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A CONSTRUCT FOR RECOMMENDING STRATEGIC MOBILE NETWORK PROMOS FOR IMPROVED SERVICE DELIVERY BASED ON PREVALENT REGIONAL NETWORK SERVICE REQUEST

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ABSTRACT

Mobile network providers make use of promos to attract more clients or consolidate on existing ones. Network service request of voice and Internet differ across locations and pre-knowledge of prevalent network service request for a given location will determine the promo type and subsequently impact positively on the network providers. This paper proposes a construct for identifying the prevalent network service of different regions of coverage. To test the construct, three quarters of telecommunication data obtained from the Nigerian Bureau of Statistics for the four major mobile network providers (Mtn, Globacom, Airtel and 9-Mobile) in 2021 were used. Clustering models such as K-Means, Agglomerative and Affinity propagation were compared to determine the most suitable. The affinity propagation model gave the best results in terms of Silhouette score, Davies-Bouldin Index and Calinski-Harabasz Index metric tests Subsequently, the Affinity propagation model was used to cluster and determine the prevalent network service of voice and Internet for the states and for each network provider. A mean-based linguistic classification identified Airtel and Glo mobile network providers as having equal subscription of voice and Internet across the states while Mtn and 9-Mobile had variable subscriptions. Suitable voice and Internet subscription promos and tariff bundles were thus recommended based on the classification.
Keywords: *Mobile Network, Clustering, Machine-Learning, Subscription Rate, Promos, Tariff Bundles*

1. INTRODUCTION

The concept of marketing is broad and includes strategic as well as operational decisions. Managers of firms, businesses etc globally are beginning to recognize the importance of developing marketing strategies for effective market competition [1]. Marketing strategies can employ strategic promotions to achieve its goal. Strategic promos are not just promos, they are specially planned to achieve set goals. Strategic promos have been suggested as an advantage for improved service delivery in a competitive environment [2]. The need for effective promos that meet the desired goal cannot be overemphasized. A well planned promo ensures a competitive advantage [3]. Ordinarily, promos are advertisements in the form of videos, audios, fliers, billboards or images from companies, institutions or establishments which are aimed to gain the attention of targeted audience to convince them to clientele with them. Promos have been proven as a tool for increasing sales and profit [4],[5],[6]. Mobile network operators have often employed promos as a means of increasing sales and regional popularity. In Nigeria for instance, major mobile network providers such as Mtn, Globacom, Airtel and 9-Mobile have continuously employed promos as a means of attracting customers [7], [8]. These four major mobile network providers are in competition to provide voice and Internet services to their numerous customers across the country.

According to 2022 Nigerian Bureau of Statistics report, Nigeria's projected population is estimated at 216,783,381. Out of this staggering number comes a total subscription of 222,571,568 [9]. This informs that most people in Nigeria subscribe to more than one mobile network provider. The reason for this is that no one mobile network provider delivers a satisfactory service of voice as well as Internet for a given location. In addition to this challenge, the quality of service varies across the respective states. Some mobile network providers may seem to be better in voice service in one state and be worst off in Internet service vice versa. In the midst of all these are the down times experienced across all the network providers during maintenance and poor weather. Hence, customers continue to migrate from one network provider to another in search of either voice or internet service.

Due to the inconsistent service delivery, mobile network providers use promos to entice, attract and encourage their customers as they give out voice and Internet data bonuses as good will. Most of these promos are implemented through different tariff bundles. These bundles group and identify Internet and voice subscribers into a single plan with a fixed subscription cost. One thing that is lacking in the promo tariff bundles is that they are implemented without pre-knowledge of prevalent or preferred service need (voice or Internet) of the different locations. In Nigeria, some states are more urbanized than others. The level of urbanization plays a major role in influencing the network service need. The level of urbanization also to a large extent determines the versatility and range of services offered by the network providers to the users. This goes a long way to influencing the network need of that state.

Promos can serve as avenues through which mobile telecommunication providers access the level of service delivery and satisfaction of their clients. The number of people participating in a promo is an indication of how a mobile service provider is rated among several others. If a service provider has a good rating, several people will like to participate in their promo. The response rate of promos gives the network service providers an insight on the level of service delivery and satisfaction from their clients. Having a fore knowledge of clients' opinion about a particular network service provider especially in a location helps the management to make both short and long term plans towards boosting their product in such locations and improving service delivery.

However, not all promos can be said to be effective. Promos which are not strategically planned may not produce the desired results. Strategic promos should be encouraged in mobile industries. There are two ways that mobile network providers can benefit from strategic location based promos. One is by taking full advantage of the pre-knowledge of the most sought after network service in a given location and solidifying grounds on it. The second is by improving on weaker services by promoting it in areas where they are not so popular. The objectives of this research therefore are (i) to present a construct for identifying prevalent network service for strategic promo execution, (ii) to test the construct using Nigerian subscription data (iii) to recommend to mobile network operators, suitable promos for a given location.

2. RELATED WORKS

2.1 Promos for improved service delivery

Good promos have been linked to improved organizational performance [10]. The authors employed a systematic literature review that is aimed at ascertaining the effect of promos on organizational performance. in the study, more than 25 papers on empirical and theoretical studies were reviewed. Findings show that each individual promo has an impact on organizational financial performance especially on profitability, growth, cash flow, new product advertisement and operational performance. In the case of mobile networks, promos generally attract more subscription which advertently results in improved service delivery for such locations. The aim of every network provider is to attract customers through efficient service delivery and affordable cost. In locations where certain services are weak, good and strategic promos are necessary tools for improving marketing. Service quality, price and customer relationship management within a region influence peoples' subscription to a particular network [11]. Since quality of service is a major factor that determines subscription, mobile network operators strive to improve on their quality of service by initiating promos, giving discounts and incentives as well as incorporating new technologies in their infrastructure. Technology is paramount to improving service delivery [12]. Technology has been employed in improving service delivery by making use of an E-service delivery framework using IT (information technology) infrastructure [13]. The authors explored the advantages in employing IT to provide quality service delivery especially in a competitive market. The authors went ahead to proffered practical ways of improving service delivery through provisions like accessibility, reliability, responsiveness which IT provides. However, the suggestions do not suffice for strategic promo requirement.

2.2 Application of machine learning in promo execution and service delivery

Machine learning (ML) has been applied in service delivery. A framework for identifying the preferred service of a region and optimizing the service in such regions was proposed [14]. Using a machine learning approach, the preferred network service (Voice and Internet) of a given region was identified based on previous subscription within such region. Clustering machine learning algorithms were employed to classify the regions with their respective preferred service need. This provided the mobile network operators the necessary information to reform policies and improve infrastructure in such regions based on preferred need. However, there were no link between the preferred network service and associated promos of mobile network operators. Machine learning was also applied in communication networks to improve resource management, enhance route and path allocation [15]. Similarly, ML was used in network optimization and in management of network resources through deep learning [16],[17] and to improve wireless communication for edge-cloud computing [18]. In the same vein a deep learning approach made up of several ML models were used to train users in a wireless network to ascertain the optimal channel access strategy required to achieve resource allocation [19]. All these point to the relevance of ML in improving service delivery but do not provide answers to how specifically machine learning could be used for strategic promos.

2.3 Proposed frameworks for improved promos and service delivery

Frameworks, suggestions and theories have been proffered as approaches for improving service delivery. A framework of E-service delivery was suggested as a tool to ensuring superior quality mobile service in India [20]. The framework leverages on IT infrastructure and is aimed at enhancing service delivery. However, with the expansion of IT infrastructure, the framework efficiency is in doubt as the system may get complicated and hinder operational efficiency rather than enhancing it. Another framework was proposed specifically for developing mobile (active) network services that ensure service resiliency and efficient resource management [21]. The research specifically aims at improving service mobility and does not take into cognizance, the network service prevalent in the region and how to promote it. It can be argued that such efforts at improving service mobility should rather consider first the different mobile network services of voice and Internet that should be mobilized based on the interest of the clients in a given location. A descriptive research approach was applied to investigate challenges associated with wireless network in remote and large network areas and proffer solutions towards enhancing the services [22]. The study was aimed at improving service delivery by improving frequency range and distance to the nearest booster towers in such regions. The study looked at ways of increasing the capacity of networks to transmit and receive data in such areas where connection was weak. However, the shortfall in the proposed frameworks is that none offered a suitable or practicable strategic promo implementation that could boost service delivery.

2.3 The Research Gap

There is need for mobile networks to employ specific strategies in selecting their promos before execution so as to achieve their goal. One way of doing that is by localizing network service request so that every region is known for a certain service request. The service request of a region can also change with time but it should always be known to the network providers. It is therefore pertinent to develop a framework that incorporates the service need of the clients within a locality. If for example, majority of the clients prefer and patronize a service provider based on consistent Internet services, then promos should be directed towards either sustaining existing patronage or improving voice services and maximizing Internet services and so on. In this paper, a framework that employs strategic promo is proposed. The framework makes use of the clients popular service need within a location to suggest suitable promos for such location/region. The framework aids mobile network providers in deciding what type of promo to undertake for specific regions and also improves their service delivery. Considering the amount usually spent on promos which may or may not yield positive results, it is necessary to have a strategic promo guide for mobile network operators. The proposed framework provides such support by identifying the preferred service need of the different locations with a view of using promos to optimize the service delivery in such locations.

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3. Methodology

This research adopts an experimental approach to substantiate the proposed construct. Data on active voice and internet per state, porting and tariff information was obtained from National Bureau of Statistics (NBS). The dataset has a historical information comprising of second, third and fourth quarter of both voice and internet records of users for 2021 [6]. The second quarter was for June 2021, third quarter was for September 2021 while the fourth quarter was for December 2021. The historical attribute makes it possible to study the behaviour of each network provider in a given location service area over a period of time. For each state and network provider (Mtn, Airtel, Globacom and 9-Mobile/Etisalat), the voice and data records were tabulated in line with the associated quarter depicting the period in 2021.

3.1 Conceptualizing the problem

The basic services rendered by mobile network providers in Nigeria are classified into voice and Internet services. Hence, the promos usually focus on enticing tariff bundles that offer either or both of these services. Some of the promos in form of tariff bundles undertaken by the mobile network providers in Nigeria are shown in Table 1.

Table 1: Nigeria Network Providers And Their Promo Tariff Bundles

S/No	Promo	Benefit	Service Target
Mtn			
1	mPulse	A learning platform for kids	Voice call
2	Awuf4u	Reward on every recharge from N100 & above	Voice call
3	BetaTalk	Rewards customers with 250% airtime bonus and 250% Data bonus on every recharge from N1	Voice call & Internet
4	Mtn Truetalk	A prepaid tariff allows you enjoy FLAT rate of 14kobo/sec for calls across all local Networks in Nigeria after paying a daily access fee of ₦10	Voice call
5	Mtn Extra talk	This bundle gives you more airtime than data	Voice call
6	Mtn Extra data	This bundle gives you more data than airtime	Internet
Airtel			
1	Airtel Ovajara	Offers 8 times more on every recharge	Voice call
2	Airtel SmartTrybe	With the best rates on data and calls to all networks, night browsing for your favorite movies, series and music and special campus data deals	Voice call & Data/Internet
3	Airtel smartTalk	Allows you enjoy a flat rate of 15k/sec for calls across all local Networks	Voice call
4	Airtel Smart Premier Bundle	provide unlimited voice, SMS and data, as well as international calls.	Voice call & Data/Internet
Globacom			
1	Glo Always on	Your line will not be suspended, disconnected or de-activated for one full year even if you do not make/receive calls, text or browse for the entire period	Voice call
2	Glo Berekete 10X	A bonus-based prepaid tariff plan which rewards customers with 10 times the value of every recharge in the form of amazing voice and data benefits	Data/Internet & Voice call
3	Glo 11k Per Sec	A price plan which allows customers call all networks in Nigeria at 11k/sec after deduction of N10 on first call of the day	Voice call
4	Glo 22X plan	Subscribers who recharge with N100 will be credited with N2,200 value.	Voice call & Data/Internet
9Mobile			
1	9konfam	Bringing families and friends closer while providing an extraordinary nine times the value on all recharges of N100 and above	Voice call & Data/Internet
2	Moreflex plus	Customers enjoy more call minutes, data	Voice call & Data/Internet
3	Moreclip	Customers enjoy up to 350% bonus on recharge	Voice call
4	Morelife Complet	A voice-based prepaid package that allows	Voice call

	e	customers to make calls at 11k/s to all networks in Nigeria and to top international destinations	
5	More Business	Includes market analysis, strategy, financials for your business	Voice call & Data/Inte rnet

There are 36 states in Nigeria including the federal capital territory. The four major network providers cover every state in Nigeria. A network coverage of the major providers as seen in [23] is shown in Figure 1.

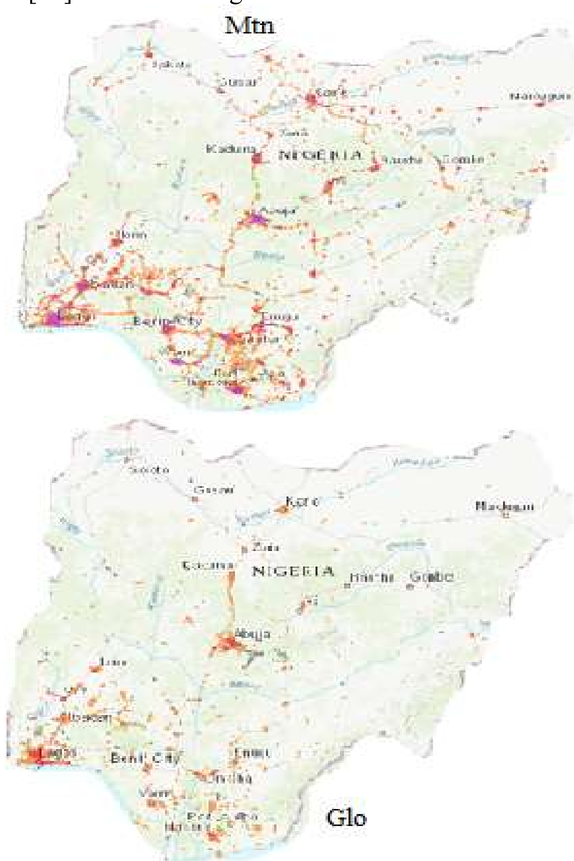


Figure 1: Nigeria's Network Providers Subscription

The dispersion of network coverage for the four major network providers across Nigeria is shown in Figure 1. Mtn has more coverage than other providers while 9-Mobile have the least coverage. Notably, urbanized states such as Lagos, Rivers, Enugu, Kano, Abuja and others are more densely subscribed across the network providers.

However, in each of these states, the rate of subscription differ. Hence, there is a tendency that a mobile network provider may be wasting limited resources without directing their promos to specific network service. Such resources if well directed will definitely improve service delivery. The problem therefore is to specifically identify the weak performing network service in terms of voice and Internet subscription across the states. To do just that, we propose a construct that will cluster the Nigerian states based on the preferred network service subscription for the four major network providers. The problem formulation is summarized in Figure 2 as shown.

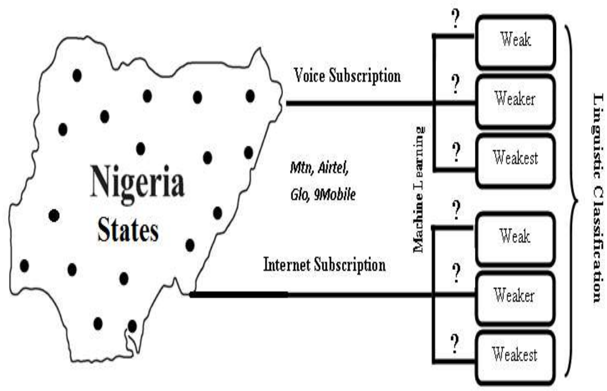


Figure 2: Problem Formulation

3.2 The proposed construct

The construct is a 4-task procedure that specifically clusters network service based on the strength of their subscription across the states. The construct is made up of the following tasks;

a. Data extraction task

The data extraction task is responsible for extracting the input data required for the machine learning. The data extraction task interfaces with the source database of each network provider and extracts relevant subscription data across the states upon which inference is to be made. The extracted data is aggregated to obtain a single output variable for each state for voice and Internet subscription respectively. The aggregated output for both services is thus defined as a pair given as;

$$AG_{output} \rightarrow S_i[I_i, V_i] \qquad 1$$

where I_i represents an aggregated output for Internet subscription and V_i is the aggregated output for voice subscription. S_i represents the individual states.

b. Inference task

The Inference task analyses the extracted data using machine learning approach. The extracted data is an unlabeled data which requires an unsupervised machine learning approach. The purpose of the machine learning models is to ascertain from existing data and associated history the states that have similar characteristics based on the preferred subscription service and thus cluster them together. The models will thus reveal a clustering information upon which the network providers could optimize their promo type for each state. The machine learning models take the aggregated output for each state comprising of Internet and voice subscription as parameters (Eq 1) and cluster them based on their similarities.

The machine learning approaches considered in this paper are;

i. K-means model:- K-means is a popular machine learning model known for clustering data. It identifies peculiarities across data points and clusters them together. The K-means algorithm repeatedly divides the a dataset into k different clusters in such a way that each data point belongs to the group which it shares similar characteristics with. The K-means algorithm is given as:

Step 1: *Determine the appropriate number of clusters for the states as k.*
Step 2: Select random k points called centroids.
Step 3: Assign each data point to their closest centroid, to eventually form the predefined k clusters.
Step 4: Compute the variance and place a new centroid for all the newly formed clusters.
Step 5: Repeat the step 3
*Step 6**:** If reassignment takes place, then repeat step 4 otherwise, conclude.*

ii. Affinity propagation model:- The Affinity propagation model also clusters data into groups. The Affinity propagation model is distinct from others because it does not depend on a pre-defined number of clusters *k* but rather clusters the data by iteratively adjusting its key working matrices such as the responsibility and the availability matrices to ascertain the number of clusters *k* and how the data points are assigned to the clusters. The use of the Affinity propagation model is justified as it has been employed to develop a hybrid based recommender system [24]. The affinity propagation model was also a preferred model for clustering in [25] while in other scenarios, it was successfully used to identify similarities in image processing [26]. The Affinity propagation algorithm is given as:

Step 1: The similarity matrix is first computed which shows the the similarity between pairs of data points using metrics like Euclidean distance
Step 2: The responsibility matrix is initialized as R(i,k) representing the responsibility of data point i to be the exemplar for data point k.
Step 3:After that the availability (A) is initiated, where A(i, k) shows the availability of data point k to choose data point i as its exemplar.
Step 4:The responsibility and availability matrices are iteratively updated at this step until a convergence is reached.
Step 5:The net responsibility for each point is calculated for each data point by summing its responsibility and availability respectively.
Step 6:The exemplars or cluster centres are identified as data points with high net responsibility.
Step 7:Finally each data point is assigned to the nearest exemplar to form clusters depending on their similarity

iii. Agglomerative model:- The Agglomerative model just like the others is also an unsupervised learning model that collates data points according to hierarchy. The modeling approach is derived from Hierarchical Clustering , hence it can also be referred to as Agglomerative Nesting (AGNES). The model has been applied to segmentation and clustering [27]. The clustering is based on similarities between data points. The states that share similarities in terms of Internet and voice subscription rates are clustered together. Agglomerative clustering is an iterative process which combines the most similar cluster pairs until all data points are merged into a bigger cluster [28]. The steps in Agglomerative modeling are:

Step 1: Find the distances that exist between all the clusters.
*Step 2: Hence, group cluster pairs having the **minimum distance** into a new cluster.*
Step 3: Find the distances between clusters, including this new cluster. Repeat the steps until one single cluster is left.

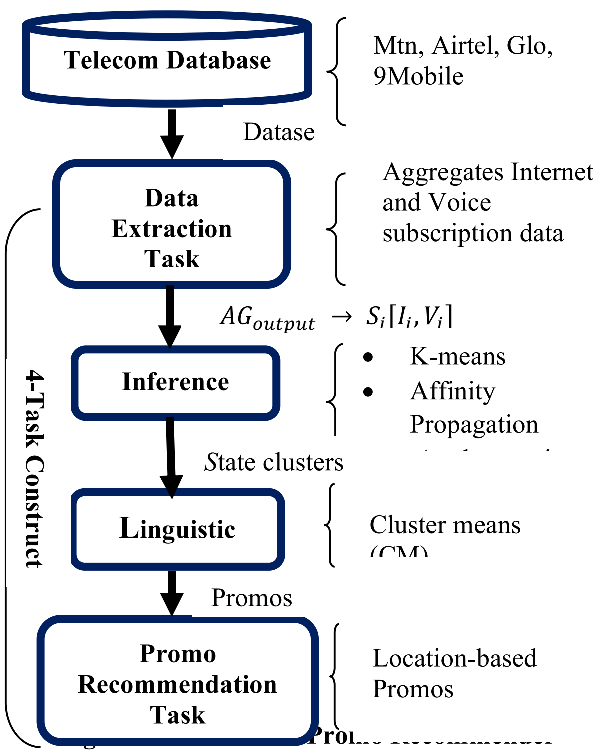
c. Linguistic classifier Task

The linguistic classifier task gives a pronounced interpretation of the results of the Inference task. It classifies the output of the machine learning models into linguistic groups using the mean of the respective clusters. The linguistic groups is dependent on the number of identified clusters. The linguistic groups employed in this paper are *"Highest", "Higher", "High", "Average", "Fair", "Low", "Very Low"*. The results from the linguistic classifier task represents the output parameter upon which a promo suggestion for a specific network provider is based.

d. Promo Recommender Task

The Promo recommender task makes use of the output from the Linguistic classifier task to proffer adequate promo recommendations for the various states. The recommendations aids the network providers in planning a suitable service delivery and at the same time maximize profit. Apart from that, the Promo Recommender task also presents the network service providers a remedial action by highlighting the particular network service that will need improvement in that region.

The proposed 4-task construct is therefore presented as shown in Figure 3



Construct

4 EXPERIMENTAL EVALUATION AND RESULTS

An experimental demonstration of the construct was done using data obtained from the National Bureau of Statistics (NBS) on Internet and voice subscription for the three quarters of 2021. The aggregation for the 1st, 2nd and 3rd quarters in 2021 for each of the network providers as well as the Internet and Voice pair S_i $[I_i, V_i]$ were computed using:

$$I_i = \sum_{i=1}^{3} \frac{IQtr_i}{3} \quad (2)$$

and

$$V_i = \sum_{i=1}^{3} \frac{VQtr_i}{3} \quad (3)$$

The layout of the aggregation is shown in Table 2.

Table 2: Aggregation And Layout Of The Dataset

Voice Calls & Internet/Data																
	Mtn				Airtel				Glo				9Mobile			
State	2nd Qtr	3rd Qtr	4th Qtr	Ave	2nd Qtr	3rd Qtr	4th Qtr	Ave	2nd Qtr	3rd Qtr	4th Qtr	Ave	2nd Qtr	3rd Qtr	4th Qtr	Ave

Using the parameter pair $S_i[I_i, V_i]$, the inference task employed K-means, Affinity propagation and Agglomerative machine learning models to draw inference from the data. For K-means and Agglomerative modeling, the number of clusters (k) was determined for the respective network providers using the elbow and dendogram approaches respectively. Using Pycharm (community edition version 2022) python integrated development environment (IDE), the experimental data from the respective mobile network providers for the three quarters under consideration were modeled and summarized in Table 3. Three performance metric measures were also computed for each model and recorded as shown.

Table 3: Cluster Summary And Metric Measure Result

Cluster Id	No of Clusters	No of States	Silhouette Score	Davies-Bouldin Index	Calinski-Harabasz Index
MTN					
K-means					
0	3	8	0.6237	0.4597	123.3379
1		6			
2		23			
Agglomerative					
0	3	23	0.6237	0.4118	87.2314
1		6			
2		8			
Affinity Propagation*					

0	6	6	**0.5558**	**0.2625**	**262.3116**
1		1			
2		1			
3		1			
4		13			
5		15			
AIRTEL					
K-means					
0	5	9	**0.5662**	**0.3659**	**236.79**
1		3			
2		11			
3		1			
4		13			
Agglomerative					
0	6	9	**0.5569**	**0.3794**	**281.56**
1		3			
2		9			
3		1			
4		9			
5		6			
Affinity Propagation*					
0	7	9	**0.5666**	**0.3729**	**404.97**
1		5			
2		6			
3		12			
4		3			
5		1			
6		1			
GLO					
K-means					
0	4	10	**0.6383**	**0.3381**	**198.46**
1		17			
2		6			
3		4			
Agglomerative					
0	4	17	**0.6383**	**0.2835**	**181.74**
1		6			
2		4			
3		10			
Affinity Propagation*					
0	5	16	**0.6593**	**0.3102**	**371.16**
1		7			
2		4			
3		1			
4		9			
9MOBILE					
K-means					
0	4	12	**0.6100**	**0.3681**	**472.65**
1		6			
2		4			
3		15			
Agglomerative					
0	4	15	**0.6100**	**0.3864**	**423.44**
1		12			
2		4			
3		6			
Affinity Propagation*					
0	7	6	**0.5682**	**0.3553**	**805.30**
1		10			
2		2			
3		1			
4		1			
5		2			
6		15			

Table 3 shows the metric measures and the associated output for the four major mobile providers. The performance measures considered are Silhouette Score, Davies-Bouldin Index and Calinski-Harabasz Index. The Silhouette score evaluates the cohesion within clusters, the Davies-Bouldin Index measures the mean similarity that exist between a luster and the one most similar to it while the Calinski-Harabasz Index compares the variance relationship between the clusters. Based on the experimental data, the Affinity propagation model consistently proved to be the best for modeling the four mobile network providers respectively. The reported silhouette scores and Calinski-Harabasz Index scores were higher in most cases while the Davies-Bouldin Index scores were lower showing that the clustering results were better than other models. The experimental data for the four mobile network providers were thus modeled using Affinity propagation approach. The clustering of the data for the four networks is shown in Figure 4.

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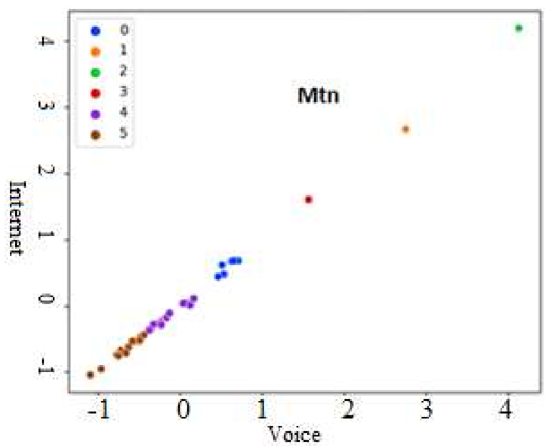

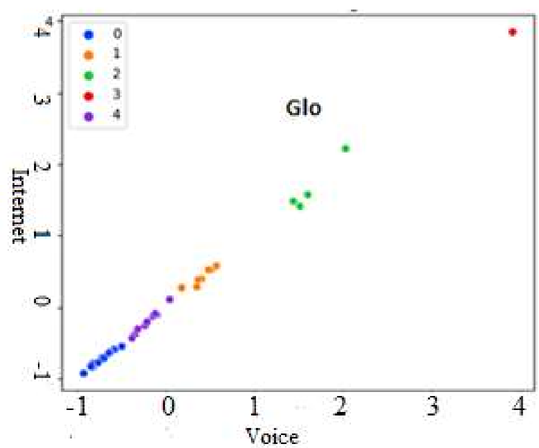

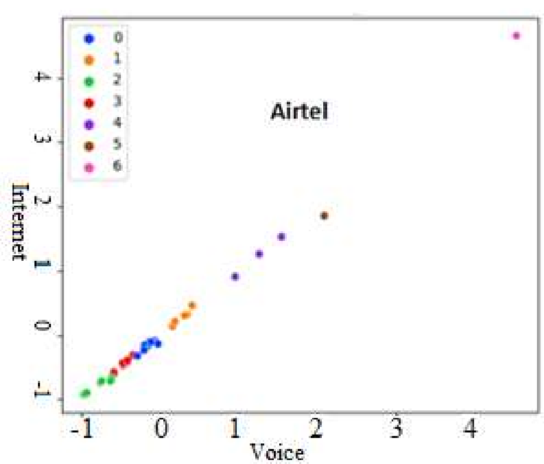

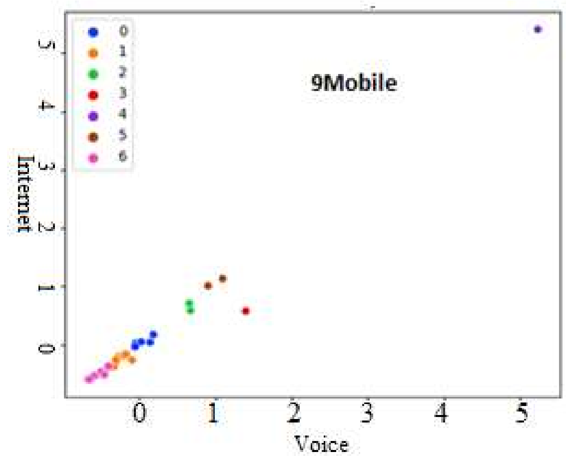

Figure 4: The Affinity Propagation Clustering Of The Four Network Data

Having obtained the respective cluster numbers for the various mobile network providers using Affinity propagation model, the mean-based linguistic classification was carried out on the clusters. For each cluster, the mean of the voice as well as Internet subscription of the respective states under the cluster is computed for the four network providers and recorded in Table 4. The coloured clusters are the ones identified as having different linguistic classification and which need to be improved on. The red color earmarks the network service which needs to be promoted.

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Table 4: Mean-Based Classification

0	10	232620.87	Low	68154.17	Low	Akwa Ibom, Cross River, Delta, Edo, Enugu, Imo, Katsina, Kwara, Plateau, Sokoto
1	6	363734.67	Fair	114161.61	Fair	Abia, Anambra, Benue, Nassarawa, Niger, Oyo
2	2	827341.67	**High***	290435.83	Higher	Fct, Ogun
3	2	667142.80	**Average***	218414.67	High	Kaduna, Rivers
4	**1**	1017859.00	Higher	206430.00	**Average***	Kano
5	1	2857907.00	Highest	1028756.00	Highest	Lagos
6	15	101351.40	Very Low	25586.96	Very Low	Adamawa, Bauchi, Bayelsa, Borno, Ebonyi, Ekiti, Gombe, Jigawa, Kebbi, Kogi, Ondo, Osun, Taraba, Yobe, Zamfara

Finally, the Promo Recommender task highlights the weak subscription service states by comparing the linguistic classification of Internet and Voice network services for each cluster and for every network provider. The respective current intensity as well as the identified network service for improvement are shown in Table 5.

Table 5: Output Of The Promo Recommender Task

S/No	Network	States	Promo Type	Current Intensity	Network Service to be improved upon
1	Mtn	Anambra, Delta, Fct, Kaduna, Oyo, Rivers,	Betatalk and Mtn extra data	Average	Internet
2	Mtn	Ogun	mPulse, Awuf4u, Mtn Truetalk and Mtn Extra talk.	Low	Voice
3	Mtn	Abia, Adamawa, Bauchi, Edo, Enugu, Imo, Katsina, Kwara, Niger, Ondo, Osun, Plateau, Sokoto	Betatalk and Mtn extra data	Fair	Internet
4	Mtn	Akwa Ibom, Bayelsa, Benue, Borno, Cross River, Ebonyi, Ekiti, Gombe, Jigawa, Kebbi, Kogi, Nassarawa, Taraba, Yobe, Zamfara	Betatalk and Mtn extra data	Low	Internet
5	9-Mobile	Fct, Ogun	Moreclip, Morelife Complete	High	Voice
6	9-Mobile	Kaduna, Rivers	Moreclip, Morelife Complete	Average	Voice
7	9-mobile	Kano	9konfam and Moreflexplus	Average	Internet

5. INTERPRETATION OF RESULTS

The interpretation of the results will be based on; prevalent network service for the various states, proposed promos and states where the network providers show some strength

5.1 Prevalent network service for the various states

Among the network providers studied, the Airtel and Globacom network providers were found to

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be equally patronized in subscription on both Voice and Internet services across the states. However, the Mtn and 9-Mobile had different patronage in subscription. For instance, the Mtn recorded a high Voice subscription and an average Internet in states such as; Anambra, Delta, Fct, Kaduna, Oyo, Rivers. a low Voice but high Internet subscription in Ogun, an average Voice and fair subscription in Abia, Adamawa, Bauchi, Edo, Enugu, Imo, Katsina, Kwara, Niger, Ondo, Osun, Plateau, Sokoto and finally a fair Voice and low Internet subscription in states like Akwa Ibom, Bayelsa, Benue, Borno, Cross River, Ebonyi, Ekiti, Gombe, Jigawa, Kebbi, Kogi, Nassarawa, Taraba, Yobe, Zamfara. The 9-Mobile on the other hand recorded a high Voice and Higher Internet in Fct and Ogun, average Voice and High Internet in Kaduna and Rivers, a higher Voice but average Internet in Kano respectively.

5.2 Strategic and Recommended promos

The experiment shows that the Mtn mobile network provider needs to focus on promoting tariff bundles that entice customers towards Internet subscription in the following states; Anambra, Delta, Fct, Kaduna, Oyo, Rivers. Examples of such tariff bundles include; Betatalk and Mtn extra data. Mtn has a low Voice subscription in Ogun, hence they should promote tariff bundles such as mPulse, Awuf4u, Mtn Truetalk and Mtn Extra talk. In Akwa Ibom, Bayelsa, Benue, Borno, Cross River, Ebonyi, Ekiti, Gombe, Jigawa, Kebbi, Kogi, Nassarawa, Taraba, Yobe and Zamfara, Mtn should focus on promoting their Internet subscription request too. On the other hand, the 9-Mobile should promote their Voice subscription in Fct, Ogun, Kaduna and Rivers using especially tariff bundles such as; Moreclip, Morelife Complete. In Kano they should promote Internet subscription using 9konfam and Moreflexplus.

5.3 Strength of the Network Providers

Mtn network appears to be strong in Lagos but show remarkable weakness in places like Akwa Ibom, Bayelsa, Benue, Borno, Cross River, Ebonyi, Ekiti, Gombe, Jigawa, Kebbi, Kogi, Nassarawa, Taraba, Yobe, Zamfara and Kano generally. Airtel has its strong hold in Lagos and Kano while it is weak in Abia, Cross River, Enugu, Gombe, Imo, Jigawa, Kebbi, Nassarawa, Ondo, Osun, Plateau, Taraba and actually very weak in places like Bayelsa, Ebonyi, Ekiti, Kogi, Sokoto, Zamfara. For the Glo network, they are strong in Edo, Fct, Ogun, Oyo and Lagos but weak in Abia, Adamawa, Akwa Ibom, Bauchi, Bayelsa, Borno, Cross River, Ebonyi, Ekiti, Gombe, Jigawa, Kebbi, Sokoto, Taraba, Yobe, Zamfara. Finally for 9-Mobile, they are strong in Lagos, Kano, Fct and Ogun but weak in states like Adamawa, Bauchi, Bayelsa, Borno, Ebonyi, Ekiti, Gombe, Jigawa, Kebbi, Kogi, Ondo, Osun, Taraba, Yobe, Zamfara respectively.

6. IMPLICATION OF FINDINGS AND RECOMMENDATIONS

Obviously, the first implication of the findings is that network service request differ from region to region. What is good for a particular region may not be good for another. Hence mobile network providers need to focus on promoting specific network service rather than doing a general promo. Prior research on mobile promos presents modalities and frameworks for profit making promos without suggesting or highlighting strategies for achieving that. This work however proposes a framework with a strategy for promo execution which is lacking in other promo frameworks. Having a pre-knowledge of prevalent network service request for a region enables the network operators or providers to strategically plan for the appropriate promo for such region. If a specific region need more Internet than voice service, then mobile network providers in such area may decide to undertake promos aimed at sustaining Internet service subscription or in promos that will improve service as well as subscription on voice service. Hence promos are not just done without a specific strategy.

7. SUMMARY AND CONCLUSION

In this paper, a 4-task mobile network strategic promo construct was proposed. The construct identifies the preferred network service of voice and Internet for a specific locality using clustering approach to enable the network operators to have a pre-knowledge of the preferred network service of every region under coverage and strategically plan for a promo that will improve service delivery. The construct was tested using data from Nigeria's telecommunication. The second, third and forth tier telecommunication data of 2021 were extracted and analysed. The construct successfully clustered the different states based on their rate of voice and Internet subscription/usage for the four major mobile telecommunication networks thereby providing the required strategy for mobile operators to plan and execute promos successfully. The construct employed three major clustering machine learning models which include K-Means, Affinity propagation and Agglomerative models. Despite the small dataset which is limited to the 36 states and the capital territory, the Affinity propagation model showed remarkable better performance than the other machine learning models that were compared hence, the clustering was based on the affinity propagation model. The results of the experiment show the strength of the construct in identifying the prevalent network service for all the states in Nigeria. The construct went further to recommend the appropriate strategic mobile promos for the respective network providers based on the identified network service for the respective states. The construct also revealed the weaknesses and strengths of the various network providers and identifies areas of improvement. For mobile promos to have much impact, they should be strategically planned to address specific service need of the people in that region. However, for mobile network to achieve strategic promo planning, there is need to rely on subscription data. Hence, the construct can only be relevant when current subscription data for mobile network operators is available. The construct testing was limited to only 2021 subscription data, it will be interesting to know how the states will cluster based on previous data.

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