Small Businesses and Digital Financial Services

Predictive Modelling and Segmentation for Market Sizing and Product Design

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Creating Markets, Creating Opportunities

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Executive Summary

Micro, Small, and Medium-Sized Enterprises are the backbone of vibrant and dynamic economies. But they are sometimes hard for financial institutions to identify because of the methods they use to conduct their transactions. As a result, many MSMEs do not get access to financing and financial products that are designed specifically to support businesses. Identifying these MSMEs and addressing their needs can be very advantageous for digital financial service providers. This report discusses predictive data models to help a mobile network operator in Sub-Saharan Africa[1], identify MSMEs in its market and better understand how to serve them.

The MNO has a large market share in the country and tens of millions of transactions pass its digital financial services channel each month. This report examines those transactions to determine how many are made by individual consumers and how many are made by entrepreneurs and business owners who use personal accounts to conduct business. The report postulates that a significant number of MSME owners conduct commercial transactions through their personal accounts and are therefore not being identified as business customers and are not being afforded the benefits of business customers.

This research shows that MSMEs can be accurately identified with a high degree of statistical confidence. Moreover, the analytic method can be used to segment those MSMEs into more granular business profiles. The segmentation algorithm is driven by patterns of how MSMEs use mobile money. The emerging segments differ in their business characteristics and their financial needs.

Multiple research components generated comprehensive insights into the MSME segment in the study country. Apart from analyzing mobile money usage patterns, the team also conducted a survey with 1,275 MSMEs. The survey data was used to inform the development of an MSME identification model and to study and profile businesses.

Key results across research components are as follows:

Supervised segmentation – An initial analysis of mobile money transactions identified key segments of highly active and likely businesses. A large number of those 11,500 potential MSMEs are informal channel workers who are operating businesses using their individual mobile money subscriptions. This provides an opportunity for DFS providers to leverage the networks of these informal channel workers and to register them as formal agents and merchants. They are already behaving as such.

Qualitative MSME segmentation (using survey data) – A survey of 1,275 small businesses that use the partner MNO's mobile money service improved the understanding of different MSME groups and answered questions about the characteristics, needs, attitudes towards, and perceptions of mobile money of MSMEs in the country. These businesses can be segmented into four clusters: Non-Agent Entrepreneurs, Savvy Mediums, Basic Small, and Mobile Money Agents. These groups differ in business size, level of technological sophistication, and level of financial inclusion. Their mobile money transaction characteristics mirror the qualitative profiles that emerge from survey data. Based on these findings, the paper discusses strategies to best engage with respective segments.

Predictive modelling, identification and behavioral clustering of identified MSMEs - IFC developed a robust model for MSME identification from mobile money transaction behavior. It has been shown to be 98 percent accurate in identifying which mobile money subscribers are MSMEs. It identifies 32,600 MSMEs among the MNO's customer base, which represents an important proportion of heretofore unidentified commercial activity segment on the DFS channel. Some of them overlap with the 11,500 potential MSMEs that were segmented in the initial supervised segmentation. The predictive model provides a low-cost and fast approach to identifying and monitoring large numbers of MSMEs on a regular basis.

1 *Operator and country were anonymized for confidentiality.*

Identified businesses were further clustered into meaningful sub-segments based on mobile money transaction features. All segments show high levels of mobile money transaction activity. Above all, Acceptors, Airtime Traders, Service Providers (see table 2 for definitions) are most active in terms of transaction count, transaction value, average transaction amounts, as well as the average number of parties that they transact with on a regular basis. Among MSMEs identified, the average revenue per month is approximately 9 USD - this is more than five times higher than the average revenue from normal individual consumers. Meanwhile, for net balances held on the wallet, MSMEs hold an average of 102 USD, as compared to around 30 USD for individuals.

To engage with small businesses as customers, it is essential for DFS providers to be able to identify MSMEs, to know them well and to understand their financial challenges. Leveraging combined results from this research supports the MNO's efforts to develop DFS products that are better tailored to the specific needs of MSMEs. Information and results can be used for product development and subsequent specific targeting of identified MSME segments.

Key Results

- A significant number of high-value customers on the digital channel are formal and informal businesses that transact using consumer-oriented products.
- MSMEs with an individual mobile money subscription can be identified based on their mobile money transaction behavior. IFC developed a robust model that achieves 98 percent accuracy in predicting and identifying which mobile money subscribers are MSMEs.
- Data-driven modelling and segmentation can identify MSMEs on consumer channels and sub-segment them further into micro-, small-, and medium-sized tiers.
- Profiles and patterns emerge that help to sub-segment MSMEs based on their usage of mobile money, their business characteristics, financial needs, and current use of formal banking services.
- Identification and segmentation of businesses that use mobile money services provides valuable information for product design and targeted marketing.

Introduction

Micro, Small, and Medium-Sized Enterprises are important job creators that help advance financial inclusion in Sub-Saharan Africa, a region expected to add 18 million people to the labor force every year until 2035[2]. However, MSMEs still lack adequate access to both financial capital and business tools that could help them to prosper and grow. Supporting and engaging them as a customer segment offers a good opportunity for digital financial service providers that are able to tailor services and products specifically for MSMEs.

The value of using data to transform insights into action and to advance financial inclusion has been well documented by organizations across Africa[3]. With the availability of lower cost computational resources and data applications, companies have been able to sort their customers into niches and segments, enabling them to better understand the individual needs of customers. That has made it easier to manage and deploy strategies that are tailored to specific categories of customers.

For DFS providers, segmenting the client base opens possibilities for targeted product design, marketing, and pricing that better meets the respective needs of businesses. Moreover, better serving these segments will drive financial inclusion. Businesses are regular and very active users of mobile money services. Reaching out to MSMEs and offering them mobile money products tailored to their needs has the likely additional benefit of broadening the service provider's proportion of high-value customers.

Given the lack of business-specific digital financial services that are offered, MSMEs and individual customers often use the very same services for business and personal needs. That means that many person-to-person (P2P) transactions may in fact be business transactions. Despite using common products, these segments are likely to transact differently, with different service needs. Data-driven analytics can identify these different usage patterns to inform which users belong to which segment.

The core questions that this research collaboration set out to answer are:

(a) Can businesses (MSMEs) be identified and segmented in the customer base?

(b) Can businesses be further sub-segmented into MSME tiers?

(c) What is the profile/are the patterns of mobile money usage of those MSMEs segments?

The research project included a comprehensive survey of MSMEs who use mobile money. The sample size and geographical distribution were made after preliminary analyses of the MNO's transactional data. Survey results provided 'ground truth' data used for developing a model to identify MSMEs based on their mobile money transaction patterns. Survey data also helped to further segment MSMEs into behavioral, geographic, and functional sub-segments as well as to validate assumptions and hypotheses used in algorithms.

2 *IMF, 2015. Regional Economic Outlook: Sub Saharan Africa*
3 *For examples and case studies see the IFC, 2017 (b) Data Analytics and Digital Financial Services Handbook*

Data

Two sources of data drive the analyses presented in this report: mobile money transaction data of an MNO in Sub-Saharan Africa as well as newly collected survey data with MSMEs in the same country that use the MNO's mobile money product for business transactions through individual subscriptions. Analyses were conducted with each dataset separately for (behavioral) segmentations as well as with the two datasets merged for the predictive modelling exercise.

Mobile Money Transaction Data - All data was encrypted and analyzed using best-practice data governance structures. A total of seven months of mobile money transaction data were included into the final data models[4] and subscriber level data were aggregated to monthly transaction tables per transaction type, with additional geospatial information (cell tower locations). The chosen architecture allows future scalability and ease of use of data models.

MSME Survey Data - A detailed survey of businesses that have individual mobile money subscriptions with the MNO provided the ground truth data for the MSME identification model. The collected data served as training data (true positives) to identify MSMEs in the individual subscriber base based on their mobile money transaction behavior. The survey data also constitutes the basis for the qualitative segmentation of MSMEs to inform the development of mobile money products that are tailored to the businesses' unique usage patterns and needs. Between June and August 2018, 1,275 MSMEs were surveyed in the commercial center (72% of surveys) as well as in other smaller urban and rural locations in the study country.

Table 1: Business categories based on numbers of employees

NUMBER OF EMPLOYEES	MSME CATEGORY
1 employee	Soho = Small/Home Office
2-9 employees	Micro Enterprise
10-49 employees	Small Enterprise
50-199 employees	Medium Enterprise

Sampling of MSMEs

Two different sampling approaches were used following a segmentation and listing of likely MSMEs based on an initial analysis of mobile money transaction data. The list of likely MSMEs was used for a random selection of 250 respondents with quota for sub-segments that came out of the supervised segmentation. For the rest of the survey sample, enumerators randomly contacted MSMEs in commercial areas with a minimum quota of businesses to be interviewed per survey location and business size category (Sohos[6], Micro and Small Enterprises). The definition for business size categories that was followed for this survey is presented in table 1. This definition is in line with IFC's SME definition in terms of number of employees.

Filter questions for respondent selection

Enumerators selected eligible respondents with four filter questions. Respondents had to be users of mobile money and they had to have an individual mobile money subscription that they use for business transactions. The minimum transaction frequency was set to at least two transactions per month to make sure the analysis would be able to pick up variation in transaction behavior when datasets were merged. Lastly, respondents had to have a decision-making role in the company they work for.

Topics covered in the survey

The survey instrument covered individual socio-demographic respondent information, details about respondents' access and usage of mobile phones, an assessment of the business(es) respondents are working for, respondents' banking level and trust in the formal banking system, respective mobile money usage for business purposes as well as a section capturing the perception of the used mobile money service and questions testing the appetite for mobile money product features. The survey also included questions to identify the drivers and barriers of digital financial service usage among interviewed businesses in their country. These questions were posed along the six components of a framework for the identification and description of the drivers and barriers of DFS that were developed based on an IFC ethnographic study[7] on the perception and attitudes towards mobile money in four African countries. The study country chosen for this research collaboration is the first country that the framework was applied to outside of the original study countries[8] (Senegal, Cameroon, DRC, Zambia).

4 *The months covered are February, April, May, June, September and December 2017 as well as January 2018.*
6 *Soho stands for "Small office/Home office". The acronym is used here for individual entrepreneurs.*
7 *IFC, 2017 (a). A Sense of Inclusion: An Ethnographic Study of the Perceptions and Attitudes to Digital Financial Services in Sub-Saharan Africa.*
8 *For more information on how the ethnographic framework was applied, see: Heitmann S., Buri S., Davico G. and Reitzug F., 2018, Operationalizing Ethnographic Research to Grow Trust in Digital Financial Services, EPIC Conference Proceedings 2018*

Methods

The study seeks to answer two core questions: 1) if micro, small, and medium-sized businesses can be identified and segmented from the transaction behavior of individual mobile money subscribers; and 2) what are the profiles and mobile money usage patterns of different MSME segments.

The core questions were assessed during three phases of the research:

- **Phase I:** an initial analysis of transaction data and segmentation of potential businesses in the individual mobile money customer base.
- **Phase II**: a survey to collect ground truth and behavioral characteristics.
- **Phase III:** development of a model that identifies MSMEs based on their transaction behavior .

Two clustering exercises were conducted. One used survey data ('Qualitative Segmentation' - part of Phase II) and the other one mobile money transaction behavior of identified MSMEs ('Quantitative Segmentation' - part of Phase III).

Reading through the analyses of the three phases and their outcomes throughout this report may become confusing in parts, since they result in different numbers of identified segments, clusters and MSMEs respectively. For clarification, figure 1 provides an overview of the research phases and their resulting numbers of identified and interviewed MSMEs. It also lists the different segments and clusters that were identified throughout the analyses and visualizes their partial overlap across phases.

Figure 1: Overview of Research Phases

Phase I

Supervised Segmentation

Development of expert-based MSME definitions & segmentation based on transaction data

11,500
segmented MSMEs

5 resulting segments:

1. Acceptors
2. Service Providers
3. Airtime Traders
4. Cash-In / Cash-Out Agents
5. Bulk Sender Agents

Phase III

Predictive Modelling & Quantitative Clustering

MSME Predictions using an Average Trading Days Composite Index & subsequent K-means clustering

32,600
predicted likely MSMEs

6 resulting clusters:

1. Acceptors
2. Services Providers
3. Airtime Traders
4. Low Value Bulk Senders & Receivers
5. Medium Value Bulk Senders & Receivers
6. High Value Bulk Senders & Receivers

Phase II

MSME Survey & Qualitative Clustering

K-means clustering using 'ground truth'/ survey data

1,275
interviewed MSMEs

4 resulting clusters:

1. Basic Smalls
2. Non-Agent Entrepreneurs
3. Mobile Money Agents
4. Savvy Mediums

SUPERVISED SEGMENTATION

In Phase I, mobile money transactions were analyzed using expert-based definitions of segments to identify highly active users. Based on their transaction behavior, most of these users were classified as informal channel workers who appeared to be running businesses through their personal mobile money channels.

After a detailed analysis of mobile money transaction data, interactive sessions were held with the MNO operational and management teams, during which the transactional characteristics of businesses were discussed. Thresholds and transaction-based filtering criteria were defined to segment potential MSMEs using local domain and operational knowledge and previous insights. The process of defining and labelling potential business segments based on an initial analysis of transaction data in collaboration with the MNO is referred to in this report as Supervised Segmentation. Matching the transaction data with ground truth survey data and the development of a predictive model to identify MSMEs was only done at a later stage of the project.

During the supervised segmentation, transactional data was aggregated and weighted based on four key features: a composite measure of the average trading days per transaction type and per month[9]; the average count of second parties[10]; the average monthly transaction count[11]; and the average monthly transaction amount[12] of individual mobile money subscribers.

This initial analysis set the definitions of what types of MSMEs might be identified later in the individual subscriber dataset. The resulting segments and their definitions based on transaction metrics are shown in table 2. Results were so clear that labels or "personas" could be allocated to the segments. Segmentation patterns are consistent throughout different phases of the analysis and therefore given labels are also meaningful and largely consistent with the ones from the segmentation of MSMEs identified through the predicted modelling in Phase III.

Table 2: Definition of Segments resulting from Supervised Segmentation

<table>
<tr><th>SEGMENT LABELS</th><th>SEGMENT DESCRIPTION</th><th>AVG TRADING DAYS PER MONTH</th><th>AVG COUNT OF 2ND PARTY SUBSCRIBERS</th><th>TRANSACTION TYPES</th><th>NUMBER OF TRANSACTIONS</th></tr>
<tr><td>Acceptors</td><td>Acceptor accepts P2P for payments of goods or services.</td><td>> 10</td><td>> 5</td><td>Cash-in or P2P Received</td><td></td></tr>
<tr><td>Bulk Sender Agents</td><td>Bulk Senders use their subscriber account to do bulk P2P transfers to multiple people.</td><td>> 10</td><td>> 5</td><td>Cash-out or P2P Sent</td><td></td></tr>
<tr><td>Cash-in/ Cash-out Subscribers</td><td>Cash-in or Cash-out Subscribers facilitate rebalancing liquidity of other agents by doing Cash In/ Out Transactions.</td><td>> 15</td><td>> 4</td><td>Cash-in or Cash-out</td><td>> 10</td></tr>
<tr><td rowspan="2">Airtime Traders</td><td rowspan="2">Airtime Traders do large amounts of airtime sales and purchases.</td><td>> 19</td><td></td><td>Airtime</td><td>> 50</td></tr>
<tr><td colspan="4">> 250 Airtime transactions per month</td></tr>
<tr><td>Service Provider Agents</td><td>Service Provider Agents facilitate service provider payments for multiple 2nd parties</td><td>> 3</td><td>> 9</td><td>3rd party remittances (e.g. paying bills)</td><td></td></tr>
</table>

9 *Average trading days per month = AVG across transaction types (AVG Number of trading days of a subscriber per relevant transaction type per month)*
10 *Average count of 2nd Parties = AVG (Count of distinct 2nd parties a subscriber transacted with per month)*
11 *Average transaction count = AVG (Number of transactions per distinct transaction type per month)*
12 *Average monthly transaction amount = AVG (Total value of transactions/ Total number of transactions)*

MSME CLUSTERING USING SURVEY DATA

A survey of MSMEs that use individual mobile money accounts for business transactions provided the ground truth data for the subsequent predictive modelling. A sample of respondents was selected from the list of informal channel workers identified in Phase I. Clustering businesses using information from the survey data later allowed to describe characteristics of four business profiles for MSME sub-segments and to develop guidance on how to best approach them in terms of marketing and product offering.

Analysis using K-means clustering led to the identification of four primary segments among the 1,275 interviewed MSMEs and mobile money customers. The segments are spread across demographics such gender, location, and company size. Identified clusters reflect characteristics such as economic maturity, technology awareness, and risk-aversion. The four clusters are labelled *"Basic Smalls"*, *"Non-Agent Entrepreneurs"*, *"Mobile Money Agents"*, and *"Savvy Mediums"*.

Although being a mobile money agent was not used as a segmentation characteristic, segments emerged that are strongly aligned with those that are formal or informal mobile money agents. The majority of entrepreneurs in the Mobile Money Agents cluster are not registered agents with the chosen MNO. However, they are often informal businesses that found a business value proposition by using their individual mobile money subscriptions. The fact that they emerge so clearly as a cluster and that their answers show that this agent group better understands and uses mobile money more actively than other segments, confirms the meaningfulness and interpretability of the identified four clusters. Results of the qualitative segmentation are further empirically validated through the transaction behavior of each segment that was observed after matching survey and mobile money transaction data.

Matching survey data with mobile money transaction data helps to compare the four business clusters that emerge from the survey data with the segments from the supervised segmentation discussed previously. Figure 2 shows that the biggest proportion (63 percent) of interviewed businesses among those that match with the supervised segments are mobile money agents.

This was expected since large parts of the supervised segments were identified as informal mobile money channel workers that behave in part as formal agents. A large group of matching businesses (23 percent) classify therefore appropriately as Service Provider Agents in the supervised segmentation (top grey horizontal flow bar in Figure 2). Other Mobile Money Agents classify as Acceptors, Airtime Traders, or Cash-In/Cash-Out Agents accounting for 12 percent of the matching businesses respectively. Supervised segments from Phase I were largely found to be informal mobile money channel workers.

Figure 2: Sankey Diagram - Overlap of Segments based on Survey Data (Qualitative Segmentation) and Segments from the Supervised Segmentation

PREDICTIVE MODELLING FOR MSME IDENTIFICATION & BEHAVIORAL CLUSTERING OF MSMES

After an initial expert-based segmentation in Phase I and the collection of ground truth data as well as a qualitative segmentation of interviewed businesses in Phase II, the core analysis and development of the predictive model was done in Phase III building upon insights and results obtained during the previous phases.

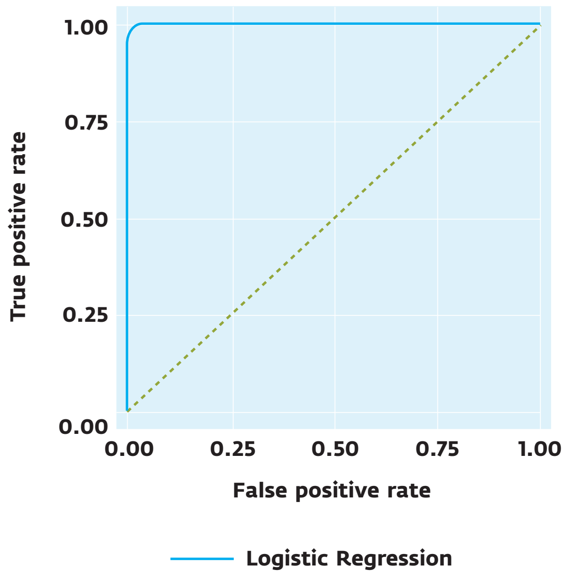
Mobile money transaction data was ultimately matched with survey data of MSMEs (true positives[13]) to train models on business related transaction behavior. The final model predicts and identifies with high accuracy who the MSMEs are among individual mobile money subscribers. MSMEs that were identified through the predictive modelling were clustered and sub-segmented into six clusters based on their mobile money transaction behavior for further insights.

Different methods were applied for the predictive segmentation. It is important to use more than one algorithm to predict the outcome of data and to compare the results of multiple algorithms and models to ensure consistency of results. Using just one algorithm can predict false positives (identifying subscribers as MSMEs that aren't).

The same transactional metrics that were used for the initial supervised segmentation were also tested as features for the predictive modelling. Different machine learning algorithms were used and compared for the predictive modelling. First, meaningful features were identified using correlation analysis. The team then moved towards more complex algorithms, such as a decision tree and a random forest algorithm, using the same features. A composite index of customer activity that includes different measures of average trading days per month was identified as the most important and the average transaction count as the next most important feature.

A logistic regression algorithm was ultimately employed to identify and predict who were MSMEs. Consistent results on key features across previous analysis steps and algorithms provided the confidence for going forward with a composite index of the average trading days per person to predict the probability of a subscriber being an MSME[14]. This straightforward design of the final model allows easy interpretation, replication, and application of results by service providers. Succinctly, the model identifies businesses in terms of high-active transaction users consistently over a rolling window of time.

Figure 3: Logistic Regression – Receiving Operator Characteristic (ROC) Curve



Results are conclusive. The model can predict whether a subscriber is an MSME by calculating the composite index of average trading days per subscriber and per month. Applying this algorithm to the transactional data of the MNO, identified 32,585 likely MSMEs in January 2018 (based on the latest available transactional data) with almost 98 percent accuracy (Figure 3). Figure 3 shows the accuracy of the model and confirms that the true positive versus false positive rate is extremely good (blue line is far away from the green dotted line).

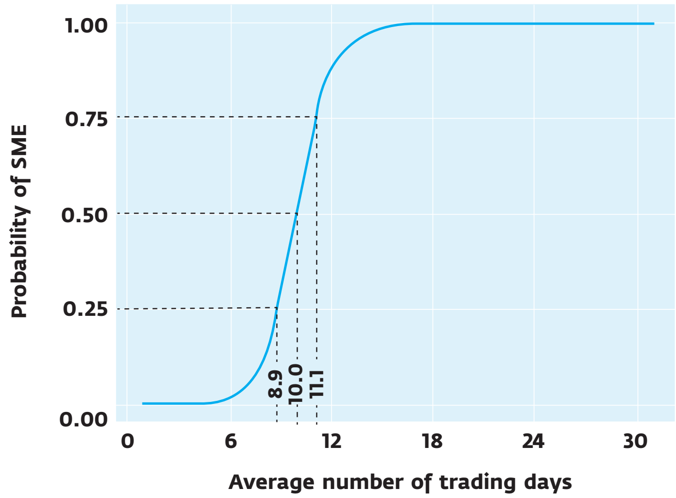
Figure 4 clearly shows the correlation between average trading days and MSMEs. The greater the average number of trading days across transaction types, the more likely that a subscriber is an MSME. It was decided to stick with a strict threshold of 15 days for MSME identification to ensure high model accuracy.

The 32,585 users that were identified this way as very likely MSMEs, were clustered based on their mobile money transaction behavior using K-centroid clustering. The ideal number of clusters identified using this method was six. These clusters all had similar attributes as the initial supervised segmentation in Phase I.

13 *715 interviewed MSMEs could be identified in the transaction database. They represent the true positives. A random sample of 1,000 individual mobile money provides the true negatives (non-MSMEs). As the dataset of individual subscribers consisted of about 4 million subscribers, first, 6 different random sample of 1,000 were used to train 6 different datasets. The machine learning algorithms were trained using these 6 combinations of data. Resulting model accuracies were all within 1 percent of each other which provided the confidence to ultimately only use one random sample.*

14 *The outcome was also tested with a second feature, which only added a marginal contribution to the outcome of the algorithm.*

Figure 4: Logistic Regression: Probability to be a business based on the Average Number of Trading Days



COMPOSITE INDEX OF THE AVG NUMBER OF TRADING DAYS PER CUSTOMER AND MONTH	PROBABILITY OF A SUBSCRIBER BEING AN MSME
8.9 Days	25%
10 Days	50%
11.1 Days	75%
12 Days	85%
15 Days	98%

Key insights – Predictive modelling and identification of MSMEs

- MSMEs with an individual mobile money subscription can be identified based on their mobile money transaction behavior.
- IFC developed a robust model for MSME identification that achieves 98 percent accuracy in predicting and identifying which mobile money subscribers are MSMEs.
- The model identifies 32,585 MSMEs among the customer base of mobile money users of an MNO in Sub-Saharan Africa.

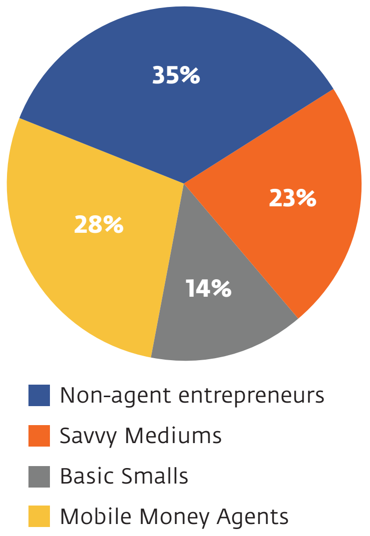
Results

Both the qualitative segmentation based on survey results as well as the quantitative segmentation based on the predictive modelling of mobile money transaction behavior provide valuable information about MSMEs and their specific DFS needs and usage patterns.

QUALITATIVE MSME SEGMENTATION USING SURVEY DATA

Based on survey data, four MSME segments were identified: *basic smalls*, *non-agent entrepreneurs*, *mobile money agents*, and *savvy mediums*. They can be distinguished through their size, technological sophistication, mobile money usage patterns, and their perception and usage of traditional financial services. Among the businesses that were interviewed, non-agent entrepreneurs make up the biggest proportion (35 percent in Figure 5), followed by mobile money agents and savvy mediums. Basic smalls constitute with 14 percent, the smallest survey segment.

Figure 5: Distribution of interviewed MSMEs across Clusters



The emerging segments from the clustering that used survey data are mostly consistent with the other transaction data-based segmentations presented in the report section on 'Behavioral quantitative MSME Clustering'. Interviewed businesses that were segmented as Mobile Money Agents appear, for example, in the transaction data-based segmentations as High Value Bulk Senders and Receivers as well as Service Provider Agents.

All of the entrepreneurs who were interviewed use mobile money for business operations. MSMEs show a high level of trust in mobile money services and financial institutions; 76 percent express their trust in banks and MFIs. An even higher percentage trust MNOs (88 percent). More than 60 percent of respondents agree that mobile money services are meant for businesses like theirs. Mobile money is generally perceived as a non-discriminatory option to manage money. Adoption of technology does not seem to be a barrier for entrepreneurs, and they say they have a good understanding of mobile money services.More than 50 percent of respondents said they think that banks are the safest place to save money. In comparison, 38 percent of respondents said mobile wallets are the safest place. More than 70 percent of entrepreneurs who were interviewed believe that using mobile money agents means less privacy.

Businesses have been using mobile money on average for 3.5 years. The main reasons they started using mobile money was the speed of service, convenient pricing, and the ease of use of mobile money services. Issues with mobile money that have been experienced by the biggest proportions of respondents are poor geographic coverage, missing transaction receipts, as well as liquidity issues with agents. Entrepreneurs look for safety, speed, and simplicity when using mobile money for conducting business transactions. More than 75 percent of entrepreneurs are interested in business-oriented DFS products for conducting transactions such as paying salaries, receiving payment from clients, paying suppliers, collecting money from retailers, and transferring funds to and from bank accounts.

The following profiles describe each segment's characteristics, including mobile money transaction behavior and use of financial services. The profiles also include guidance on how to engage different business segments in digital financial services.

Non-Agent Entrepreneurs

Segment Characteristics - None of the MSMEs in this segment are mobile money agents. These MSMEs are most likely engaged in informal businesses for themselves, such as Small office/Home office businesses, or with a small team. Non-Agent Entrepreneurs have on average six employees. Their lines of business are trade, e-commerce, manufacturing, and services.

Use of Mobile Money and other Financial Services - Non-Agent Entrepreneurs have a relatively low engagement with mobile money at present. That presents MNOs with an opportunity to unlock revenue by targeting those businesses more specifically.

Non-Agent Entrepreneurs seem to behave more opportunistically in their businesses and are therefore also more likely to value flexibility in mobile money services. Across segments, they are the least likely to have a bank account; only seven percent reported having a bank account. Among the banked non-agent entrepreneurs, 45 percent have had a bank account for less than four years.

Strategic advice for engaging Non-Agent Entrepreneurs - When reaching out to non-agent entrepreneurs, the recommended strategy is to grow their current engagement and usage of mobile money financial services by focusing on business-specific features and key concerns like latency or security. Offering them low-cost incentives for enrollment and increased usage of the channel is another way to engage them and maintain activity levels. Transaction frequency should be a core indicator to measure and monitor this segment.

Table 3: Mobile Money Transaction Profile of Non-Agent Entrepreneurs

MOBILE MONEY TRANSACTION PROFILE OF NON-AGENT ENTREPRENEURS	
AVG trading days per month	2.6
AVG monthly transaction count	3.3
AVG monthly 2nd party count	1.5
Monthly transaction value per subscriber	25.3 USD
AVG transaction amount	23.4 USD
Main transaction types used	• Airtime purchases (7 per month)
Average mobile money account balance	46.2 USD
ARPU[15]	1 USD

15 *Approximate Average Revenue per Users (ARPU) = Total value of fees paid per month and segment / MSISDN Count per respective segment*

Savvy Mediums

Segment Characteristics - Savvy Mediums show a higher level of technological sophistication and are more receptive to new technology and services for business purposes. They are more likely to be mid-size companies with an average of 25-26 employees and they have more formal and established practices. Their lines of business are construction, real estate, transportation, storage, logistics, trade, e-commerce, and services.

Use of Mobile Money and other Financial Services - Savvy Mediums have greater exposure to traditional business institutions and workforces. They are more likely to value services that integrate with transactional financial services and credit facilities. They are the largest segment that already have a bank account; 78 percent report having a bank account. Savvy Mediums have varied financial transaction needs for their business operations that mobile money can help them with. They use mobile money because they value the service above all for its speed (32 percent) and convenient pricing (25 percent).

Strategic advice for engaging Non-Agent Entrepreneurs - Savvy Mediums are a more formal category of business. Messaging to them should reflect that. Partnerships with financial and business service providers for targeted products and promotions are one possible engagement strategy. Business supplier networks are also extremely high-value communities that can be targeted with tailored products.

Table 4: Mobile Money Transaction Profile of Savvy Mediums

MOBILE MONEY TRANSACTION PROFILE OF SAVVY MEDIUMS	
AVG trading days per month	3.6
AVG monthly transaction count	7.8
AVG monthly 2nd party count	2.8
Monthly transaction value per subscriber	162.6 USD
AVG transaction amount	42.9 USD
Main transaction types used	• Airtime purchases (20 per month) & • P2P transfers (15 per month)
Average mobile money account balance	61 USD
ARPU	2.3 USD

Basic Smalls

Segment Characteristics – Basic Smalls are more likely to be technologically averse and have difficulty with new technology. There is comparatively less opportunity to upsell products to this segment. These MSMEs average seven employees and have lower turnover. Their lines of business are manufacturing, trade, and financial services, offering among other things, mobile money or transfer services.

Use of Mobile Money and other Financial Services – Seventy-nine percent of Basic Smalls do not have a formal bank account. They are very sensitive to cost and cash-flow arguments and less receptive to value-add. Asked about the main disadvantages of mobile money, 45 percent of Basic Smalls complained about prices being too high; 42 percent said the service was not often available; and 39 percent express concern about the security of the service.

Strategic advice for engaging Non-Agent Entrepreneurs - To engage Basic Smalls, emphasize ease of use for essential functions such as sending and receiving money, and monitoring account balances. Other engagement strategies can be to conduct prolonged messaging on very specific value propositions of mobile money. Topics could be safety and ease of paying wages. Generally, engagement and marketing towards Basic Smalls should focus on peace of mind, emphasizing network security, support, and clarity of transaction confirmations.

Table 5: Mobile Money Transaction Profile of Basic Smalls

MOBILE MONEY TRANSACTION PROFILE OF BASIC SMALLS	
AVG trading days per month	4.2
AVG monthly transaction count	7.7
AVG monthly 2nd party count	3.3
Monthly transaction value per subscriber	191.1 USD
AVG transaction amount	52 USD
Main transaction types used	• P2P transfers (21 per month) & • Cash Withdrawals (12 per month)
Average mobile money account balance	57 USD
ARPU	4.4 USD

Mobile Money Agents

Segment Characteristics - Mobile Money Agents are very independent and are likely to be micro or Soho sized enterprises with two-to-three employees on average. Their lines of business are financial services, mobile money services, and transfer services. Agents in this segment can be both formal agents as well as informal channel workers.

Use of Mobile Money and other Financial Services - Mobile Money Agents are very familiar with a variety of mobile money networks. More than 80 percent use different mobile money services at least once a day and 86 percent say they understand mobile money marketing material. Eighty-nine percent of mobile money agents say that they know how to activate a mobile money account; 70 percent know what to do when a transaction fails; and 89 percent know how to make a transaction using a cell phone. As non-agent entrepreneurs, they are frequently involved in informal business as primary or secondary income. Twenty-eight percent of Mobile Money Agents use mobile money mainly because it is fast; 16 percent cite convenience as the reason they use it; and 16 percent say it allows them to improve their income. Ninety-four percent of informal mobile money agents are interested in becoming formal agents. Most of them, 67 percent, have no formal bank account, and the majority say banking services are for rich people and larger, formal businesses.

Strategic advice for engaging Non-Agent Entrepreneurs - Strategically, for MNOs they may be more relevant as a channel than as individual users themselves. Most are informal agents that found a business case in using their individual mobile money subscriptions and promotions. There is an opportunity to sign them up as formal agents and to leverage their networks of customers. These informal mobile money agents can be targeted with promotions such as new customer sign-up rewards. Messaging should focus on concrete value propositions. Key messages could focus on cost of transactions, time to transact, and security of transactions. Loyalty programs are another engagement strategy to encourage recommendations over competitors.

Table 6: Mobile Money Transaction Profile of Mobile Money Agents

MOBILE MONEY TRANSACTION PROFILE OF MOBILE MONEY AGENTS	
AVG trading days per month	5.1
AVG monthly transaction count	11.1
AVG monthly 2nd party count	4.1
Monthly transaction value per subscriber	509.2 USD
AVG transaction amount	52.8 USD
Main transaction types used	• P2P transfers (61 per month) & • Cash Withdrawals (22 per month)
Average mobile money account balance	67.3 USD
ARPU	5.9 USD

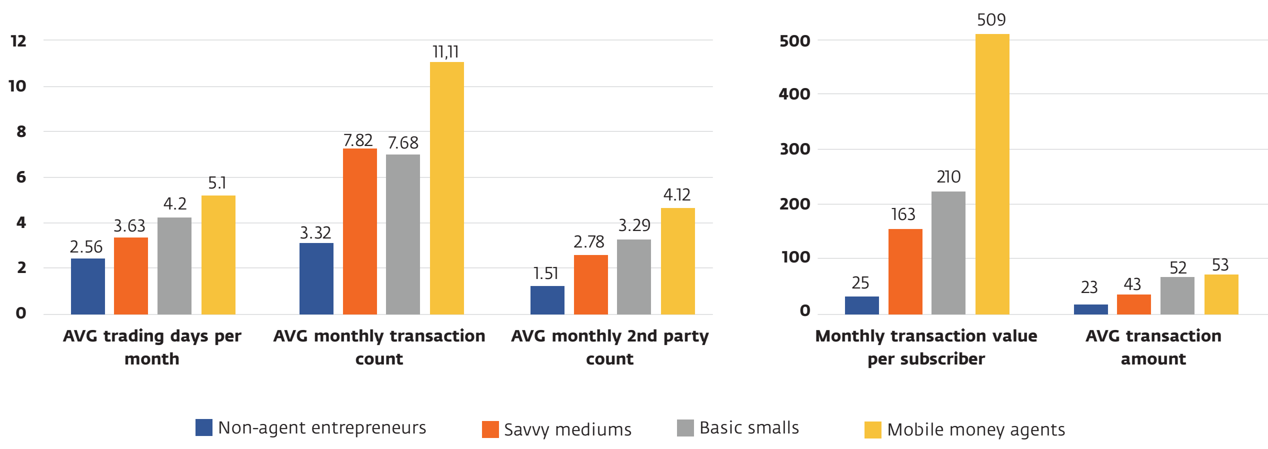
Transaction behavior of qualitative MSME segments

Matching survey data with mobile transaction data helps to compare the transaction behaviors[16] of the businesses that were interviewed and validates the meaningfulness of the clustered segments.

Transaction activity in comparison – As expected, mobile money agents are the most active of the four segments. They transact with the highest frequency and value and have the most second party contacts (yellow bars in figure 6).

Non-agent entrepreneurs have the lowest level of transaction activity, both in terms of frequency and volume (blue bars in figure 6). Basic Smalls have slightly higher levels of transaction activity across different metrics than Savvy Mediums (orange and grey bars in figure 6).

Figure 6: Transaction Activity of MSME Segments identified based on Survey Data



Average Revenue Per User[17] of segment members – For DFS providers, these small businesses contribute about twice the revenue per user as individual mobile money subscribers. Nevertheless, they generate less revenue from monthly transaction fees than informal channel workers and any of the other business segments that were identified through the predictive modelling and quantitative clustering. Across the qualitative survey segments presented in this section, the ARPU is highest for the Mobile Money Agents Segment and the lowest revenue per user comes from Non-Agent Entrepreneurs.

16 *Out of the 1,275 MSMEs interviewed, 715 businesses could be matched with the mobile money transaction database. Across segments, 106 Basic Smalls, 237 Non-Agent Entrepreneurs, 227 Mobile Money Agents as well as 155 savvy mediums were matched.*

17 *The ARPU is calculated here as the total value of fees paid per month and segment divided by the number of subscribers in the respective segment.*

Key insights – Qualitative MSME segmentation

- MSMEs that use mobile money services can be segmented into four meaningful clusters: *Non-Agent Entrepreneurs*, *Basic Smalls*, *Savvy Mediums*, and *Mobile Money Agents*. Asking for key characteristics when signing up new mobile money customers may allow DFS providers to identify and classify new business clients directly into these groups.

- *Non-Agent Entrepreneurs* are most likely to be engaged in informal businesses for themselves or with a small team. Their level of financial inclusion and mobile money usage is the lowest across the segments.

- *Savvy Mediums* are more likely to be involved in medium-sized enterprises with more formal and established practices. Most of them already have a formal bank account.

- *Basic Smalls* are small companies, both in real terms (few employees) as well as in business terms (low turnover). They have low levels of financial inclusion and are very price sensitive.

- *Mobile Money Agents* are mostly individual entrepreneurs or are engaged in micro-sized companies. They are often working as informal businesses but are interested in becoming formal agents. Despite their mastery of mobile money services, most are not formally financially included and think bank accounts are for larger, formal businesses.

- Transaction characteristics of these segments mirror the qualitative profiles that emerge from survey data. *Non-Agent Entrepreneurs* have the lowest levels of mobile money transaction activity whereas *Mobile Money Agents* clearly outperform other segments in terms of transaction activity.

BEHAVIORAL QUANTITATIVE MSME CLUSTERING USING MOBILE MONEY TRANSACTION DATA

Results of the Supervised Segmentation

The supervised segmentation that resulted from an initial diagnostic analysis of mobile money transaction data and a set of expert-based definitions[18] of likely MSMEs, returned a total of 11,500 potential MSMEs in the transaction database. They can be sub-segmented into five categories of likely businesses - *Acceptors*, *Bulk Sender Agents*, *Cash-In/Cash-Out Subscribers*, *Airtime Traders*, and *Service Provider Agents*. Among those likely businesses, Cash-in/Cash-out Agents and Airtime Traders constitute the largest proportions.

The supervised segmentation also generated other important insights, such as potential misuse of the current value proposition of airtime and P2P transactions of some individual mobile money subscribers. Informal agents, entrepreneurs, and businesses were found in the subscriber data that used their individual subscriptions to gain more income.

They are informal channel workers that are informally volunteering as agents. These entrepreneurs are already actively behaving as agents by providing agent-like services to earn informal commission value. This finding has important implications for DFS providers in terms of agent roll-out and strategic engagement. The presented segmentation provides an opportunity to identify, engage, and formalize the role of informal channel workers as formal agents and merchants. Leveraging already existing customers to become formal agents or merchants that way could support the often expensive and costly task of rolling out a functioning active agent network.

Based on the supervised segmentation in Phase I, only a first subset of informal channel workers and likely businesses could be identified compared to the list of MSMEs that was later identified with the help of the more comprehensive and rigorous predictive modelling (results presented in the next section). Table 7 below shows the characteristics and key metrics of the mobile money transaction behavior of each segment.

Table 7: Transaction characteristics of MSMEs identified through Supervised Segmentation

	AVG TRADING DAYS PER MONTH	AVG MONTHLY TRANSACTION COUNT	AVG MONTHLY 2ND PARTY COUNT	AVG TRANSACTION AMOUNT IN USD	TOTAL TRANSACTION VALUE IN JAN 2018 IN USD
Acceptors (do Cash-Ins or receive P2Ps)	16	37	17	28	1.5 million
Bulk Sender Agents (do Cash-Outs or send P2Ps)	18	70	34	22	0.9 million
Cash-in/ Cash-out Subscribers (do Cash-In or Cash-Outs)	18	31	12	41	8.2 million
Airtime Traders (do Airtime Purchases and Sales)	25	208	1	1	0.6 million
Service Provider Agents (do 3rd party remittances e.g. paying bills)	10	28	1	78	4.8 million

Key insights – Supervised Segmentation

- Segmenting highly active mobile money users based on expert-based definitions and exploratory analysis of their mobile money transactions helps identify five segments of likely MSMEs – *Acceptors*, *Bulk Senders*, *Cash-In and Cash-Out Subscribers*, *Airtime Traders*, and *Service Provider Agents*.

- A large number of identified likely MSMEs are found to be informal channel workers that already act actively as informal agents and merchants using their individual mobile money subscriptions to gain more income. There is opportunity for DFS providers to leverage their networks and to sign those businesses as formal agents and merchants.

18 *See section 'Supervised Segmentation' - p.9 - for a reminder of the definitions that were developed and defined to segment MSMEs for a reminder of the definitions that were developed and defined to segment MSMEs.*

Results from the Clustering of Predicted MSMEs

The predictive model expands the analysis of the supervised segmentation to identify – or predict – expected MSMEs from the overall transactional customer base. The model identified about 32,600 likely MSMEs the MNO's mobile money customer database. They were clustered into six segments based on their mobile money transaction behavior. The six clusters -- *Acceptors*, *Airtime Traders & Service Providers*, *Service Providers*, as well as *Low, Medium and High Value Bulk Senders and Receivers* – all transact very differently regarding the frequency, volume and number of contacts they interact with and their use of specific transaction types. Bulk Senders and Receivers constitute 89 percent of identified businesses (blue clusters in figure 7).

Table 8 lists the six segments that resulted from the behavioral clustering and characterizes their behaviors through key metrics of transaction activity. The cluster descriptions below show how usage patterns of segments vary not only in terms of general transaction metrics but also regarding the types of transactions that they conduct. The clusters can be used to target new MSMEs for segmented value propositions.

Figure 7: Distribution of identified MSMEs across Clusters

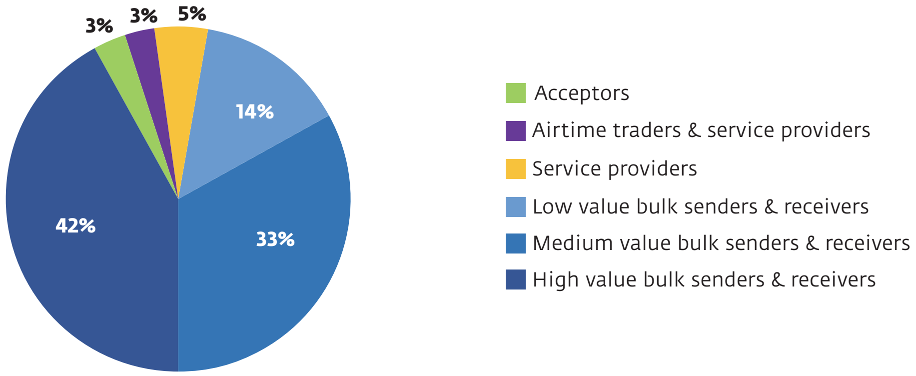


Table 8: Transaction characteristics of Clusters of MSMEs identified through Predictive Modelling

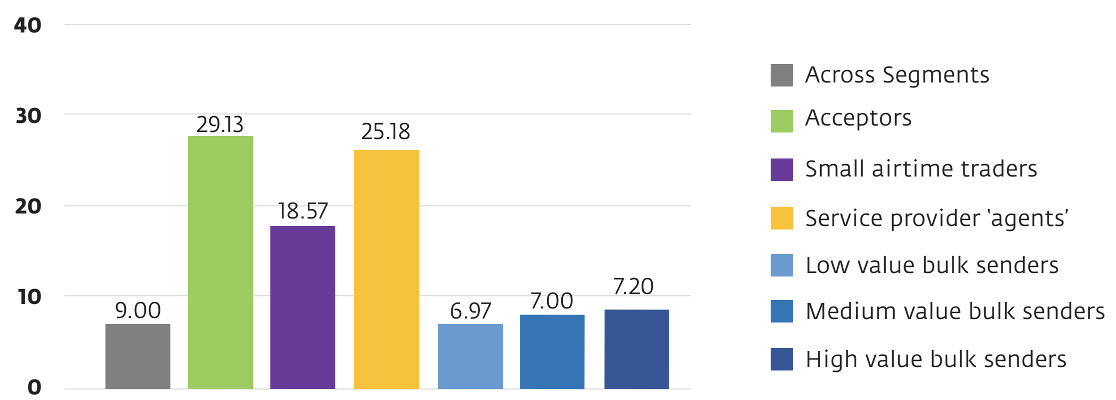
	AVG TRADING DAYS PER MONTH	AVG MONTHLY TRANSACTION COUNT	AVG MONTHLY 2ND PARTY COUNT	MONTHLY TRANSACTION VALUE PER SUBSCRIBER IN USD	AVG TRANSACTION AMOUNT IN USD
Acceptors	20	33	7.5	2,850	40
Service Providers	19	54	6.6	1,690	21
Airtime Traders & Service Providers	25	157	11.9	2,330	16
Low Value Bulk Senders and Receivers	26	66	2.6	190	3
Medium Value Bulk Senders and Receivers	21	35	2.1	180	5
High Value Bulk Senders and Receivers	17	26	2.4	210	8

Use of Transaction Types by Cluster - Acceptors mainly conduct high volumes of 150 to 200 P2P transactions per month. Service Providers are providing services to their informal customers by making transactions for them. Service Providers are doing less P2P transactions but conduct predominantly third-party transactions. They conduct on average 150 third party remittances per month as well as 100 airtime transactions and bill payments. The cluster of Airtime Traders and Service Providers' conduct an average of 100 third party remittances per subscriber and their average number of airtime transactions is with 300 transactions per month also very high. They also do about 200 P2P transactions a month, which means that this cluster's behavior is very similar to what we would expect from a business. Airtime Traders and Service Providers demonstrate intensive usage of mobile money across different transaction types. Low Value Bulk Senders and Receivers handle large transaction volumes but lower transaction amounts both for their P2P and airtime transactions. Medium Value Bulk Senders and Receivers have subscribers who conduct fewer transactions than Low Value Bulk Senders and Receivers, but they conduct 35 percent larger P2P amounts. High Value Bulk Senders and Receivers have the biggest cluster of identified MSMEs, 42 percent. These subscribers are showing 20 percent less activity than Medium Value Bulk Senders and Receivers, but 35 percent larger P2P amounts.

Clusters of identified MSMEs overlap with Supervised Segments - The approximately 32,600 MSMEs that were identified through the predictive modelling in Phase III overlap meaningfully with the 11,500 MSMEs classified during the supervised segmentation in Phase I. MSMEs identified as Acceptors in the predictive modelling are also most likely to be classified Acceptors according to the expert-based definition from the supervised segmentation. Similarly, Service Providers that emerge from the predictive modelling are mostly likely to be defined Service Provider Agents, according to the supervised segmentation. The same holds for the predicted Airtime Traders and Service Providers. Identified MSMEs overlap with the supervised segments of Airtime Traders and Service Provider Agents. Lastly, the identified clusters of Low, Medium and High Value Bulk Senders and Receivers from the predictive modelling are likely to be among the Bulk Senders and Receivers as classified in the supervised segmentation in Phase I. However, their more varied use of transaction types might indicate more diversified MSMEs. Low Value Bulk Senders and Receivers, for example, also have high airtime transaction volumes. Medium and High Value Bulk Senders and Receivers also accept mobile money payments.

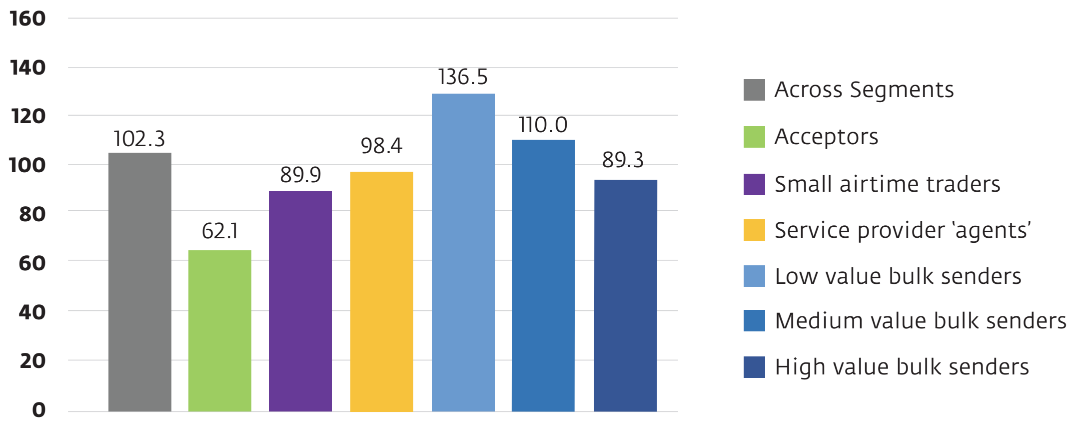
Average Revenue Per User of cluster members - In terms of value that DFS providers may get out of the different clusters of businesses, the ARPU of these segments is consistently higher than the average revenue from the qualitative segments discussed earlier (see end of section 'Qualitative MSME Segmentation using Survey Data' - p.18). The average revenue through mobile money transactions from identified businesses is more than five times higher than the one from normal individual consumers.

Figure 8: Clusters of predictive modelling - ARPU in USD



The average revenue per month across identified businesses from the predictive modelling is 9 USD (grey bar in figure 8). The highest value segment are Acceptors with an ARPU of more than 29 USD (green bar), followed by Service Provider Agents that bring an average revenue of 25.18 USD (yellow bar), and Smaller Airtime Traders with an ARPU of 18.57 USD (purple bar). Together these high value clusters, from a DFS provider perspective, account for 11 percent of identified MSMEs, as shown in figure 7. In contrast, the different clusters of Bulk Senders and Receivers have comparatively low average revenues per users, ranging from 6.97 USD to 7.2 USD, as illustrated in figure 8. They constitute the largest share of identified MSMEs.

Figure 9: Clusters of predictive modelling - AVG monthly account balance in USD



Mobile money account balances - Interestingly, businesses in clusters that have a high average revenue per user are not necessarily the ones that have the highest account balances on their mobile wallets. Bulk Senders and Receivers that had comparatively low ARPUs (below 7.5 USD - blue bars in figure 8) have account balances on their mobile wallets between 89 USD and 137 USD (blue bars in figure 9). Low Value Bulk Senders and Receivers, shown in Figure 9 as the light blue bar, is the cluster that holds the highest amounts on their accounts, in excess of 136 USD.

Key insights – Clustering of predicted MSMEs

- Predictive modelling identified 32,600 MSMEs among the customer base of mobile money subscribers of an MNO in a country in Sub-Saharan Africa. These businesses can further be clustered into the six meaningful subgroups – *Acceptors*, *Service Providers*, *Airtime Traders* and *Service Providers*, as well as *Low*, *Medium* and *High Value Bulk Senders and Receivers*.

- Identified clusters of MSMEs overlap with the groups from the initial supervised segmentation. Hence, validating identified business user groups.

- All segments show high levels of mobile money transaction activity. *Acceptors, Airtime Traders & Service Providers* are the most active in terms of transaction count, transaction value, average transaction amounts, and the average number of second parties that they transact with on a regular basis.

- The approximate average revenue per customer per month among identified MSMEs is on average more than five times higher than the one from normal individual mobile money consumers. They hold an average balance of 102 USD on their mobile wallets.

Implications

Results from both the qualitative and quantitative modelling done during the project have implications for DFS providers, above all MNOs attempting to service MSMEs and their growth. Results contain a wealth of information regarding the MSME market.

Additional model validation - For additional model validation, it is recommended that the MNO conducts follow up calls or visits with a sample of the MSMEs that were identified through the predictive modelling. During this validation process, additional information can be gathered. The MNO should first confirm that the algorithm did not predict a false positive, and it should also confirm that the MSMEs identified are not already using the MNO's agent and/or business profiles. Additionally, the service provider should enquire why respective MSMEs use an individual subscriber profile to transact so frequently instead of using other available value propositions. Possible reasons might be that they have found a better value proposition by using an individual subscriber profile, that they are not aware of other value propositions, or even that the current value propositions are not tailored to their specific needs.

Product development – Understanding the above as well as combining and leveraging the qualitative information obtained about businesses from the survey and the quantitative information about the transaction behavior of different segments will aid with product design. Incorporating the results and using design approaches to then develop new business-specific DFS products helps to offer a better value proposition to micro, small, and medium enterprises. The integration of survey results is crucial in the design phase. The survey results contain valuable ethnographic factors and behavioral metrics that can assist providers to understand, for example, individual MSME's barriers to use DFS, risk behavior, as well as their trust in the different products and financial institutions.

Targeted outreach to MSME segments – Modelling and segmentation of MSMEs helps to identify business clusters among existing mobile money clients as well as support the acquisition of new MSMEs. By collecting key information about new subscribers, DFS providers can directly identify and segment businesses during registration. By knowing which customers are MSMEs, DFS providers can effectively target them with tailored marketing messages that encourage continued active usage of mobile financial services.

In a competitive DFS landscape, having the ability to understand and anticipate the needs of MSMEs gives a DFS provider a competitive market advantage. The model that was developed through this project identified more than 32,000 potential MSMEs among the partners MNO's individual mobile money subscribers. That is approximately 16 percent of the country's total MSMEs. Although a rough estimate, this number is an indicator of the potential impact that segmentation and data driven analysis can have on the market and the continuous monitoring and measuring of transactional data might provide an MSME pipeline for future growth.

Having information like this available for DFS providers to act upon, supplemented by qualitative survey insights, is a substantial market differentiator that can aid in increased product offerings, retention and financial inclusion for currently underserved and underbanked MSMEs.

Conclusion

This research showed that MSMEs with an individual mobile money subscription can be identified based on their mobile money transaction behavior. They can even be further sub-segmented into meaningful MSME tiers. Profiles and patterns emerge that help to sub-segment MSMEs based on their usage of mobile money, their business characteristics, and their financial needs.

In Phase I, the initial segmentation based on transaction analysis and expert-opinion could already identify probable MSMEs as well as different types of informal channel workers that are using the mobile money channel with individual subscriptions for business purposes.

In Phase II, clustering the more than 1,200 MSMEs that were interviewed and that are mobile money users helped to describe business profiles that can inform product design and targeted marketing. DFS providers can use this information in the future to filter and classify new customers as traditional consumers, agents, or other MSMEs. Depending on the sub-segment and profile they fall into, MNOs can then provide tailored products and messaging that address their specific concerns and needs more effectively.

In Phase III, IFC built on information garnered from the first two phases to ultimately develop a robust model that can predict with 98 percent accuracy which individual mobile money subscribers are MSMEs. Using the latest data available to the team (January 2018), the model identifies more than 32,000 MSMEs among existing mobile money users, a sizable proportion of the country's MSMEs.

The next step for the MNO is to use and operationalize the results by integrating them into product design for MSMEs, taking into account segmentation characteristics when signing up new mobile money customers, to develop segment-specific marketing messages and to reach out to identified MSMEs through phone calls or client visits for additional model validation. Apart from additional model validation, areas of potential future research include studying and mapping the suppliers and client networks that MSMEs transact with through mobile money. This will help to further advance the understanding of how these businesses operate and help DFS providers identify networks of potential users in the ecosystem to leverage and engage with.

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