“Analytical approach to digital channel performance optimization of mobile money transactions in emerging markets”

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ANALYTICAL APPROACH TO DIGITAL CHANNEL PERFORMANCE OPTIMIZATION OF MOBILE MONEY TRANSACTIONS IN EMERGING MARKETS

Abstract

Understanding marketing channel performance is a crucial and complex task for the mobile financial technology segment of the mobile industry in emerging markets. However, poor techniques and capabilities for channel optimization of the mobile money users across available channels by the service providers often undermine the performance of these channels. The research aims to develop a target selection and campaign optimization framework for mobile money customers along two channels of transactions. It is complemented by mapping the appropriate campaign techniques across digital and non-digital channels of mobile money transactions. The key analytical method is the combination of fuzzy c-means clustering and RFM algorithm for the target selection development through the usage logs of customers (n = 300) of a mobile service provider. The results indicated that fuzzy c-means clustering and RFM algorithm are efficient for target selection. Also, the mapping of clusters with the appropriate channel of transactions revealed that mobile money users' transactions could be optimized along the digital channel. The analytic model's output enables appropriate cross-selling and up-selling campaigns that optimize the service provider revenue from existing and new mobile money users within the customer base. The channel evaluation revealed mobile application channels to be a promising and future channel for mobile money transactions as smartphone penetration continues to grow in emerging mobile markets. That is a positive sign of the digital channel's future potential for mobile money transactions in developing markets.

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INTRODUCTION

The mobile money sector has witnessed a significant penetration in emerging mobile markets in recent years (Bongomin, Ntayi, Munene, & Malinga, 2018). The term "mobile money" is used across the telecommunication and banking industry with broad meaning and interpretation across different markets (Dermish, Kneiding, Leishman, & Mas, 2011; Gosavi, 2018). Electronic financial services that are carried out via a mobile phone is termed mobile money. Mobile money services are classified into three major segments: mobile banking, mobile payment, and mobile transfer (IOM, 2013; Aker, Boumnijel, McClelland, & Tierney, 2016). While mobile banking has been widely used in academic literature as mobile money, it refers to only one segment of mobile money services (Chikalipah, 2017). Mobile banking is a mobile channel for customers of financial institutions to access their bank account and carry out payments and transfers. This service requires a formal bank account for it to be used by an individual. On the other hand, mobile payment and mobile transfer services are carried out by mobile service providers' customers through mobile phones without a need for formal bank accounts (Gichuki & Muhi-Mutuku, 2017).

Though a registered mobile customer does not need any other requirement to have a mobile wallet than to activate the mobile wallet, however, many mobile customers are not active mobile money customers. In some markets, some operators have less than 50% of their customer base doing mobile money transactions (Mothobi & Grzybowski, 2017). The study develops a framework for mobile operators to retain and increase active mobile money users through a robust marketing campaign optimization technique.

An electronic account linked to the mobile line of the customer mobile phone gives access to these services. This electronic account is known as a mobile wallet, protected by a personal identification number (PIN). Once a transaction takes place, the mobile wallet account is credited or debited accordingly. This study focuses only on the mobile payment and mobile transfer aspect of mobile money. Therefore, through this study, mobile money is limited to payments and transfers from mobile phones that do not require a formal bank account. Usually, mobile phone users deposit cash into their mobile wallet at the outlets of a mobile service provider or at the designated outlets that belong to operator recruited agents. The agent receives the money from the customer and transmits it to the mobile operator through the agent's mobile phone. For a mobile phone user who wishes to withdraw cash from the mobile wallet, the user will need to go to a mobile money agent outlet. However, due to the rapid growth of the money space, there is a lot of integration and collaboration within the ecosystem (Chauhan, 2015; Mawejje & Lakuma, 2017). As a result of cooperation and inclusion within the ecosystem, mobile phone users can now collect money from their mobile wallets through the Automated Teller Machine (ATM) in some developing markets.

The research examines the optimization of mobile money revenue performance from the mobile operator perspective through robust target selection and channel of transaction. The study focuses on how mobile operators can maximize the potential of their mobile money customers from acquisition, growth, and retention stages by leveraging the comprehensive marketing strategy of their exiting core mobile services (Baeshen, Beynon, & Daunt, 2017; Bongomin, Ntayi, Munene, & Malinga, 2018). Several optimization techniques are examined along with other factors that influence the mobile money customer lifecycle within the customer base of a mobile operator. Fuzzy c-means clustering is combined with RFM (recency, frequency, and monetary) model to develop target selection techniques for mobile money customers. The model's selection output provides cross-selling and up-selling campaign opportunities that optimize the service provider revenue across the existing and new mobile money users within the customer base.

This study's originality resides in the selection model of how mobile operators can optimize their revenue from mobile money services. The model links both the analytics that will assist in targeting and profiling the right customers to the offering and programs that can influence customer behavior to generate increment revenue through mobile money transactions. For the target selection, fuzzy c-means is combined with the RFM algorithm to model customer behavior for appropriate treatment. Details of offering and mapping along with one-to-one marketing approach through appropriate transaction channel and selection output are also discussed. The next section opens with a description of related work, followed by the analytical method used and ends with results, discussion, and conclusion.

1. LITERATURE REVIEW

1.1. Related works

Mobile money services exist in over sixty percent of developing countries (GSMA, 2017). In 2008, the service entered Afghanistan and came to India in 2013. In Europe, mobile money services came into Romania and Albania in 2014 and 2015, respectively. However, unlike the normal cellular customer management process, mobile money customer base management is different (Zins & Weill, 2016). Typically,

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in the prepaid market, which is predominantly most of the mobile markets in emerging markets, a mobile customer is said to be active if such a customer performs a revenue-generating event within the 90 days (GSMA, 2017). These are the reported customer base of mobile operators to the regulators, and this forms the basis for the market share that is published by the regulatory bodies (Ndiranju & Nyamongo, 2015; Mothobi & Grzybowski, 2017). However, in measuring the active customer base of mobile money users, most developing markets define the active base following mobile money transaction that is done by a customer within 30 days. With this definition of active mobile money users, the management of the mobile money customer base becomes more complicated than the usual mobile customer base (Chigwende & Govender, 2020).

Also, research has shown that a mobile user who uses the SIM card for mobile money transactions has up to six chances of staying with the operator than a mobile phone user who does not use the SIM card for mobile money transactions (GSMA, 2017). Therefore, it is profitable for operators to convert as many as they can within their customer base to mobile money customers to reduce the problem of customer base inactivity and dormancy. The research develops a framework for revenue optimization techniques through which mobile operators can increase mobile money service usage. The framework includes all the campaign methodologies across the acquisition stage, development stage, and win-back or retention stage of the dormant mobile money users.

Moreover, previous results have shown that there are strong relationships and complex interdependencies among channels (Genler, Dekimpe, & Skiera, 2007; Chen, Kou, & Shang, 2014). Hence, as indicated by Kabadayi (2011), firms' transaction costs can be minimized if sales channels are appropriately chosen and match with the business. Crucial factors of multi-channel marketing and distribution such as channel relationship, channel function, channel cost, and performance have been well researched along several dimensions (Hughes, 2006; Chen, Kou, & Shang, 2014; Mang'unyi & Govender, 2019). Among channels of mobile money transactions, two channels stood out. One is a digital channel, the future channel as smartphone penetration continues to grow in emerging markets. The other is the channel that makes mobile money service usable without an internet connection. This channel solves the financial inclusion problem in rural areas of the developing countries. The next subsection gives details of these two mobile money channels.

1.2. Mobile money transaction channels

The study considers mobile money customers along their channel of transactions regarding mobile payment and mobile transfer from their mobile wallet. Two transaction channels upon which customers can carry out mobile money services on their devices are discussed (see Table 1).

Table 1. Mobile money channel evaluation

Channel	Pros	Cons
USSD (Unstructured Supplementary Services Data)	No software installation is required Device-independent, it will work on any device User-friendly menu interface Encryption is in-built in the SIM card, providing satisfactory security No information is stored on the device Usage is tied to the registered phone number which aids the authentication process of the user No internet connection is required	Limited session length Security (encryption) is wholly dependent on the mobile phone provider Frequency of dropped sessions may be high depending on the quality of mobile operable network
Mobile application	User-friendly and rich user interface More functionality available Phone authentication in real-time can be built into the transaction process	Installation of updates is often required Limited to smartphone users only; Requires additional security and authentication features A customer requires internet to make mobile money transaction
Web application	User-friendly for business and SMEs More functionality available Authentication is seamless	Can process multiple and large transactions at once Requires installation of mobile operator application Requires additional security and authentication feature Internet connection is required

Only USSD and mobile application channels are considered as the mobile money transaction channel in this study. The web portal channel is mostly used for bulk payment and transfer by businesses. USSD is widely used by mobile agents to carry out payment and transfer services for mobile customers across developing markets (Sanganagouda, 2011). USSD is real-time communication technology and session-based. It is used for several supplementary services by a cellular network in sending messages and interactions between a mobile client and an application server (Desai, 2011; Taskin, 2012). A request only needs to be invoked on a mobile phone by merely dialing of an asterisk (*) and hashes (#) (Nyamtiga, Sam, & Laizer, 2013). Another channel for mobile money services is the mobile application channel. The mobile application channel is rapidly developing for mobile money payment and transfer in emerging markets. It consists of software that runs on mobile devices and performs specific tasks for the user of the mobile phone (MMA, 2018). Mobile operators develop their mobile applications and ask their customers to download the app to perform mobile money services on their mobile applications. Unlike the USSD channel, operators often incentivized their customers through other mobile services for downloading the mobile app.

As connected smartphones are daily increasing in developing markets, mobile operators are also thriving to converge most of their services and make them available on their mobile applications. The convergence is vital for the mobile operator because data services, which are their core services, can only be promoted on these smart devices. However, most mobile phone users are still non-smart users, as the penetration of smartphones in developing markets is below 50% (Asuming, Osei-Agyei, & Mohammed, 2019).

However, mobile customers can carry out mobile money services in a more friendly way with the mobile application, only that the adoption of the channel is limited compared to the USSD adoption in developing countries. While mobile operators will continue to grow this digital channel, it remains the future channel for mobile money services.

1.3. Clustering techniques

It is beneficial and exciting in applying data mining techniques to marketing data and information (Gai, Qiu, & Sun, 2018). Data mining reveals unknown and hidden patterns through these techniques to better understand customer behavior in a large customer base. To be able to understand customer behavior within the marketing channels, data mining also helps. One of the most popular techniques in data mining in marketing is clustering (Nayeri & Rostami, 2016). These techniques have been proven useful for marketers in various forms of segmentation required to improve business performance (Tsekouras & Sarimveis, 2004). Rather than applying the same go-to-market strategy for the entire customer base of mobile money users and prospective users in a market, segmentation through clustering techniques would enable specific treatment to each cluster and reduce channel associated cost and marketing spend.

Dongen (2000) describes clustering as a mathematical study of methods used to recognize natural groups within a class of finite entities. There are several clustering techniques. There are some, which are definite to fuzzy clustering, hierarchical clustering, and other techniques. Traditional approaches include the hierarchical Ward's method (Ward, 1963) and crisp c-means, which is non-hierarchical (Johnson & Wichern, 2002). The structure of hierarchical clustering is a tree-like shape with a progressive agglomeration of objects. On the other hand, non-hierarchical approach split objects following a pre-specified number of clusters by establishing center centroids. It assigns objects to cluster when reaching the attribute domain's closest center point (Andrews & Beynon, 2010).

Fuzzy clustering has proven to be an appropriate technique for attending unclear data that usually exists because of incomplete answers or information with informants' biases. Fuzzy c-means provide us an opportunity to consider the object's ambiguous cluster membership. The primary question that needs to be answered when implementing clustering techniques are provided by Ketchen and Shook (1996) as follows:

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- What is the choice of the clustering constructs to hold the segmentation of objects?
- How many numbers of clusters would be created?
- How would findings be interpreted from each cluster analysis?

Two mobile channels of transactions along the behavior of customers that use these channels for mobile money transactions are evaluated through a fuzzy modeling method in this study. Fuzzy c-means (FCM) are used to cluster in the product-space of RFM variables (Bezdec, 1981). The algorithm's ability to search for spherically distributed clusters in the datasets makes it a choice for many applications in the literature. The definition of obtained clusters from the clustering is done on the product space variables. When Gustafson-Kessel (GK) (Gustafson & Kessel, 1979) algorithm is used, the fuzzy clustering becomes the product space of the RFM variables (Gustafson & Kessel, 1979). The algorithm leverages adaptive distance measure, which results in ellipsoidal clusters, to adapt the clusters' shape to the distribution across the data points. While the focus of this study is not so much on the details of the FCM and GK algorithm, the study uses the FCM algorithm to analyze the importance of two different mobile channels to different customer groups. This generates strategic insights for mobile operators on targeting different customer segments for mobile money transactions across various channels.

The fuzzy c-means clustering techniques are used in this study for profiling mobile money users. This aims to determine the appropriate selection and targeting across USSD and mobile application transactional channels for effective revenue optimization programs and campaign implementation. Several revenue optimization methods and different campaign methods exist for generating incremental revenue across the customer base. However, these campaigns cannot be maximized if marketers cannot accurately profile and target different groups for different programs across different channels accurately. If selection and targeting are not correctly done through robust modeling and techniques, the implementation of the programs below the line can lead to revenue dilution and value erosion (Nayeri & Rostami, 2016).

2. RESEARCH METHODOLOGY AND DATA

2.1. Data collection

The model is developed with transaction data from a mobile service provider in an emerging market. The data set contains mobile money transactions and other mobile services usage and behavioral activities on the network. Each customer has a user ID and the usage history of mobile money transactions for the last 90 days. The entire data set contains customers with different mobile money transactional behavior. It includes customers who performed mobile money and other cellular activities on the network. Also, some customers only performed other mobile services without performing mobile money transactions. Other relevant fields within the data set are the channel of transactions, while some customers were consistent with a channel for their mobile money transactions, some leveraged multiple channels within a short period, according to the dataset.

The study analyzes a random subset of customers from the pool of customers within the data set ($n = 300$). From the randomly selected sample of mobile customers, 145 of them have used at least one mobile money service in the last 60 days.

2.2. Model development

This section explains the selection model, which consists of both the fuzzy clustering and the RFM algorithm. The fuzzy c-means and the RFM model aim to identify the right mobile money customers and the right channels upon which a revenue optimization opportunity or campaigns can be deployed across the mobile operator customer base. Figure 1 shows the architecture and the methodology of the model development and the campaign optimization structure.

Fuzzy clustering is a type of unsupervised algorithm technique that partitions into different groups. These groups are overlapping by leveraging both similarity and dissimilarity within and among the groups, respectively. The significant disparity between the general clustering technique and fuzzy clustering is the ability of fuzzy

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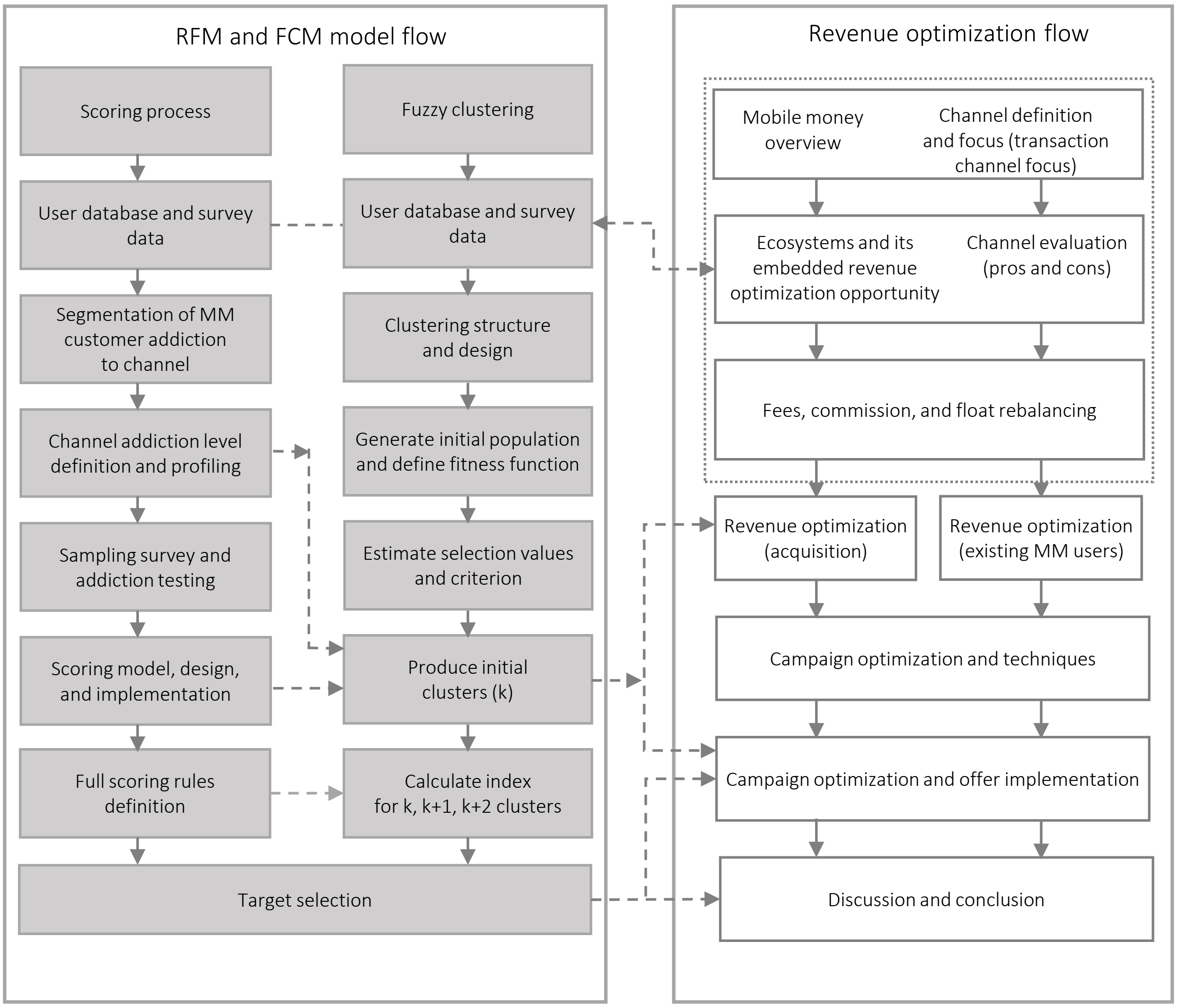

Figure 1. Target selection models – fuzzy c-means (FCM) and RFM

clustering to assign data points to more than a cluster. The converse is the case for classical clustering techniques. A decision must be made on the most suitable cluster for a data point in case data points belongs to more than a cluster in classical clustering. The number of clusters is also known in advance (Ansari & Riasi, 2016). The equation represents the objective function of this algorithm as follows:

$$J=\sum_{i=1}^{c}\sum_{k=1}^{n}u_{ik}^{m}d_{ik}^{2}=\sum_{i=1}^{c}\sum_{k=1}^{n}u_{ik}^{m}\left\|x_k-v_i\right\|^2. \quad (1)$$

Whenever the value m that is a real number is larger than 1, x_k is the k data point, v_i represents the centroid of the i cluster, u_{ik} represents the degree to which the data point k belongs to a cluster i, and $\left\|x_k-v_i\right\|$ is the Euclidean distance between k data point and i cluster center. A matrix U can be defined by using u_{ik} with c rows and n columns so that every individual element of the matrix can have value 0 and 1. The algorithm is similar to classical c-means if all the elements of a matrix U are either 0 or 1. The elements in each column must sum up to 1, while all elements of the matrix U can have any value between 0 and 1. In other words:

$$\sum_{i=1}^{c}u_{ik}=1, \forall k=1,....,n. \quad (2)$$

Equation (2) shows that the sum of the proportions of each data point belonging to each of the c different clusters should be equal to 1. By minimizing the objective function with the above condition together, one has:

$$V_i=\frac{\sum_{k=1}^{n}u_{ik}^{m}x_k}{\sum_{k=1}^{n}u_{ik}^{m}}, \quad u_{ik}=\frac{1}{\sum_{j=1}^{c}\left(\frac{d_{ik}}{d_{jk}}\right)^{\frac{2}{(m-1)}}}. \quad (3)$$

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Several clustering techniques can be used for solving U and V along with several iterations. However, the most popular among these techniques is the fuzzy c-means and Gustafson-Kessel clustering methods. When RFM variables (Table 2) are used for the mobile money customer clustering along two different channels, the clustering space consists of the product-space of RFM features due to the small dimensionality of the feature space of the RFM.

Table 2. The research approach for target selection model and revenue optimization opportunity

Optimization areas	Description
Recency	When did the customer make his last mobile money transaction?
Frequency	How often does the customer make a mobile money transaction within a defined cycle?
Monetary	What is the value of the transaction the customer makes on his mobile wallet within a defined cycle?

3. RESULTS

In carrying out the clustering and developing both the FCM and RFM models, the data of 300 mobile customers were collected and normalized. Out of the 300 mobile customers, 145 of them have used at least one mobile money service in the last 60 days. The analysis focuses on 145 mobile money customers. Also, data from the business intelligence system of the mobile operator compliments the survey data.

The normalized data includes variables such as the customer's tenure on the network, the time the customer became an active mobile money user, and the time of the most recent transaction of mobile money service. The frequency of transactions and value of transactions are also covered. For the fuzzy clustering, the GA-Fuzzy clustering application was used. The customers are divided into five clusters, as shown in Table 3. The clusters are "very good user," "good user," "medium user," "low

Table 3. Clusters definition and characteristics obtained from the combined algorithm

Cluster	Description
Very good user	Very low recency (current users); high frequency and very high transaction value
Good user	Low recency (current users), high frequency and high transaction value
Medium user	Medium recency (starts showing dormancy trait), medium frequency and medium transaction value
Low user	High recency (showing high dormancy trait), low frequency and low transaction value
Very low user	Very high recency (dormancy is very high), very low frequency with a very low transaction value

Table 4. Recency distribution

	Recency – RFM + FCM								
Cluster	P10	P20	P30	P40	P50	P60	P70	P80	P90
Very good user	1	2	3	3	4	5	7	8	10
Good user	12	15	18	21	24	28	28	29	33
Medium user	32	33	35	37	37	38	38	39	40
Low user	42	43	43	45	45	46	47	47	48
Very low user	50	52	52	53	54	55	55	56	57

Table 5. Frequency distribution

	Frequency – RFM + FCM								
Cluster	P10	P20	P30	P40	P50	P60	P70	P80	P90
Very good user	2	4	7	11	20	22	34	40	50
Good user	1	1	2	3	7	9	13	19	21
Medium user	1	1	1	1	1	1	2	3	5
Low user	1	1	1	1	1	1	1	2	2
Very low user	1	1	1	1	1	1	1	1	1

Table 6. Monetary value distribution

Monetary – RFM + FCM									
Cluster	P10	P20	P30	P40	P50	P60	P70	P80	P90
Very good user	1,250	3,455	5,456	7,546	9,998	13,678	18,540	35,006	48760
Good user	300	350	1,705	3,555	8,457	11,560	17,650	19,560	30,557
Medium user	300	350	350	350	350	350	385	5,465	10,500
Low user	300	300	300	300	300	300	300	750	5,500
Very low user	350	350	350	350	350	350	350	350	3,568

user," and "very low user." Each of the clusters has characteristics that are defined through the RFM model in Table 3.

The cluster center for each of the criteria was calculated. Percentile distribution of transaction activity delay was also calculated across clusters for the channel of the transaction, as shown in Tables 4, 5, and 6. Delay represents the number of days of inactivity between two consecutive days of transaction activity. About 70% of the medium users are trial users with only one day of activity. About 80% of low users are also trial users. These two clusters qualify for optimization campaigns that will give other mobile services as a bonus or incentive for any mobile money transaction the customer performs. The threshold of the transaction's value can be a campaign reward condition for the customer to get the instant mobile service reward, which can be data volume or other value-added services with a defined validity.

4. DISCUSSION

There are several ways in which mobile operators can optimize revenue from mobile money services across the customer lifecycle stages. Mobile money as a service cannot be dissociated from the traditional cellular business of providing voice, data, and other value-added services. If an operator wants to maximize the opportunity embedded in this growing financial technology channel, it must leverage the existing mobile services to drive mobile money adoption and usage. Apart from a seamless activation process and a transparent commission structure that must be put in place to maximize the opportunity within the ecosystems, the methods in which revenue can be optimized from the lifecycle stages of mobile money service are as follows:

- *Other incentives for mobile money activation:* To drive the adoption of mobile money services by the operators' existing customers, other mobile incentives must be used to drive customer adoption. Upon activating and setting up the mobile number PIN, customers can be given free megabytes of data or on-net voice to call with a defined validity. Also, all commissions and fees for the first set of transactions can serve as incentives.

- *Dormancy management:* The majority of the active mobile money users will fall into the inactive state due to their non-performance of mobile money transactions within 30 days. These customers will still be active on the network side if they perform other mobile services related events. Therefore, the operator can always reach them through targeted programs. There must be standard customer base management programs for such a segment of the customer base. For example, their transaction fee can be waived for their next transaction to bring them back into the active state. Customers must be reminded of the inherent value of using the service. Merchants and acceptors also must be compensated to encourage and remind customers that they can pay from their mobile wallet in their outlets when they purchase goods and services. Merchants can intentionally promote the use of a specific operator in their outlets if they have a robust program for merchants and acceptors.

The nature of mobile money transactions that is keeping every user activity on the base must be understood. Customers should be incentivized along with their transaction type and encouraged to use other services of mobile money. For example, if what the customer does all the time is cash-out, such a customer should be incentivized below the line to carry out a cash-in transaction and get a GSM bonus

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as incentives. Programs should be developed so customers can pay their bills using mobile money and get their first fee waived. Merchants and acceptors should be encouraged by giving them a special commission rate following the volume of transactions driven by their outlets. The operators should manage all parties within the mobile money ecosystems as they are all critical to the operator's mobile money performance. Also, existing mobile money users should be engaged below the line and manage across all their lifecycle.

The implementation of all these below the line and segmented campaigns requires the availability of robust capability and tools that are integrated with all network elements for seamless delivery of such targeted campaigns. For an operator to optimize revenue potential from mobile money customers, campaign management tools must be in place. Integration among mobile money systems and the billing system must be perfect so that customers can be rewarded in real-time with GSM services immediately after a mobile money transaction is performed. While these integrations and systems are expensive, their payback time is almost immediate compared to the incremental revenue they generate.

CONCLUSION

As mobile financial technology continues to penetrate deeply into the mobile service providers' core businesses, techniques that have been well developed for optimizing the GSM-related services must also be leveraged for the financial technology leg of the mobile business. Many mobile operators try to run the mobile money business in isolation. The study shows that operators cannot maximize mobile money's revenue potential without using GSM-related services as a means of campaign incentives for transaction optimization.

A target selection technique for mobile money campaigns in emerging markets is developed in this study. Fuzzy c-means are used to cluster the customer base in conjunction with the RFM algorithm, which normalizes the prepaid nature of the mobile market in emerging markets. Clusters are generated with their associated characteristics. Campaign optimization techniques are defined for new mobile money users and existing users along the entire lifecycle of mobile money users. This makes it easy to match the clusters with appropriate campaigns and programs suitable for revenue optimization at every stage. For mobile money transactions in developing economies, the mobile application is interactive, easy to use, and increases the frequency of transactions for customers addicted to this channel. However, the low penetration of smartphones in emerging markets has limited the uptake of this channel. USSD channel has the highest frequency of transactions and adoption by almost all the users with an average value of the transaction that is lower than that of the mobile application channel.

One limitation of this study can be seen in the sample of the 300 mobile money users. While the sample base may not be exhaustive, the study draws insights from a comprehensive and extensive customer behavior within the randomly selected sample. Thus, the research opens the door for further research opportunities that exist in the exploration of other transaction channels within the mobile money ecosystems.

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