Acta logistica - International Scientific Journal about Logistics
Volume: 11 2024 Issue: 2 Pages: 269-280 ISSN 1339-5629

https://doi.org/10.22306/al.v11i2.510 *Received: 05 Dec. 2023; Revised: 01 Jan. 2024; Accepted: 16 Feb. 2024*

Health supply chain forecasting: a comparison of ARIMA and LSTM time series models for demand prediction of medicines

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Keywords: LSTM, ARIMA, health supply chain, medicines, prediction model.

Abstract: The ever-accelerating revolution along with digitalization of the healthcare industry has revealed the power of machine learning and deep learning prediction models in addressing health supply chain logistic issues. The purpose of this study was to predict the demand for medicines using autoregressive integrated moving average (ARIMA) and long short-term memory (LSTM) time series models while comparatively analysing their performance for medicine demand prediction to optimize the flow of supplies in the health system. Using data generated in Rwanda public health supply chain, in our study focused on predicting the demand of the top five medicines, identified as highly supplied (amoxicillin, penicillin v, ibuprofen, paracetamol, and metronidazole). We evaluated the models' outputs by root mean square error (RMSE) and the coefficient of determination, R-squared (R^2). In comparison to ARIMA, the deep learning LSTM model revealed superior performance with better accuracy and lower error rates in predicting the demand for medicines. Our results revealed that the LSTM model has an RMSE value of 2.0 for the training set and 2.043 for the test set, with R^2 values of 0.952 and 0.912, respectively. ARIMA has an RMSE value of 9.35 for the training set and 8.926 for the test set as well as R^2 value of 0.24 and 0.16 for the training and test sets, respectively. Based on these findings, we recommend that the LSTM time series model should be used for demand prediction in the management of medicines and their flow within health supply chain due to its remarkable performance for prediction task when applied to the dataset of our study.

1 Introduction

In the current digitally interconnected and high-technology driven world, the health system and clinical settings have challenges in successfully managing an enormous volume of health supply chain data with the aim of providing the high-quality healthcare services that consumers would expect [1]. Organizations must adopt advanced technologies and data science methodologies, such as deep learning and machine learning approaches including prediction models. In return, these approaches and technologies offer more accurate supply chain forecasting, operational efficiency and improved logistic function, while also optimizing the service delivery process, management of financial, logistic aspects and effective use of resources [2].

Time series predictions is a core part of data science that has numerous applications. Accurate predictions are imperative in health supply chain forecasting tasks to help in designing and implementing evidence-based decisions at operational, strategic, and tactical level [3]. Traditional econometric methods such as ARIMA may require comparative studies due to the increase in data complexity and their volume for achieving more accurate forecasts in the health supply chain. On the other hand, as digital technology builds up, deep learning prediction models, such as LSTM time series models, are being applied more frequently for time series prediction in the health sector and this include medicine demand prediction and supply planning [4]. According to a study focusing on deep learning LSTM models for COVID-19 forecasting using upgraded method published by Luyu Zhou et. al. 2023, LSTM -based models have been recognized as part of prediction models with the most advanced ability and accuracy for time series data [5]. Despite the increasing significance of machine learning models in health supply chain forecasting, research in this area is still lacking and limited, most notably in terms of how to adopt, integrate and accurately use machine learning and deep learning approaches. While most research has focused on using prediction models to predict disease burden or their occurrence, there is a need to advance the health supply chain by exploring the potential contribution of advanced prediction models for medicine demand prediction [6].

This study seeks to fill this void by undertaking a comparative examination of LSTM and ARIMA predictions models, with a particular emphasis on identifying which of them perform better in the framework of health supply chain forecasting. While LSTM and ARIMA models are both known for their ability to perform demand predictions, our study intended to compare them and determine which may contribute most effectively in health supply chain forecasting through reliable demand prediction for medicines with less complexity, greater accuracy, and prospective applicability [7]. The goal of this study is to make a comparative analysis of LSTM and ARIMA models' performance in health supply chain forecasting. With this aim, we will be able to improve the automation of demand for medicines and thus optimize supply chain forecasting tasks and logistic technical aspects. In the end, these achievements will culminate in boosting the delivery of healthcare services.

The rest of this paper is organized as follows: in addition to the previous first section, in section 2, we present the literature review and section 3 discusses the methodology with a brief description of the applied models for our study, ARIMA, and LSTM prediction models. While this section focused on the theoretical context and the ways we did the accuracy measurements, in sections 4, the results and discussions of the study are described with a contrast to what have observed in other similar studies. Finally in section 5, we wrap up the study and provide a conclusion and recommendations based on our study findings.

2 Literature review

Digital transformation in the health supply chain, along with the automation of demand prediction and supply planning have the ability to optimally allocate resources, resulting in considerable cost savings and improved service delivery. This change lowers human errors, speeds target achievement, and promotes the use of predictive algorithms in the demand and supply planning of important drugs in clinical settings [8]. Health products and medical supplies are crucial for preserving human health and well-being, but they also contribute significantly to healthcare expenses, particularly in LMICs with limited resources. Because of the importance of medicines and medical equipment in healthcare service delivery, as well as the issues of wastefulness and inconsistency in supply and demand planning, data-driven prediction models must be used to accurately predict their demand [9]. This also contributes to the management of logistics associated with both the supply and flow of medicines at different levels of healthcare delivery.

According to a study by Roy and Mitra in 2021, which concentrated on the use of machine learning for demand prediction of essential medicines, their findings confirmed that machine learning-based prediction models have the potential to optimize the pharmaceutical supply chain, resulting in reduced expenses as well as more affordable medicine [10]. Similarly, in their study Makridakis et al. 2020, emphasized a track-record of progresses in prediction performance over time, the need to capture the uncertainty in prediction tasks, and aspects that may be wrong for prediction tasks in social settings. They also discussed what is known and what is not clearly understood or still unclear and thus requires further research [11]. Additionally, the potential and efficacy of demand prediction models based on shallow neural networks, including deep learning neural networks such as LSTM, for estimating future medicine demand was confirmed by Rathipriya et al. 2023, who focused on demand prediction models for time-series pharmaceutical data with the goal of suggesting marketing and sales tactics in pharmaceutical companies [12].

A study conducted by Absar et al. 2022, on the usefulness of deep learning LSTM models for predicting the spread of infectious diseases, indicated that the models may provide insights and contributions to accurately predict the spread of infectious diseases' outbreaks such as COVID 19. Based on these findings, LSTM models could provide insightful forecasts and help to appreciate the trend and gravity of the diseases while informing decision-makers about how to proceed cautiously and take the needed measures to bring the situation under control at the most convenient time [13]. LSTM works particularly well with sequential data and typically excels at capturing long-term dependencies, putting them in the greatest position for time-series data, and therefore, may be applied in the health supply chain to predict demand, events or operations [14]. For example, when predicting the trend of patients to be admitted, LSTM models can be applied by a health setting to optimize the appropriate utilization of beds, the flow of personnel and materials including medicines or medical supplies and equipment. Furthermore, the LSTM and multivariate time-series models can be used in demand prediction and supply planning for lifesaving product such as blood donations, as they may be applied in health supply chain to ensure timely availability and accessibility of them [15]. Also, these may help in improving effective financial management and well-coordinated flow of medical supplies while keeping ideal inventory levels and preventing expiries, shortages, out of stock, and overstock

ARIMA is a time series prediction model with autoregression, differencing and moving average components. It is commonly applied for short to medium term predictions. ARIMA prediction models' applicability in the health supply chain, may be used to ensure effective inventory management and flow of accurate information while anticipating the consumption pattern of medicines, which may serve in preventing stock outs or wasteful resources with surplus stock [7,16]. A health institution can profit from the use of ARIMA models to predict the demand for medical supplies and thus anticipate patient needs. ARIMA models may also be used to anticipate the presence and severity of an outbreak using historical data, which can provide helpful information for planning suitable public health interventions. A prominent example of this may be the use of predictive models for a contagious illness, which may help decision-makers allocate resources for containment, preventative measures, and treatment options, as occurred during the COVID-19 period and other infectious diseases [17,18].

ARIMA and LSTM models can both reliably perform the demand prediction task as they are enabled to depict complex trends in time-series data, and in this regard, they are increasingly being applied to health supply chain forecasting. While these advances in forecasting tasks are beneficial in terms of presenting competitive advantages, they contribute differently depending on how they are applied and the context or type of dataset applied to [7]. In the context of this study, both ARIMA and LSTM are contrasted in relation to their performance in the health supply chain, particularly their performance and accuracy for predicting the demand for medicines. The adoption and integration of machine learning and artificial intelligence in health supply chains such as the application of LSTM and ARIMA time-series models, provides a competitive advantage, particularly through the improved prediction accuracy and appropriate management of changing dynamics in medicines demand prediction [19,20]. For example, the use of LSTM and ARIMA in health supply chains may enable more dynamic and adaptive prediction, where LSTM time series model may typically target sudden changes in patient admission patterns, and then ARIMA models refine short-term predictions based on recent trends [7].

The adoption of LSTM and ARIMA models for the demand prediction of medicines provides a valuable contribution towards data-driven inventory management, resource allocation, and improved overall operations and efficiency in in health supply chains [7]. However, better accuracy from either LSTM or ARIMA models as well as the choice of which one to consider may be dependent on or suited to a kind of dataset or context [21]. Therefore, we have compared these two types of models to determine which one should provide better accuracy when applied to public health supply chain data generated by the electronic logistics management information system (e-LMIS).

3 Methodology

This section gives an overview of how we performed our research while establishing how to predict the demand of medicines using selected top five medicines supplied in Rwanda. The methodology involved several steps, such as collecting data, preprocessing data, choosing models, and figuring out how to interpret their performance for demand prediction of medicine as a core forecasting task in public health supply chain.

3.1 Study setting

Rwanda is a small landlocked country in East Africa with a t land area of 26,338 km2. According to the findings of the fifth population and housing census (PHC), Rwanda's population exceeded 13.2 million in December 2022 [22]. The country has promoted the delivery of health care through various initiatives, including streamlined supply and consistent availability of medical supplies. In relation to the flow of medicines, the eLMIS which a digital platform used in all public health facilities, helped in the record, storage and visibility of supply chain data.

3.2 Data collection and preprocessing

In our study, we used data from eLMIS for a period of 7 years, from January 2015 to December 2022, to perform demand prediction of medicine. The time frame for prediction has been set out in relation to use of the eLMIS as both a logistic and digital tool for the management of health products in Rwanda which was launched in 2015. The Figure 1 below, shows the trends of to five selected as top supplied medicines in quantity.

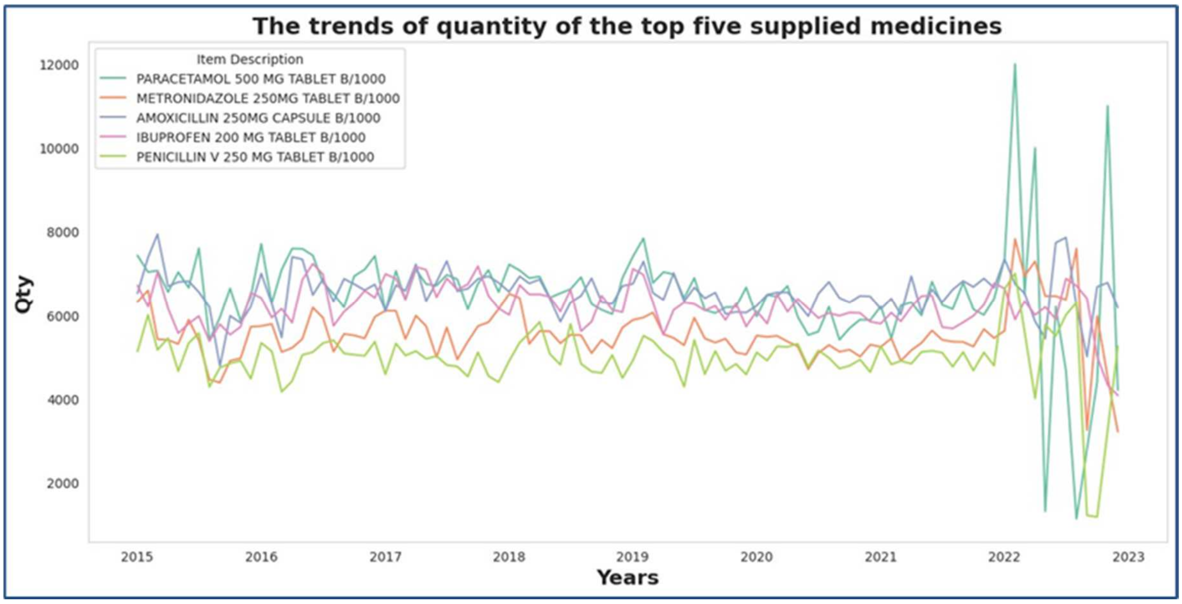

Figure 1 The trends of supplied quantity for each of the top five supplied medicines by time (2015-2022)

In terms of data cleaning, we removed outliers and handling missing numbers to ensure that the data was correct. Any mistakes or flaws in the data were fixed to maintain data's integrity. The table 1 presents the total quantities supplied during the study period and illustrates the category for each of the five selected medicines. As highlighted in the above Figure 1 but also illustrated in the above Table 1, we have considered the top five drugs that were supplied in high quantity in the Rwanda public health supply chain. After preprocessing our dataset, we identified that these top five medicines included amoxicillin 250 mg, paracetamol 500 mg, ibuprofen 200 mg, metronidazole 250 mg, and penicillin v 250 mg.

Table 1 The five selected highly supplied drugs

Name of Drugs	Quantity	Medicine's therapeutic group
Amoxicillin 250 mg capsule b/1000	79,167,273	Antibiotic
Paracetamol 500 mg tablet b/1000	74,623,247	Anti-inflammatory and analgesic
Ibuprofen 200 mg tablet b/1000	60,479,173	Anti-inflammatory and analgesic
Metronidazole 250 mg tablet b/1000	49,252,008	Antibiotic (nitroimidazole class)
Penicillin v 250 mg tablet b/1000	38,029,381	Antibiotic

3.3 Description of models

For model selection, we used LSTM, and an ARIMA for demand prediction of the five selected medicines as highly supplied. We were interested in contrasting LSTM and ARIMA to see which one works best when dealing with massive amounts of data generated by the supply chain for medicines. We were interested in the comparison of LSTM and ARIMA prediction models to see which one works better when dealing with massive amounts of data related to the flow of medicines and information in the health supply chain. While the LSTM Model is a deep learning framework that is made to find temporal patterns in data sequences, the ARIMA model is an econometric model using a time series forecasting method, in our study, we had to set up the model with the right factors for order. Both the LSTM and ARIMA models were selected because of their applicability in demand prediction tasks and thus we intended to validate their performance in advancing the management of health supply chain [19].

3.3.1 Description of the LSTM model

The application of LSTM models has become increasingly common as an advanced data analytical method to address a wide range of issues related to learning from time series data during demand prediction. LSTM is known as A type of RNN that has emerged as an effective and scalable model for many forecasting tasks that imply learning sequences of data [23]. The LSTM cell multiplies X, c, and h with various weight tensors and processes them with unique activation functions. Thus, cell memory and hidden state have been adjusted. The next input tensor time step will use the recalibrated c and h values. The LSTM cell will produce two outputs, namely the cell memory and the hidden state. These outputs will persist until the final time step is reached [24]. The equation 1 below provides a description of the LSTM model (1):

$$
\begin{aligned}
C_t^{\sim} &= \tanh(X_t Y_{xh} + G_{t-1} Y_{hh} + a_h) \\
C_t &= f_t C_{t-1} + i_t C_t^{\sim} \\
G_t &= o_t \tanh(C_t) \\
f_t &= \sigma(X_t Y_{xf} + H_{t-1} Y_{hf} + a_f) \\
i_t &= \sigma(X_t Y_{xi} + G_{t-1} Y_{hi} + a_i) \\
o_t &= \sigma(X_o Y_{xh} + G_{t-1} Y_{ho} + a_o)
\end{aligned} \tag{1}
$$

where the cell state is represented by $C_t^{\sim}$ which carries previous timestamp and current timestamp, forget gate $by\ f_t$ helps to decide wich informations to remember or to forget, input gate $by\ i_t$ quantifies the value or importance of information carried, and gate $by\ o_t$ helps to provide model output.

X_t: input to the current timestamp, H_{t-1}: hidden state of the previous timestamp, Y_{xf}: weight associated with the input, Y_{hf}: weight associated with the hidden state, and σ represent the sigmoid function. The sigmoid layer outputs numbers between zero and one, describes how much of each element should be passed through. A value of zero means "release nothing", while a value of one means "release everything".

The LSTM model is capable of acquiring knowledge and optimizing a mathematical function that takes a sequence of observations as input and generates a new observation as output. According to input-output patterns, observations are collected and organized. This context uses a single-step predictive model with numerous input time steps and one output time step. A Vanilla LSTM model with one hidden and output layer was used for prediction. The 200-layer LSTM model forecast. Every layer used ReLU activation. LSTM model input shape was determined by predictor dimensions. LSTM model also showed predictive consistency in steps and features [25].

While the incorporation of kernel (0.06), recurrent (0.05), and bias (0.02) regularizers successfully addressed the problem of overfitting in the model, the utilization of a dropout rate of 0.2 was discovered to effectively address the issue of overfitting by selectively eliminating layers at the specified rate. The aim was to clarify and understand the model. The RMsprop optimizer calculated the mean square error of the loss function. In each of the 200 iterations, the model was given X and Y coordinates. Using a trained model and the previous month's data, we can predict future values. Assuming a time step of 6, historical medical data can be used to estimate the next six months. The basic functionality of LSTM models is maintained by a memory cell called the "cell state" throughout their lifetime. A horizontal line runs vertically from the highest to the lowest in the diagram. A conveyor belt transports the data.

3.3.2 Description of ARIMA model

The ARIMA model uses statistics to look at a set of times. Historical values from time series, such as lagging values and prediction errors, are used to extract useful information. The ARIMA model has three numbers: p, d, and q, where "p" is the order of the autoregressive terms, "q" is the order of the moving average terms, and "d" is the number of differences needed to show that a time series is stationary [16]. The ARIMA model, which stands for autoregressive integrated moving average, employs lagged data from its optimal results when the predictive variables are both independent and uncorrelated. The process of differentiation serves as the primary method for achieving stationarity in a series. In contrast, this procedure involves the subtraction of the previous value from the current value. The variable "d" represents the minimal number of differentiations necessary to achieve stationarity in the series.

It is crucial to note that the differentiation parameter, denoted "d", assumes a value of zero in instances where the time series has already achieved a condition of stability. In the context of significance, the terms "p" and "q" refer to statistical measures commonly used in hypothesis testing and statistical inference. The variable "p" is used to denote the order of the autoregressive term. A "forecasted quantity of Y shifts" is a set number of Y shifts used as forecaster. The moving average verdict's position in the sequence is "q". Based on the parameters, the ARIMA model must compute the forecast error. Time series analysis often uses statistical autoregressive and moving average models. The ARIMA model merges autoregressive and moving average time series models. As presented through Equation 2, the autoregressive model describes a situation in which *Yt* value is decided only by its past values. Previous values of y_t, called "lags of y_t", affect its value [26].

Equation (2) below, provides a description of the ARIMA model.

$$\boldsymbol{Y_t = \sigma + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \cdots + \beta_p Y_{t-p} + \epsilon_1} \quad (2)$$

where, Y_(t-1) is the lag1 of the series, β_1 is the coefficient of lag1 that the model estimates and is ϵ 1 is the intercept term, which is also estimated by the model.

3.4 Analysis and interpretation of results

The study looked at how both LSTM and ARIMA models performed in demand prediction of medicines. Time series forecast plots were presented to show how well the models could be used in health supply chain forecasting for the selected medicines. This study followed ethical rules on data privacy, use and protection. Authors have secured the authorization to access the data as needed and they have ensured that all the data used were anonymized to preserve data privacy. It is also important to know that this study has some flaws. We acknowledge that the volume and reliability of data may affect the prediction tasks that our models did not take into account outside factors like policy changes or unpredicted events but in forthright terms, the methodology applied was appropriate in relation to the dataset we used during our research. In relation to the assessment criteria that we considered, we were able to conduct a thorough analysis and reached relevant conclusions regarding the accuracy and performance of the applied models. The evaluation metrics used to evaluate the model success are RMSE and R^2. With RMSE, the errors are approximately squared before. The RMSE gives more weight to larger errors and this may show that RMSE is much more useful when the errors are large and significantly affects the model performance. This avoids the absolute value of the error, and this notation is useful in many mathematical calculations. Even in this metric, the lower the value is, the better the model will perform. The R^2, also known as the coefficient of determination, is a metric indicating how well a model fits a given dataset. It indicates how close the forecasted value or quantity plotted is to the actual data values. The R^2 value lies between 0 and 1, where 0 indicates that this model does not fit the given data and 1 indicates that the model fits perfectly to the dataset provided.

4 Results and discussion

In this section of the article, we discussed the study's findings, which involved LSTM, and ARIMA models to predict the demand for the selected five medicines, vastly supplied in the public health supply chain of Rwanda. The section provides a lookout on how well the models worked, highlight the most significant findings and which prediction model is recommendable model to be used for the demand prediction of medicines.

4.1 Evaluation of ARIMA and LSTM time series models

The findings of this research demonstrated that in comparison to ARIMA models, employing LSTM time series model for predicting the demand medicine is promising and more accurate based on its performance. To assess the performance and accuracy of the models, RMSE and R^2 metrics were used. These metrics offer insights into the accuracy and explanatory power of the model. The assessment metrics for several models, including both the training and testing sets, are displayed in Table 3. The LSTM model achieved a RMSE of 2.0 on the training set, accompanied by an R^2 score of 0.952. These results suggest a high level of accuracy for medicine demand prediction. The LSTM model demonstrated strong generalization capabilities on the testing set, as evidenced by its attained RMSE of 2.043 and R^2 score of 0.912. The results indicate a relatively low level of demand prediction performance for ARIMA time series while the accuracy and performance were good and preferably recommendable for LSTM time series models. Our findings are congruent with what was shown in a study conducted by Lou et. al. 2022, who examined the ARIMA, deep neural networks (DNN) and LSTM models in predicting the burden of diseases. According to their study, LSTM models perform well as a novel approach for making accurate foreacasts of the burden of pneumoconiosis [21]. On the training set, the ARIMA model similarly fared poorly, with an RMSE of 9.35 and R^2 value of 0.24. As presented in Table 3, the findings of the testing set were equally disheartening, with an RMSE of 8.926 and R^2 value of 0.16, which indicated that the model was unable to capture the underlying patterns in the data.

Based on a comparative viewpoint of the models' results, we understand that the LSTM model does better than the ARIMA model. The small drop in performance from training to testing shows that the LSTM model does not overfit and performed well through a reworking of a similar trend and adaptation to new information. Based on these results, the LSTM model can be recommended as a useful tool for demand prediction of medicines.

Table 3 Presentation of results from the evaluation of models

Model	Set	RMSE	R Square
LSTM	Train	2.0	0.952
	Test	2.043	0.912
ARIMA	Train	9.35	0.24
	Test	8.926	0.16

4.2 Presentation of plots for time series model prediction

The plots resulting from LSTM and ARIMA time series predictions are showed in Figure 2, Figure 3. Notably, the LSTM model consistently generated more accurate predictions than the ARIMA models as the predicted and actual amount overlays for LSTM time series prediction only.

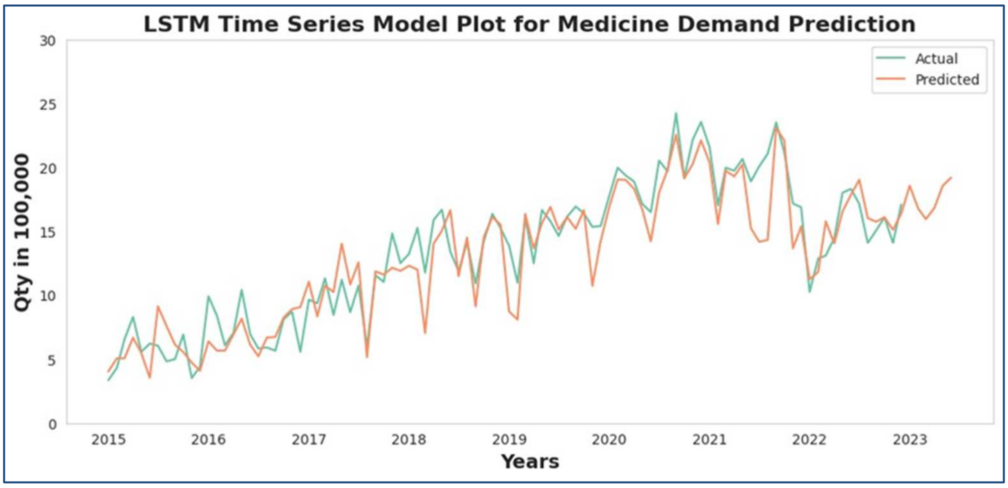

Figure 2 Presentation of the plot for demand prediction of medicines with LSTM model

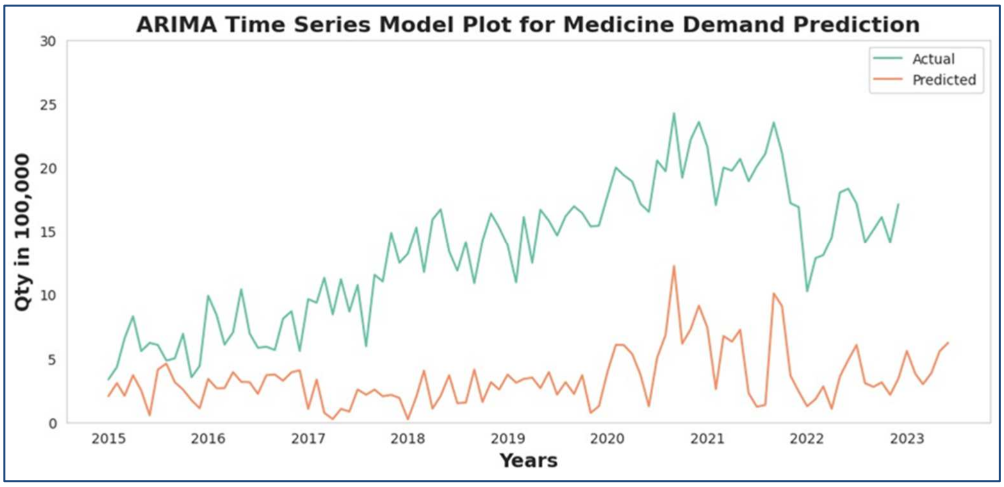

Figure 3 Presentation of the plot for demand prediction of medicines with ARIMA model

4.3 LSTM forecast model results for the selected medicines

In figures (Figure 4-Figure 8), we present the prediction outcome that the LSTM model made for the five drugs that were prescribed the most frequently in Rwanda. The capacity of the LSTM model to effectively predict future trends in medicine demand is demonstrated by these visualizations. The LSTM model ability to predict the demand for selected medicines overlaps with regularly observed behaviour and trends. Overall, our findings showed a higher performance of the LSTM model in comparison to ARIMA model, in demand prediction of the selected medicines. Thus, LSTM models make a best option that is recommended for predicting the demand of medicine in the health supply chain. The ARIMA model, despite its widespread application, demonstrated only moderate degrees of accuracy for our forecasting task and from this perspective, at this step, only the LSTM prediction plots are presented in figures (Figure 4-Figure 8), as follow:

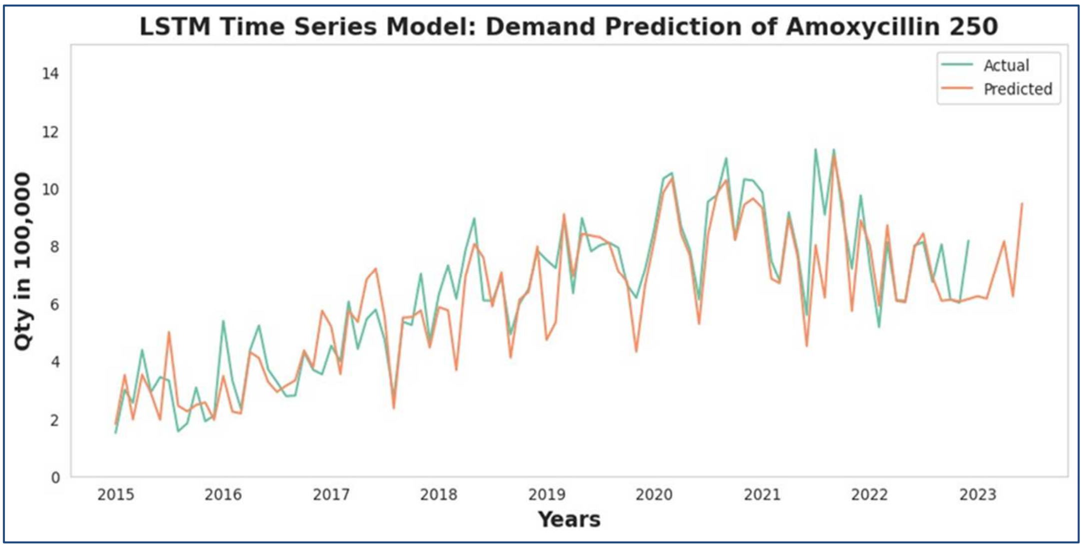

Figure 4 Demand prediction of Amoxicillin 250 mg using LSTM time series model

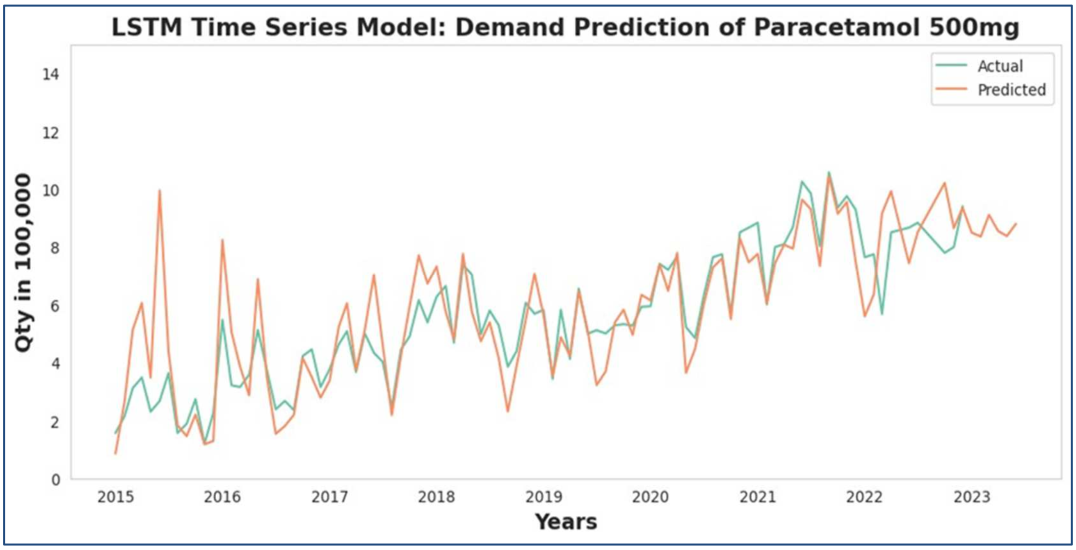

Figure 5 Demand prediction of Paracetamol 500 mg using LSTM time series model

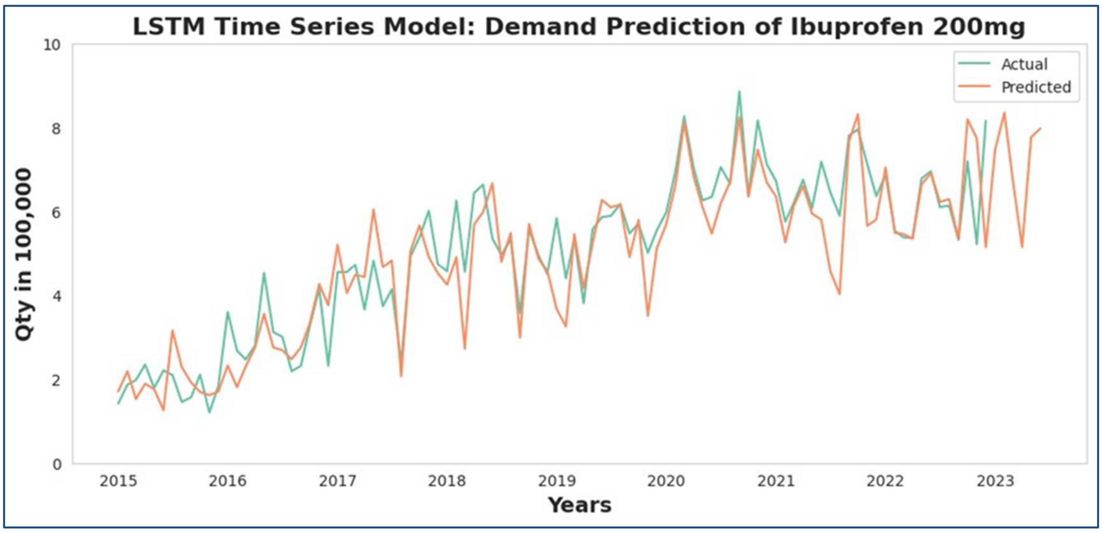

Figure 6 Demand Prediction of Ibuprofen 200 mg using LSTM time series model

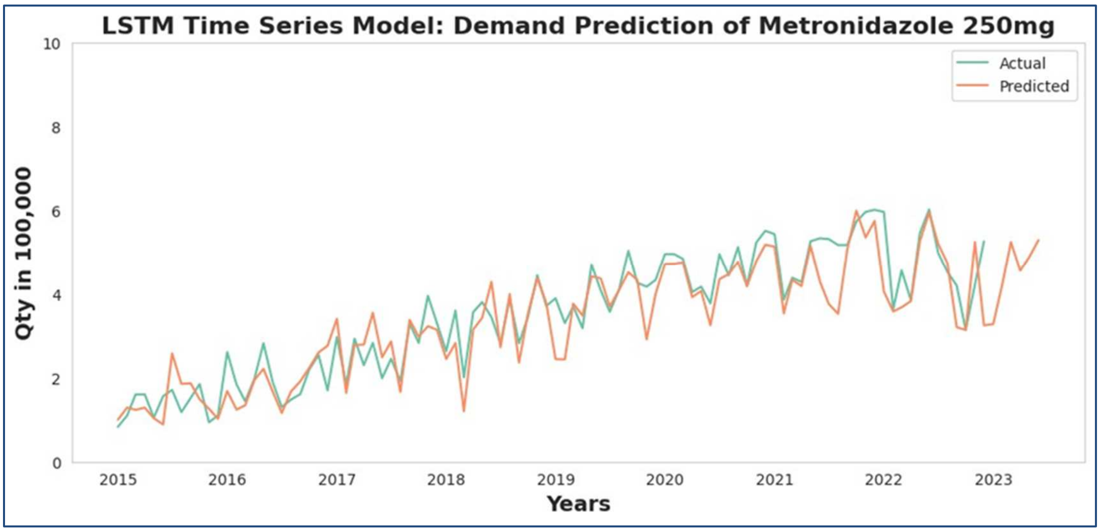

Figure 7 Demand Prediction of Metronidazole 250 mg using LSTM time series model

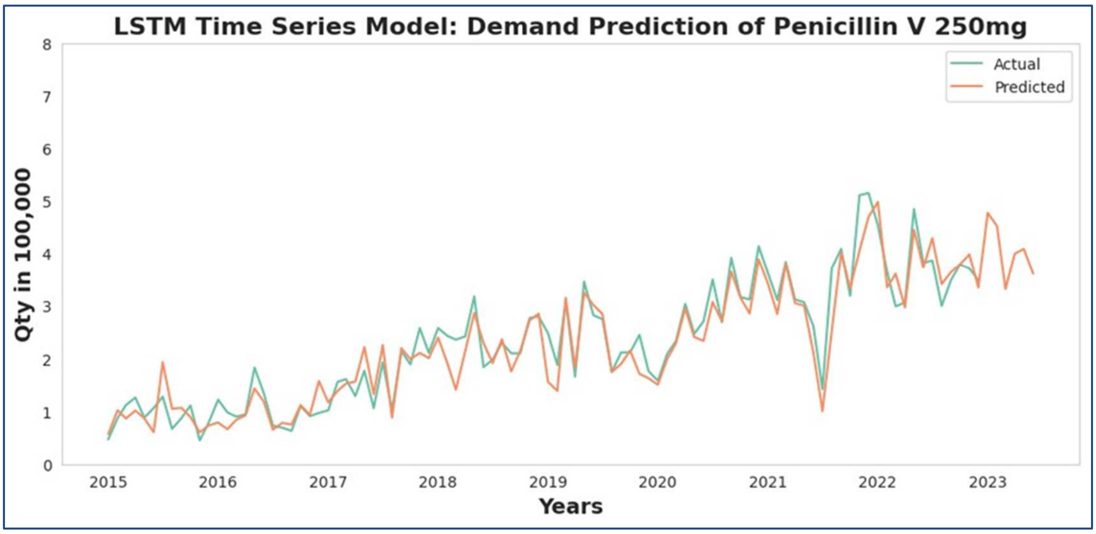

Figure 8 Demand prediction of Penicillin v 250 mg using LSTM time series model

The LSTM prediction plots in figures (Figure 4-Figure 8) are consistent with our model's performance measurements as presented in Table 3 where the quantitative assessment of our models gives important information about how the LSTM and ARIMA models worked. With an RMSE of 2.0 on the training set and 2.043 on the testing set, LSTM was very accurate. The model's ability to explain differences in the data is shown by the high R^2 values of 0.952 and 0.912 for the training set and test set, respectively. On the other hand, the ARIMA model did not show good performance, which was clear from the fact that their RMSE values were higher and their R^2 scores were lower. This stark difference shows that LSTM is better to recommend in medicine demand prediction for public health supply chain tasks.

4.4 Discussion of the results and analytical viewpoints on models' performance

Our study looked at how LSTM and ARIMA predictive models can be integrated in health supply chain forecasting tasks for demand prediction of medicines. Our research gave us valuable information about how well these models worked and their implications for health supply chain management. Additionally, our study had a broad goal: to compare the ability of different models to guess and find the most accurate model for demand prediction of medicines. The LSTM model showed a better prediction performance, illustrating how well it can be used in predicting the future demand of medicines. This level of performance in demand prediction is of great importance in the healthcare industry, especially regarding to effective handling and management of health-related supplies, including medicines.

When viewed alongside earlier studies, our findings are congruent with previous research investigating or making a comparison of LSTM and ARIMA models' demand prediction abilities. Azzouni et al. 2020, in their study, confirmed the LSTM model's performance for time series prediction as having greater accuracy when compared to other methods they used. In their study, the LSTM model was compared to some well-known time series predictive models from both statistical and computational intelligence methods, including ARIMA, exponential smoothing (ETS), artificial neural network (ANN), K-nearest neighbors (KNN), RNN, support vector machines (SVM), and single layer regression (SLR). In terms of accuracy measurements, the experimental results demonstrated that the LSTM model had a prediction power that surpassed the other approaches studied [24]. In a similar way, our findings, which focused on time series demand prediction of medicines, can be supported in the same context as similar findings were reported in other studies conducted in different contexts or using different dataset types. For instance, Hsu et al. 2022, published a study that focused on the prediction of adherence to medical treatment with temporal modelling in cardiovascular disease management. The study highlighted that temporal models that use sequential data outperform non-temporal models, with LSTM showing better performance in prediction and achieving an area under the curve (AUC) of 0.805 [3]. Another study carried out by Nasseri et al. 2023, looked at the use of LSTM networks and extra tree regressors (ETRs) in tree-based ensemble prediction. The study's findings paved the way for future research by suggesting an investigation of the comparison of deep learning techniques and tree-based ensembles in various prediction instances. The findings of a such study may inform decision-making in sales management, product flow, operational and other logistic aspects, as well as promotional tactics with the goal of strengthening supply chain management [27].

Because medicines and health products are usually so costly, it is paramount to point out, in relation to the findings of our study, that the use of data-driven prediction models is a foregone decision to recommend in the health supply chain as this will optimize the accuracy of demand prediction for selected medicines. This is of utmost importance especially in LMICs, where a lack of resources exacerbates existing barriers to health access [28,29]. The implications of our study's findings regarding the enhancement of health supply chain management are substantial and may make a significant contribution to the availability of medicines while streamlining investment strategies in the supply of medicines and preserving cost-effectiveness. Accurate demand predictions are crucial for optimizing inventory levels, minimizing shortages, or overstocks, and ensuring that medicines are readily available to meet patient requirements [10]. The success of the LSTM model in this regard suggests that deep learning techniques can considerably boost the efficiency of health supply chains. Additionally, the practical implications of our research are substantial as for effective health supply chain management, accurate prediction of demand of medicines is needed. As demonstrated, the higher accuracy of the LSTM model provides health professionals with a valuable tool for optimizing inventory levels, ensuring that medicines are always available when needed, and minimizing inefficiencies.

The LSTM Model performed better and presented a notable finding of our study with a higher performance in demand prediction of the selected medicines. Our study's findings are important for assuring efficient and effective management and flow of medicines, while also contributing to budget allocation and financial aspects of health supply chain. With a 95.2% performance rate in demand prediction, the LSTM model exhibited remarkable precision. This accuracy was consistent across different types of medicines, demonstrating the model's adaptability and applicability to a variety of pharmaceuticals. In contrast, the ARIMA model exhibited less accurate forecasts. ARIMA, a conventional time series method, expressed difficulty capturing the complex temporal patterns inherent in our health supply dataset for medicine demand prediction, resulting in less precise forecasts. Our findings are consistent with the findings of a study conducted by Wang et al. 2021 that focused on the use of ARIMA and LSTM for demand prediction based on short lead time and on-time delivery supply, and another study by Siami-Namini et al. 2018, in which he compared ARIMA and LSTM time series models. Both studies' findings revealed that LSTM models outperformed ARIMA models in terms of prediction accuracy [7,20]. The accuracy of ARIMA model was inferior to that of LSTM model, when using the dataset from e-LMIS in to predict the demand of the selected medicines. This, however, does not intend to question the prospective use of ARIMA models in different settings of very suitable datasets, particularly when it is used in combination through hybrid model as illustrated in a study conducted by Siamba et. Al. 2023, which concluded that a hybrid ARIMA-ANN model produces better predictive and forecast accuracy compared to a single ARIMA model [17].

Our research shows that the LSTM model showed potential added value for demand prediction of medicines and this makes it a must-have for health professionals who want to handle their inventory more effectively. Our study highlighted the application of LSTM predictive models in public health supply chain, showing the possibility for more accuracy in demand prediction and reliable options to optimize financial management and appropriate use of the budget allocated to medicines. The research outlined important insights and showed the necessary supply chain improvements and advances that enable a smooth flow of health product within the health supply chain while also indicating areas that necessitate further study. Our study has limitations, such as the size of the sample and the time span, which we referred to when building our dataset. Future researches should employ larger samples in future studies and investigate additional aspects that may influence the demand prediction of medicines. Further research on a hybrid time series models which may incorporate bigger sample size and diverse data sources, might provide more insights into making accurate forecasts for the demand of medicines. The integration of machine learning and deep learning models in health supply chain provides notable progress health supply chain forecasting by enabling an accurate prediction of medicines' demand which is a critical component to ensure a well-coordinated logistical function and health service delivery. It is deemed pertinent to streamline the flow of medicines and relevant logistic information for optimizing the availability of and accessibility to medicines, especially in LMICs' public health settings, as highlighted by Kaushik et. al, after examining the benefits of time series prediction models in their study [30,31]. The findings of this study are unquestionably intriguing and have confirmed the bridge between specific fields such supply chain, logistics and information management. Similarly, the findings of our study validate the potential use of machine learning and deep learning for medicine demand prediction in health supply chain forecasting.

5 Conclusions

In summary, our research indicates that deep learning models, specifically LSTM, exhibit significant and potential added values in health supply chain forecasting tasks. The measurement of our models provided important insights into how the investigated models performed the demand prediction for the five selected medicines. With an RMSE of 2.0 on the training set and 2.043 on the testing set, LSTM performed well and thus showed a better accuracy for demand prediction in health supply chain and therefore, performed well the demand prediction for the selected medicines. The model's performance and ability to detect variations in the data were demonstrated by the high R^2 values of 0.952 and 0.912 for the training and test sets, respectively. The ARIMA model, on the other hand, did not perform well, as demonstrated by its higher RMSE values and worse R^2 scores. The difference in prediction performance suggests that LSTM is the best option for predicting demand of medicine and thus contributing to health supply chain forecasting tasks.

These models have the capacity to fundamentally transform the manner in which health institutions predict their demand of medicines and lifesaving products, resulting in financial savings, improved aspects of logistics, and more effective use of resources. Health professionals and supply chain managers ought to consider the adoption of an LSTM time series model as a means to guarantee the continual flow of medicines within different levels of supply chain. The importance of accurate predictions using machine learning predictive models has become progressively crucial as the demand for health services continues to expand alongside high budget implications. We are persuaded that our study's findings have a significant impact in health supply chain forecasting, especially for the demand prediction of medicines. The study proposes LSTM as a deep learning time series prediction model, for addressing one of the primary concerns of health sector settings, which relates to how the demand of medicines is accurately performed. We would want to call more study focusing on machine learning and deep learning approaches and their use in health supply chain forecasting for ensuring an open to trust and reliable evidences to inform decision-making processes on their adoption and implementation. Finally, improving health supply chain forecasting through accurate demand prediction of medicines will facilitate the delivery of health services, optimized resource allocation and improved logistics throughout the entire healthcare system.

Author contributions: All authors, collectively contributed to study conceptualization, methodology, data analysis, and discussion of the results. They have reviewed and approved the final manuscript for publication.

Funding: This research received no external funding.

Study approval: The study used historical data from public health supply chain in Rwanda and did not involve humans. It is approved by the National Health Research Committee under Ref No: NHRC/2020/PROT/015. The Ministry of Health (Rwanda) provided a collaborative note and authorized access to data.

Informed consent statement: Not applicable.

Data availability statement: Data cleaning and data analysis related codes are available.

Conflicts of interest: The authors declare no conflicts of interest.

Acknowledgments: We would like to express our sincere gratitude to everyone who contributed to this study.

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Review process
Single-blind peer review process.