SARIMA Statistical Model to Predict the Consumption of Anxiolytics as a Treatment for Mental Illnesses

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Abstract: - The prevalence of mental health diseases and excessive consumption of anxiolytics has increased in the world. In this scenario, the need arises to determine a model that describes the behavior of pharmacological consumption of anxiolytics in Ecuador, in addition to allowing this general behavior to be projected over time. With a descriptive, exploratory, and non-experimental methodological approach conditioned on obtaining statistical data from official national and international organizations. The population of interest was generalized using flow-type temporal data on the effective consumption of anxiolytics, consisting of 144 monthly records in the period from January 2011 to December 2022. The records represent the proportion of people who consume anxiolytics in relation to the population total available in the statistics of community health care with mental illness disorders of the Ministry of Public Health. In this sense, a viable option is the construction of a temporary SARIMA model. Due to its temporal nature and the management of monthly records, robust estimation was chosen as an option by applying machine learning that efficiently decomposes and extracts both the seasonal and trend components present in the data. Determining the pharmacological consumption of anxiolytics depends on the seasonal factor (months) and the presence of a marked tendency to gradually increase over time, a situation that must be regulated because it represents a situation of drug dependence and overdose. Furthermore, the built model presented adequate suitability when quantifying statistical metrics: RMSE = 5.25% and MAPE = 1%. It is concluded that the proposed model explains the behavior of the consumption of anxiolytics in Ecuador to mitigate situations that occurred in the affected person (anxiety or depression) in the last three months, according to the specification of deterministic and random components identified in the estimated model.

Key-Words: - SARIMA model, prediction, anxiolytics, medical prescription, mental illness, drug dependence, seasonal factor, overdose.

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1 Introduction

A public health problem worldwide that has been relevant is associated with the detriment of mental health conditions in the population. Although it is true, one of the aspects that define mental health is related to the study of anxiety and depression levels in a vulnerable population. Currently, population indicators exhibit a trend that expresses higher levels of anxiety and depression.

Anxiety disorders, being a mental health problem with the highest prevalence worldwide, tend to affect 6.7% of the population (8.8% of women and 4.5% of men). Where this percentage tends to increase to 10.4% when considering the combination of “anxiety signs or symptoms”, or alternatively, when evaluating only the behavior of anxiety, a constant prevalence is described throughout adulthood, between 10% and 12% for women. On the other hand, this history of anxiety disorder occurs between the ages of 35 and 84. In an expanded way, when symptoms are taken into account, that number increases between 16% and 18% in prevalence for anxiety, [1].

According to data published by [2], there is a 25% increase worldwide in the population affected by consuming a greater amount of medications prescribed to treat depression. In this context, the worldwide comparative indicator of the high prevalence of anxiety and depression disorders is expressed in the consumption of medications that are greater than 100 daily doses per thousand inhabitants.

Considering the description of behavior regarding depression in the context of the Republic of Ecuador, its characterization turns out to be multifactorial and difficult for doctors to diagnose. According to the study by [3], an evaluation of the attitudes present in Ecuadorian doctors towards depression was carried out, focusing on a lack of confidence in the management of this condition and delimiting the need to implement continuous training and updating in medical professionals. With these limitations, the problem increases when assigning an appropriate treatment to the patient's clinical condition.

To maintain controlled levels of anxiety and depression disorders, the diagnosis leads the medical specialist to prescribe anxiolytics because this consumption allows the treatment of anxiety disorders, generalized anxiety disorders, panic disorders, social phobia, and depression, [4].

It is a reality that excessive consumption of anxiolytics tends to produce dependence and tolerance, implying that treated people may need increasingly higher doses to obtain the same effect. Additionally, anti-anxiety medications can interact with other medications and substances, such as alcohol, which can increase the risk of serious side effects, [5], [6].

Furthermore, it is important to highlight that the consumption of anxiolytics must be supervised by a mental health professional, since their inappropriate use can have adverse effects such as dependence and addiction, drowsiness, problems with coordination and memory capacity, memory visual and/or verbal, memory work, confusion, and disorientation, among others, [5], [6].

Currently, the need to control this type of non-communicable disease in relation to mental health and the phenomena inherent to the socioeconomic aspects derived from drug use that characterize the current epidemiological profile of Ecuador are highlighted. Indeed, it represents a key and priority aspect for improving the health of the population and the national health system.

For this reason, the general area of this line of research, based on the machine learning paradigm [7], has focused on the development of a statistical model that allows predicting the consumption of anxiolytics as a direct treatment to mitigate mental illnesses. This model is based on a univariate time series methodology applied to data related to the consumption of anxiolytics and the clinical resources available so that the patient is treated for a certain pathological condition based on the control of mental health. These statistical data are made up of records from official entities in Ecuador.

Regarding the methodological background for empirical developments, data mining and time series modeling are prominent in explaining phenomena that occur in society, whose beginning was a relative boom based on the contributions of [8]. Since then, research and development have focused on various aspects of this field. The research by [8] led to obtaining concrete answers to fill the gaps that were registered in the area of time series modeling.

Research on stochastic methods addressed by machine learning within artificial intelligence was founded by [7], and the different aspects of data pre-processing were consolidated by [9]. These contributions led to multiple contributions that were enriched as scientific articles were published.

The problem with real social environment data sets is that they have complex structures that are described with different connotations associated with the way the data is distributed, exhibiting underlying patterns over short- and long-term time periods, and even redundant data points and errors that create complicated condition for time series analysis.

This complexity was assumed and adjusted through the construction of hybrid models in different investigations, [9], [10], [11]. The contributions of these authors were what promoted the empirical applicability of the statistical methods developed as well as the applicability of the most recent machine learning methods.

As new models are developed according to the nature of the variables of interest and data collection on a scale of appropriate measurements, the estimates provided under the machine learning paradigm are increasingly precise and efficient [7], which will govern a timely decision-making process.

Within these methodologies are SARIMA-type time series models, which represent a class of models that are used to predict future values based on past values. These models are particularly useful for predicting anxiolytic consumption, as these data have shown seasonal and trend patterns.

Added to this scenario is the presence in Ecuador of limitations in access to data and information related to mental and brain health conditions. Many times, these failures at the national level are attributed to the management of information according to bioethical criteria that limit data access in certain sociodemographic regions.

Based on the aforementioned limitations present in the Republic of Ecuador, a public health problem with high prevalence in recent years is framed, considering the main prevalence in the increase in the consumption of anxiolytics as a consequence of several factors (stress, anxiety, and depression), [4].

Stress is expressed as an important risk factor for anxiety and depression. Anxiety is considered a normal response to stress, but when it becomes excessive or uncontrollable, it can become an anxiety disorder, while depression represents a mood disorder that can cause feelings of sadness, hopelessness, and loss of interest in things and activities, [4].

It is necessary to have a good description of the phenomenon to be able to establish strategies for the early detection of possible mental disorders and study the implications of the appropriate use of anxiolytic medications to channel a significant impact on people's quality of life, [12].

The above represents alternatives that determine the construction of a statistical model for the prediction of the pharmacological consumption of anxiolytics as a treatment applied to mental illness disorders in Ecuador during the period 2011-2022. Likewise, the identification of the predictive components and consumption patterns of anxiolytics helps to better understand the determining components of mental health in Ecuador and develop health policies more adapted to the specific needs that promote the psychological well-being of the Ecuadorian population, [12].

In essence, the objective of the present study focused on the construction of a SARIMA model that assumes a seasonal process. This construction was carried out based on the perspectives expressed in research developed with this statistical methodology, [13], [14], [15], [16]. Assuming model construction using a machine learning approach to obtain seasonal time series modeling under Python 3.11 in a PyCharm 2024.1 integrated development environment.

2 State of-the-art

Machine learning is used to diagnose mental health problems, as it allows us to broadly examine data patterns that indicate certain illnesses. This data can be collected and curated from various official sources, including hospital records, brain imaging scans, and social media posts.

In these modeling scenarios, different algorithms are designed, including supervised learning algorithms, which are trained on previously labeled data. Or, failing that, unsupervised learning algorithms, can discover patterns in the data without the need for labeling or prior identification of an explicit description.

Once the model is built and trained with the data set of interest, specific predictions are determined. Indeed, one can consider determining whether a person has a certain mental health condition based on their data or, alternatively, studying the behavior implicit in records related to mental disorders.

Machine learning researchers make predictions using the patterns learned from new data sets and the comparative results resulting from the structure of the identified models to carry out decision-making processes.

Despite the high prevalence of mental health illnesses, they are currently misdiagnosed and undertreated. As a multifactorial problem, it includes comorbidity with other diseases that complicate an adequate diagnosis [17], the inability of doctors to make correct diagnoses as a consequence of the complexity of overlapping symptoms [17], or the combination of subjective dependence on the actions taken by patients.

In other cases, there is abuse in its use that causes excessive drug consumption. Another triggering factor is related to the lack of human resources for mental health treatment, [18]. All of these limitations have contributed to underdiagnosis, preventing people who require help from obtaining the necessary care.

Due to the need to promote the description and prediction of behaviors in the consumption of anxiolytics that cause multiple problems, including dependence, tolerance, and overdose in patients, there is a need to specify how the trend and seasonality components are described in these disorders that are described with the consumption of anxiolytics through the application of machine learning. In essence, build a mathematical model that expresses the aforementioned behavior in terms of time dependence by estimating a time series model with the presence of a marked seasonal component and heteroskedasticity in the data.

Based on the above, time series prediction models collect observations over a designated time period, where each observation represents a specific time (t), and then predict future outcomes based on past events. On the other hand, seasonality is presented as a marked component in the construction of the model because it is an integral part that explains the behavior of individuals under drug consumption. This dictates that the demand for medicines fluctuates with the seasons and the inherent conditions of the patient. So it underscores the need for forecast models to skillfully incorporate these seasonal nuances, [19].

In this sense, consider guidelines from [20] that have evaluated the comparative efficiency between methodologies related to the construction of simple regression models with respect to time series models with autoregressive components integrated with moving averages (ARIMA) to explain and predict future epidemics. In this context, comparative advantages were found with the use of ARIMA models with a seasonal component over simple regression models. These findings have been valid when considering including in the models the periodic seasonal variations, the underlying changing trends, and the random perturbations that are inherent characteristics of a time series. In addition, it was ruled to use associations in sequentially lagged relationships to predict future values, [21], [22].

In this context, the optimal use of prediction techniques under the machine learning paradigm was reflected as necessary to evaluate epidemiological studies, marking absolute relevance in applying these models to research on social well-being and predicting volatility in social behaviors.

On the other hand, worldwide, the pharmaceutical industry states that studies on the evaluation of population behavior in the consumption of anxiolytics as an indicator of healthcare policies must be carried out using predictive models that largely represent forecasting options and decision-making as fundamental alternatives in the process of configuring the management of processes related to the anticipation of future trends, [23].

With respect to innovation and overcoming the challenges in the traditional approach, significant advances have occurred in recent years that have led to the generation of new advanced algorithms under the machine learning paradigm in correspondence with the provision of robust computational resources provided by the language (Python programming comes in its different versions).

Unlike what is presented in the construction of inferential models, descriptive analysis in the construction of time series models is assumed in the findings of [24], which considered essential aspects such as the use of the simple exponential smoothing methodology to explain the constant consumption of medication. If a notable trend in medication consumption occurs, the implementation of double exponential smoothing is recommended. For oscillating consumption that presents a marked seasonal component, basic and not very robust descriptive methods must be used, such as triple exponential smoothing, which is also referred to as the Holt-Winters equation. In a similar direction, there are the contributions of [25], concluding on the benefits of building a Holt-Winters model, which analyzes trend and seasonality in prediction. However, the aforementioned descriptive methodology loses precision by requiring long-term predictions.

3 Materials and Methods

3.1 Type and Design of the Research

The study focused on the management of secondary data from records, forming a documentary research design. For the purposes of model estimation, the time horizon was managed from January 2011 to December 2022 as an exogenous variable. All information on medication dispensing was purified, transformed, and stored in a database in the Python 3.11 programming language. Due to its temporary nature and the management of monthly records, the robust option for construction lies in a mathematical model: ARIMA(p,d,q)x SARIMA$(P,D,Q)_s$.

This model is ideal for extracting the seasonal and trend components underlying the data in the temporal process. In data collection, the inclusion criterion was followed, consisting of patients of all ages and of both sexes who had been prescribed an anxiolytic during the study period. It should be noted that no clinical trial was conducted with an incident factor, which represents a scientific study that does not tend to violate the principles of bioethics and confidentiality.

3.2 Research Methods

Descriptive research was carried out at a documentary level as a result of collecting information from the repositories Scielo, Scopus, Google Scholar, and Science Direct to support this research with content analysis from scientific articles with temporal relevance within the last 5 years, consisting of publications published from January 2019 to December 2023.

For the empirical evaluation, an analytical investigation is defined based on the construction of a mathematical model on the variable under study in this investigation, framed in the prescription for the consumption of anxiolytics represented on a DHD measurement scale (daily dose defined per 1,000 inhabitants/day) according to data from the Community Mental Health Network and State Addiction Recovery Centers.

3.3 Research Focus

Based on the quantitative information recorded on medication consumption, a database was created considering the following variables: temporary coverage from January 2011 to December 2022. On the other hand, medication consumption is defined as the observed series (Anxiolytics related to time defined in monthly records). The resulting model underwent internal validation, which represents a statistical technique used to evaluate the performance of a predictive model using the same data that was used to train the model.

3.4 Study Population and Sample Selection

The population of interest was generalized into flow-type temporal data, which represents the effective consumption of anxiolytics as constituted by 144 monthly records in the Republic of Ecuador. Temporal coverage as a sample of interest was defined as all records of consumption of anxiolytics for the treatment of mental illnesses within the period from January 2011 to December 2022.

3.5 Data Collection Techniques and Instruments

In the statistical data collection phase, the database of the Project for the Creation and Implementation of Services of the Community Mental Health Network and State Addiction Recovery Centers (PCISRSMCCE) was used to a greater extent, in line with the contributions of other instances such as the Ministry of Public Health of Ecuador, specifically the National Directorate of Normalization and the National Directorate of Disabilities, [4]. In relevance, these data have been collected through the logistics of these official entities through formal requests to officials responsible for the mental health component of the institutions of the Comprehensive Public Health Network (RPIS) and private institutions with and without profit.

Statistical data was collected and refined with other secondary sources within the 2019 Global Burden of Disease (GBD) study developed by the University of Washington [26], as well as official records on the burden of mental disorders in the Region of the Americas: Profile of Ecuador and statistics from the Pan American Health Organization, [27]. In addition, data from the National Directorate of Disability, Rehabilitation, and Palliative Care in Health was used, which established that in Ecuador there are 48,078 records for the year 2023 of people with intellectual and mental disabilities, in a universe of 480,776 people with some type of disability. This represents 10% of the total number of people with disabilities in Ecuador, [28].

3.6 Seasonal ARIMA Process Methodology (SARIMA)

The methodology for the construction of ARIMA stochastic processes with a seasonal component, as referred to in the scientific literature as SARIMA, is based on the fulfillment of a series of phases: identification and specification of the underlying components, estimation of the model parameters, statistical validation, and prediction, [7].

The previous treatment of the data is framed by the use of transformations in the logarithmic series (Box-Cox) and the application of regular and seasonal differentiation to normalize the series and obtain stationary data. Then, using machine learning algorithms under the PyCharm integrated development environment and the Python programming language, the optimal mathematical structure is determined and the parameters are estimated according to the appropriate order in the different stochastic models identified. In the last procedure, the best model is found after cross-validation with training and test data to discriminate suitability in the model.

If the anxiolytic consumption series $\{X_t\}$ presents a component marked with period s, it can be eliminated by applying the seasonal difference operator with a lag of order s =12, equivalent to the data collection periods, and thus obtain a series $\{Y_t\}$with a process structure WEAPON.

In addition, if the temporal process exhibits a regular trend and a marked seasonal component, the order of regular (d) and seasonal (D) differentiation is defined. If d and D are non-negative integers, then $\{X_t\}$it represents a model under a multiplicative seasonal process, which is produced by the interaction of a regular part $ARIMA(p, d, q)$in conjunction with a seasonal part $SARIMA(P, D, Q)_s$ with s a seasonal period.

The series, differentiated into its regular and seasonal components, is denoted as an ARMA process:

$$Y_t = (1 - B)^d \ (1 - B^s)^D X_t.$$

Which is defined by:

$$\varphi_p(B)\Phi_P(B^s)Y_t = \theta_q(B)\Theta_Q(B^s)\varepsilon_t , \{\varepsilon_t\} \sim \varepsilon_t \, N(0, \sigma^2)$$

Where:

$\varphi_p(B)$: Represents the polynomial that assumes the delay operators of the autoregressive coefficients that make up the regular part of the model.

$\Phi_P(B^s)$: Represents the polynomial that assumes the seasonal delay operators of the autoregressive coefficients that make up the seasonal part of the model.

Y_t: Consumption of anxiolytic medications related to the time defined in monthly records.

$\theta_q(B)$: It represents the polynomial that assumes the delay operators of the moving average coefficients that make up the regular part of the model.

$\Theta_Q(B^s)$: Represents the polynomial that assumes the seasonal delay operators of the moving average coefficients that make up the seasonal part of the model.

ε_t: A random disturbance must be adjusted to normal behavior with a zero mean and constant variance.

This type of model is called $SARIMA(p, d, q) \times (P, D, Q)_s$. In essence, according to [29], the seasonal ARIMA model includes autoregressive and lagged moving average terms.

The ARIMA seasonal process methodology is used to forecast the future of a time series that presents a seasonal pattern (s = 12 months). To do this, data from historical data series are used to estimate the parameters of the ARIMA model for the regular part and the seasonal part in their autoregressive and moving average components. Once the parameters are estimated, the model can be used to forecast the future of the time series, [30].

The structure or components that constitute the specification in this type of multiplicative component model involve identifying the dynamics of seasonal processes based on the stochastic process under study. In this sense, it must be described as follows:

- The trend component, which represents the general growth of the time series observed or under study,
- The seasonal component, which represents the seasonal fluctuations of the series,
- The non-stationary component, which represents the random fluctuations of the time series that represent the pharmacological consumption of anxiolytics in Ecuador.

Models under a seasonal ARIMA process come with multiple applications when complex structures must be implemented under stochastic processes that exhibit a variety of seasonal patterns, including additive and multiplicative seasonal patterns. They can also be used to forecast time series that exhibit a variety of non-stationary patterns, including linear and non-linear patterns, [31]. The strong advantage of using this type of model lies in the advanced accuracy of short-term prediction results, [32].

3.7 Seasonal ARIMA (SARIMA) Process in Python

This section describes the commands and parameters used to build ARIMA models, which are described by using the statsmodels.tsa.arima_model module, proceeding to import the data and the hyperparameters p, d, and q (in that order) using a machine learning algorithm to decompose a time series into its seasonal, trend, and random disturbance components, [33]. Below is the fit() call in this module, which returns a trained model that is used for evaluation and inference. Another alternative is based on defining the ARIMA.fit command for the specification and estimation of the model parameters, [34].

This model overview provides several statistical measures to evaluate the performance of the ARIMA model in the Python programming language, based on scores given by the criteria AIC (Akaike Information Criterion), BIC (Bayesian Information Criterion), HQIC (Hannan-Quinn Information Criterion), and the standard deviation of innovations (innovations are the difference between the actual value at time t and the expected value at that moment of time). However, measures such as AIC, BIC, and HQIC depend significantly on the probability learned from the training data. Additionally, to check the percentage fit of the trained model to the collected data that defines the time series, the plot_predict command of the ARIMA forecasting Python environment is used, which is obtained by training the actual and predicted values on top of each other by plots. This line graph is calculated from the weights learned and trained by the model. The above allows us to check how well the prediction works based on the learned coefficients, [33].

3.8 Evaluation of the Quality of the Proposed Model

In consideration of evaluating the adequacy of the predictions with the estimated model, available error metrics, or Key Performance Indicators (KPI), were used: root mean square (RMSE), mean absolute error (MAE), mean percentage error (MPE), mean absolute percentage error (MAPE), the correlation coefficient (to measure similarity), and the minimum allowed error.

4 Results

4.1 Seasonal ARIMA (SARIMA) Process Specification

In this context, the performance of the different models that have been identified under the seasonal decomposition machine learning algorithm was adjusted step by step through routines developed in the Python 3.11 programming language under the PyCharm 2024.1 integrated development environment. These performances summarize the best mathematical structure to identify, as shown in Table 1.

Table 1. Specification and estimation of parameters for the ModelARIMA$(\mathrm{p},\mathrm{d},\mathrm{q})\mathrm{x}(\mathrm{P},\mathrm{D},\mathrm{Q})_{\mathrm{S}}$

Variable Dep.: Y	No. Observations: 119
Model :	
SARIMA(3, 1, 1)x(1, 0, 1, 12)	Log Likelihood 235.108
Date: Fri, 23 Feb 2024	AIC -454,215
Time: 13:01:22	BIC -432,050
Sample: 01-01-2011 -12-01-22	HQIC -445.215

Source: Results generated by Python 3.11

This package, Python 3.11, adapts series to models $ARIMA(p,d,q)x(P,D,Q)_s$, that is, the autoregressive and moving average parts for the regular and seasonal components in the series under study. In this sense, the estimation of the parameters in the model that was determined through the package is shown (Table 2) in this case a multiplicative model:

$$ARIMA\ (3,1,1)x\ ARIMA(1,0,1)_{12}.$$

Table 2. Estimation of parameters for the Model ARIMA$(\mathrm{p},\mathrm{d},\mathrm{q})\mathrm{x}(\mathrm{P},\mathrm{D},\mathrm{Q})_{\mathrm{S}}$

	coef	std err	z	P>|z|	[0.025	0.975]
intercept	9.72E-06	3.89E-05	0.25	0.803	-6.67E-05	8.60E-05
ar.L1	-0.2973	0.115	-2,585	0.010	-0.523	-0.072
ar.L2	0.0354	0.139	0.256	0.798	-0.236	0.307
ar.L3	0.4628	0.135	3,419	0.001	0.198	0.728
ma.L1	-0.8993	0.103	-8,721	0.000	-1,101	-0.697
ar.S.L12	0.9601	0.096	10,041	0.000	0.773	1,148
ma.S.L12	-0.7909	0.255	-3,099	0.002	-1,291	-0.291
sigma2	0.0010	0.000	6,132	0.000	0.001	0.001

Ljung -Box (L1) (Q): 0.80	Jarque-Bera (JB): 125.70
Prob (Q): 0.37	Prob (JB): 0.00
Heteroskedasticity (H): 0.34	Skew : -1.22
Prob (H) (two-sided): 0.00	Kurtosis : 7.43

Source: Results generated by Python 3.11

Where the mathematical structure is built by developing the following expression:

$$(1+0{,}2973L-0{,}00354L^2-0{,}4628L^3)(1-0{,}9601L^{12})(1-L)Y_t=(1+0{,}8993L)(1+0{,}7909L^{12})\varepsilon_t$$

The previous mathematical formulation is simplified to a non-stationary seasonal multiplicative model ARIMA(3,1,1)x(1,0,1) $_{12}$ defined as follows:

$$\boldsymbol{Y_t=\mu+\phi_1.Y_{t-1}+\phi_2.Y_{t-2}+\phi_3.Y_{t-3}+\theta_1.e_{t-1}+\theta_2.e_{t-2}+\gamma_1.Y_{t-12}+\delta_1.e_{t-12}+e_t}$$

This model is used to analyze time series that present a non-stationary trend and seasonality, the graphical representation of which is shown in Figure 1. The non-stationary trend is adjusted by specifying the significant autoregressive and moving average coefficients in its regular part, while the seasonal part is adjusted by specifying the seasonal autoregressive and moving average coefficients. Moving average coefficients are used to remove random noise from the time series.

$$\boldsymbol{Y_t = 9,723x10^{-6} - 0,2973.Y_{t-1} + 0,0354.Y_{t-2} + 0,4623.Y_{t-3} - 0,8993.e_{t-1} + 0,9601.Y_{t-12} - 0,7909.e_{t-12} + e_t}$$

In essence, the estimated model suggests that the explanation of anxiolytic consumption in Ecuador, at a deterministic level, is defined in its regular component in terms of the events that occurred in the population within the last three months with the consideration of random events that occurred. The last month and in its seasonal component, both at a deterministic and random level, it depends on what happened in the previous month.

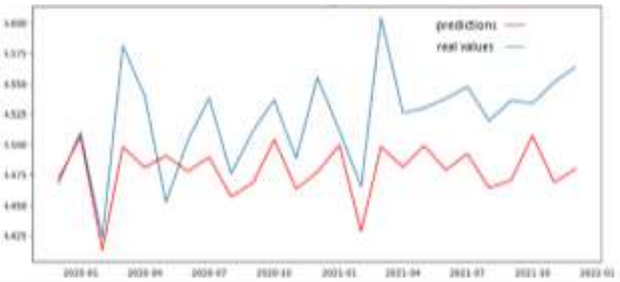

Fig. 1: Internal validation of the pharmacological consumption of anxiolytics using the mathematical modelARIMA $(3,1,1)$x $\mathrm{ARIMA}(1,0,1)_{12}$
Source: Results generated by Python 3.11.

When evaluating Figure 1, consistency is reflected in the projection achieved between the observed and fitted values through the structure of the estimated statistical model. Therefore, to delve into the benefits of the model, a more precise evaluation must be carried out in terms of the metrics obtained in the quantification of forecast errors. The ultimate goal is to verify the suitability of the specified structure according to the temporal coverage of the data.

4.2 Metrics to Evaluate the Suitability of the Specified Model

In this section, Table 3 establishes the metrics to evaluate the adequacy of the prediction errors in the identified model, for which the mean absolute error (MAE = 4.51%) and the mean absolute percentage error (MAPE) are used. = 1.01%), the root mean square error (MSE = 2.76%), and the root mean square error (RMSE = 5.25%).Which exhibit values close to zero, an ideal situation to argue that the identified model represents a solid structure to make predictions regarding the pharmacological consumption of anxiolytics for the treatment of mental disorders in patients in Ecuador, 2020-2022.

The results shown in Table 4 describe the evolution of the predictions with a confidence level of 95%, which allows us to infer a gradual increase in the prescription for the consumption of anxiolytics on a DHD measurement scale (daily dose defined by 1,000 inhabitants/day). The prediction limits of 95.0% for the forecasts are decisive to emphasize an increase in the consumption of medications for the treatment of mental health disorders in Ecuador. In short, regarding the consumption of anxiolytics, according to the model's predictions, this DHD should increase to 95.77 in the month of December 2023.

Table 3. Adequacy metrics in model forecastsARIMA $(3,1,1)$x $\mathrm{ARIMA}(1,0,1)_{12}$

Metrics	Mistake
MAE	0.045103
MAP	0.010067
MSE	0.002765
RMSE	0.052582

Source: Results generated by Python 3.11

Table 4. Predictions for the year 2023 on the pharmacological consumption of anxiolytics using the mathematical model ARIMA $(3,1,1)$x $\mathrm{ARIMA}(1,0,1)_{12}$

Period	*Forecast*	*Limit Lower 95.0%*	*Limit Top 95.0%*
Jan-23	4.3107	88.9741	99.6473
Febr-23	89.6427	84.2977	94.9877
Mar-23	98.9746	93.5747	104,375
Apr 23	94.5173	88,554	100,481
May 23	96.2622	90.2949	102,229
Jun-23	94.9075	88.8527	100,962
July 23	96.1003	89.8572	102,344
Aug-23	92.7024	86.4296	98.9752
Sept-23	93.9671	87.6046	100.33
Oct-23	97.4577	90.9897	103,926
Nov-23	93.7357	87,216	100,255
Dec-23	95.7761	89.1733	102,379

Source: Results generated by Python 3.11

5 Discussion

As an initial aspect of discussion, the importance of taking into account that prediction using mathematical models for the consumption of anxiolytics as a mitigation measure for mental illness represents a complex and constantly evolving area. In this scenario, it is necessary to apply a multidisciplinary approach that encompasses psychology, psychiatry, neuroscience, and computer science to offer more robust findings, [35]. Mathematical models can be a promising tool to understand the implications of the evolution of mental disorders that are explained by the increase in pharmacological consumption, as well as focus on public policy formulation to dictate improvements in treatment strategies.

In this line of discussion, the benefits determined in the research of [19] consolidate through their study that using the mathematical structure of an ARIMA time series model is vital to analyzing past data in order to predict future trends, taking advantage of the ability to use the random component of lagged moving averages to smooth time series data, leading to easy interpretation of chance behavior. These models are suitable for predictions of inherent behavior and the development of technical analysis.

To continue highlighting other benefits of the ARIMA methodology with seasonal components, the study by [36] determines important information about how ARIMA, exponential smoothing models, and the ANN artificial neural network methodology compare, including the use of combined models aimed at consolidating research that aims to establish interesting conclusions. Although the combination of techniques is not widely used, it leads to better predictions.

The increases observed in the trend of anxiolytic consumption in Ecuador during the temporary coverage from 2011 to 2022 can probably be explained by a higher prevalence of depression and risks associated with consumption associated with adverse effects and dependence that are evident as a common situation in other countries in clinical practices, [37], [38], [39], [40]. This situation may be due, as established by [41], to increases in the diagnosis and treatment of depressive disorders and changes in the structure of the population, since depression in Ecuador represents a multifactorial public health problem.

The determining findings of the present study are compared with similarity to those reported in similar studies where the tendency to consume has increased due to the effect of the COVID-19 pandemic, in which there has been an increase in the prevalence of depressive and anxiety disorders, [42], [43], [44]. In fact, the consumption of anxiolytics is associated with the relative increase in the prescription of medications by doctors, which causes greater demand in the population. These results coincide with those exhibited by a study carried out in Spain that evaluated both the prescription and sale of anxiolytics and antidepressants, [45].

According to the approaches of the studies consulted, they indicate that the consumption levels characterized as low analyzed by the OECD between the years 2020 and 2021 have been below 40 daily doses per thousand inhabitants (DHD). Among the countries that are configured at these levels are: Costa Rica, Estonia, Lithuania, Hungary, South Korea, and Latvia, [46].

However, the scenario presented by the Republic of Ecuador is framed at average levels of 87 DHD. This leads us to affirm that not only depression is the cause of these discomforts, but unprecedented stress represents another determining factor. Furthermore, according to [46], other conditions that increase the pharmacological consumption of anxiolytics are work limitations, managing ample support from family or loved ones, and the environment of community participation.

6 Conclusions

The relatively high prevalence of mental health disorders occurs in the Republic of Ecuador, which translates into a significant impact on pharmacological consumption, causing a deterioration of the clinical situation in civil society and a negative impact on the economy.

In this context, statistical adequacy is presented in the SARIMA model (RMSE = 5.25% and MAPE = 1%), which was estimated under a machine learning paradigm. of seasonal decomposition to offer an interpretation of anxiolytic consumption in Ecuador. At a deterministic level, this model was defined by a structure underlying the events of anxiety and depression that the Ecuadorian population has experienced that triggered the consumption of anxiolytics within the last three months, coupled with the effect presented by random events related to these disorders that arise in the previous month. Regarding the existence of a repetitive pattern consistent with the seasonal component, both at a deterministic and random level, the consumption of anxiolytics in Ecuador is explained by the level of anxiety and depression that occurred in the previous month.

These tendentious components originate from the modeling of behavior that translates into the combination of deterministic and random effects that formalize a behavior of increased pharmacological consumption of anxiolytics in Ecuador above average levels of 87 daily doses per thousand inhabitants (DHD).

This situation generates the need to implement public policies to expand services and resources that lead to mitigating mental health problems, considering the significant effects that occur within one to three months in the pharmacological consumption of anxiolytics in the Ecuadorian population. In this scenario, it is recommended to promote monitoring with the establishment of mental health clinics and management for prevention, control of prescriptions, and regulation of drug consumption, as strategies integrated with primary care services in mental health.

As future lines of research develop studies that consider respecting ethical and social principles are emerging, an approach to the ethical and social implications of the use of medications to treat mental illnesses, including the associated stigma and existing deferences in access to the treatments and implications that lead to the reduction of the risk of additions and side effects due to excessive consumption of unnecessary medications. Addressing these principles opens a range of possibilities to overcome the limitations that currently arise related to the availability of clinical data to undertake larger studies. Where the combined construction of models based on the machine learning methodology prevails (Artificial Neural Networks, Support Vector Machine, Random Forest, Logistic Regression, Decision Tree) that allows explaining, based on randomized clinical trials, the factors incident to the phenomenon under study.

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