Using NLP on Social Media to Assess Consumer Risks with Digital Lending Apps in India

Eric Duflos
Jayshree Venkatesan
Juan Carlos Izaguirre
Majorie Chalwe-Mulenga

Daryl Collins
Prava Reddy
Marcia Almeida-Mendes
Derry Moore

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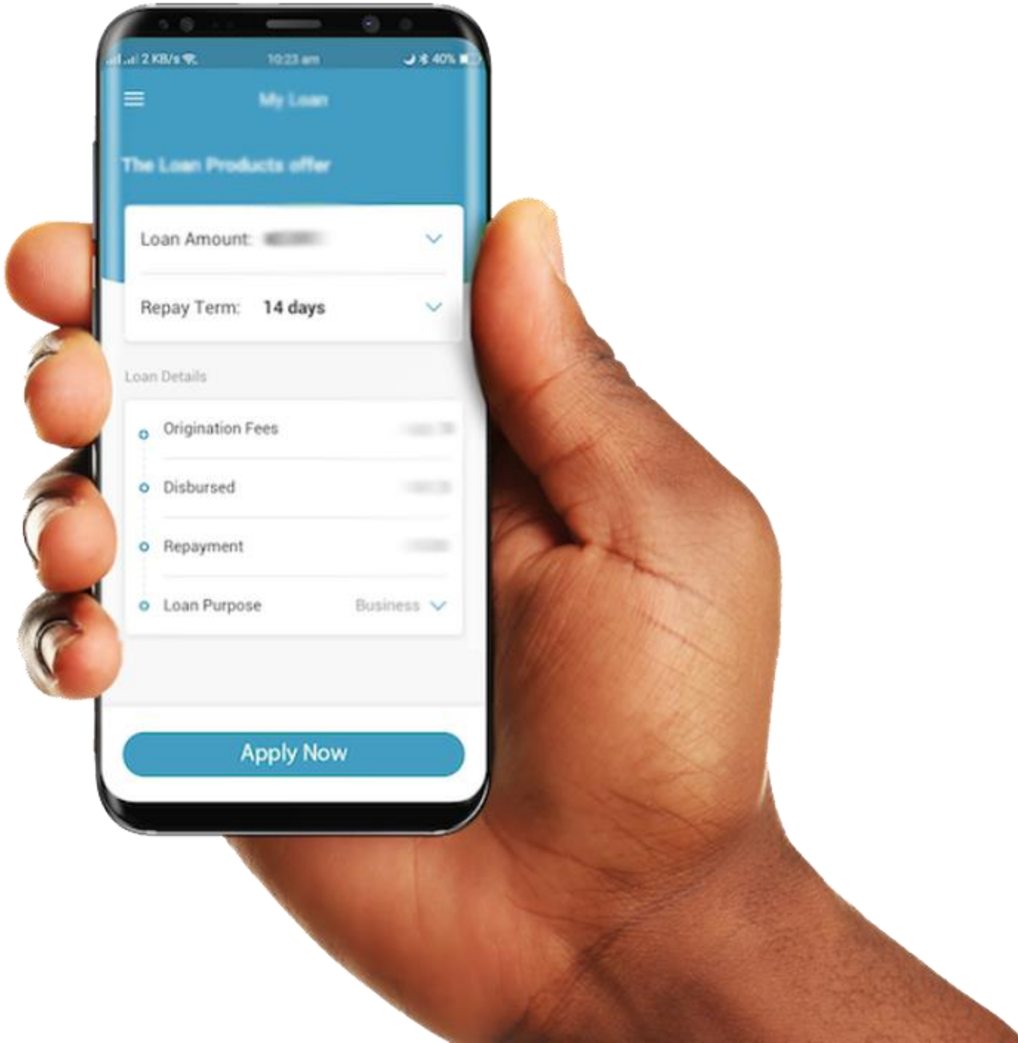

Disclaimer

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Agenda

- Introduction
- Summary of Lessons learned
- Methodology
- Key findings
- Benefits and Limitations

Introduction

CGAP Protecting Vulnerable Customers Project:
Three Workstreams

The research presented here is part of the CGAP Protecting Vulnerable Customers project. The project has **three workstreams** that aim at ensuring good outcomes for customers in their use of financial services, with a focus on women and digital finance.

- **The first workstream** aims at empowering market conduct supervisors, regulators and other stakeholders to monitor consumer risks with a market monitoring toolkit (forthcoming).
- **The second workstream** focuses on elevating the collective voice of consumers ,for example through social media, consumer associations and regulatory consumer panels.
- **The third workstream** aims at showcasing providers that adopt business models that protect customers and help them reach positive outcomes in their use of financial services.
- In addition, CGAP is conducting a cross-cutting research on the evolution of the scale and the nature of consumer risks in digital finance.

- The research with Mubulushu International is meant to test a tool that can help **monitor the market** (workstream 1), support the **collective voice of consumers** (workstream 2) and also test a **new typology of consumer risks** identified through CGAP's cross-cutting research.

Workstream 1: Market Monitoring Toolkit *(forthcoming)*

The Market Monitoring Toolkit (MMT) will be published in September 2021. It provides tools to help supervisors better understand the nature and scale of risks and problems in the market and take action. It contains guidance for each monitoring tool and country examples:

Below is the list of tools and the type of information that will be provided for each tool.

Analysis of regulatory returns	Analysis of complaints data	Phone surveys	Social media monitoring
Analysis of consumer contracts	Mystery shopping	Industry engagement	Thematic reviews

- ✓ Benefits & opportunities
- ✓ Characteristics
- ✓ How to use this tool?
- ✓ Limitations & challenges

Workstream 1: Market Monitoring Toolkit *(forthcoming)*

The MMT will include six case studies illustrating implementation of tools

Mexico	Tanzania	Kenya
Ireland	Portugal	Russian Federation

- ✓ Background
- ✓ Purpose & incentives
- ✓ Methodology & data ecosystem
- ✓ Staff & other requirements
- ✓ Vendor selection
- ✓ Benefits and impact
- ✓ Limitations & challenges
- ✓ Future plans
- ✓ Learnings

The MMT will also include the following information:

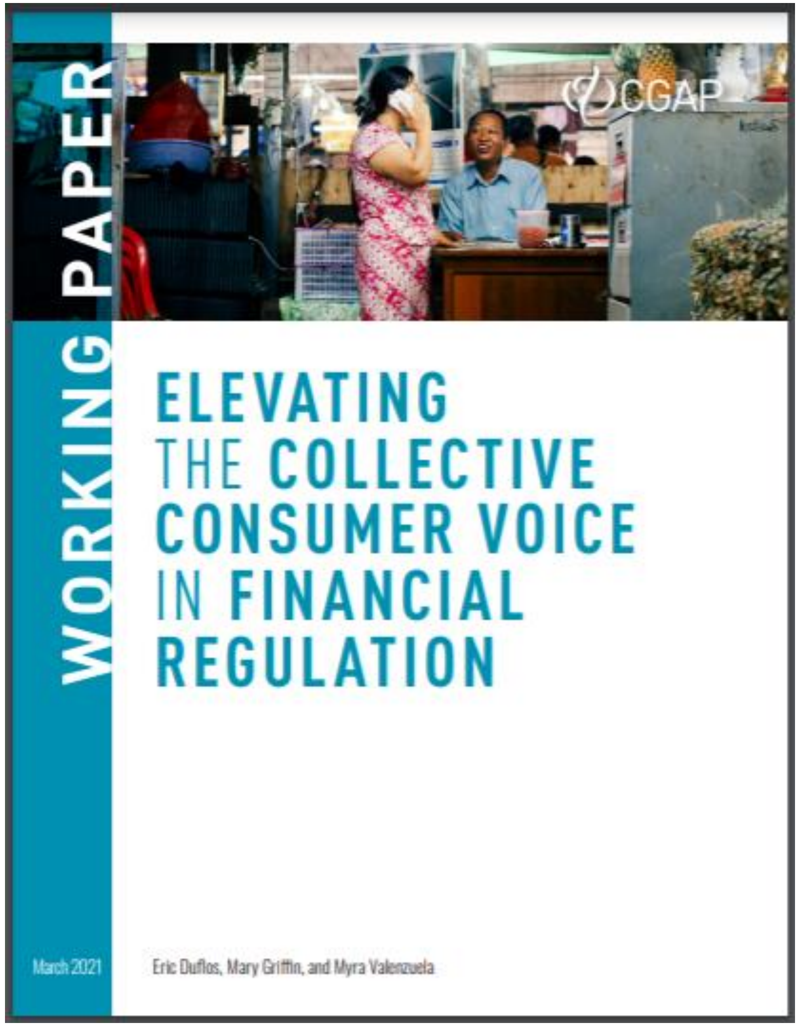
- Supplementary materials (e.g. templates, questionnaires, ToRs)
- How other stakeholders can support market monitoring
- Frequently asked questions
- Additional resources

Workstream 2: Elevating the collective voice of consumers in financial regulation

Three mechanisms identified and being tested in pilot research projects

- **Consumer associations**: currently exploring how to build the capacity of consumer associations with Consumers International.
- **Social media / Suptech**: research on NLP in India (this research) and a pilot in Peru with SBS and INDECOPI on setting a consumer listening system inclusive of social media.
- **Regulatory consumer panels**: currently testing this approach with FSCA in South Africa.

https://www.cgap.org/research/publication/elevating-collective-consumer-voice-financial-regulation



CGAP's cross cutting digital finance consumer risk research *(forthcoming in September 2021)*

As part of this research, CGAP has identified 62 specific risks organized in 4 types of risks.
We have used this typology as a reference when looking at customer risks in India.

Fraud

Examples
- Smart phone espionage
- SIM swaps

Misuses of data

Examples
- Data breaches
- Unfair practices

Lack of transparency

Examples
- Unauthorized fees
- Complex user interfaces

Inadequate redress mechanisms

Examples
- Complex redress process
- Social norms

Summary of Lessons learned

Using NLP and social media to assess digital lending apps in India

Using social media to assess consumer risks

What did we do in this research exercise?

- In this pilot project, we extracted data from Twitter and Google Play reviews relevant to digital consumer lending apps in India between January 2020 and May 2021.
- We used Natural Language Processing (NLP) – a common market tool – to analyze the data, identify **consumer complaints** and identify the degree of **urgency** with various consumer risks.
- We used the number of downloads of these apps to estimate the number of users to **“size” the extent of the problem.**
- Lastly, we used this data to identify potential **bad actors**.

IMPORTANT	Note that the objective of this pilot project was to demonstrate what can be found through NLP analysis on social media content. **To fully validate the findings, however, the coding process would require further iterations and testing**.

Lessons learned

about digital lending apps with NLP on social media data

1. **Ability of these data points to identify market risks**
   a. Google Play reviews provided an **"early warning signal"** for rising consumer risks in digital lending apps. That means the analysis picks up consumer complaints before they appear in the news media.
   b. Twitter showed **"persistence"** of complaints even after 312 apps were removed from Google Play, which shows that this analysis on consumer complaints remains the same even after a policy action is taken.

2. **Nature of the problem**
   a. 25% of all combined complaints in Twitter posts and Google Play reviews are tagged as urgent.
   b. 45% of Twitter complaints and 17% of Google Play reviews were concerning aggressive debt collection, which causes high stress among users.
   c. Claims of "fake apps" are 23% of Twitter complaints and 28% of Google Play reviews.
   However, these correlate to and echo media claims of "fake apps."

3. **Size of the problem**
   a. The overall complaint ratio to users (combined Twitter posts and Google Play reviews) is 0.25%.
   b. There are 7 sizable digital lender apps that would warrant further investigation, ranging from 1% of the market to 9% of the market.

Benefits and limitations
of this market monitoring tool

Benefits

1. Provides an **early warning system** about the market
2. Allows monitoring **unregulated** services & providers and **proactively** identifying issues, apps needing more attention.
3. Generates results **quickly and inexpensively**.
4. Provides a channel to directly **capture voice of consumers**.
5. It is possible to **detect the urgency** of different consumer complaints and problems.
6. It is possible to analyze **Hindi tweets in Hindi script,** which are important to assess the urgency of complaints.
7. This method **cannot be replaced** by looking at app ratings.[2]

Limitations

1. Not easy[1] to detect what **consumer segment** (e.g. age, gender, geography) is making the complaint.
2. No insights from those not posting tweets or reviews.
3. Cannot estimate number of users of each app.
4. Cannot fully assess consumer risk levels for each app.
5. Takes effort to find the right Twitter accounts to track.
6. Twitter data is not always tagged to a specific app.
7. Context matters: Sometimes popular news stories can be echoed in the content of Tweets.

[1] However, it is possible, using new techniques that researchers are now exploring.
[2] In this presentation we discuss "complaints" which we detect with Natural Language Processing (NLP) analysis of reviews and tweets. We also discuss "ratings" which are Google Play ratings from 1 to 5 given by those who download the app.

Methodology

Steps we took
Process and tools we used

Research — Find digital lending apps

Research — Find Google Play reviews and Twitter hashtags

python — Scrape data from Google Play and Twitter[1]

python — Clean data by removing hashtags, app names, and unnecessary characters

python — Perform topic modelling to find keywords[2]

meaning cloud, Excel — Perform topic classification on complaints and urgency

NATURAL LANGUAGE PROCESSING

Excel — Do simple analysis on complaints and urgency by app and over time

[1] Used the SnScrape library on Python, because Tweepy would only allow for 7 days back which is not ideal.

[2] Also did topic modeling in Hindi with Hindi script using snowballstemmer, Indic NLP and a database of stopwords created by multiple individuals.

How we chose the apps to analyze

The universe of digital lending apps

Our logic	Description	# of apps
We initially built our universe based on an existing consumer collective database	Number of digital lending apps from Cashless Consumer[1]	469
We then deleted those apps taken off Google Play	Number of digital lending apps taken off Google Play by May 2021[2]	- 312
This then gave us the universe of apps for this exercise	Number of digital lending apps analyzed for this exercise	= 157

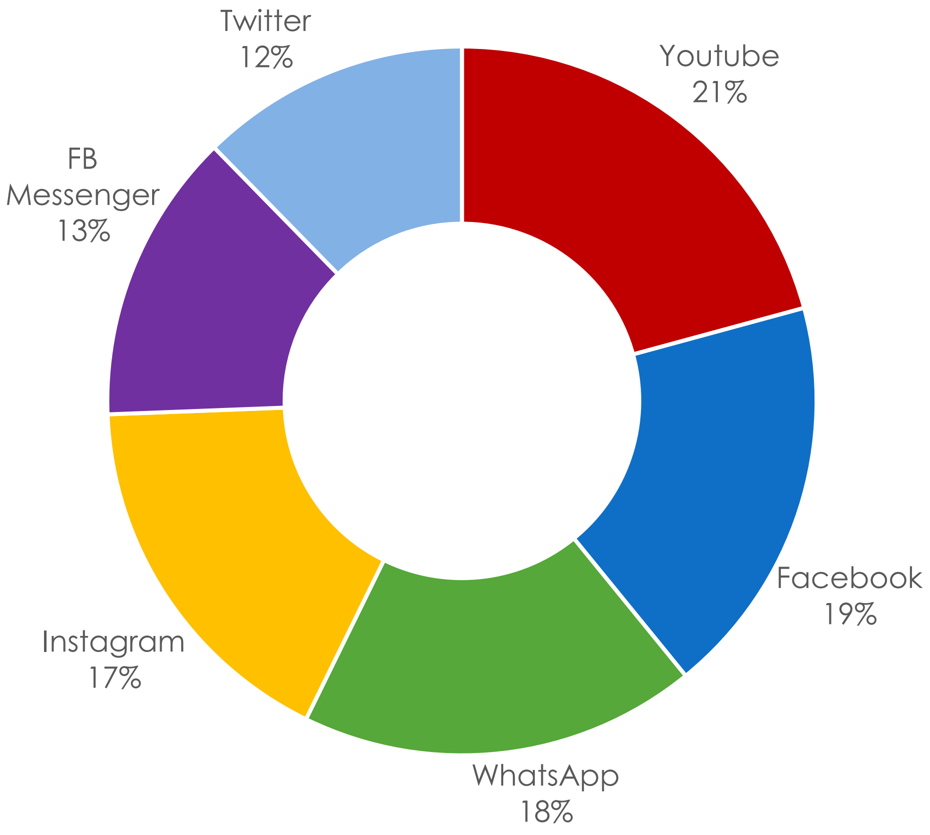
In the two months since we started this research, there are another 50 Indian digital lending apps on Google Play.

[1] https://medium.com/cashlessconsumer/fake-digital-lending-apps-database-b5de323f6d1b

[2] Determined which digital lending apps were taken down by reviewing in Google Play

How we chose which social media to analyze

Est. 448 million adult active social media users in India



Source: Statistica, as of January 2021, self-reported usage of each platform in the month.

Why did we choose Google Play reviews?

- We can link the reviews on the app to the number of downloads, allowing us to begin to size the market and the comparative number of complaints.
- Reviews are about positive and negative complaints and are open to the public.

Why did we choose Twitter?

- Twitter is used for public discussion, advocacy and generating a collective voice.
- YouTube is used for sharing videos – digital lenders use to advertise, but not for consumer complaints.
- Facebook tends to be peer-to-peer and not about sharing views; lending apps have Facebook pages and answer questions via Facebook Messenger, but they are more about advertising.
- WhatsApp and Instagram have public groups but usually by invitation or by receiving a sharable link.

Analyzed Data

79,153[1]

reviews analyzed

between January 2020 and May 2021

157 apps analyzed

Languages of reviews analyzed[2]

95.65% in English with Latin script

3.9% in Hindi with Latin script

> 1% in Marathi, Tamil, Kannada

73,485[1]

tweets analyzed

between January 2020 and May 2021

3 hashtags with **RBI, SEBI, CIBIL**

5 issue-specific hashtags

62 hashtags with names of digital lending apps

Languages[3] of tweets analyzed

73% in English

7% in Hindi

14% in combined language

> 1% Marathi, Tamil, Telugu

[1] Note that one of the weaknesses of using social media data is that we cannot guarantee that each review/Tweet is from a **unique user**.

[2] Does not include one-word reviews.

[3] Analysis in Hindi required knitting together multiple language libraries and code bases from multiple sources. However, continued progress on creating NLP resources in different languages will contribute to development of market monitoring tools using NLP globally

Which consumer complaints did we focus on?

CGAP Typology	Risk	Examples
Fraud	**Information/Identity stealing** ID information could be used for ill-intentioned purposes	This number 8792662456 from my cash app. Call me back to back and call my contacts without my permission. they calling my contacts and misusing my personal data. #BanLoanApps @RBI @RBIsays @CyberGujarat @DelhiPolice @GujaratPolice @BanegaAb
	Fake app or scam Complaints that apps deliberately fail to register payments or do not provide loans at all	'@RBI @SCSC_Cyberabad Loanfront Digital landings app scams m Already paid my loan amount but civil showing me not paid @GoLoanFront
Lack of transparency	**Hidden terms** Complaints that terms for loan repayment, disbursement or interest rates were not fully disclosed at the time of contract	"@Early_Salary your third party recovery agents call me 10 times today and also send me dhamki massage daily morning..and also you charge me 10000 rs extra intrest charges. please send me charges details #OperationHaftaVasooli@indSupremeCourt @KiritSomaiya https://t.co/yZ4ztYswBB"

Which consumer complaints did we focus on?

CGAP Typology	Risk	Examples
Inadequate redress mechanisms	**Unresponsive complaints procedure** Complaints about not being able to reach customer service or not getting a satisfactory response from them	I have repaid my loan amount but still app showing active loan.. emailed sent so many time no response received. Too slow customer service.
	Complaints channels too costly Complaints of transactional costs or time-consuming process	Worst first impression, It has been 13 days already the money is not yet disbursed to my Bank account where it's said they ONLY take 1 business day..No way to speak to any customer care service over a phone call and if u talk about emails it remains unanswered everytime... Every step is check marked except the last one where my money should be disbursed.... Now i fear that the loan is not disbursed and they are planning to auto debit EMI they have signed a mandate... This is ridiculous.
Misuses of data	**Inaccurate data** Concerns about apps having / reporting wrong data about them	Please update correct consumers credit score details, many banks & nbfc's are giving wrong details to systems, especially HDFC BANK..... please check & verify details then update... it is humble request to your system please first collect all data from banks & nbfcs then update....
	Aggressive marketing or cross-selling Complaints of excessive calling, pushing undesired services	This app ruined my credit score, after login so many marketing calls and sms received from various sources, it means paisa bazar leaks our important data, useless and senseless customer care Executives [...]
	Aggressive debt collection Complaints of harassment through visits, excessive SMS or calls to customer and others in their contact list	'@zeebusiness @AnilSinghvi_ #OperationHaftaVasooli Sir kisi door ke relative ne credit card ka bill nahi pay kiya They found me on Facebook nd started calling me on my mobile also on landline and using very bad abusive language. I don't know what to do..

Natural Language Processing:
Topic Modelling vs Topic Classification

NATURAL
LANGUAGE
PROCESSING

Step 1 Topic Modelling

python™

Finding topics by groups of keywords

- We run the dataset on Python© to find which words are likely to occur together
- The output is a set of keywords, which helps us see emerging themes

Topic	Keywords	Theme
0	customer, service, call, response, team, send, mail, support, care, number	Recourse

Step 2 Topic Classification

meaning cloud

Refining topics, informed by Step 1 results

- We then set "rules" for MeaningCloud© to find relevant entries
- The output is a set of phrases that describe a complaint

Category	Rule
Poor recourse channel → dispute channels unresponsive	call|helpline|callcenter|callcentre|mail|email|e-mail|chat AND "pick up" OR pickup|pick|centre|center|busy|number|disconnect|same|reply|respond|response|answer|automated|robotic

Pipeline (|) is same as "OR"

Topic Classification

Detecting types of complaints and urgency of each

NATURAL LANGUAGE PROCESSING

Topic	Search rule[1] to find relevant entries	Example of relevant entry
Identity or information stealing	(information OR data) AND (personal OR confidential)	"This number 8792662456 from my cash app. Call me back to back and call my contacts without my permission. they calling my contacts and misusing my **personal data**."

- Topic Classification **works like a very complex word search on a word document**
- The software scans the data set for entries that match the rules and classify them accordingly

Finding urgent complaints

- We also classified urgent complaints using:
  - Language of distress
    - **Pleading** and **Cursing**
  - Highly "charged" language
    - **Suicide and Mental Anguish (abuse)**

'@RBI My issue is I took loan from a (CREDIME APPLICATION) amount 3000 available in Play Store everytime but due to covid19 I lost my job,iam facing problem for daily food,support team created a group on my name as fraud ,they taken my contacts and Black mailing me **please** help sir

[1] Note: rule is simplified here for illustration purposes. It can be written with various parameters to refine search.

Key Findings

Customer "complaint" journey

How consumers use Google Play reviews and Twitter in their complaint journey

Google Play reviews about complaints procedure and Twitter complaints about "fake app" refer to the rejection process, earlier in the journey

Google Play and Twitter complaints about aggressive debt collection is further down the customer journey and mostly for the paying process, when in default.

Decision-making

Investigating; considering; using an ancillary product, like phone top-ups

Applying

KYC process; providing personal data

Result

Approval or rejection

Disbursement

Loaned funds become available

Loan repayment

A) Default

B) Not default

After payoff

Consumer's digital credit journey

Describing the nature of the problem

Which complaints are most often cited, and which are the most urgent?

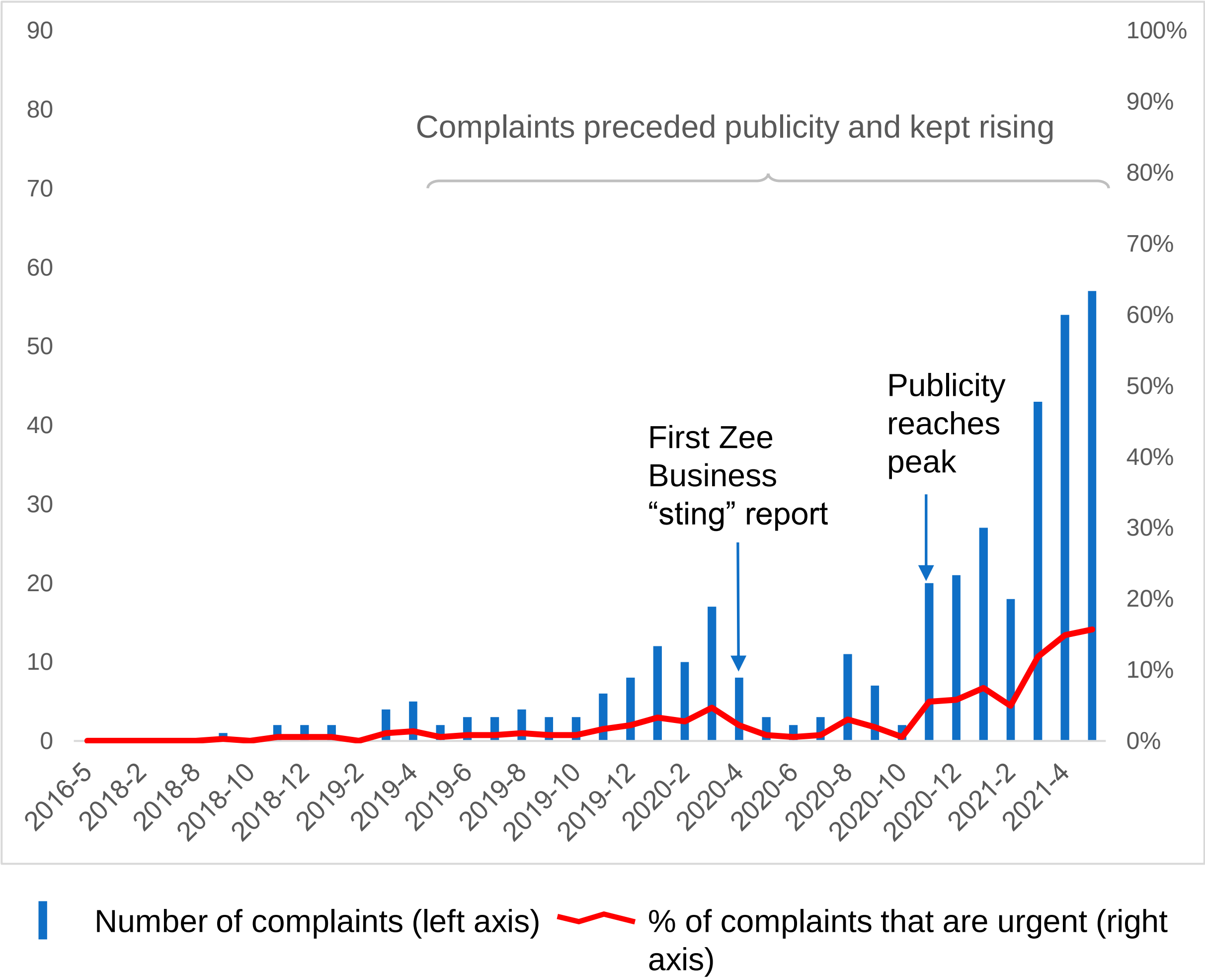
Twitter

Google Play reviews

Google Play reviews

show potential to be an “Early Warning Signal”

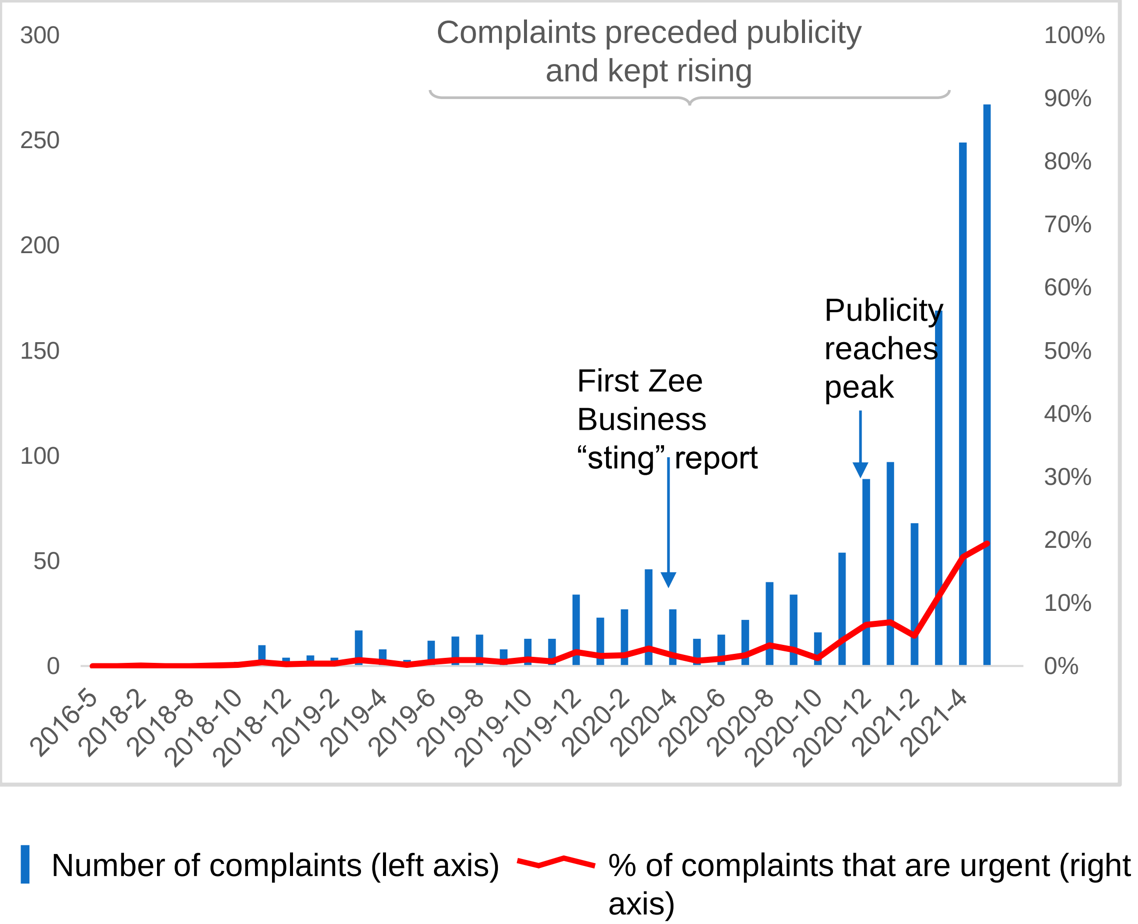
Misuses of data: Aggressive debt collection



- Reports of aggressive debt collection started **climbing in late 2019**, well before the first Zee Business “sting” report in April 2020 and news articles in December 2020.
- The number of complaints and the urgency of them are **both rising** at the same time.
- There is an initial peak in early 2020 and then new peaks being hit in 2021.

Google Play reviews
show potential to be an “Early Warning Signal”

Poor recourse channel: Complaints procedure

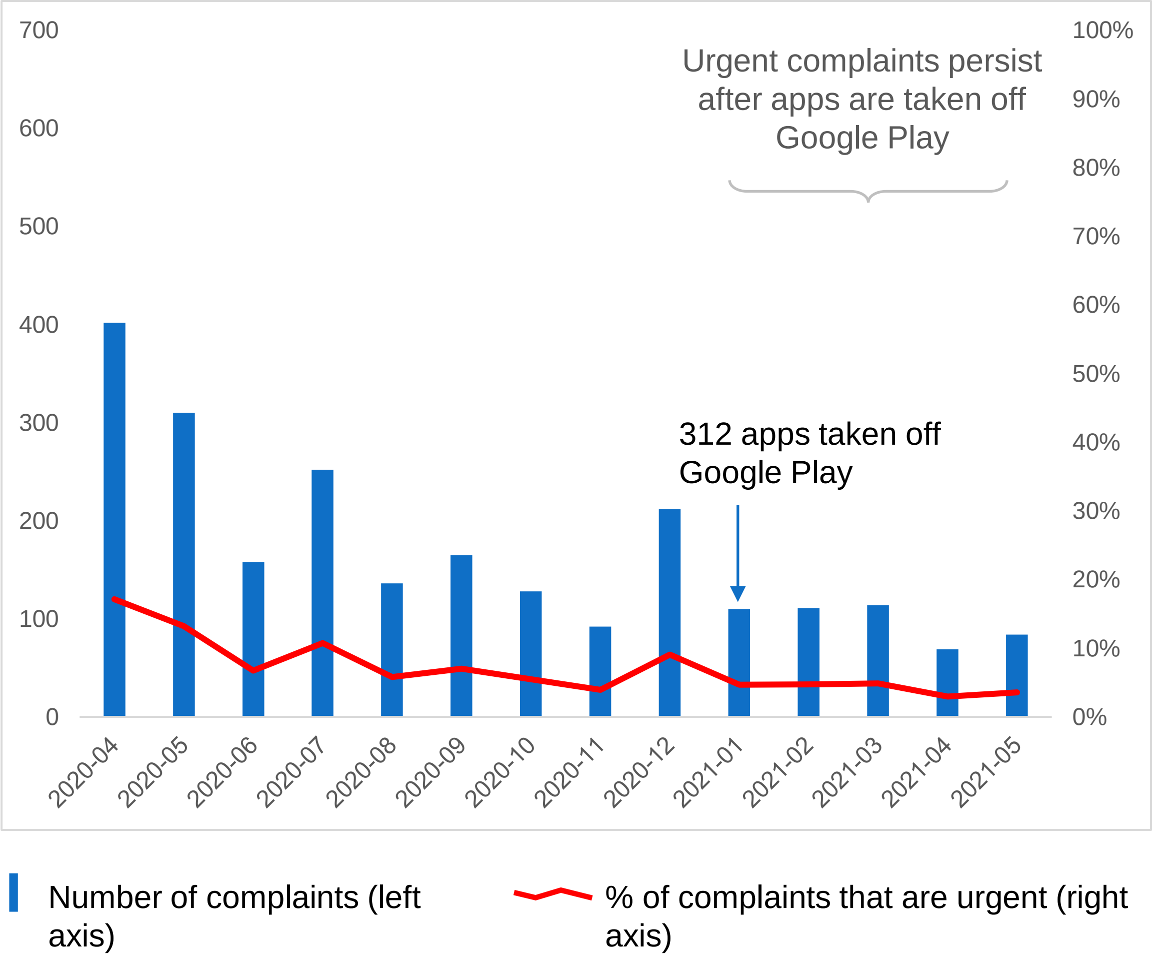


- Reports of poor recourse channels started climbing in early 2020, **before** the first Zee Business “sting” reports in April 2020 and news articles in December 2020.
- The number of complaints and the urgency of them are **both rising** at the same time.

Twitter

show persistence even after shutting down many apps

Lack of transparency: Aggressive debt collection

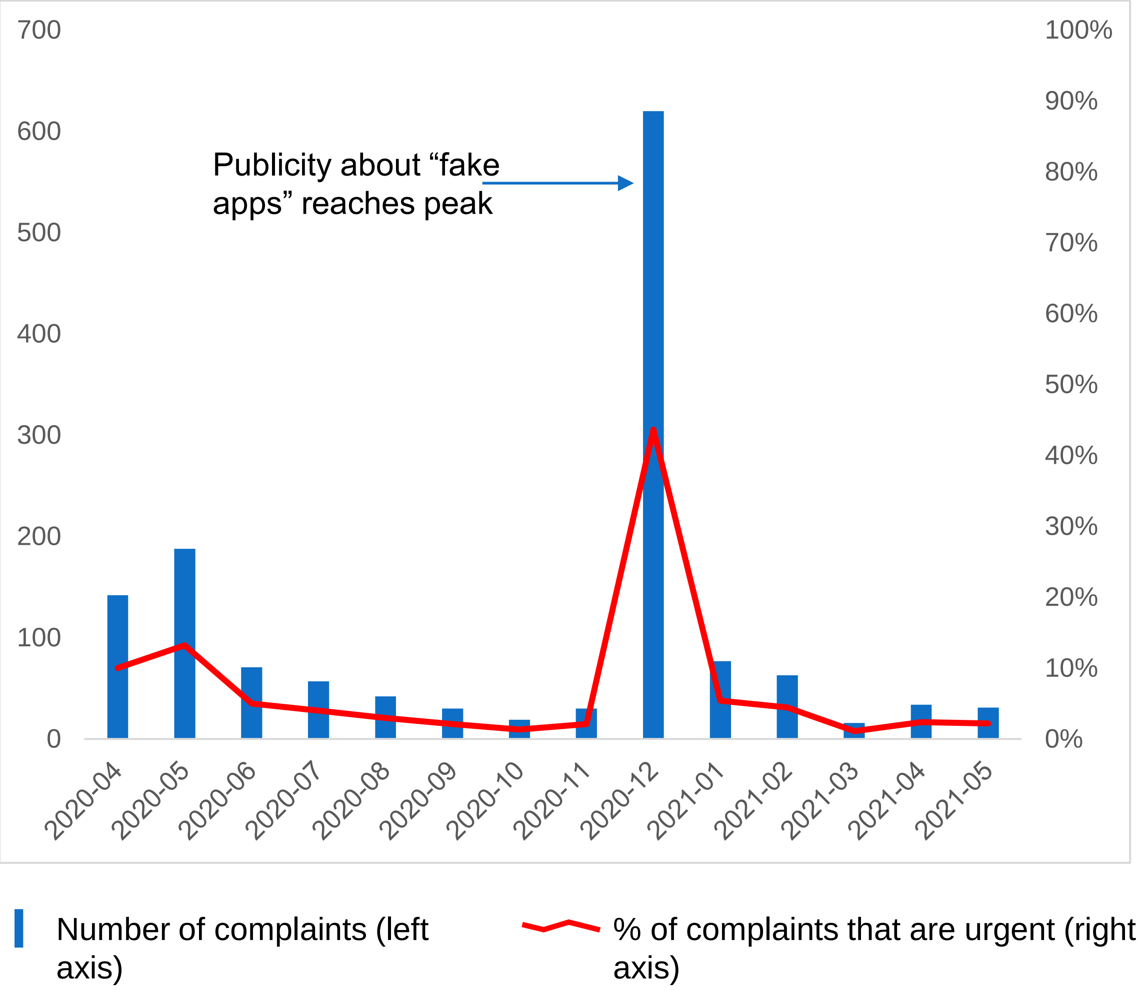


- Twitter shows that complaints and urgency of complaints persist **even after apps taken off Google Play** in January 2021.

- Note that two-thirds of the complaints from Twitter are **topic-specific** while only one-third are **app-specific**. Therefore, Twitter represents more of a view of the market than specific apps.

Twitter
false signal?

Fraud: Claims that this is a "fake app"

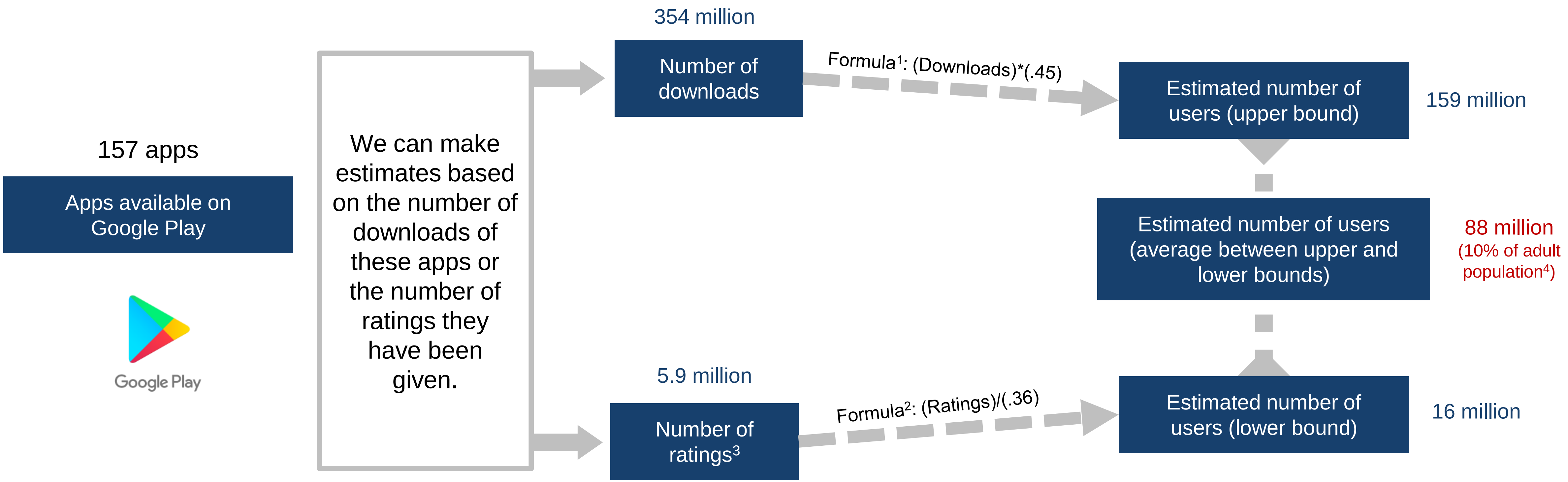


- The most complaints about "fake apps", along with a spike in urgency came exactly as there **were many news stories about digital lending apps.**

- With a Twitter channel, which is public, there is a possibility that this is a **"false signal"** that reflects reactions from the news stories rather than real complaints.

Sizing the problem:
How many users of digital lending apps are there?[1]

We used two different approaches to make a conservative estimate.
BUT a weakness of analyzing social media data is that we can only estimate number of users.



[1] Globally, less than half (~45%) of downloaded (or installed) apps are used (Simform).
[2] Globally, only about 1/3 (36%) of customers give feedback (CFIGroup).
[3] Note that our analysis searches Google Play reviews and Tweets for different *complaints*. This is different from *rating* from 1 to 5 that a user might give an app on Google Play.
[4] World estimates for population between 15 – 64, 2020

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Sizing the problem:
Market-level indicators

	Complaints to user ratio	% urgent	% aggressive debt collection
Twitter	0.46%	23.2%	48.9%
Google Play	0.18%	19.3%	12.5%
Combined Twitter and Google Play Reviews[1]	0.25%	24.5%	16.0%

[1] Note that the table above represents only those apps which have app-specific Twitter hashtags, which is only 1/3 of the sample for Twitter.

Sizing the problem:
Potential “bad actors”

	% of market[1]	Complaints to user ratio	% urgent	% aggressive debt collection
Benchmark				
Overall market	100%	0.25%	25%	16%
From the top 75% of the market				
App 1	3%	0.04%[2]	81%	39%
App 2	1%	0.04%[2]	91%	35%
App 3	9%	0.001%	29%	46%
App 4	7%	0.01%	53%	43%
App 5	2%	0.02%	45%	35%
App 6	1%	0.02%	49%	28%
App 7	1%	0.20%	59%	40%
Worst performers in market				
App 8	0.002%	9.9%	74%	25%
App 9	0.014%	0.73%	57%	17%

Note that app names are concealed as this was a pilot only.

[1] Based on number of downloads; [2] Highest of top 75% of apps by download

Benefits and Limitations

Benefits

of using social media to monitor digital lending apps market

NLP analysis on social media can complement other market monitoring tools to assess consumer risks in digital credit:

1. Acts as a broad monitoring tool that can detect **early warning signals** about the market.
2. Helps monitor consumer issues following a **policy or industry response** (e.g. after apps being removed from Google Play).
3. Runs **inexpensively** and can be done **frequently** to provide ongoing market monitoring.
4. Detects trends on specific complaints in the market and the **urgency** with which they occur.
5. Directly captures the **voice of consumers** and gathers quantitative and qualitative information on the nature of consumer risks and outcomes.
6. Proactively and **preemptively** identifies consumer issues and apps that might warrant further investigation.
7. Allows monitoring and better understanding of **unregulated** providers and services.

Limitations

of using social media to monitor digital lending apps market

This tool cannot:

1. Detect the number and nature of complaints from those who cannot or will not “tweet” or complete a Google Play review.
2. Comprehensively and precisely assess the level of consumer risks for each app.
3. Identify the profile of those who make the complaints.
4. Validate estimates of number of users of each app.

Other limitations:

- Context matters: Sometimes popular news stories can be echoed in the content of Tweets.
- It can take effort to find the right Twitter accounts to track.
- Twitter data is not always tagged to a specific app.