allemliloan&hl=en_IN&gl=IN

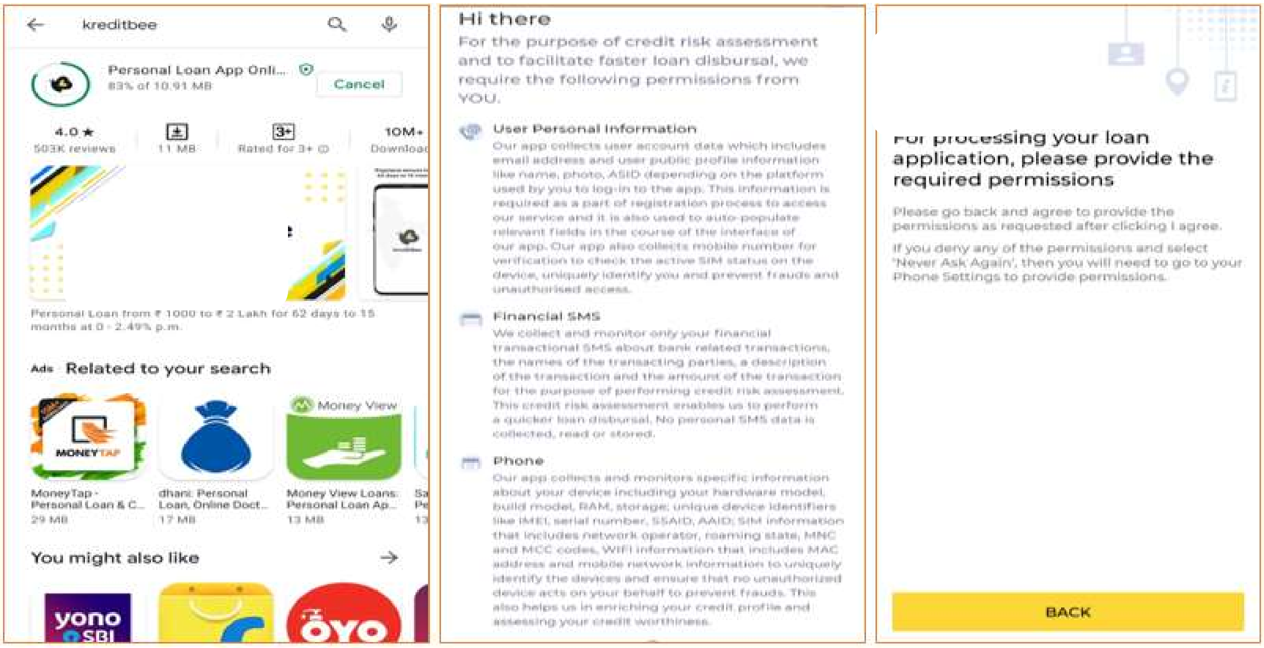
86	Binsta - Instant Personal Loan App	6/19/2021	https://play.google.com/store/apps/details?id=com.binsta.app&hl=en_IN&gl=IN
87	RupeesLand	6/21/2021	https://play.google.com/store/apps/details?id=com.rupeesland.app.cash.money.pay.credit.loan&hl=en_IN&gl=IN
88	KreditFinserv- Personal loan at 0% Processing Fee	6/23/2021	https://play.google.com/store/apps/details?id=com.finserv.kredit&hl=en_IN&gl=IN
89	eRupee Instant Personal Loan App	7/14/2021	https://play.google.com/store/apps/details?id=com.emakn.eszhn&hl=en_IN&gl=IN
90	Cash Advance	7/16/2021	https://play.google.com/store/apps/details?id=com.cashadvance.advancecashen&hl=en_IN&gl=IN
91	Quick Loan Pro	7/18/2021	https://play.google.com/store/apps/details?id=com.alertpear.fastloan2&hl=en_IN&gl=IN
92	Rupee Cash	7/19/2021	https://play.google.com/store/apps/details?id=com.rupeecash.cashrupeecacash&hl=en_IN&gl=IN
93	Go Loans	7/19/2021	https://play.google.com/store/apps/details?id=com.snangoloans.bgoloanzmloan&hl=en_IN&gl=IN
94	Kredipe-Personal Online Loan App	7/21/2021	https://play.google.com/store/apps/details?id=com.cpzwqz.kredipe&hl=en_IN&gl=IN
95	Fast Rupee - Online Loan App	7/22/2021	https://play.google.com/store/apps/details?id=com.fastrupee.fastrupeepeefa&hl=en_IN&gl=IN

96	Rupee Loan	7/22/2021	https://play.google.com/store/apps/details?id=com.rupeeloan.loanrupeeloanbbo&hl=en_IN&gl=IN
97	Loan Instant - CashLoan	7/22/2021	https://play.google.com/store/apps/details?id=com.nmddeveloper.onlinefastloanmaker.loangetapr&hl=en_IN&gl=IN
98	Need Rupee Instant Personal Loan App	7/24/2021	https://play.google.com/store/apps/details?id=com.makipl.ndrepl&hl=en_IN&gl=IN
99	SalaryLoan	7/27/2021	https://play.google.com/store/apps/details?id=com.salary.loan.instant.personal.emi.cash.loan&hl=en_IN&gl=IN
100	Small Loan	7/30/2021	https://play.google.com/store/apps/details?id=com.smailloan.loansmailloanwx&hl=en_IN&gl=IN
101	Loan Fortune - Instant Loans Online	7/30/2021	https://play.google.com/store/apps/details?id=com.loanfortune.fortuneloanloan&hl=en_IN&gl=IN
102	POPO Loan - Personal Loan	8/3/2021	https://play.google.com/store/apps/details?id=com.clrfulwis.dbrdtrazd.cfwdrz&hl=en_IN&gl=IN
103	TimePe - Instant Credit Line & Loan App	8/8/2021	https://play.google.com/store/apps/details?id=com.timepe.app&hl=en_IN&gl=IN
104	InstaCredit - Instant Personal Loan App	8/13/2021	https://play.google.com/store/apps/details?id=com.arinfosoft.instacredit&hl=en_IN&gl=IN
105	Fast Speed Loan : Instant Personal Loan	8/30/2021	https://play.google.com/store/apps/details?id=com.funzilla.instantloan.fastloan.speedloan.androidapp&hl=en_IN&gl=IN

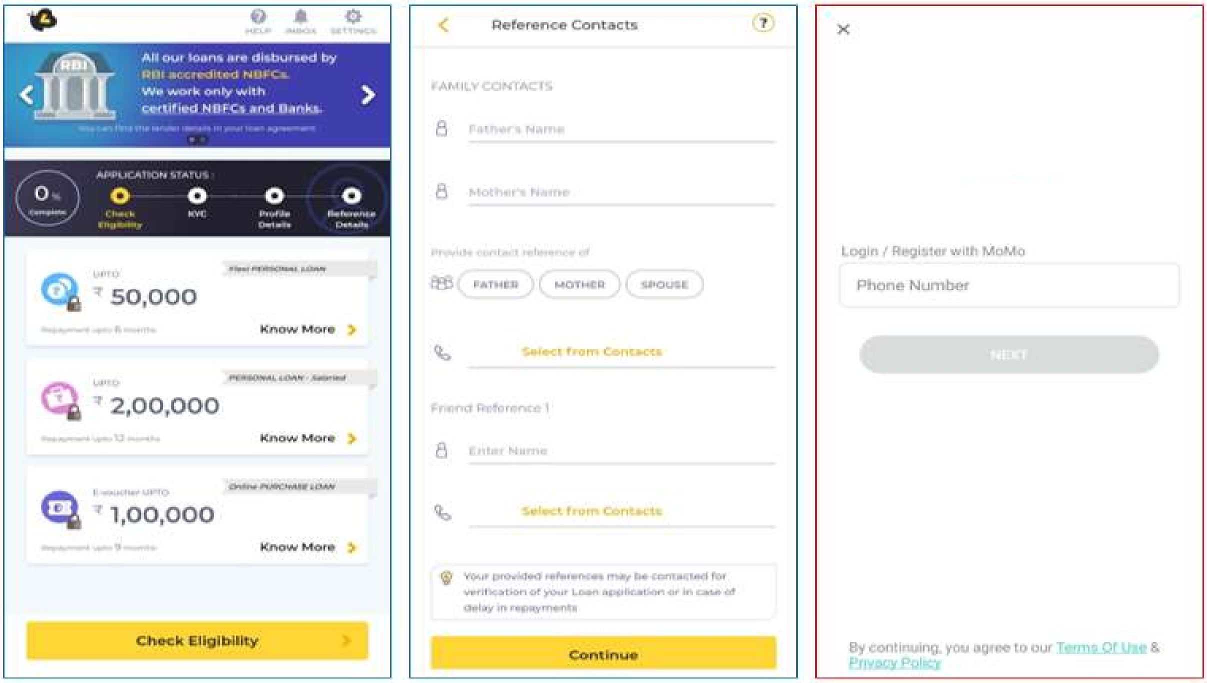
106	InstaLoan - Instant Personal Loan App	8/31/2021	https://play.google.com/store/apps/details?id=com.instaloan.app&hl=en_IN&gl=IN
107	SharpLoan-Personal Loan APP	9/2/2021	https://play.google.com/store/apps/details?id=com.sharploan.android&hl=en_IN&gl=IN
108	Now Loans-Instant Personal Loan App Online Loan	9/22/2021	https://play.google.com/store/apps/details?id=com.india.nowloan&hl=en_IN&gl=IN
109	Personal Loan - Gold male	10/14/2021	https://play.google.com/store/apps/details?id=com.gold.phonpay.paytm.pay.cash.pro&hl=en_IN&gl=IN
110	Cash Cow - Personal loan	10/14/2021	https://play.google.com/store/apps/details?id=com.indiacashloan.cashcow&hl=en_IN&gl=IN

3. Process Chart

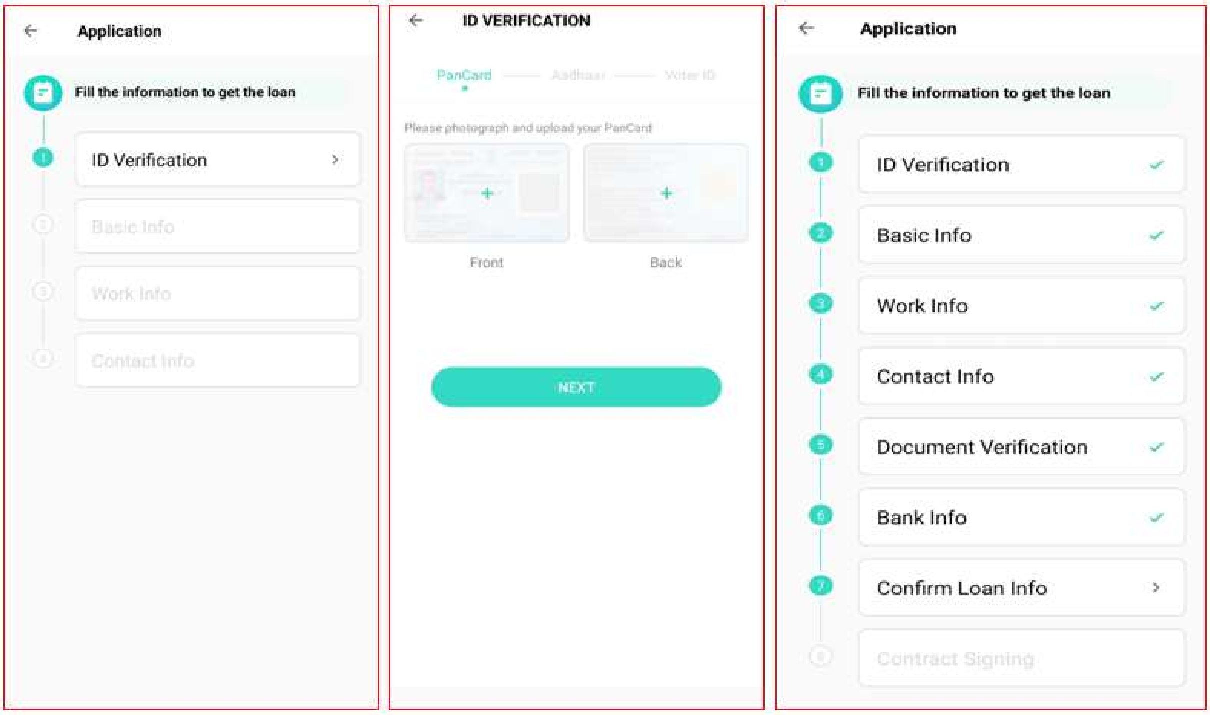
a. Installation Process



b. Sign Up



c. User detail filling, verification and application of loan



4. User Reviews (5 to 1 star ratings)

Marak Richil
★★★★★ 19 April 2022
2919

I was bit skeptical as my credit score recently reduced due to a loan which I am trying to close but I don't know where to pay as they stopped auto debit from my account. Other than that all my active account has timely repayment history. But kreditbee may have ignored that portion and approved my loan request. although the amount is small, but sometimes it can be very useful. The payable interest and service charges can be justified as they are just doing business. Thanks!

Bijoy PAUL
★★★★★ 29 April 2022
322

Mainly the Agent's presentation is very well and they are very friendly and their concept is very clear and reliable. Almost Kreditbee is one of the best lending partner. Very nice very well very secure...

Techabhi
★★★★☆ 13 March 2022
809

After reading many negetive feedback in play Store, I took chance and applied. I applied for 30k at night and balance credited in morning. Surprisingly it worked well. But interest rate is high enough. It is better to plan and apply personal loan from bank for lesser interest rate. But when we require emergency money, it is better than beg to somone.

Subash king Yasss
★★★★☆ 22 March 2022
384

As soon as I uploaded my documents amount has been credited to my account,I tried many apps but no one responded so quickly and credited money ,but if there issue in paying back it is not good to me if any extra hidden charges are there I would be upset ,so hoping for the best for supporting me while paying back....another review will be next thanks u all for the best . however it is best app I have seen

Vaibhav Desai

★★★★★ 29 April 2022

Everything is good. I close my 1st loan and applied for next loan but they can't increase amount for next loan. That's why i m disappointed with kreditbee. And also they charge huge amount for processing and intrest.

Swati Mishra

★★★★★ 7 May 2022

1

App is not bad ....I using this app since months every thing is fine but credit limit is very low .. while I make a repay on time after that If limit is not increase that's affected

Yash Malhotra

★★★★★ 30 April 2022

13

I used this app to take loan 2 times my payment history is good and I was assured last time that you take this loan and repay on time Then next time I will be eligible for a higher amount I take the loan and repayed it on time . But the same I have no bigger amount to take So sorry if in 2 times I can't get a good amount it's useless with such a smaller account to use it Thanks Call me when you have a better option for me

Pawan Chauhan

★★★★★ 6 May 2022

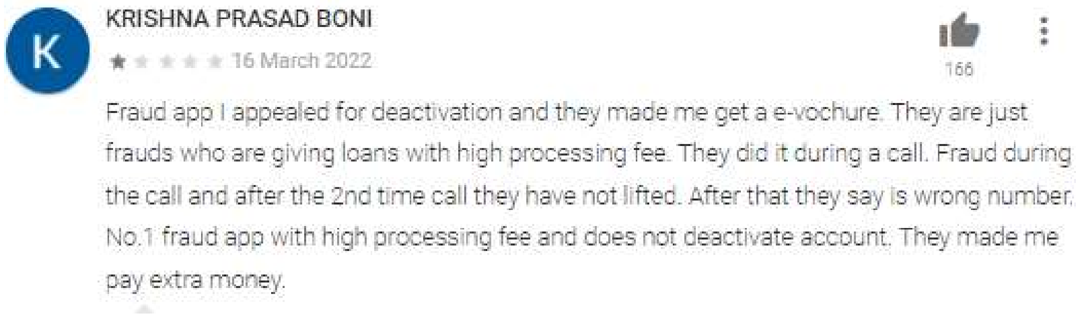
I have applied for a loan and loan also approved and i have also get approval letter but I waiting from 3 rd of may loan not credited in my account its showing under transfer process. I have called many time on customer care number but no resonce also not getting mailing resonse.

Snehal Jadhav

★★★★★ 2 April 2022

3128

I paid my current due n 2 future dated dues today so as to close the current loan and apply for higher loan amount. But now your app says I'm not eligible. Last month itself you also provided credit card benefit now that is also disabled. Very bad service experience. There should be some manul intervention as well to check customer's worthy. Very bad service experience.


KRISHNA PRASAD BONI

16 March 2022

166

Fraud app I appealed for deactivation and they made me get a e-vochure. They are just frauds who are giving loans with high processing fee. They did it during a call. Fraud during the call and after the 2nd time call they have not lifted. After that they say is wrong number. No.1 fraud app with high processing fee and does not deactivate account. They made me pay extra money.

5. LIWC Variables

No.	**Category**	**Abbrev**	Description/ Examples
1	Positive tone	tone pos	good, well, new, love
2	Negative tone	tone neg	bad, wrong, too much, hate
3	Positive emotion	emo pos	good, love, happy, hope
5	Negative emotion	emo neg	bad, hate, hurt, tired
6	Sadness	emo sad	sad, disappoint, cry
7	Risk	risk	security, protection, pain, risk