

Using Open APIs To Drive Financial Inclusion Via Credit Scoring Built on Telecoms Data

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Abstract: Financial exclusion remains a significant challenge in developing economies. It has been shown that access to credit facilities is a strong predictor of financial inclusion. Credit reporting and scoring remain effective tools for both traditional and alternative lenders, however, access to credible credit data and scoring mechanisms is one of the biggest roadblocks that alternative lenders in developing economies face. While some lenders have developed systems that leverage social media analytics and data harvested from smartphones in order to create a scoring system, the poor and vulnerable are still excluded from such scoring systems. There have been significant advances in the use of telecoms data for credit scoring, making it a promising alternative to credit bureau data. However, readily available data is still an issue. With the increase in the development and use of open APIs, telecoms data could be made readily available for credit scoring, while addressing privacy and other issues. This paper is a conceptual paper that proposes a model for the use of Open APIs from telco data for credit scoring that will ultimately increase access to credit, and ultimately financial inclusion in Africa.

Keywords: APIs, Credit Scoring, Economic Development, Financial Inclusion, Call Detail Records

1. Introduction

Technology continues to play a significant role in the financial industry and has been crucial for the adoption of financial inclusion. As technology continues to evolve, application programming interfaces (APIs) are beginning to play a more significant role in interconnectivity and service delivery in the financial services industry [1]. In recent years, open APIs have started to undergo standardization, and have been shown to be effective in promoting the interoperability, accessibility, and decentralization of data [2, 3]. In the same vein, mobile phones have become ubiquitous in recent years [4] and hence, have produced, and continue to produce, a massive digital footprint. The sheer amount of big data that is being created from the use of mobile phones alone is impressive and can be harnessed in order to predict user behavior.

Although still in its early stages, research based on the

analysis of the reliability of mobile phone data in the determination of creditworthiness has demonstrated that loan repayment behaviors can be predicted from mobile phone transaction records [5, 6]. Hence, call data for credit scoring shows a lot of promise as an alternative to credit bureau data. The main challenge to this in Africa and most developing economies is the availability and accessibility of data [7]. There is a need for an avenue whereby customer mobile phone data can be made available to lenders while still taking care of privacy and misuse risks. In this paper, we propose a model for the use of open APIs to take care of these barriers to the use of call data credit scoring as a tool to drive credit for financial inclusion.

2. Literature Review

Economic theorists and researchers have shown empirically that access to financial services, including credit, promotes economic development [8]. Facilitating the

availability of credit gives room for individuals and businesses to access investment capital, which in turn leads to growth in economic activity. Domeher and Abdulai argue that the role of credit in the development of the world's economies is even more crucial for developing economies [9]. The 2009 Financial Access report by the Consultative Group to Assist the Poor (CGAP) showed that there are about four times more loans per adult in developed countries than there are in developing countries [10]. As of 2014, more than half of the adults in the poorest households in developing countries did not own bank accounts [11].

Credit reporting and scoring remain effective tools for both traditional and alternative lenders. It has been shown that a functional credit reporting system solves the problem of asymmetric information between borrowers and lenders, which inevitably leads to adverse selection and moral hazard [12]. In situations where access to information is unavailable or asymmetric, the credit system becomes inefficient and out of reach to consumers [13]. On the other hand, information sharing alleviates these issues, as well as preventing information monopoly and over-indebtedness [14]. It also leads to the overall reduction of default and interest rates, and the general improvement of the borrower pool within the credit market [7]. Credit registries, by generating and providing access to information that aids lenders in the assessment of risk and decision making, contribute to the development of credit markets [11]. Jappelli and Pagano [15], and Miller [12] offer empirical evidence on credit reporting activities in different economies around the world to support the thesis that the availability of credit information enhances credit market growth [12, 16].

Access to credible credit data and scoring mechanisms is one of the biggest roadblocks that alternative lenders in developing economies face. The credit information systems in many developing countries are either non-existent or are still in their developmental stages, and information sharing between lenders is limited [7]. There are several reasons for this. Financial institutions in developing countries do not usually implement financial inclusion policies unless they see these policies as viable business propositions [10]. Linh *et al.* point out that while credit constraints exist in almost all economies, their effects are greater in developing countries as a result of collateral shortage and imperfect credit markets [17]. Jappelli and Pagano suggest that the effectiveness of credit bureaus in developing countries is hindered by the existence of a large informal credit market and that this effectiveness can be improved if credit bureaus are granted access to data from informal lenders [18]. The reality is that access to credit bureau data is expensive, and most times, out of reach for informal lenders. Empirical investigations carried out by Miller [12], and Jappelli and Pagano [15], show that the presence of credit information systems is closely related to credit market growth as well as lower credit risks in developed economies.

A number of economies have started to adopt novel scoring mechanisms that make use of alternative data. The rapid pace of development in technology and e-commerce is

making new avenues available for harnessing consumer data [12] and this is fueling the drive for financial inclusion across the world. One recent scoring mechanism that is gaining popularity is social media-driven credit scoring [13]. China's widely debated plan to implement a nationwide social credit system (SCS) by 2020 is one good example. With the continuing rise of reputation-based quantitative tools and social media networks, theorists are starting to wonder if the SCS will remain exclusive to the Chinese economy [19]. Economists are also postulating the use of data mined from utility payments, rental histories, clickstream behaviors, and even psychometrics in predicting loan repayment behavior [20]–[22]. Another mechanism, which is at this time not as well known or researched as the SCS, is credit scoring based on telecoms data. The research by Blumenstock, Cadamuro, and On, and Björkegren and Grissen, demonstrated that loan repayment behaviors can be predicted from mobile phone transaction records [5, 23]. The advantage that this will have over SCS is that while 76% of the world's poorest own mobile phones, only half of that group have access to the internet [24].

The use of mobile phone data as an alternative data source for predicting consumer behavior has been the topic of research and several studies in the last decade. In this section, we highlight notable research work that demonstrate the viability of mobile phone data as an alternative data source for credit scoring.

Blumenstock, Cadamuro, and On demonstrated in their research that an individual's mobile phone use history can be used to infer their socioeconomic status and that this information can be used to accurately and reliably reconstruct the economic characteristics of the population in any given economic market [23]. Their study made use of the mobile phone metadata from 856 unique individuals in Kigali, Rwanda, 1.5 million call detail records (CDR) over a period between December 2007 and March 2011, and data from two demographic health surveys (DHS). The correlation between actual wealth (as reported in the phone surveys) and predicted wealth (as inferred from mobile phone data) showed their model's ability to correctly identify the poorest individuals.

Björkegren and Grissen [5] evaluated the performance of mobile subscribers from telecoms data in a middle-income South American country where mobile subscribers are being transitioned from pre-paid to post-paid plans. Their sample included both banked and unbanked customers, and they compared the telecoms data they obtained with Credit Bureau models, which allowed them to evaluate consumer behavior with the Credit Bureau data as a benchmark. They found that the use of mobile data has the potential to achieve useful predictive accuracy when it comes to consumer behavior. They also found that past performance can be used to train the scoring model in order to improve its accuracy.

De Oliveira *et al.* carried out trials to make predictions on personality traits based on individual mobile phone call behavior [6]. They were able to show from their initial trial that call detail records (CDR) and social network analysis

(SNA) were successful in inferring the big five personality factors (openness, conscientiousness, extraversion, agreeableness, and neuroticism).

Pedro, Proserpio, and Oliver conducted a study using real credit default data from about 60,000 mobile consumers in a Latin American country and benchmarked the data from a traditional credit scoring mechanism against the data from mobile phone usage [25]. They were able to model consumers' propensity to default on credit based on their mobile phone usage. They combined data from mobile phone usage logs and financial information from credit default reports to train their user models. From their findings, they proposed the use of MobiScore, an approach that leverages passive mobile phone network data to build a model for predicted credit behavior using supervised machine learning.

Ruiz et al used logistic regression (LR) and support vector machine (SVM) models in comparing mobile phone data and data from traditional credit scoring systems. Their model outperformed traditional credit scoring methods and proved that non-traditional data can be effective in building algorithms that can identify creditworthy borrowers.

This section has given evidence that mobile phone data can be used as a predictor of credit repayment behavior and hence can be used as a platform on which to build a credit scoring system.

3. Methodology

3.1. Availability, Accessibility, and Sharing of CDR Data

The telecommunications (telecoms) sector is a fast-paced and competitively intense one. As a result, telecom providers are more and more concerned with upping their competitive intelligence game [26]. This competitiveness, while a positive tool to drive the growth of the Telecoms sector, poses a problem to the use of mobile phone data for credit scoring. Most Telcos consider customer data, including CDR, proprietary, and hence, their business policies and strategies restrict the sharing of data [27]. This makes access to credit data difficult for large lenders and close to impossible for the smaller ones.

It is important to facilitate a system whereby data sharing is secure, seamless, and effective. It is also important to ensure that the mechanism of data sharing is regulated. There would need to be in place some form of incentive for the Telcos to share their data. One possible way to achieve data sharing is through government directives, which could ride on the back of financial inclusion.

3.2. Open APIs to Facilitate Availability, Accessibility, and Sharing of Data

As technology continues to evolve, application programming interfaces (APIs) are starting to play a more significant role in interconnectivity and service delivery in banking [2] because they allow different applications, services, and interfaces to connect to each other seamlessly

[28]. Open APIs provide a viable solution to the issue of data availability and accessibility. They have the potential to allow lenders to have access to the required Telco data in order to make credit available to customers with little or no traditional credit history. This is made possible as a result of their underlying technology providing an interface (which is developed based on a set of agreed-upon standards) and a layer of abstraction that reduces complexity and allows external systems to connect to the API provider's systems without any knowledge or access to the API provider's system specifics [2].

3.3. Process Flow

1. A data broker (such as a lending company or a financial institution) will bind to the API endpoint provided by the Telco to request call data for a mobile subscriber.
2. The Telco will contact the mobile subscriber via USSD, email, SMS, App notification, or any other appropriate means, informing them that a data broker has made a request to access to their data, and if such access should be granted. The details of the financial institution/lender requesting information and the reason for the request must be clearly displayed to the customer.
3. The mobile subscriber will give approval by dialing a USSD code or through other means of authentication. The consent must be clear and explicit.
4. The API broker will connect to the data broker via their webhook and supply them with the specific data.

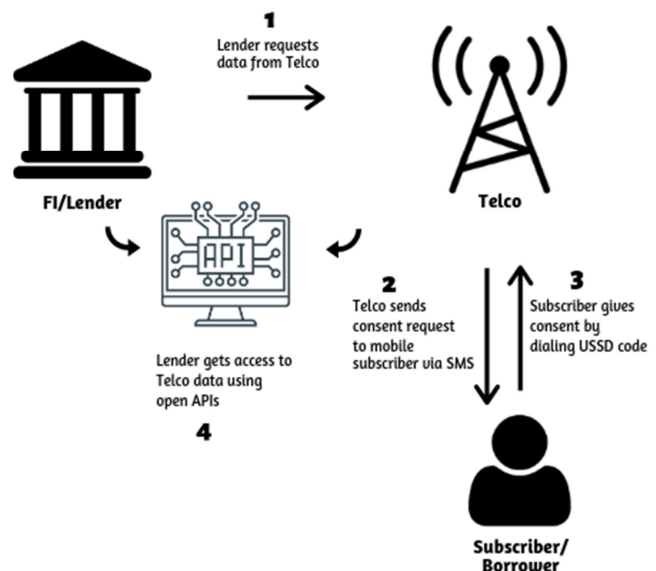


Figure 1. Process flow for data sharing.

3.4. Use Case

Here, we present a use case for a micro-loan, using Nigeria as a case study. A recent report dubbed Nigeria "the poverty capital of the world" [29] with 95.9 million people living in extreme poverty (i.e. living on below \$1.90 a day) [24, 30]. The Global Findex Database showed that 4% of the world's unbanked adults live in Nigeria and that between 40-64% of

adult Nigerians are excluded from any form of financial services [24], including access to credit [31, 32]. A report released by the National Bureau of Statistics for the third quarter of 2019 showed that 97.3% of all loans issued within that quarter were in excess of NGN 10 million, which shows that less than 3% of these loans are within the reach of most of the population [33]. As of September 2018, Nigeria had 97.5 million unique mobile subscribers and a penetration rate of 49%, and a smartphone adoption rate of 36% [34, 35]. These figures show that adopting a credit scoring system based on mobile phone data would be both beneficial and feasible in Nigeria. Below is a brief outline of how the system would work:

A data-sharing framework backed by the Central Bank of Nigeria (CBN) and the Nigerian Communications Commission (NCC) should be created, compelling banks to use telco-data for credit scoring. The CBN has made several efforts to compel commercial banks to extend credit to borrowers, including punitive policies, with limited success [36]–[38]. This data-sharing framework will be a great step towards achieving that goal, as well as compelling the Telcos to share data.

Requisite hashing algorithms should be used to ensure data is safe in transit and at rest. The algorithm will also ensure that only the intended recipient can make sense of this data.

A reward scheme should be created to incentivize Telcos to share data. As an example, the Telcos can get 10% of the interest on any loan granted, as well as a fee for each API call made.

To protect the poor and vulnerable, the CBN, in conjunction with the banks and Telcos, should launch a massive campaign to the poor and vulnerable to protect their phones, their PINs, and other personal information.

There should be a scheme to refund those who get defrauded so that faith in the system can be guaranteed.

Only those licensed by the CBN should be allowed to have access to this data.

4. Discussion

4.1. Preventing Data Misuse

It is important that in such a system involving the sharing of personal information, there are measures put in place to prevent the inappropriate use of data. Apart from the corporate data security policies of the data brokers and Telcos, the following should be put in place to this effect:

1. Every data broker must be licensed by the appropriate regulatory body in charge of communications and data sharing.
2. Every data broker must also be licensed by the governing body that governs its primary area of jurisdiction. For example, the Central Bank.
3. Both the data brokers and the Telcos will be governed by the data protection laws of the country within which they operate.
4. Only data explicitly approved by the customer, via

informed consent, shall be allowed to be shared by the organization to the authorized API endpoint of the financial services provider.

5. The documentary requirements and internal processes, including but not limited to the turnaround time for approving access by data providers, must be approved by the required supervisory regulator. No financial institution should be subjected to lesser or more stringent authorization processes or be required to provide additional documentation beyond what has been defined by the approved requirements.

4.2. Permitted Operations

1. Obtaining subscriber information, including basic information such as name, gender, address, date of last SIM change, date of last use, etc.
2. Obtaining call records including loading of airtime. All counterparty phone numbers should be hashed to provide privacy and prevent the possibility of any party combining and correlating these records from fragments of customer data requests. Start and end dates must be required for this data.
3. Obtaining location history. Granular records of geospatial data will be provided. Start and end dates must be required for this data.
4. Obtaining transaction history. Records of all value-based transactions conducted by the customer will be provided. Including airtime purchases, data purchases, and the respective timestamps of all such transactions.

4.3. Security Requirements

The following should be the minimum requirements for integration into the system:

1. All data brokers must use SSL over HTTP2.
2. Passwords must be hashed and not encrypted.
3. Data brokers must never expose information on URLs. For example, the API keys must never be part of the URL.
4. Data brokers may use the OAuth2 authorization framework.
5. All input parameters must be validated at the edge before being passed on to the backend for processing.

4.4. Dealing with Privacy Issues

To ensure that subscriber information is protected along the value chain, all identifiable telephony data must be hashed using at least SHA-2 with SHA-3 recommended. The data provider must specify the algorithm used for the hash in the response payload.

1. Every phone number within a call record will be hashed by the combination of data broker-client key, a session key, the mobile subscriber phone number, and the caller party phone number such that the counterparty numbers are hashed and secure, but still unique within the provided data.
2. The same number calling two different users whose data

have been provided via this means can never be the same.

3. The number calling the same mobile subscriber whose data has been accessed multiple times will not be the same as it would have a different hash as a result of having a different session key.

4.5. Benefits of this Credit Scoring Model

Financial exclusion remains a significant challenge to the developing world. The Global Findex database showed that as of 2017, there were about 1.7 billion unbanked adults worldwide and that 50% of these people lived in Bangladesh, China, India, Mexico, Nigeria, and Pakistan [39]. These unbanked individuals would automatically be exempt from traditional credit scoring mechanisms which depend on information gleaned from bank accounts, insurance policies, credit card data, etc.

Sub-Saharan Africa is the fastest-growing mobile region in the world with over 400 million mobile subscribers and an overall subscriber penetration rate of 44% in 2018, and this figure is expected to grow to 623 million by 2025 [40]. This means that there could be up to 400 million people in Sub-Saharan Africa alone who could have access to credit facilities if mobile phone data is used to create a credit scoring system.

5. Conclusions

Credit scoring and reporting are important tools in any economy as they make the provision and availability of essential financial services possible; this, in turn, promotes economic development. For most developing economies where a large portion of the population is un(der) banked and financially excluded, the use of traditional credit scoring mechanisms has been ineffective in extending credit facilities to the poor and excluded. In most of these economies, credit scoring mechanisms are either non-existent or are still in their developmental stages, and information sharing is limited and asymmetric.

To tackle these issues, a credit scoring mechanism that makes use of mobile phone data has been proposed in this paper. Mobile phone data has been shown to be a predictor of credit repayment behavior [20, 23, 41], and while 1.7 billion people in the world do not have bank accounts, two-thirds of this number own mobile phones [24] and this figure is predicted to increase in the coming years [39]. Adopting open APIs will ensure that mobile phone data is made available to authorized lenders and hence will be effective in dealing with the issues of information asymmetry and availability. Open APIs will allow the interoperability, accessibility, and decentralization of this data [2, 3].

This method which harnesses the potential in alternative credit data and open APIs is promising, especially for developing economies, and can be instrumental in fueling the drive for financial inclusion across the world.

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