A Proposed Framework For Mobile Internet QoS Customer Satisfaction Using Big Data Analytics Techniques

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ABSTRACTS

In the past few years, the Nigeria telecommunication industry has experienced tremendous growth and changes to the extent that customers find it much easier to access the internet through their mobile phones. However, the growth in mobile telecoms subscribers comes with challenges of quality of service, which lead to fluctuations in customer satisfaction. Therefore, the present study proposed a customer satisfaction prediction model through the Key performance indicators obtained from the objective measurement of the network traffic using extended and exhaustive study of the literature. The proposed framework would guide mobile network operators on strategies to embark on in order to retain their customers within the network.

Keywords: QoS, QoE, Prediction model, Customer perception, big data analytics and Customer satisfaction.

I. INTRODUCTION

Over the past decades, the telecommunications (telecoms) sector has been the fastest growing industry around the world. For instance, the telecoms industry experienced a tremendous growth of mobile internet users from 3.69 million in 2000 to 3.27 billion in mid 2015 with 45% internet penetration (Internetworldstats, 2015). Also, as at mid 2015, Nigeria has a total of 67.1 million internet users with a total country population of 178.5 million and with an internet penetration rate at 37% (Internetworldstats, 2015). However, the growth of mobile internet users comes with the challenges of network coverage and slow data penetration (Azeez, 2015; Isabona & Ekpenyong, 2015). These challenges result to flunctuations in services (e.g., mobile voice, video, text and data transmission) provided to the customers by the mobile network operators (MNOs) (Rugelj, Volk, Sedlar, Sterle, & Kos, 2014).

In the telecoms industry, among the key drivers of MNOs success are customers experience, expectations, requirements and perception about the quality of service (QoS) and Quality of Experience (QoE) provided by the MNOs (Agboma & Liotta, 2012). This suggest that, QoS and QoE information are expected to have huge impact on customer satisfaction in terms of the gap between the customer experience and customer expectations (Ibarrola, Saiz, Zabala, & Cristobo, 2014). Hence, the present study considers customer satisfaction as the most significant quality evaluation criteria to determine customer loyalty and retention with a particular network.

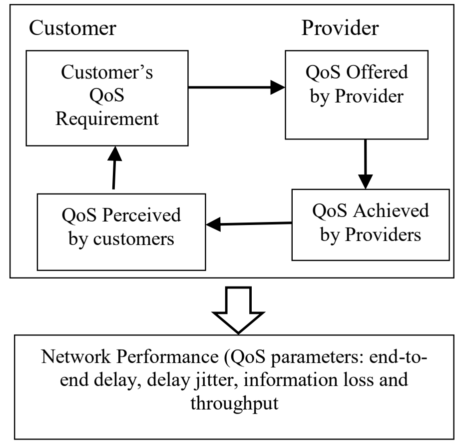
To achieve the quality criteria and improve customer satisfation, the present study employs big data analytics technique as proposed by ITU (2014). The technique has the ability to analyse large data generated in the network traffic of MNOs and one form of the data analytics techiniques is predictive analytics, which has the potentials to predict the future based on past occurrences. As a result, the present study propose a mobile internet customer satisfaction prediction model using big data analtytics techniques, which is envisage to predict the future customer satisfaction from the previous experiences of the customers while using the service. The remaining structure of the paper is as follows: section 1 discusses the literature on QoS and QoE in mobile telecommunications. Section 2 provides information on QoS and QoE Measurement, while section 3 dwells on Big data analtytics and section 4 provides the framework on customer satisfaction prediction model. Finally, section 5 concludes the paper.

II. QoS AND QoE IN MOBILE TELECOMMUNICATIONS

According to International telecommunication Union-Telecommunication (ITU-T) Recommendation E.800 (1994), QoS is describe "*as the collective effect of service performances that determine the degree of satisfaction of a user of the service*." The description implies that network performance is an antecdent of QoS, which determines the satisfaction of customers with the service provided by the MNOs. Gilski and Stefański (2015) mention that degradation in QoS can be attributed to congestion, delay in network and limited bandwidth as a result of poor capacity management. In order to monitor such degradation in QoS and ensure allocation of network resources in the case of anomalies detection, the measurement of mobile internet QoS relies on specific parameters such as throughput, information loss ratio, delay and connection set up time (Farid, Shahrestani, & Ruan, 2013; Shaikh, Fiedler, & Collange, 2010; Reichl, Tuffin, & Schatz, 2013). The use of these parameters for QoS measurement enable MNOs to detect variations between the QoS offered and delivered to their respective customers. In addition, Farid et al. (2013) show that the underlying network technologies, network congestion, heterogenous natures of the network traffic and radio channel have effect on QoS condition. Therefore, network traffic management and optimization technologies should be employed in order to enable MNOs improve customer QoS. In fact, customer experience and the technical aspect of QoS is most approporiate for QoS network traffic management. This assumption is in line with the four-layered QoS model defined by ITU-T Recommendation G1000 (2001). This include the QoS requirement, QoS offered, QoS perceived by the customers and QoS achieved by the MNOs. The relationship between the four layers constitutes the overall management of QoS in such a way that the delivering of QoS required by the customers can be planned ahead by the MNOs. This is achievable through monitoring of the network performance. Figure 1 provides a diagrammatical representation of the four-layered QoS model that entails the fundamentals of the practical management of QoS.

Several studies (Ibarrola, Liberal & Ferro, 2010; Koivisto & Urbaczewski, 2004; Stankiewicz, Cholda & Jajszczyk, 2011) had used the four-layered QoS measurement to analyze the relationship between perceived QoS and network performance of MNOs. For instance, Koivisto and Urbaczewski (2004) find no linear relationship between perceived QoS and network performance as indicated by the ITU-T.

Figure 1: Four-Layered QoS

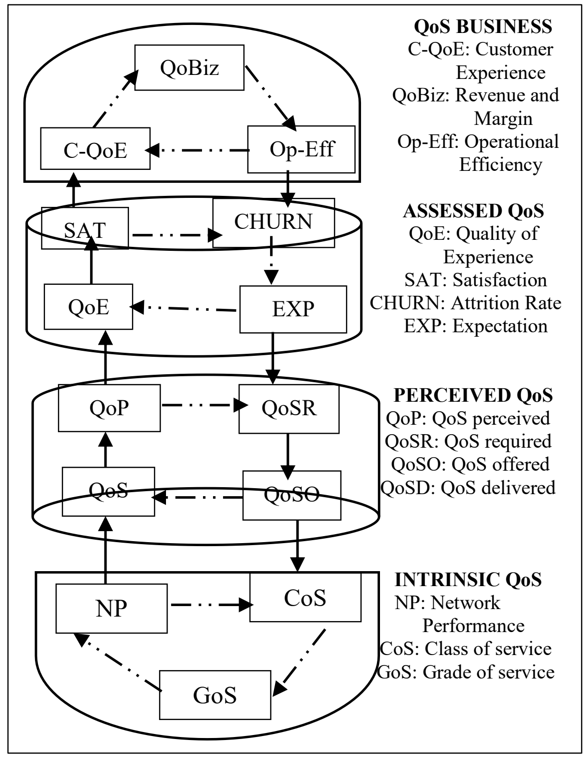


Source: (Farid, et al., 2013; ITU-T Recommendation G1000, 2001).

On the contrary, Ibarrola et al. (2010) and Stankiewicz et al. (2011) document a strong correlation between the network performance and the perceived QoS by the customers. Ibarrola et al (2010) study on QoS management for internet service providers indicate that the recommended process for managing QoS is through the analysis of quality performance measurement, quality of information as perceived by the customers and customer's level of satisfaction. In doing this, it is imperative to define the criteria that are significant to the customers, identify the relationship of such criteria with the network performance, customers perception and expectations. This view is supported by Stankiewicz et al. (2011) whereby they categorise network performance as an instrinsic QoS based on the general QoS model developed by Hardy (2001). The model consists of three layers namely instrinsic QoS, perceived QoS and assessed QoS. The instrinsic QoS describes the network performance, though it is network-centric, but it is very significant to all the aspects of perceived and assessed QoS that is customer- centric (Stankiewicz, et al., 2011). The perceived QoS which reflects the four-layered QoS is influenced by different factors such as the customer experience with the service along with the customers opinions. The layer is the core of the QoS management because it provides the definition of Key performance indicators (KPIs) and Key quality indicators (KQIs), which are useful for defining the QoS required by the customers (Ibarrola, et al., 2014). The assessed QoS comprise of the expectations of customers with the services provided by the MNOs in terms of billing, ordering and correction of errors that occurred while using the provided service (Hardy, 2001). However, ITU-

T introduced a new term called quality of experience (QoE), which can be used to evaluate customer experience with service provided by MNOs. ITU-T P.10/G.100 (2008) describe QoE *as "the overal acceptability of an application or service as perceived subjectively by the end-user."* Kilkki (2008) note that the emergence of QoE is because, it is essential to monitor the customer experience with the service and justify the services based on the experience of the customers using the services. In a similar way, Ibarrola et al. (2014) document that QoE has significant influence on customer satisfaction in terms of the gap between customer experience and customer expectation. In addition, QoE, customer satisfaction, customer expectations and attrition rate constitutes assessed QoS, which implies that the variations in the QoS and QoE parameters has negative or positive influence on customer's satisfaction. Subsequently, Ibarrola et al. (2014) extend the QoS model of Hardy (2001) and Stankiewicz et al. (2011) by adding QoS business to the model which comprises of the customer experience, operational efficiency as well as revenue and margin. Ibarrola et al. (2014) mention the QoS model QoXphere and state that the interactions between each layer of the model would enhance the MNOs to offer a satisfactory services to their customers by monitoring the information provided in each of the layers. The QoXphere model is shown in the Figure 2.

Figure 2: QoXphere Model



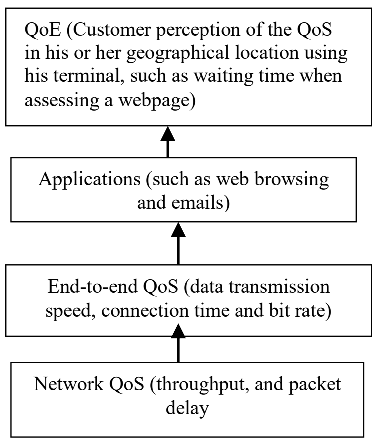
Source: Ibarrola et al. (2014)

III. RELATIONSHIP BETWEEN QoS AND QoE

According to De Moor et al. (2010) and Fiedler, Hossfeld and Tran-Gia (2010), QoS mainly focus on what is happening within the parameters (such as throughput, packet loss and delay), while QoE place emphasis on why the customers is behaving in a particular way. A generic problem observe in the QoS parameters can translate to QoE problem such as glitches, artifacts and excessive waiting time (Fiedler, et al., 2010). Shaikh et al (2010) argue that response time is very essential when relating QoS with QoE. In the case of mobile internet a bad experience in network behaviour may frustrate the customers and declare such service useless, thereby reducing the service utility.

Service utility as describe by Ibarrola et al. (2010) constitute the network QoS, availability and customer care. Therefore, waiting and response time of the network as well as response time of customer complains specifically dominate the experience of mobile internet customers while using the service (Egger, Hossfeld, Schatz, & Fiedler, 2012; Singh, et al.,2013). For example, when the customer is browsing the internet through the mobile phone, the QoS parameters deals with the data transmission speed and availability of the network services in respect to prompt response during navigation through the web pages. However, the QoE in this case deals with how long the customer can wait when a delay is encountered and the response time to rectify the delay if the customer place a call to report to the customer care (Diaz-Aviles, et al., 2015). Thus, customer satisfaction can be deduce by mapping the web browsing session time and customer perception of the quality of the web browsing session (Rugelj, et al., 2014). This would enable the possibility of determining how changes in QoS parameters can influence the experience of customers as well as the impact of QoS service utilities and customer experience on customer satisfaction. Based on the aforementioned arguements, the present study propose a mobile internet QoS and QoE relationship that would enable the proper correlation between the QoS and QoE while measuring QoS and estimating QoE of the mobile intenet customers.

Figure 3: Mobile Internet QoS and QoE Relationship



IV. QoS AND QoE MEASUREMENT

Generally, there are two basic types of measurement for QoS perceived and QoE of the customers. This includes subjective and objective measurement. According to ITU-T Recommendation E.802 (2007) and ITU-T Recommendation G.1030 (2015) subjective measurement is based on human judgement mostly carried out through surveys, while objective measurement makes use of technical means usually algorithms to examine the specific network- related problems with QoS. The subjective measurement may falsify results, time consuming and costly (Fiedler et al., 2010). In contrast, the objective measurement has the capability to imitate and predict customer perception based on the network parameters (Singh et al., 2013). Nonetheless, the objective measurement has the ability to extract customer perception from the detailed analysis of customer behaviour generated through the network traffic, thereby identifying the relationship between the technical parameters and actual customer behaviour (Brooks & Hestnes, 2010; Shaikh et al., 2010). In lieu of this, Spiess, T'Joens, Dragnea, Spencer and Philippart (2014) assert that QoE is a big data problem, because the customers data generated through the network traffic is large and customers perception about the service provided by the MNOs depend on the network reliability, coverage, customer care, service provisioning and billing. Similarly, Yin, Jiang, Lin, Luo and Liu (2014) state that QoE is a direct feedback on network performance, which implies that, if QoE is below expectation, it signifies that there is a problem with the corresponding QoS metrics. On the other hand, if the QoS metric is lower than a threshold, it means that there is a problem in the network performance. Zheng et al. (2016) as well mention that the big data obtained from the objective measurement platform has the potentials to uncover hidden insights on the customers experience that can be used by the MNOs to improve their services. Therefore, customer satisfaction can be modelled by mapping the QoS and QoE metrics using the big data generated in the objective measurement platform or customer historical data of the network traffic of the MNOs. These data can be analysed using big data analytics and can be used by the MNOs to improve the services offerred to their customers.

V. SUGGESTED CUSTOMER SATISFACTION PREDICTION FRAMEWORK

The sugested framework is based on Ibarrola et al. (2014), Farid et al. (2013), Ibarrola et al. (2011), Ibarrola et al. (2010) and ITU-T Recommendation G1000 (2001). The parameters of the framework are derived from detailed analysis of prior literature. The three main elements of the framework are objective measurement, QoS parameters and QoE parameters. The QoS parameters consists of end-to-end delay, information loss, availability, and data transmission speed (throughput), while QoE consists of network response time, waiting time and customer complaints response time. The combination of all these elements along with their parameters can be used for customer satisfaction prediction model by mapping the QoS parameters and QoE parameters This is because the network data which consitute the QoS parameters support the use of big data analtytics algorithms. This can futher be enhanced by predicting the future occurrences of the network traffic. This would enable the determination of variations in the QoS provided by the MNOs and the QoE observed by the customer while using the mobile internet services. Figure 4 presents the framework.

Figure 4: Customer Satisfaction Prediction Conceptual Framework

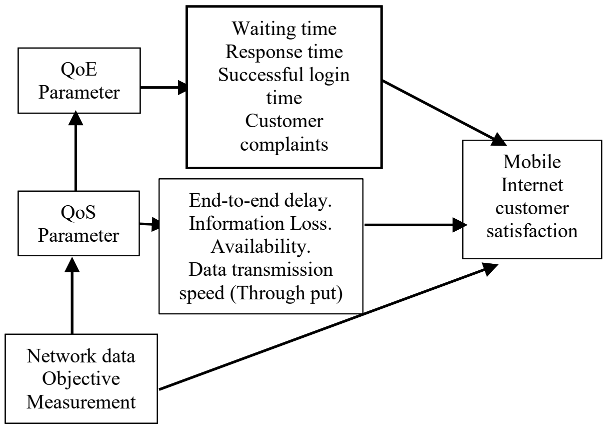


Table 1: Parameters of customers satisfaction prediction framework from the Literature

Authors	Elements	Parameters
Diaz-Aviles et al. (2015); Egger et al. (2012); Fiedler et al. (2010); Shaikh et al. (2010)	QoE	Waiting time, Response time, Successful login time, customer complaints response time.
De Moor et al. (2010); Fiedler et al. (2010); Farid et al. (2013); Gilski and Stefański (2015); Ibarrola, et al. (2010); Ibarrola et al. (2011); Ibarrola et al. (2014); Reichl et al. (2013).	QoS	End-to-end delay, Information loss, Availability, Data transmission speed(Through put)
Brooks and Hestnes (2010); ITU-T Recommendation E.802 (2007); (ITU-T Recommendation G.1030 (2015); Shaikh et al. (2010); (Singh, et al., 2013)	Objective Measurement	Network data Measurement

VI. BIG DATA ANALTYTICS

Big data is a collection of large amount of structured and unstructured data that is difficult to analyze using the traditional data management tools (Tiwari, Chaudhary, & Yadav, 2015). The term big data is characterised in terms of volume, variety, velocity, value and veracity of the data (Chandarana & Vijayalakshmi, 2014; ITU, 2014; Sharma, Vaidya, Chaudhary, & Jora, 2015; Tiwari, et al., 2015). Volume describes the mass and quality of the data, velocity entails the speed of data generation, variety comprises different types of generated data, veracity bring about the accuracy and quality of data sources while value constitutes the potentials of the data to be used to a particular analysis (Chandarana & Vijayalakshmi, 2014; ITU, 2014; Sharma, et al., 2015; Tiwari, et al., 2015). All these characteristics constitute data generated through the network traffic in telecoms industry. The massive amount of data is generated on a day to day basis because of the tremendous increase on the customers mobile internet data subscription. Additionally, the data is of different types such as customer data and application usage behaviour, customer care data, demographics data and traffic data (ITU, 2014). The fast speed of the data generated in the network traffic complies with the big data velocity and is accurate enough because it is generated through the objective measurement (Chandarana & Vijayalakshmi, 2014; ITU, 2014). Thus, appropriate big data analtyics tools or techniques can be used to extract important insights useful for an improved decision making which can be used by MNOs to improve their services.

Generally, there are three types of big data analytics; namely; descriptive analytics, predictive analytics and prescriptive analtytics (Arora & Malik, 2015). Descriptive analytics employs the use of historical data generated through the network traffic to extract important information from the data. Predictive analytics is concerned with forcasting the future by predicting the future occurrence based on the previous historical data generated through the network traffic. Predictive analytics focuses on decision making through the useful insights extracted from the historical data. This is feasible by having a strong understanding of the suitable analytical techniques which constitutes the statistical analysis, machine learning and data mining algorithms.

According to P. Chen and Zhang (2014), statistical techniques is use to exploits the correlation and casual relationship between diiferent variables. Data mining allows the extraction of valuable information from data, while machine learning makes use of different algorithms to evolve behaviours based on the empirical data. Examples of such algorithms are artificial neural networks, support vector machines, association rules, naïve bayes, k-nearest neighbours, decisions trees,classification, regression, ensembles classifiers, random forest, restricted random forest and many more (Mushtaq, Augustin, & Mellouk, 2012). In addition, P. Chen and Zhang (2014) state that there are several big data framework such as

Hadoop Apache and map/reduce, Dryad, Apache mahout and many more that has the potentials of embedding data mining, statistical and machine learning algorithms to execute large scale data analysis and produce accurate prediction models. Hadoop Apache is the most widely used big data framework because of its reliability, completeness and high scalability (Lim, Chen, & and Chen, 2013; P. Chen & Zhang, 2014).

VII. KEYS STAGES OF CUSTOMER SATISFACTION PREDICTION MODEL FRAMEWORK

The customer historical data constitutes the customer behaviour and experiences while using the internet service. Thus, it is possible to analyse the historical data to extract end-to-end performance metrics that would provide insight on how to improve the services provided by the MNOs and predict the customer satisfaction based on the relationship exihibited between the QoS and QoE. In addition, Ibarrola et al. (2014) QoXphere model show that network performance (end-to-end performance) is an antecedent of QoS and QoE is an antecedent of customer satisfaction. As a result, the present study focuses on applying descriptive and predictive analtytics method using the historical data generated through the network traffic of the Nigeria MNOs to extract useful information regarding the QoS and QoE parameters, that can be used to predict the level of customer satisfaction. The descriptive analytics provides the summary of descriptive statistics for the large datasets, this will allow the observation of the correllation between the QoS and QoE.

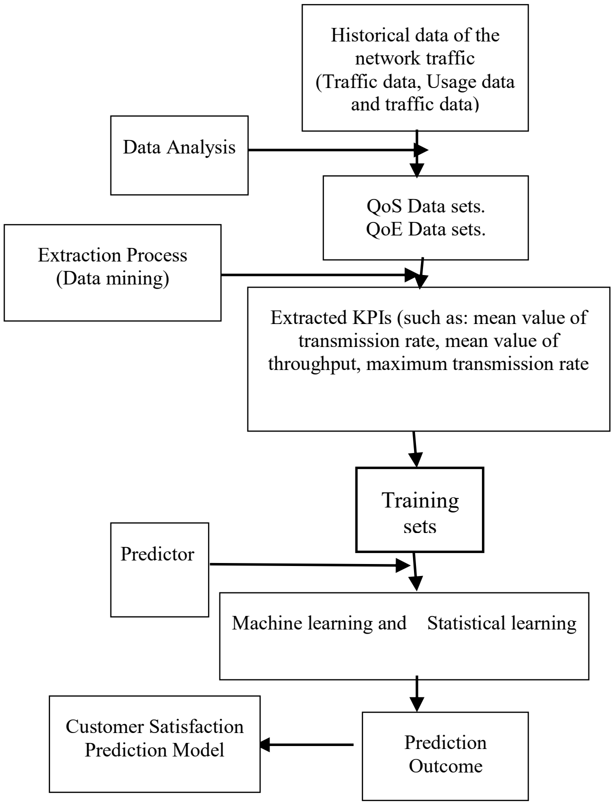
Predictive analytics that generate a prediction model is a central problem in machine learning and it produce a model from the training data set in a diverse large data sets (Kim, Kim, & Kim, 2016). The procedure of prediction modelling is to discover and learn accurate models from a large data sets of the customer historical data. The most significant factor that affect performance of such models depends on the accuracy of the generated prediction model. Because the prediction model is a data-driven model that is generated from an infinite sets of samples called training set. Oftentimes, the training set is a limited sample size, so, real model generated from the data is required to describe all the data points within the large data sets (Kim, et al., 2016). Therefore, algorithm evaluation is required in order to determine the accurate performance of such prediction models.

In the proposed customer satisfaction prediction model, the KPIs extracted are the parameters that are directly obtained from the objective measurement platform of the network traffic. The obtained KPIs is assumed to constitutes the information that can be used to map the network QoS and QoE of the mobile internet to determine the variations in the threshold of the QoS parameters and QoE of the customers. Based on Rugelj et al. (2014)'s study, it can be assumed that past experience of customers can present a key factor like delay that affects the customer perception of quality and satisfaction. Therefore, the impact of past experience on the present customer perception can be determined by measuring the delay observed by the customers while loading a mobile web page, data transmission speed and the service response time (availability). In addition, the prediction of the customer satisfaction can be modelled based on customer's tolerance of the delay, response time of the internet services and the response time of the customer care to rectify potential faults of the network. This is because the KPIs measurement incorporates current customer experience and perception. Hence, variations in customer expectations with the customer experience can be deduced. This would be adopted to model the customers satisfaction prediction based on the objective measurement of the KPIs. As a result, key stages of the mobile internet QoS customer satisfaction prediction model is shown in Figure 5.

VIII. CONCLUSION

This study proposes a framework for mobile internet customer satisfaction prediction model. To achieve the propose framework, a mapping of the QoS and QoE relationship is considered using the KPIs obtained from the objective measurement of the mobile network traffic.

Figure 5: Key Stages Of Proposed Mobile Internet Qos Customer Satisfaction Prediction Model



The proposed model is envisaged to be implemented in the future with the aid of big data framework. The proposed framework is expected to solve the challenges encountered in QoS provisioning and flunctuations in customer satisfaction. This is possible by predicting the customer satisfaction based on the the previous experience of the customers which would assist the MNOs to understand the trends of the network traffic and make intelligent decisions that would enable them to improve their network performance. The study is forseen to contribute to the growing literature in the area of using big data analytics for improving the mobile internet QoS that would enhance customer satisfaction.

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