IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 19 June 2024, accepted 15 July 2024, date of publication 24 July 2024, date of current version 2 August 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3432653

RESEARCH ARTICLE

Forecasting Competence of Colombian Mobile Communication Network Providers Using Artificial Intelligence Models

ERNESTO CADENA MUÑOZ, LUIS FERNANDO PEDRAZA, AND CESAR AUGUSTO HERNANDEZ, (MEMBER, IEEE)
Technological Faculty, Universidad Distrital Francisco José de Caldas, Bogotá 111931, Colombia
Corresponding author: Ernesto Cadena Muñoz (ecadenam@udistrital.edu.co)

This work was supported in part by the Comision de Regulación de las Comunicaciones under Grant 908-2021.

ABSTRACT Cellular networks have become an important part of our society. Every day, we use our cell phones to work, study, or entertain, and users are looking for more bandwidth, lower prices, and quality of service. On the other hand, the providers keep a continuous competition for the market, trying to keep their users or acquire new ones, rethinking the business to make it competitive. It is key to understand the dynamic of the cellular services business and the competence of the operators to adequate it and give the users a better service and experience. This paper focuses on analyzing the market of these services in Colombia with the public data of the providers, using artificial intelligence models to predict future competence and giving a complete knowledge of the cellular service's behavior in Colombia by measuring the dominance and other competence index like HHI, Linda, and Stenbacka. These indexes are calculated, and some forecasts are made. As a result, an automated model has been developed and can be updated with the latest data published online. Our work shows each provider's behavior in three main aspects: income, traffic, and number of users, which regulators frequently analyze. The index results show highly concentrated mobile services and a low-competition market. They can be used as a starting point for regulators and providers to measure the changes in regulations or the need for a new one or analyze the market conditions.

INDEX TERMS Mobile communication, competence level, forecasting, telecommunications regulation, artificial intelligence.

I. INTRODUCTION

The fast growth of internet services and the large amount of data generated by all mobile services have been growing in the last decade, increasing the need for high-speed mobile services with a low delay connection. Technologies like 5G or 6G are the leaders in the mobile services market, keeping the legacy networks connected and offering new services and capabilities of this new technology [1]. In Colombia, most of the network is 4G providers, after the spectrum assignation process, are starting to offer 5G services and the installation of the infrastructure needed, expanding the services and increasing the capacity of the whole network in terms of bandwidth, connectivity, speed, and keeping the levels of exposure to radiofrequency low to comply with actual regulation of the country [2]

The services have changed with each new generation of Mobile services, and users have different experiences depending on the generation, the provider, the cell phone, or even the location. Still, it is key to understand the impact of technology in the mobile services market and how the providers have responded. The relation of the actions taken by the regulation authorities in the field creating or adapting the laws and regulations and how it is reflected in users, incomes, traffic, or other variables [3].

However, understanding the mobile services market is not easy. A law, a new provider, new services, or even a pandemic scenario can change the market. Some years ago, regulator

The associate editor coordinating the review of this manuscript and approving it for publication was Hassan Tariq Chattha.

authorities started sharing information on mobile services, and interest in its analysis and the kinds of trends or patterns that will be discovered has grown [4].

In Colombia, Law 1341 of 2009 is the main regulation for Telecommunication and promotes access, universal service, and radio spectrum management. Also, Law 1978 of 2019 was presented to update it and give more relevance to connectivity, including some definitions and changing part of the spectrum management. In these definitions, mobile telecommunications services without infrastructure or license appear through the mobile virtual network operator (MVNO) modality, which must be analyzed to understand the changes in the market [5].

As in many countries, Colombia has a monopoly market in Mobile Services. Provider Claro has more than 54% of the mobile services market, making a competitive scenario difficult. The regulator needs to analyze the market to modify or create a regulation that helps the providers maintain fair competition, positively impacting the final users. This is represented by low prices and better conditions for users, which increase the satisfaction of mobile service [5].

In this paper, we analyze the Mobile Services Market based on data from the last decade and use known indexes like HHI, Linda, and Stenbacka to measure competence in Colombia. Finally, artificial intelligence techniques are used to predict competition in the market. This information can be used as input for regulator decision-making.

The rest of the paper is organized as follows: Section II presents the related work; Section III describes the system model and the indexes used to measure the competition in mobile services in Colombia; Section IV presents the forecast and index calculation results; and Section V shows the conclusions.

II. RELATED WORKS

Mobile networks have evolved significantly over the decades. With electronics and Internet advancements, mobile services have become necessary for work, study, and entertainment in our daily lives. However, like any service, mobile networks require government authorities to regulate them in each country. This creates a dynamic market where service providers and regulators must continuously update their policies and laws to manage traffic, prices, and services effectively. Understanding market behavior under specific regulations or introducing new services or competitors is challenging [6].

Companies like Cisco predict the global monthly mobile data traffic will be over hundreds of Exabytes. To respond to that demand, providers must increase their investments to buy more bandwidth and enlarge capacity or adopt innovative pricing plans, increasing operational costs. They face fierce competition for attracting subscribers to their network services while the market changes, making the mobile service market more competitive [1].

Organizations like the International Telecommunication Union (ITU) and manufacturers like Samsung and Huawei are working on 6G network design, technology developed to communicate everything, and, as a center point, artificial intelligence. The 6G standard shows stability, security, and a better use of spectrum resources. The innovation is made thinking of a user that uses applications and a large quantity of data with a high-speed data rate and needs to use platforms and technologies that think about scale economies and intelligent services beyond real-time. This means changes in the market's economy and business, which need to be analyzed; the business adapts according to customer behavior and needs and recognizes that each user can be a content creator and have social networks that manage big data [7].

Added to this, another business model appears and needs to be analyzed: the MVNOs, which are service providers based on a strategy that, through an agreement with an established standard mobile service provider, obtains access to network services and infrastructure to offer plans to its users at a rate of its original price to keep the obtain rentability. Now, the world of eSIM cards is expanding, and without the need for a physical SIM or a complex configuration, the business is expanding, too. In this eSIM ecosystem, they can offer new services in many countries, such as tour packages or business models based on multiple wholesale agreements, or may be targeted to different groups, such as IoT users [8].

In Colombia, new service providers play a different scenario; they have to enter where a monopoly operator can exist and compete with it, or if it is an MVNO, associate with it and design a business model to obtain profits. Their lack of experience has become problematic when facing the industry's dynamic development. Technical issues like the fast attenuation of the signals, interference, and poor quality of service (QoS) lead to lower values of satisfaction and experience, making them return to the old providers [9].

Service providers can set service prices and conditions for users depending on the regulatory framework (no regulation, partial regulation, or full regulation). In some cases, monopolies can form, allowing a single operator to dominate the market and alter it to their advantage, making competition difficult. In contrast, a competitive market without monopolies encourages providers to compete on price, quality, and other variables, leading to better conditions and prices for end users [6].

Telecommunications companies strive to offer various innovative services to maintain customer loyalty through innovation, pricing, and Quality of Service (QoS) in a highly competitive market. Government regulations can either foster or hinder competition, making it essential for regulators to assess the impact of these variables to make informed regulatory adjustments [10].

The telecommunications industry is highly dynamic, with each new generation of technology bringing new opportunities and regulatory challenges. Service providers aim to deliver high-quality services while maintaining business viability and profitability. Measuring market competition is crucial to effectively managing prices, QoS, and detecting monopolies [11].

Much of the research on mobile communication services has focused on customer satisfaction, evaluating consumer demand and service quality through literature surveys and questionnaire methods, finding that many factors affect user satisfaction. Other works organize the people in groups, trying to find the individual characteristics and model satisfaction for each group. Another solution uses data mining processes to capture the satisfaction level of the mobile services, finding the user needs, knowing that 4G/5G implementation increases the services and capabilities of the network and makes it competitive with other kinds of networks available in the market [9].

The competition assessment has been a topic of extensive debate in economic literature. Traditionally, competition can be measured using market indexes such as the number of providers, dominance, and competition indexes that use market shares. Another often-used one is the Herfindahl-Hirschman Index (HHI), which can calculate incomes, users, or profit values. Each metric provides a different perspective on competition, but capturing the full complexity of this concept remains challenging [12].

To address these challenges, concentration ratios like the four-firm concentration ratio and the HHI measure the share of the most significant providers of the market. Higher values indicate lower competition. The H-statistic compares the observed HHI with the HHI expected under perfect competition, where higher values suggest less competition [13].

Studies have directly estimated concentration ratios in mobile services using competitive levels or indexes to show the concentration level and competitiveness of the mobile service providers in a country. The Global Competitive Index (GCI) is often used alongside the HHI to estimate the competitiveness of mobile telecommunications services in various countries, demonstrating the effectiveness of these indexes [14], [15].

For example, the author in [16] analyzed the mobile telecommunication market in Serbia using the HHI, while similar analyses were conducted in Morocco. In [17], authors used the HHI to examine competition in Ghana's telecommunications sector, highlighting regulators' challenges in establishing effective laws to regulate the mobile market. Aguilar et al. presented empirical results for five Latin American countries, emphasizing the need to analyze each country's unique market behavior, considering factors such as the number of users and pricing [18].

Another commonly used index is the Stenbacka index, which measures a service provider's dominance level [19]. Regulators have employed this index to study market dominance and competition in telecommunications. The Stenbacka index complements the HHI by providing insights into market concentration, asymmetry, and dominance, helping to understand the interaction between market agents and the competition landscape [19], [20].

In [21], the authors' research highlights that competition among service providers is primarily driven by the size of their installed bases, with indirect network effects also playing a role. This analysis underscores the importance of network effects and installed base size in platform competition.

Most techniques for data forecasting are focused on customer churn, but in this case, they can also be used to predict user, income, and traffic data. Logistic regression is widely used for forecasting with a set of training data. Decision trees are also used as predictive learning techniques in business analytics. They generate high interpretability and a robust rule method. They have been used in applications like the future stock markets and customer-related decisions [22].

Artificial Intelligence techniques like deep learning and algorithms like convolutional neural networks (CNN) are used to classify problems in telecommunication datasets. Recurrent Neural Networks (RNN) are also used for forecasting in telecommunication services. A hybrid deep learning architecture has also been proposed using the CNN technique and the long short-term memory (LSTM). The authors in [23] work with the schemes of LSTM and RNN to obtain good results.

Despite the availability of various market competition measures, there is a lack of studies analyzing the Colombian market. This paper aims to fill that gap by calculating and analyzing competition indicators such as the HHI and Stenbacka index using open data generated by the government. The goal is to understand market competition and behavior over time, identify improvement opportunities, and provide feedback to the authorities in Colombia.

Most AI techniques have been used to forecast sales or churn in mobile services, and random forest or decision trees are applied [24]. Techniques like CNN and RNN are used for classification problems in mobile services. This paper presents how to use AI techniques to obtain Mobile Service Market forecasting using the last data obtained by the providers.

Each AI technique has its strengths and weaknesses in telecom prediction tasks. Machine learning offers high accuracy and interpretability but requires large datasets. Deep learning excels with complex, unstructured data but can be resource-intensive and less interpretable. Time series forecasting provides insight into temporal patterns but may struggle with non-stationary data. Reinforcement learning offers dynamic decision-making but requires careful tuning and simulation.

Deciding a technique depends on specific telecom use cases, data availability, computational resources, and the trade-off between predictive accuracy and interpretability. Integrating multiple techniques or hybrid approaches often yields the best results by leveraging their complementary strengths.

This paper implements some AI techniques, and the best MAPE results for each case are always calculated, keeping the best technique results for forecasting. It is highlighted that the present work is the first study in Colombia, and the results obtained are consistent with previous results of the techniques in other areas, analyzing MAPE values. In the

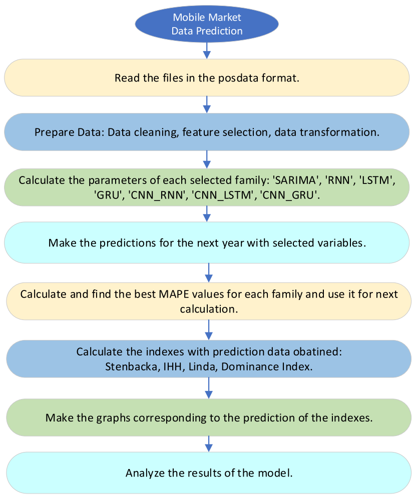

FIGURE 1. System model for competence forecasting.

literature, no other work uses AI to forecast competition indexes like Linda, Stenbacka, and HHI in Colombia; the regulator calculates it but does not analyze the possible values in the future, which is a valuable result of this study.

III. SYSTEM MODEL

This section describes the model, starting with the data used and explaining the variables, environment, and experiment scenario. The regulator authority, called Comisión de Regulación de las Comunicaciones (CRC), has collected data for the last decade. This paper uses the last open data containing some variables from Colombia's mobile market. The model can be seen in Figure 1.

The process begins by loading a compressed file extracted from Postdata [25], which contains the software's most recent history of mobile phone users in the country. After this, a data cleaning and extraction process uses techniques that detect incorrect information or out-of-parameters. Also, standardization and homogenization of the variables selected to be the source of the model are carried out: Incomes, subscribers, and prepaid and postpaid traffic [26]. These variables were selected after analyzing the results of previous regulator studies and the main information contained in the database. They were selected along with the CRC.

Then, the hyperparameters of interest are calculated for each family of the selected artificial intelligence models, except for SARIMA, which does not require this intermediate process. The hyperparameters required for the subsequent calculation algorithm are calculated for the other families: RNN, LSTM, GRU, CNN-RNN, CNN-LSTM, and CNN-GRU.

With the hyperparameters ready, we execute each forecasting algorithm of the 7 families with a time of 12 months ahead of the last data found in the input files.

The general and specific MAPE are calculated for every provider in each family, providing the necessary input to select the best forecasting for each case.

The optimized forecasting results are used to calculate each index, such as Stenbacka, IHH, Linda, and the Dominance Index.

Graphs of the index forecasting are made for the same 12-month period forward to observe the expected movement according to the optimized result of all the models generated.

Finally, the obtained results are analyzed, a task that depends on the market's temporary and updated results.

Next, we will define the forecasting methods and indexes used to analyze the competition in the model.

A. METHODS USED FOR FORECASTING

For the generation of the model, 7 methods were used that will be described below:

1) THE SEASONAL AUTOREGRESSIVE INTEGRATED MOVING AVERAGE (SARIMA)

The SARIMA algorithm analyzes time series data with seasonality and non-stationary patterns. It integrates the autoregressive and moving average components with differencing and seasonal terms. By applying SARIMA, we can effectively eliminate seasonality and non-stationarity, enabling more accurate time series analysis [27].

SARIMA is used in several applications, including economics, finance, meteorology, and epidemiology. It is defined by three main components: seasonal, autoregressive, and moving average. The seasonal component includes the stationary patterns in many cycles of time. The autoregressive models the relation of the current data with the past data, and the moving average component considers the error as the combination of the actual error with the past errors.

Estimating the parameters of a SARIMA model uses statistics, maximum likelihood estimation (MLE), or iterative algorithms, depending on the model's complexity and the available computational resources [28].

Selecting the appropriate SARIMA model involves choosing the values of the parameters (p, d, q, P, D, and Q). This can be achieved by analyzing the data patterns, autocorrelation and partial autocorrelation plots, and statistical tests. Model validation is crucial to ensure accuracy and reliability, which can be achieved using cross-validation or out-of-sample testing techniques.

In time series analysis, determining the values of (p, d, q) and (P, D, Q) is critical. These orders determine how the seasonal and non-seasonal elements will be modeled. The main variables are p, representing the order of the autoregressive component; d, indicating the degree of first differencing, q denoting the order of the moving average component, P which specifies the order of the seasonal autoregressive component, D referring to the degree of seasonal differencing, and Q representing the order of the seasonal moving average component [29]. The SARIMA model is defined as (1) [30]:

$$\varphi_p(B)\Phi\varphi_p(B^s)\nabla^d\nabla_s^D y_t = \theta_q(B)\Theta_Q(B^s)\varepsilon_t \tag{1}$$

where the forecast variable is represented by y_t. The polynomial of the regular autoregressive component of order *p is* $\varphi_p(B)$, while the polynomial for the regular moving average component of order q is $\theta_q(B)$. For the seasonal components, $\varphi_p(B^s)$ represents the seasonal autoregressive polynomial of order P and $\Theta_Q(B^s)$ denotes the seasonal moving average polynomial of order Q.

The operators ∇^d and ∇_s^D are used to remove non-seasonal and seasonal non-stationarity, respectively. Here, B is the backshift operator, which shifts the observation at time t back by one time period. The error term ε_t is assumed to follow a white noise process and s specifies the length of the seasonal cycle [30].

Another very used model is the SARIMAX an improved version of SARIMA, which integrates explanatory variables to obtain better results. It is usually expressed as:

$$\varphi_p(B)\Phi_P(B^s)\nabla^d\nabla_s^D y_t = \beta_k x_{k,t}{}' + \theta_q(B)\Theta_Q(B^s)\varepsilon_t \quad (2)$$

here $x_{k,t}{}'$ represents the vector containing the k-th input explanatory variables at time *t,* and β_k denotes the coefficient corresponding to the k-th exogenous input variable. The conditions for stationarity and invertibility are identical to those found in ARIMA [30].

2) THE RECURRENT NEURAL NETWORKS (RNN)

The RNNs are structured to handle sequential data by preserving a hidden state that retains information about previously encountered sequence elements. These networks are utilized in various applications, such as predicting future values in times series, processing and understanding natural language, and recognizing patterns in speech [31].

RNNs comprise processing units called neurons, which are connected in layers and have recurrent connections that allow them to maintain internal states. This structure allows them to model dependencies over time in the input data.

The association between the RNN nodes can be seen in the following Figure 2 [31]:

Several variants of RNNs are designed to address these challenges. Among the most common are Gated Recurrent Neural Networks (GRU) and LSTM Neural Networks, which use gate mechanisms to control the flow of data and information and avoid gradient fading.

The RNNs are AI models designed to analyze data sequences through their continuous connections, which means the cycle nodes network. Although it may seem unpredictable, since neural networks move in one direction, precisely defining recurring edges ensures no ambiguity. In RNNs, the parameters are used in each step as the sequence unfolds. While connections normally produce activations through layers synchronously, dynamic connections transmit data over consecutive time steps. Therefore, they can be similar to feedforward neural networks; the parameters for each layer, both conventional and recurrent, are consistently applied across multiple time steps [32].

In the following figure, the recurrent connections on the left are cyclic elements; on the right, they are divided into steps where conventional connections are computed synchronously.

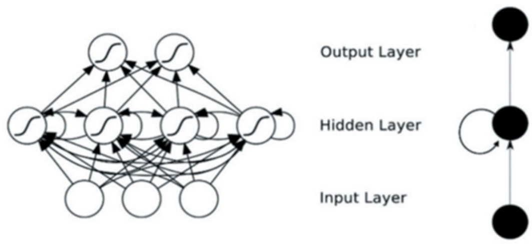

FIGURE 2. **RNN architecture [31].**

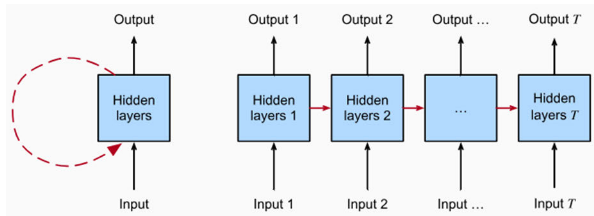

FIGURE 3. **RNN layers [32].**

Mathematically, for an RNN at each time step t, the hidden State is:

$$h_t = \sigma_h(W_h x_t + U_h h_{t-1} + b_h) \quad (3)$$

In this context h_t denotes the hidden layer vector at time t, x_t represents the input vector at time t, W_h is the weight matrix associated with the previous hidden state, and b stands for the bias term. The activation function σ is a sigmoid function [32].

The Exit function is represented by:

$$y_t = \sigma_y(W_y h_t + b_y) \quad (4)$$

where y_t is the output at t, W_y is the weight matrix of output, b is the bias for the output and σ is another activation function.

The process is repeated continuously for all the data. RNNs can be used for forecasting and sequence generation tasks [32].

3) THE LONG SHORT-TERM MEMORY NEURAL NETWORKS (LSTM)

The LSTM is an RNN variant designed to model long-term dependencies in sequential data. LSTMs are effectively applied in several applications like predictions and natural language processing [33].

The basic architecture of an LSTM consists of memory units called "memory cells," which can hold data for a long time. LSTMs use gate mechanisms, such as forget, input, and output gates, to regulate the data flow in the network and avoid the gradient fading/scanning problem.

Not long after Elman-style RNNs used backpropagation, the issue of learning long-term dependencies emerged due to vanishing and exploding gradients. Gradient clipping can mitigate exploding gradients but requires a more sophisticated approach. One of the earliest and most effective solutions was

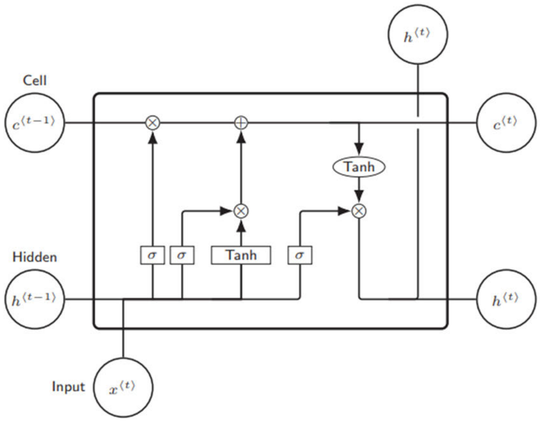

FIGURE 4. LSTM cell structure [34].

the LSTM model, introduced by Hochreiter and Schmidhuber. Unlike standard RNNs, LSTMs replace each recurrent node with a memory cell. These memory cells have an internal state and a self-connected recurrent edge with a fixed weight of 1 [32].

The concept of "long-term memory" is derived from this idea: in Simple RNNs, long-term memory resembles dumbbells. These dumbbells represent weights that change gradually during training, encoding broad information about the data. Short-term memory, on the other hand, is represented by fleeting activations that pass from one node to the next. The LSTM model introduces a new kind of memory, the memory cell which uses multiplicative nodes.

The structure of the LSTM cell can be seen in the following figure [34]:

The LSTM network has the input, forget, and output gates. The mathematical expression is:

$$\begin{aligned} f_t &= \sigma(W_f \times [h_{t-1}, x_t] + b_f) \\ i_t &= \sigma(W_i \times +[h_{t-1}, x_t] + b_i) \\ o_t &= \sigma(W_o x_t + W_o) \\ \widetilde{c}_t &= \tanh(W_c \times +[h_{t-1}, x_t] + b_c) \end{aligned} \tag{5}$$

In this context, W denotes the weight matrix, b denotes the bias vectors, x_t represents the input at the current time step, h_{t-1} is the LSTM output from the previous cycle, and σ represents the sigmoid activation function. The forget gate mechanism computes the portions of the previous memory values to be discarded from the cell. Furthermore, the input gate controls the new information to be added to the cell state [34].

4) THE GATED RECURRENT UNITS (GRU)

The GRU is an RNN that models long-term data sequentially, which is more efficient than LSTMs. GRUs have gained popularity due to their simplicity and computational efficiency compared to LSTMs while maintaining similar performance on many tasks [35].

The GRU represents an improved version of RNN. Designed to work with sequential data such as voice, text, or time series, the GRU employs gating techniques to control the information flow. Similar to the LSTM network, it is faster in the training process and more efficient due to its smaller number of parameters. Each recurrent unit in a GRU includes an update gate and a reset gate [36].

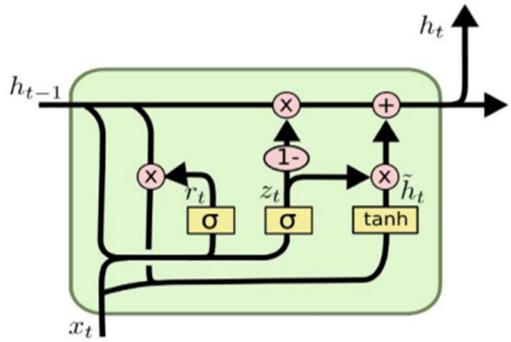

FIGURE 5. GRU network [36].

The GRU's update gates are crucial in managing long-term memory, enabling the model to choose pertinent information from past time steps to carry forward. This adaptive functionality allows the model to retain or discard all past information, effectively mitigating the vanishing gradient problem. Conversely, the reset gate governs the network's hidden state or short-term memory. This gate is pivotal for emulating long-term dependencies, as it dictates whether to remember or forget the prior hidden state information. The architecture of the GRU network is shown below.

The equations used for its calculation are [37]:

$$\begin{aligned} z_t &= \sigma(W_z x_t + U_z h_{t-1}) \\ r_t &= \sigma(W_r x_t + U_r h_{t-1}) \\ \hat{h}_t &= \tanh(W x_t + U(r_t \odot h_{t-1})) \\ h_t &= (1 - z_t) \odot h_{t-1} + z_t \odot \hat{h}_t \\ y &= \sigma(h_t W_y) \end{aligned} \tag{6}$$

the weights are W from the input to the hidden layer, U for the hidden layer, Wy from the hidden layer to the output layer, and Wz from the input to the update gate. Additionally, z_t represents the weight matrix from the input to the update gate, and Wr is for the update gate. The reset gate input r_t is from input to the reset gate, and Ur from the hidden layer to the reset gate at the previous time, r_t represents the matrix from the hidden layer to the reset gate at the previous time, and y denotes the neural network output, while $\odot$ denotes the element-wise multiplication of matrices [37].

5) CONVOLUTIONAL AND RECURRENT NEURAL NETWORK (CNN_RNN)

Combining CNNs with RNNs has proven very effective in processing and analyzing sequential data, and it has good applications for computer vision and language processing. This combination takes advantage of CNNs' ability to obtain spatial and temporal information from data and RNNs' capability to model long-term data in sequences.

This architecture uses CNNs as a feature extractor to process the input and extract the main features. The main features are then passed to an RNN, which is used to model sequential dependencies and make forecasts [38].

6) CONVOLUTIONAL AND LONG SHORT-TERM MEMORY NEURAL NETWORK (CNN_LSTM)

A CNN is specifically designed for processing two-dimensional image input. While CNNs are good at automatically extracting and learning features from one-dimensional sequence data, they are also effective in conjunction with LSTM models. This collaboration, known as a CNN-LSTM hybrid model, enables the CNN to interpret input subsequences collectively provided to the LSTM.

The CNN-LSTM hybrid model is particularly useful for processing sequential data and finding applications in natural language processing and computer vision. This combination allows CNNs to capture spatial features from the input data while LSTMs model long-term temporal dependencies in sequences.

In this architecture, CNNs extract the main characteristics from the input data (e.g., images or text sequences), fed into an LSTM layer. The LSTM layer then focuses on learning the long-term dependencies in the data, making it effective for forecasting [39].

7) CONVOLUTIONAL NEURAL NETWORK AND GATED RECURRENT UNITS (CNN_GRU)

Combining CNN with GRU has emerged as an effective strategy for processing and analyzing sequential data. This combination allows CNNs to extract spatial characteristics from data and GRUs to model the long-term elements in data sequences.

In this architecture, CNNs extract information from input, like images or text sequences. These features are then passed to a GRU layer, which models long-term dependencies in the data and makes forecasting.

Combining CNN with GRU is used in real-world applications, such as detecting anomalies in time series, generating automatic captions for videos, and predicting stock prices in financial markets [40].

B. INDEXES FOR COMPETITION MEASUREMENT

The methods to be used in this paper are HHI and Stenback, which are described below.

1) THE HERFINDAHL-HIRSCHMAN INDEX (HHI)

This index is a commonly utilized measure for evaluating market concentration in business. It is computed by summing the squared revenue shares of all service providers within a particular market at a specific time. Mathematically, the HHI is represented as the sum of the squares of the market percentage of each company that makes up the market [41].

$$HHI_{jt} = \sum_{i \in j,t} (S_{ijt})^2 \tag{7}$$

The HHI can have values ranging from 0 to 10,000. For example, markets with HHIs below 1,500 can be categorized as unconcentrated, which means high competition. Moderately concentrated markets range from 1,500 to 2,500 HHIs, while HHIs exceeding 2,500 mean high market concentrations, potentially raising significant competitive concerns. These thresholds offer guidance in interpreting HHIs [41].

2) THE STENBACKA INDEX

This index [41] gauges a company's market dominance based on its market share. It calculates the variance between the two dominant providers in the market, indicating that these providers possess a majority of users in the market. The mathematical computation is expressed by [42].

$$S^D = \frac{1}{2}[1 - \gamma(S_1^2 - S_2^2)] \tag{8}$$

where S1 and S2 are the percentage shares in sales of the first and second mobile service providers with the highest participation, respectively. The competition parameter γ seeks to collect the main aspects of the competition. In the experiments achieved by Stenbacka, this parameter has been probed with three values (1/2, 1 and 2). With a higher parameter value, the index will be low, resulting in a high probability of finding dominance in the experiment. In this paper, the parameter value is assumed to be one according to the recommendation of Melnik et al [43].

This index will show the degree of dominance through the subtraction of one service provider compared to the participation of the largest service provider in the mobile services sector in terms of sales [44].

Low index values correspond to minimal barriers to mobile service market entry, indicating that potential competition may constrain the firm's ability to exploit its market power effectively. In contrast, high index values signify substantial entry barriers and a reduced expectation of potential competition [44].

3) LINDA

The Linda index, proposed by Remo Linda, has been employed by the Commission of the European Communities to scrutinize industry and market concentration changes within the European Union. These indexes, including the concentration ratio, focus solely on the largest providers and do not account other providers. Unlike other concentration indices like CR, Linda's indexes aim to assess oligopolistic structures that might exist [45].

$$L = \frac{1}{n(n-1)} \sum_{i=1}^{n-1} \left[\frac{n-i}{i}\right] \left|\frac{CR_i}{CR_n - CR_i}\right| \tag{9}$$

In the Linda index formula, n represents the total number of providers considered for the index calculation, CR_n and CR_i are the cumulative market share of the top n providers, and first i providers, respectively. A distinctive aspect of the Linda index is its ability to establish an "oligopoly boundary" [45].

4) DOMINANCE INDEX C

This indicator measures market concentration based on each entity's contribution to the HHI index. It also shows how dominated the market is by the industry's large companies. The result will be between the interval of [0, 1] [45], and the formula is shown below.

$$DI = \sum_{i=1}^{N} \left(h_i^2\right)$$
$$h_i = \frac{s^2}{HHI} \tag{10}$$

where N = Number of market entities, S_i is the market share of the *i-th* entity, and HHI is the Herfindahl-Hirschman index.

The smaller the non-dominant entity, the higher its value, indicating that the dominant entity exercises control over the remaining entities. The market becomes monopolistic when the maximum value 1 is reached [46].

5) CONCENTRATION RATIO -CR

The CR measures the level of market concentration in a market's main providers and it is often used because of its simplicity. The concentration ratio is calculated by comparing the shares of each provider to the whole market. The CR is calculated as shown below.

$$\mathrm{CR}_n = C_1 + C_2 + \cdots + C_n = \sum_{i=1}^{n} C_i \tag{11}$$

where C_i is the *i-th* provider share, for the largest n providers [45].

IV. RESULTS AND DISCUSSION

The model starts by loading the data from a .zip file downloaded from postdata. The algorithm developed in Python takes advantage of libraries like Panda and Numpy for data processing, and the data is organized and cleaned.

The main working variables are income, traffic, and the number of users, and they are divided into prepaid and postpaid for analysis purposes.

Each of the seven techniques is calculated for the variables, and the mean absolute percentage error (MAPE) is computed. The technique with the higher MAPE is then selected for the next stage of the process. MAPE is one of the most accurate precision techniques. It is used to calculate data accuracy in AI techniques, which include forecasting. It compares a test value with the original [47]. It is calculated as shown below:

$$MAPE = \frac{\sum_{t=1}^{n} \left|\frac{a-b}{a}\right|}{n} \times 100\% \tag{12}$$

where a is real data value, b is the result data, and n is the amount of data. The MAPE value is sometimes very high, although it has good results because values close to 0 can significantly increase its value.

As an example of the process, we take the provider "Colombia Telecomunicaciones", and we will observe the three variables for prepaid and postpaid with the forecast generated; as explained in the model, the technique with the lower MAPE value will be selected for the forecast. In this example, the SAMIRA model has the lowest MAPE value, analyzed for every provider and market. In the next subsections, the market forecast for all providers is made with AI techniques, and based on these results, the market indexes are calculated and analyzed.

A. AI MARKET FORECAST

The optimization results and forecasting for each variable with the best method of the executed families are shown and analyzed for the example. The first variable is the number of users in Colombia Telecomunicaciones's postpaid market, as shown in Figure 6.

The blue line shows the data observed in the database, and the red points show the forecast for next year.

The number of postpaid users remained at the same level as last year.

And now for Colombia Telecomunicaciones's prepaid users.

According to the results, the number of prepaid users will decrease next year.

For the second analysis variable, income, we have the following results for Colombia Telecomunicaciones's postpaid.

The incomes will vary, but the trend will increase slightly over the next year.

And for Colombia Telecomunicaciones's prepaid income.

We observe that prepaid incomes decrease compared to previous years.

And for the third variable, traffic, for Colombia Telecomunicaciones's Postpaid.

The network traffic for Colombia Telecomunicaciones's postpaid increased according to last year's trends.

And for Colombia Telecommunications prepaid traffic.

In this case, traffic increased following the trend presented in previous years. The same exercise was performed on all the providers to calculate the best forecasting technique. This data will be the input for the next stage, the index calculation, which will be explained in the following subsection.

It is highlighted that the data used for this calculation is actual data obtained from the providers in the last few years. The historical values are calculated and are consistent with the data analysis made by the CRC and Ministerio de las TIC (MinTIC) in their quarterly report for the last few years [48]. The forecast is made by AI algorithms that can be adapted to compare new data and recalculate the values automatically. This tool will be shared with the CRC to get historical values and forecasting for the next few years.

In the following months or years, the tool is expected to be updated with new actual data, and with it, results will be evaluated to measure the difference between the forecast and reality, obtain new data for the algorithms, or even add new calculation techniques.

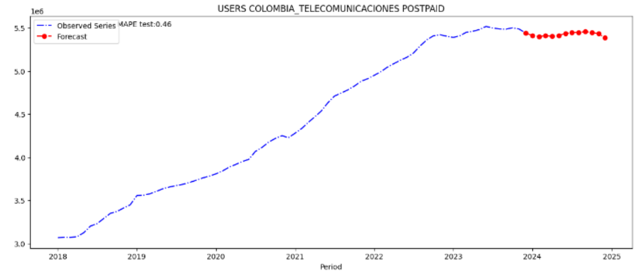

FIGURE 6. Postpaid users of Colombia Telecomunicaciones.

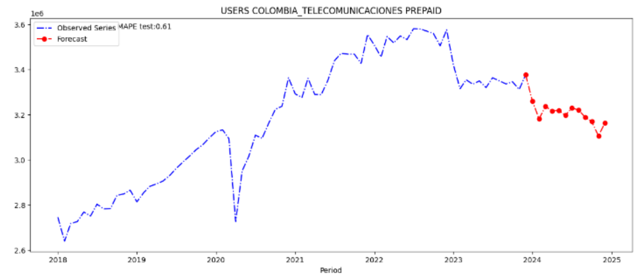

FIGURE 7. Prepaid users of Colombia Telecomunicaciones.

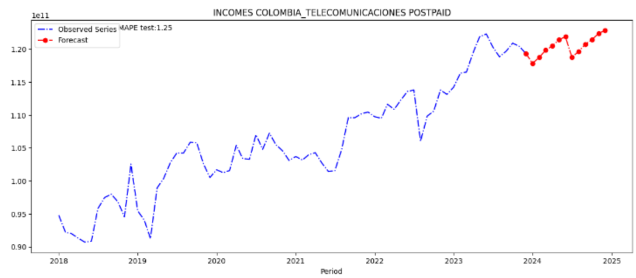

FIGURE 8. Postpaid incomes of Colombia Telecomunicaciones.

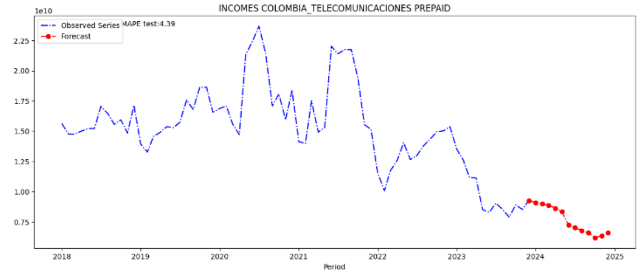

FIGURE 9. Prepaid incomes of Colombia Telecomunicaciones.

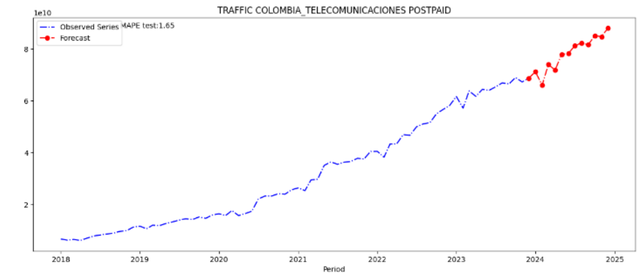

FIGURE 10. Postpaid traffic of Colombia Telecomunicaciones.

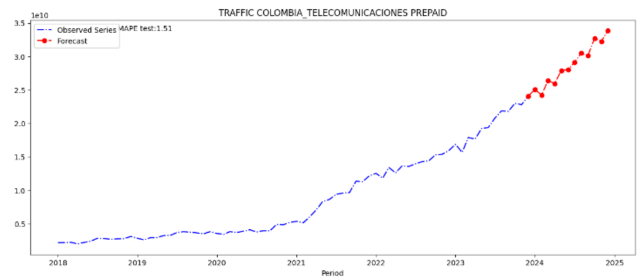

FIGURE 11. Prepaid traffic of Colombia Telecomunicaciones.

B. COMPETITION INDEXES FORECAST

For the forecast of the competition, five indexes were calculated and analyzed. These results are presented below.

1) STENBACKA INDEX

The Stenbacka index was calculated for the 2012 data and forecast for the next year. The index results are from 0-1; if it is close to 0, it means low entrance barriers and better market competence. For the first variable, incomes, the index is shown in Figure 12.

In this case, the Stenbacka index for Mobile Services Incomes has decreased in the last decade, showing that there is more competence now.

The results of the second variable, traffic, are shown in Figure 13.

In this case, the Stenbacka index for Mobile Services Traffic shows a high value, is stable, and is close to the average over the last decade; there is a high amount of traffic concentrated in the country's two main providers.

The results of the third variable, the number of users, are shown in Figure 14.

The Stenbacka number of users shows a decreasing trend, indicating the number of users will be distributed to other providers even if there is a monopoly provider.

2) CONCENTRATION RATIO

The concentration ratio is used to determine the level of market concentration. The values above 0.7 show a high concentration of the market.

The first variable to analyze is the income, as shown below.

The results show a high market concentration, far from a competitive scenario and close to a monopoly environment.

The second variable to analyze is the traffic; results are shown below.

The traffic concentration ratio results show a stable value similar to the income ratio, a high concentration that indicates concentrated traffic from the main providers.

The third variable to analyze is the number of users, as seen in Figure 17.

The number of users concentration ratio indicates a high concentration of users in the leading providers, consequently with other concentration ratio results.

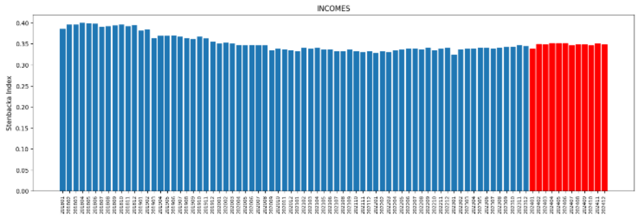

FIGURE 12. Stenbacka index for mobile services incomes.

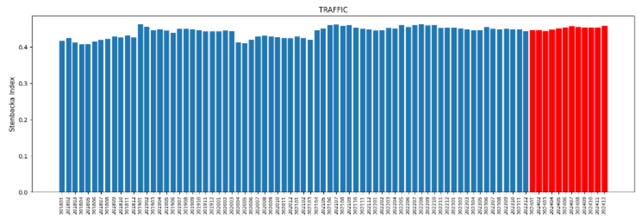

FIGURE 13. Stenbacka index for mobile services traffic.

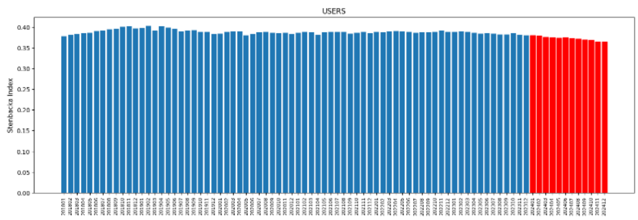

FIGURE 14. Stenbacka index for mobile services users.

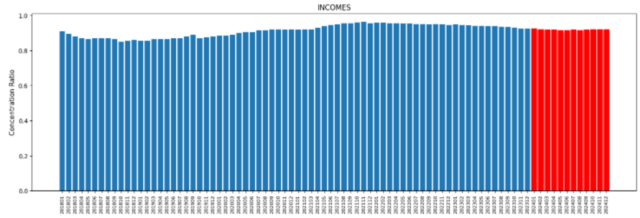

FIGURE 15. Income concentration ratio for mobile services.

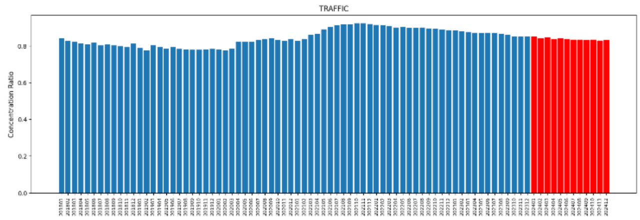

FIGURE 16. Traffic concentration ratio for mobile services.

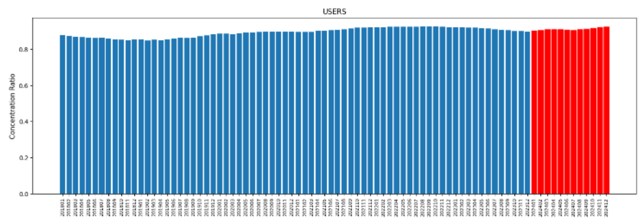

FIGURE 17. User concentration ratio for mobile services.

3) THE HERFINDAHL-HIRSCHMAN INDEX -HHI

This index is widely used to characterize the competence state in a defined market. It ranges from 0 to 10000. Values above 2500 show a noncompetitive and highly concentrated market.

The first variable to analyze is the HHI from the incomes, as seen below.

The HHI results for incomes show a highly concentrated market with low competition; the forecast stays close to the average.

The second variable to analyze is the traffic, as shown in Figure 19.

The results show high concentrated values, not as high as incomes, but considerably high, and it is a low competition indication; it decreases a few.

The third variable to analyze is the number of users, as shown below.

In this case, the HHI trends will increase in the next months and show high concentrated values; it is a low competition indication and corresponds to the other HHI values calculated.

4) LINDA INDEX

This indicator is usually used to measure the eventual existence of oligopoly and inequality between different market shares.

If the results are between 0.20 and 0.50, it is considered a moderately concentrated market, and if they are between 0.50 and 1, there is an imbalance that could affect market competition.

The first variable to analyze is the income, as seen below.

Results show that Linda's index for Mobile Services Incomes is highly concentrated and increasing, which shows a domain trend among the main providers.

The second variable to analyze is the traffic, as seen in Figure 22.

The Linda index results for the Mobile Services Traffic show an increasing trend, and the market is moderately concentrated, not as much as the incomes.

The third variable to analyze is the number of users, as shown below.

The other HHI indexes calculated show an increasing trend that indicates a highly concentrated and low-competition market.

5) DOMINANCE INDEX

The dominance index measures market concentration. Its values range from 0 to 1, where 1 indicates a monopolistic market.

The first variable to analyze is the income, as seen below.

The dominance index results for the Mobile Services Incomes show a highly concentrated market closely resembling a monopolistic market, with the main provider dominating.

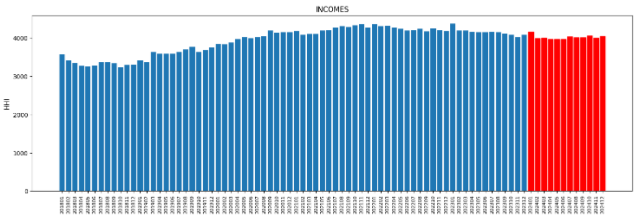

FIGURE 18. **HHI for mobile services incomes.**

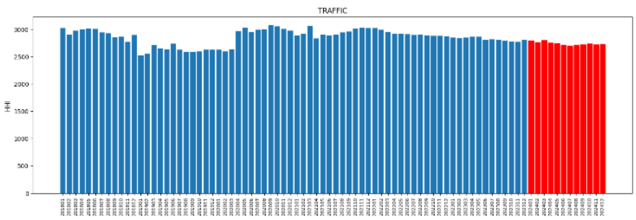

FIGURE 19. **HHI for mobile services traffic.**

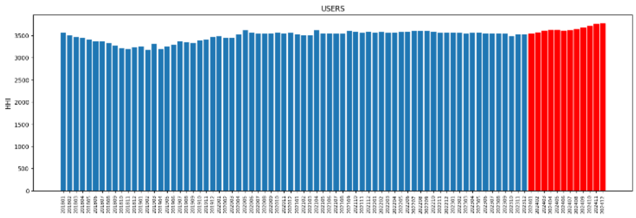

FIGURE 20. **HHI for mobile services users.**

The second variable to analyze is the traffic, as seen in Figure 25.

The results show a moderated dominance level that will decrease in the next months.

The last variable to analyze is the number of users, as shown below.

The dominance index results show a highly concentrated market that will likely increase in the next months, indicating the monopolistic market's impact on the Mobile Services Market. However, this could change by including new providers and fusion processes that will be done next year or even the 5G implementation in the country.

It is highlighted that the CRC has calculated some of the techniques for some years [49], and our results are consistent with their historical calculations. The forecast is made by AI algorithms that can be adapted to compare new data and recalculate the values automatically.

Seven distinct forecasting techniques are evaluated for each variable, with the MAPE being the primary metric for accuracy assessment. Despite potential challenges like high MAPE values, the methodology systematically identifies the most reliable forecasting technique. This approach is crucial for stakeholders in telecommunications seeking robust predictions to guide strategic decisions effectively.

The overall results across income, traffic, and number of users consistently indicate a highly concentrated market environment dominated by significant providers.

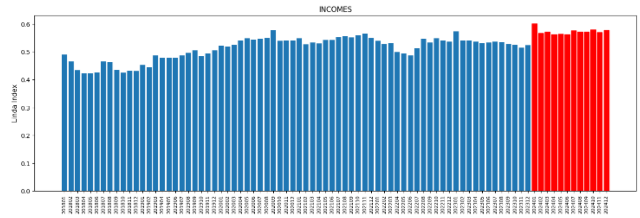

FIGURE 21. **Linda index for mobile services incomes.**

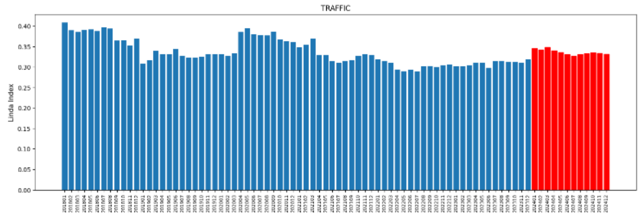

FIGURE 22. **Linda index for mobile services traffic.**

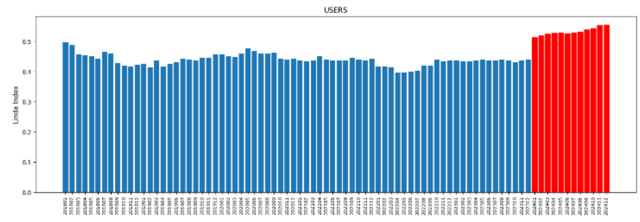

FIGURE 23. **Linda index for mobile services users.**

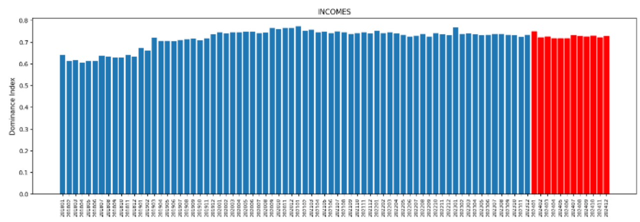

FIGURE 24. **Dominance index for mobile services incomes.**

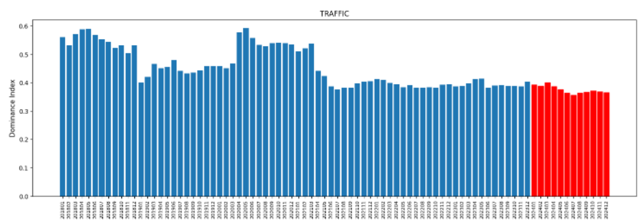

FIGURE 25. **Dominance index for mobile services traffic.**

Low competition levels suggest potential barriers to entry for new market players.

These findings underscore the importance of regulatory measures and technological advancements (e.g., 5G implementation) in potentially reshaping market dynamics.

Strategic interventions could focus on fostering competition through regulatory frameworks that promote market entry and innovation.

Initiatives to diversify market offerings and technologies could mitigate concentration risks and enhance overall market competitiveness.

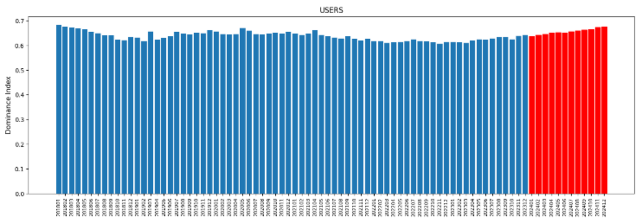

FIGURE 26. Dominance index for mobile services users.

Even if mobile network behavior is variable and users move in several mobility patterns, this work focuses on the complete values of incomes, number of users, and traffic of the whole network reported by the providers. It is not segmented by region or city. A segmented part of the data can be chosen to analyze these patterns or behaviors in future work.

V. CONCLUSION

Analyzing the mobile services market is relevant for regulatory authorities and providers. According to the available data, the index results were calculated for income, traffic, and number of users. The HHIs results for these variables show a high concentration of mobile services in Colombia while the competition is low for providers.

The Stenbacka index results for the three study variables show a dominant provider in the country, but the level has decreased in the last few years. This shows that a small part of the market has been divided by other providers.

The Linda index shows a highly concentrated market and an increasing trend. The concentration ratio for all variables indicates a high concentration of users in the main providers, consistent with other concentration ratio results. Finally, the dominance index shows a trend toward a monopolistic market with low competition.

Consequently, Colombia's mobile services market shows a dominant service provider with a big part of the market, while there is a low competition environment in a highly concentrated market. Authorities and regulators must analyze this to improve mobile service conditions for end-users.

The mix of AI techniques to forecast calculation allows us to find the best results for each provider and variable, which may differ for each case. Still, it always determines the best one by updating the data, and continuing the exercise at least each trimester is recommended, which is the updating time of the data.

In future work, AI techniques can be used in other countries in the Region or the world to understand the dynamics of Mobile Networks better, and some studies can use the updated data and forecast with one provider as a pilot to analyze results over time.

ACKNOWLEDGMENT

The authors would like to express their gratitude to CRC, Minciencias, and Universidad Distrital Francisco José de Caldas for founding this Project.

REFERENCES

[1] C. Zhang, "Pricing and service provision in 5G networks," in *Proc. Int. Conf. Comput. Netw., Electron. Autom. (ICCNEA)*, Sep. 2022, pp. 248–251.

[2] J. Garnica and J. L. Araque, "Broadband isotropic magnetic field probe to assess human exposure in the 5G FR1 band in Colombia," in *Proc. 17th Eur. Conf. Antennas Propag. (EuCAP)*, Mar. 2023, pp. 1–4.

[3] P. R. Kshirsagar, D. H. Reddy, M. Dhingra, D. Dhabliya, and A. Gupta, "A review on comparative study of 4G, 5G and 6G networks," in *Proc. 5th Int. Conf. Contemp. Comput. Informat. (IC3I)*, Dec. 2022, pp. 1830–1833.

[4] C. Panse and A. Chaskar, "Analysing the need for 5G networks based on smartphone market penetration," in *Proc. 3rd Int. Conf. Intell. Commun. Comput. Techn. (ICCT)*, Jan. 2023, pp. 1–5.

[5] A. Barrios-Ulloa, D. Cama-Pinto, F. M. Arrabal-Campos, J. A. Martínez-Lao, J. Monsalvo-Amaris, A. Hernández-López, and A. Cama-Pinto, "Overview of mobile communications in Colombia and introduction to 5G," *Sensors*, vol. 23, no. 3, p. 1126, Jan. 2023.

[6] C. Yang and Y. Kawashima, "Economic analysis of process innovation: The case study of the German telecommunication market," *Innov. Green Develop.*, vol. 3, no. 1, Mar. 2024, Art. no. 100095.

[7] T. A. Kuzovkova, V. O. Tikhvinskiy, O. I. Sharavova, and E. E. Devyatkin, "Examining the impact of strategic trends on radio frequency spectrum requirements in mobile communication system," in *Proc. Syst. Signal Synchronization, Generating Process. Telecommun. (SYNCHROINFO*, Jun. 2023, pp. 1–5.

[8] Ramneek, P. Hosein and S. Pack, "Pricing eSIM services: Ecosystem, challenges, and opportunities," *IEEE Commun. Mag.*, vol. 60, no. 7, pp. 18–24, Jul. 2023.

[9] S. Xia, "Customer satisfaction integration model of mobile communication service market based on data mining," in *Proc. Int. Conf. Knowl. Eng. Commun. Syst. (ICKES)*, Dec. 2022, pp. 1–5.

[10] M. A. Hajar, D. N. Ibrahim, M. R. Darun, and M. A. Al-Sharafi, "Value innovation activities in the wireless telecommunications service sector: A case study of the Malaysian market," *J. Global Bus. Insights*, vol. 5, no. 1, pp. 57–72, 2020.

[11] O. O. Akintokunbo, "Market focus strategy and organizational performance of telecommunication companies in Port Harcourt," *Int. J. Innov. Res. Adv. Stud.*, vol. 5, no. 3, pp. 258–263, 2018.

[12] K. Bahia and P. Castells, "The dynamic effects of competition on investment: The case of the European mobile communications industry," *J. Inf. Policy*, vol. 13, pp. 249–309, Dec. 2023.

[13] A. Diallo and G. Tomek, "The interpretation of HH-index output value when used as mobile market competitiveness indicator," *Int. J. Bus. Manage.*, vol. 10, no. 12, p. 48, Nov. 2015.

[14] A. Schneider, "Credit cooperatives: Market structure, competition, and conduct. Exploring the case of Paraguay," Munich Pers. RePEc Arch., Munich, Germany, Tech. Rep. 102309, 2020.

[15] D. Bardey, D. Aristizábal, J. S. Gómez, and B. Sáenz, "Concentration of the mobile telecommunications markets and countries' competitiveness," *Telecommun. Policy*, vol. 46, no. 1, 2022, Art. no. 102230.

[16] M. Kostić and J. Živković, "Concentration of supply on the chosen markets of serbian electronic communications sector," *Eur. J. Appl. Econ.*, vol. 18, no. 2, pp. 76–94, 2021.

[17] C. Gutiérrez-Hita, V. Zhukova, and S. Amassaghrou, "Evaluating competitiveness in the Morocco's telecommunications sector through market concentration," Elsevier, New York, NY, USA, Tech. Rep. 4662493, doi: 10.2139/ssrn.4662493. [Online]. Available: https://ssrn.com/abstract=4662493

[18] A. S. George, "The Ghanaian telecommunications market concentration—Applying the US DOJ's HHI criteria for determining market power(s)," Scripps College Commun., Ohio, USA, Tech. Rep. 4889, 2016, doi: 10.13140/RG.2.1.4248.4889.

[19] J. Confraria, T. Ribeiro, and H. Vasconcelos, "Analysis of consumer preferences for mobile telecom plans using a discrete choice experiment," *Telecommun. Policy*, vol. 41, no. 3, pp. 157–169, Apr. 2017.

[20] S. Araki et al., "Monopsony and concentration in the labour market," in *OECD Employment Outlook 2022: Building Back More Inclusive Labour Markets*. Paris, France: OECD, 2022, doi: 10.1787/0ecab874-en.

[21] S. Ono, "Competition dynamics of the mobile network industry in Japan through the evolution of mobile network services: An empirical analysis," *Otsuma J. Social Inf. Stud.*, vol. 28, pp. 63–76, Dec. 2019.

[22] A. Manzoor, M. Atif Qureshi, E. Kidney, and L. Longo, "A review on machine learning methods for customer churn prediction and recommendations for Bus. Practitioners," *IEEE Access*, vol. 12, pp. 70434–70463, 2024.

[23] Y.-C. Lai, C.-C. Kao, J.-D. Jhan, F.-H. Kuo, C.-W. Chang, and T.-C. Shih, ''Quality of service measurement and prediction through AI technology,'' in *Proc. IEEE Eurasia Conf. IoT, Commun. Eng. (ECICE)*, Oct. 2020, pp. 254–257.
[24] O. Wisesa, A. Andriansyah, and O. Ibrahim Khalaf, ''Prediction analysis for business to business (B2B) sales of telecommunication services using machine learning techniques,'' *Majlesi J. Electr. Eng.*, vol. 14, no. 4, pp. 145–153, Dec. 2020.
[25] *Plataforma de Intercambio de Datos*. Accessed: Jul. 1, 2024. [Online]. Available: https://www.postdata.gov.co/
[26] J. Brownlee, *Data Preparation for Machine Learning: Data Cleaning, Feature Selection, and Data Transforms in Python*. Melbourne, VIC, Australia: Machine Learning Mastery, 2020.
[27] Daryl, A. Winata, S. Kumara, and D. Suhartono, ''Predicting stock market prices using time series SARIMA,'' in *Proc. 1st Int. Conf. Comput. Sci. Artif. Intell. (ICCSAI)*, Jakarta, Indonesia, 2021, pp. 92–99, doi: 10.1109/ICCSAI53272.2021.9609720.
[28] G. E. Box, G. M. Jenkins, G. C. Reinsel, and G. M. Ljung, *Time Series Analysis: Forecasting and Control*. Hoboken, NJ, USA: Wiley, 2015.
[29] J. Y. Kajuru, K. Abdulkarim, and M. M. Muhammed, ''Forecasting performance of ARIMA and SARIMA models on monthly average temperature of Zaria, Nigeria,'' *ATBU J. Sci., Technol. Educ.*, vol. 7, no. 3, pp. 205–212, 2019.
[30] S. I. Vagropoulos, G. I. Chouliaras, E. G. Kardakos, C. K. Simoglou, and A. G. Bakirtzis, ''Comparison of SARIMAX, SARIMA, modified SARIMA and ANN-based models for short-term PV generation forecasting,'' in *Proc. IEEE Int. Energy Conf. (ENERGYCON)*, Apr. 2016,pp. 1–6.
[31] B. Ren, X. Xu, and H. Yu, ''Research of LSTM-RNN model and its application evaluation on agricultural products circulation,'' in *Proc. IEEE 3rd Eurasia Conf. IoT, Commun. Eng. (ECICE)*, Oct. 2021, pp. 467–471.
[32] A. Zhang, Z. C. Lipton, M. Li, and A. J. Smola, ''Dive into deep learning,'' 2021, *arXiv:2106.11342*.
[33] K. Greff, R. K. Srivastava, J. Koutník, B. R. Steunebrink, and J. Schmidhuber, ''LSTM: A search space Odyssey,'' *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 28, no. 10, pp. 2222–2232, Oct. 2017.
[34] K. Moharm, M. Eltahan, and E. Elsaadany, ''Wind speed forecast using LSTM and bi-LSTM algorithms over gabal el-zayt wind farm,'' in *Proc. Int. Conf. Smart Grids Energy Syst. (SGES)*, Nov. 2020, pp. 922–927.
[35] J. Chung, C. Gulcehre, K. Cho, and Y. Bengio, ''Empirical evaluation of gated recurrent neural networks on sequence modeling,'' 2014, *arXiv:1412.3555*.
[36] M. Subramanian, S. L. Swetha, and V. R. Rajalakshmi, ''Deep learning approaches for melody generation: An evaluation using LSTM, BILSTM and GRU models,'' in *Proc. 14th Int. Conf. Comput. Commun. Netw. Technol. (ICCCNT)*, Jul. 2023, pp. 1–6.
[37] Q. Zhang, J. Yang, J. Xing, and L. Wang, ''Combined heat and power load prediction based on optimized GRU neural network,'' in *Proc. IEEE 6th Int. Conf. Inf. Syst. Comput. Aided Educ. (ICISCAE)*, Sep. 2023, pp. 1161–1165.
[38] Z. Dong, R. Zhang, and X. Shao, ''A CNN-RNN hybrid model with 2D wavelet transform layer for image classification,'' in *Proc. IEEE 31st Int. Conf. Tools with Artif. Intell. (ICTAI)*, Nov. 2019, pp. 1050–1056.
[39] S. Prakash, A. S. Jalal, and P. Pathak, ''Forecasting COVID-19 pandemic using prophet, LSTM, hybrid GRU-LSTM, CNN-LSTM, bi-LSTM and stacked-LSTM for India,'' in *Proc. 6th Int. Conf. Inf. Syst. Comput. Netw. (ISCON)*, Mar. 2023, pp. 1–6.
[40] M. Sharma, R. Bagoria, and P. Arora, ''Hybrid CNN-gru model for handwritten text recognition on IAM, Washington and Parzival datasets,'' in *Proc. 2nd Int. Conf. Smart Technol. Syst. Next Gener. Comput. (ICSTSN)*, Apr. 2023, pp. 1–6.
[41] H. Heidorn and J. P. Weche, ''Business concentration data for Germany,'' *Jahrbücher Nationalökonomie und Statistik*, vol. 241, nos. 5–6, pp. 801–811, Nov. 2021.
[42] D. E. Durán, ''Aplicación de coeficientes de desvío para el análisis de integraciones empresariales,'' Pontificia Univ. Javeriana, Bogota, Colombia, Tech. Rep. 18508, 2015, doi: 10.11144/Javeriana.10554.18508. [Online]. Available: http://hdl.handle.net/10554/18508
[43] A. Melnik, O. Shy, and R. Stenbacka, ''Assessing market dominance,'' *J. Econ. Behav. Org.*, vol. 68, no. 1, pp. 63–72, Oct. 2008.
[44] M. O. Ortiz and J. P. H. Saavedra, ''El efecto de la intensidad de la competencia en Colombia sobre la innovación: Un análisis para el periodo 2013–2016,'' Univ. Externado de Colombia, Bogota, Colombia, Tech. Rep. 3008, 2013, doi: 10.57998/bdigital.handle.001.3008.
[45] T. Musin, ''Estimation of global public IaaS market concentration by Linda index,'' in *Proc. SHS Web Conf.* Les Ulis, France: EDP Science, 2021, p. 01014.
[46] Y. B. Apolinario, D. K. P. Quispe, P. B. V. Rodriguez, and M. J. C. Gadea, ''La concentración bancaria, medida a través de diversos indicadores: El caso peruano,'' *Revista Globalización, Competitividad Gobernabilidad*, vol. 16, no. 1, pp. 98–114, 2022.
[47] A. Al-Khowarizmi, S. Efendi, M. K. Nasution, and M. Herman, ''The role of detection rate in MAPE to improve measurement accuracy for predicting FinTech data in various regressions,'' in *Proc. Int. Conf. Comput. Sci., Inf. Technol. Eng. (ICCoSITE)*, Feb. 2023, pp. 874–879.
[48] S. de Industria and E. E. Comercio, ''Study of the internet service in Colombia,'' Superintendencia de Industria y Comercio, Bogota, Colombia, Tech. Rep. 3552758, 2015, doi: 10.2139/ssrn.3552758.
[49] CRC. *Batería Para Indicadores Para El Análisis De La Competencia En Los Mercados De Comunicaciones*. Accessed: Jul. 20, 2024. [Online]. Available: https://www.postdata.gov.co/

ERNESTO CADENA MUÑOZ was born in Bogotá, Colombia, in 1981. He received the B.S. degree in telecommunications engineering from Universidad Distrital Francisco José de Caldas, Bogotá, in 2006, and the M.S. degree in telecommunications and the Ph.D. degree in engineering from Universidad Nacional de Colombia, Bogotá, in 2014 and 2020, respectively.

Since 2016, he has been a Professor with the Department of Telecommunications Engineering, Universidad Distrital Francisco José de Caldas. He is the author of one book and several research articles. His research interests include security, software-defined radio, mobile networks, and artificial intelligence techniques.

LUIS FERNANDO PEDRAZA was born in Bogotá, Colombia, in 1979. He received the B.S. degree in electronic engineering and the M.S. degree in information and communications sciences from Universidad Distrital Francisco José de Caldas, Bogotá, in 2003 and 2007, respectively, and the Ph.D. degree in engineering from Universidad Nacional de Colombia, Bogotá, in 2017.

Since 2008, he has been an Associate Professor with the Department of Telecommunications Engineering, Universidad Distrital Francisco José de Caldas. He is the author of five books and more than 80 articles. His research interests include radio spectrum management, mobile networks, and data forecasting using artificial intelligence techniques.

CESAR AUGUSTO HERNANDEZ (Member, IEEE) was born in Bogotá, Colombia, in 1979. He received the B.S. degree in electronic engineering and the M.S. degree in information and communications sciences from Universidad Distrital Francisco José de Caldas, Bogotá, in 2003 and 2007, respectively, and the Ph.D. degree in engineering from Universidad Nacional de Colombia, Bogotá, in 2017.

Since 2007, he has been a Professor with the Department of Electric Engineering, Universidad Distrital Francisco José de Caldas. He is the author of several books and research articles. His research interests include radio spectrum management, mobile networks, and data forecasting using artificial intelligence techniques.