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Enhancing Efficiency in Public Education Expenditure through Short-Term Forecasting

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ABSTRACT. This study presents a short-term forecast of the financial expenses of a Federal Institution of Higher Education (HEI) within the context of budgetary challenges in Brazil, especially in the field of public education. Based on time series data of HEI expenditures, the SARIMA model is employed to forecast the financial needs for the upcoming fiscal months. The results demonstrate the potential of more accurate forecasts to optimize the efficiency of public spending in Brazil's educational system, as well as to support operational planning, including workforce allocation. One limitation of this study is that future research could explore some additional variables or techniques to increase the accuracy and robustness of the forecasts. Nevertheless, the findings have the potential to significantly contribute to the improvement of financial planning and resource management in HEIs, promoting a more effective allocation of resources to meet the needs of the local academic community and, consequently, increasing the efficiency of public spending in Brazil. Enhancing financial forecasting in HEIs can make it possible to achieve efficient resource allocation and greater transparency and accountability in public spending. By employing the SARIMA model for short-term financial forecasting, this study offers an innovative solution to improve financial requirements. This approach stands out by providing a data-driven method linked to the unique context of HEIs in Brazil, offering insights for improving operational efficiency.

Keywords: Higher education; efficiency; public expenditure; forecasting.

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Introduction

Forecasts play a crucial role in shaping economic policies, as their effects on the economy can have long and diverse delays. Private entities, central banks and various government agencies invest in forecasting studies related to support informed decision-making (Wright, 2019).

In Brazil, after social security expenditures, education and healthcare represent the most significant share of public administration spending. From a long-term perspective, the literature on public finances offers theories that aim to explain the historical growth observed in the volume of government expenditures (Boueri et al., 2015).

In a general sense, the initial planning phase in any organization or company involves forecasting activity levels. This is particularly true in higher education, where various activities are dependent on student enrollment. The number of students has a direct impact on planning and budgeting, specifically in terms of state funding, determining the workforce required, appropriate size and space, and managing various kinds of costs (Sinuany-Stern, 2021).

Arvan et al. (2019) state that forecasts serve as a crucial factor in the decision-making process across areas such as purchasing, production, inventory management, finance and various other domains. Personalized and increasingly sophisticated forecasts assist managers, public workers, investors and other decision-makers (Petropoulos et al., 2022).

Education costs encompass, in particular, the development of educational enterprises at all levels, mainly financed by the State. Forecasting education expenditures is fundamental to develop solid plans and promoting progress in sustainability and equity in education (Liu et al., 2023).

To enhance the efficiency of expenditures in Brazilian government institutions, financial resources must be available at the right time for payment obligations. As the adjustment between the actual flow of income and the need to pay expenses does not occur automatically, financial managers must take preventive measures, planning expenses in a way that aligns with the behavior of incoming fund flows (Giacomoni, 2021).

Forecasting holds a significant position across various domains. Consequently, the pursuit of more precise forecasts is important, considering the potential repercussions of an inadequately developed forecast (Mancuso & Werner, 2019). Cash flow forecasting remains one of the main challenges faced by public treasuries (Karaev et al., 2022). Time series forecasting models are mathematical and computational tools that can be used to aid public policies, which are evidence guided, as well as academic research (Leite Coelho da Silva et al., 2022).

The objective of this research is to explore the effective application of forecasting methods, in particular the SARIMA (*Seasonal Autoregressive Integrated Moving Average*) model, in anticipating and planning expense payments at a Brazilian Federal HEI. SARIMA is designed to capture linear trends in financial demand by effectively leveraging periodic characteristics and proving to be particularly effective in analyzing seasonal aspects of time series data. In the SARIMA framework, model parameters are estimated by applying the least squares method or maximum likelihood estimation. This approach assumes that the residual terms conform to a normal distribution characterized by a zero mean and a constant variance (Savun-Hekimoğlu et al., 2021).

By analyzing the literature on budget improvement in the educational context, this study aims to demonstrate empirically the thesis that the implementation of the SARIMA model contributes significantly to improving financial planning in Higher Education Institutions (HEIs). Focusing on effectively adapting to seasonal demand for educational expenditures and maximizing efficiency in the use of public resources, this work aims to provide information for educational managers and researchers interested in promoting the financial sustainability of higher education institutions and other public sector organizations. This work is based on the need to establish more efficient and sustainable budgeting practices, underscoring the importance of accurate forecasts for the strategic allocation of resources in Public Higher Education.

Given the lack of consensus on the optimal modeling approach for seasonal effects, the SARIMA method was used. Despite its inherent limitations in addressing time series with seasonal patterns, SARIMA stands as one of the fundamental and traditional models for time series forecasting (Moon et al., 2022). In addition, the SARIMA model is widely used in multiple forecasting problems (Liu et al., 2021). It is particularly favored for demand forecasting due to its simplicity and effectiveness. In scenarios that exhibit non-linear patterns with seasonal characteristics, SARIMA is commonly used, requiring the inclusion of two sets of data encompassing the associated events and another for their frequency. The application of SARIMA is fundamental in these cases (Nayeri et al., 2023).

The contribution of this study is primarily practical: the proposal was implemented in a real scenario, in the context of forecasting the demand for resources in the public sector, specifically in HEIs. The research highlights the importance of improving the accuracy of cash flow forecasts and the distribution of resources by the public treasury. By applying the forecasting methods discussed in this article establishes a basis for the public organization's financial planning, enabling it to manage its resources more efficiently, alignment of budgets with forecast demands and assurance that the financial needs of the academic community are effectively met, benefiting students, teachers and staff.

In the context of the budgetary challenges faced in Brazil, especially in the area of public education, the importance of accurate and efficient short-term forecasts is essential for proper financial management of HEIs. The lack of these forecasts can hinder financial planning, leading to inadequate resource allocation and making it difficult to achieve social and economic objectives.

Materials and methods

This section outlines the importance of forecasting into the management of financial and public resources, as well as provides a brief introduction to how payments are executed through financial transfers in Brazil, along with a discussion of the forecasting methods used in this work.

Recently, the forecasting use has emerged as a highly promising trend in the financial sector, offering substantial improvements in the effectiveness of financial risk management and the decision-making processes analysis. For a long time, research into financial time series forecasting has attracted considerable attention due to its inherent importance within financial market management (Niu et al., 2020).

Time series forecasting in finance presents significant challenges due to the constantly evolving landscape and the influence of market efficiency on predictability. Consequently, several research studies have focused on forecasting financial time series in specific markets, including the USA, Malaysia, Asia, India and Europe (Simian et al., 2020). However, achieving accurate forecasts remains difficult, given the complexity of factors such as the inherent randomness of financial data, national policy uncertainty, exchange rate and psychological expectations (Niu et al., 2020).

Efficiency in public services has become a key research focus in recent years, particularly among local governments. This is due to two main reasons: government resources are limited (raising taxes is politically costly and often legally constrained) and secondly, there is a growing demand for public services from citizens. As a result, the public sector is compelled to improve its efficiency in order to deliver services despite limited resources (Benito et al., 2019). Furthermore, there is a growing trend in demand for public services due to economic development (Boueri et al., 2015).

Establishing effective governance for the public financial system plays a key role in promoting economic progress, as it is the government sector that exercises authority and monitors public economic endeavors (Albassam, 2020).

Public spending is a central component of the government budgeting process. Effective resource allocation facilitates the implementation of public initiatives and services, benefiting both individuals and non-governmental organizations. Consequently, a well-managed public spending program plays a vital role in supporting the government's efforts to attract both domestic and foreign investment by providing quality infrastructure and efficient public services. These investments promote the country's economic growth and enhance the private sector's contribution to the Gross Domestic Product (GDP) (Albassam, 2020).

However, the effectiveness of a country’s fiscal policy is heavily influenced by the relationship between the size of government in the economy, the composition of public spending, and overall economic growth. This is based on the notion that some components of public spending are more productive than others in their influence on economic activity. From this perspective, a country can enhance its economic performance by adjusting both the level and the composition of public expenditures (Divino et al., 2020). Recent economic recessions renewed interest in fiscal and financial forecasting, particularly in the monitoring of deficits and public debt. This was certainly true in the 2008 recession and seems to be even more important in the current economic crisis caused by the COVID-19 pandemic (Petropoulos et al., 2022).

However, according to Petropoulos et al. (2022), it is not so simple to state that the improvement of forecasts made by independent analysts would be achieved, especially due to the absence of political biases. This is because the accuracy of the forecast is compromised by data complexities, country-specific factors, anomalies, changes in the definition of fiscal variables and other similar factors.

In this context, in a report to the OECD, Fakharzadeh (2016) pointed out that the allocation of resources in education must be distributed fairly between educational institutions and students. In addition, it must be carried out having efficiency in mind, given the financial constraints imposed by governments. In addition, it is essential that education funding be effective, given its significant impact on social and economic goals. The budgeting process for educational expenditure plays a key role in achieving efficiency in the field of education.

In Brazil’s education sector, the organization of education systems is a shared responsibility among all levels of government: the Union, States, Federal District and municipalities. They must collaborate in a coordinated manner to fulfill this commitment. The funds destined for the financial support of these education systems derive from the tax revenues of all government spheres (Boueri et al., 2015). According to the Portal da Transparência do Governo Federal. (s.d.), the expenditure on Higher Education in 2023 reached R$30,714,546,398.64 by October 2023, accounting for 29.46% of the total spent on education in the country. The HEI studied in this paper spent R$ 189,636,261.78 by October 2023.

Regarding the payment of these expenses, the ‘payment’ stage corresponds to the third and final stage of expenditure according to Brazilian Federal Law No. 4,320/1964. Financial transfers are executed by the National Treasury Secretariat (STN), which controls the release of financial transfers (Paludo, 2017).

Disbursements are usually scheduled in monthly installments so that there is a cohesive cash flow, aligning expenditures with revenues. However, this schedule may be adjusted due to seasonal variations, shifting priorities, or fluctuations in public tax collection (Giacomoni, 2021).

Additionally, bureaucratic procedures—including monitoring systems, compliance mechanisms, and financial controls—can vary according to the size and degree of decentralization of the government agency involved. These processes, along with the broader payment and banking systems, are also influenced by the complex legal framework governing public budgeting in Brazil (Giacomoni, 2021).

Forecasting methods make predictions about future values based on time series data. These forecasts rely on assumptions about future trends and the analysis of historical patterns. The application of forecasting methods is extensive and supports decision-making across a wide range of domains. At the organizational level, forecasts are indispensable for various types of decision-making processes in different areas such as marketing, sales, production/purchasing, finance and accounting (Fildes et al., 2022; Montgomery et al., 2015).

Recently, there has been a significant revision and expansion of exponential smoothing techniques in many fields. As a result, the methodology has been formalized within a statistical framework, enabling the incorporation of statistical principles into estimation and forecasting procedures (Villegas & Pedregal, 2019). Regarding the techniques used to predict future results, there are multiple options that can be employed and the selection of which fits best depends on the specific characteristics of the data and the desired level of accuracy (dos Santos et al., 2020).

Data analysis is an important preliminary step in selecting the forecasting model to be used. Time series charts should be constructed and visually inspected to identify recognizable patterns, such as trends and seasonal or other cyclical components (Montgomery et al., 2015). To generalize prevailing trends with the objective of predicting future values, time series are broken down into three main components: a trend cycle component, a seasonal component and a residual component (Hyndman & Athanasopoulos, 2018).

A methodology commonly used to forecast time series data is ARIMA, an acronym for autoregressive integrated moving average. This approach involves the analysis of autocorrelations, stationarity and the possible differentiation of data (Chacón et al., 2023). An ARIMA model is made up of differentiation components, autoregressive (AR) components and moving average (MA) components (Box et al., 2015). George Box and Gwilym Jenkins popularized ARIMA models in the early 1970s (Bacci et al., 2019). According to Wang (2011), the model checks each variable using autoregression (AR) and moving averages (MA).

According to Makridakis et al., (1998), the steps in the ARIMA model are as shown in (Figure 1):

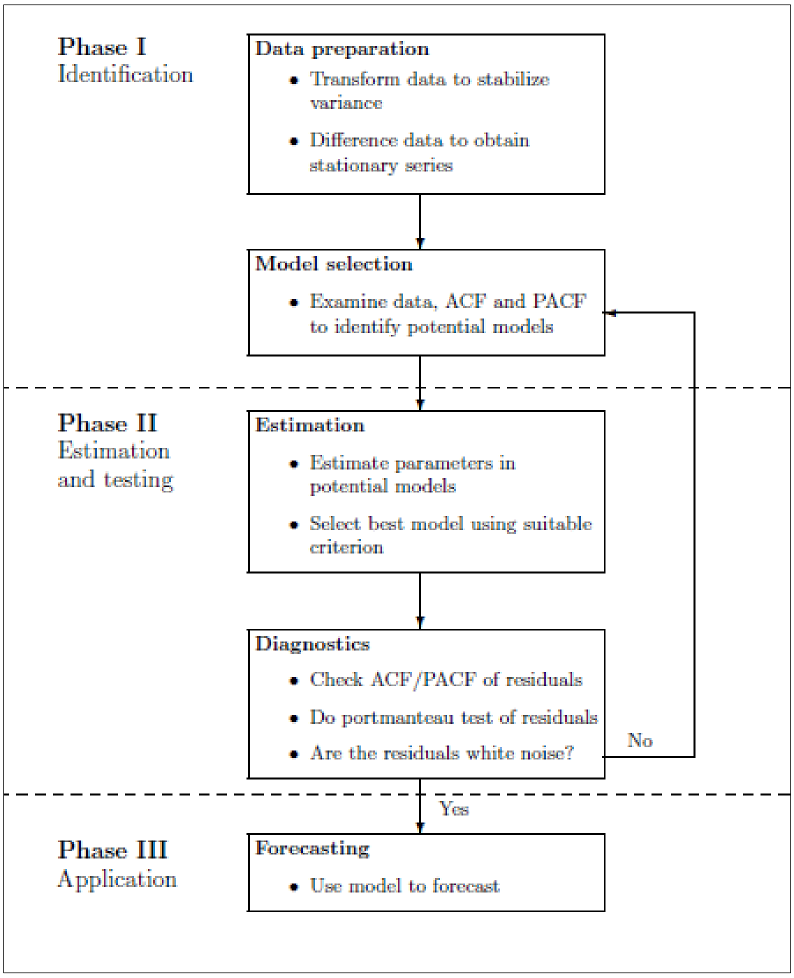

Figure 1. Schematic representation of the ARIMA method.

Makridakis et al., (1998).

For Chacón et al. (2023) and Montgomery et al. (2015), the time series can be divided into stationary and non-stationary forms, based on statistical properties. A time series is considered stationary when its statistical characteristics, such as mean, variance and autocorrelation, remain constant over time.

This characteristic considerably facilitates the forecasting process. In order to use these models for forecasting, it is essential to understand whether or not the stochastic process that produced the dataset evolves over time, or if the process is stationary (Bacci et al*.,* 2019). The utilization and calibration of an ARIMA model suitable for the dataset aims at addressing autocorrelation, resulting in the acquisition of uncorrelated residuals (Assunção et al., 2020).

However, if the data shows seasonality or a trend, the series is no longer stationary, as these factors have varying influences at different times. In these cases, differentiation techniques are used to calculate the disparities between consecutive observations, transforming the series into a stationary form and allowing the researcher to produce reliable results (Chacón et al., 2023).

The models used to represent stationary linear processes are autoregressive models of (p) order - AR (p) - moving average models of (q) order - MA (q) - and autoregressive models of (p) order, grouped with moving average models of (q) order - ARMA (p, q). In linear stationary processes, the data fluctuates around a constant mean, regardless of time, and the variation of the fluctuation remains constant over time (Bacci et al., 2019).

The ARIMA model is referred to as ARIMA (p, d, q), in which 'p' is the autoregressive (AR) component and 'q' the moving average (MA) component (Wang et al., 2023); 'd' represents the number of differentiations applied to make the time series stationary. A series is considered stationary when its mean, variance and autocorrelation remain constant over time. ARIMA/SARIMA models require the series to be stationary to ensure more reliable and statistically robust forecasts (Box et al., 2015).

Bacci et al. (2019) states that the ARIMA model can be represented by the linear function of the last observed values of the variable being predicted and the most recent errors in the prediction of an ARMA model. Y_t represents the projected value in period t. ε_t denotes the stochastic error during period 't', specifically a regularly distributed random variable with zero mean, constant variance and zero covariance. φ_i (i = 1, 2, 3, ..., p) represents the autoregressive parameters, while 'θ' (j = 1, 2, 3 ..., q) stands for the moving average parameters. These indicators are shown in (Equation 1):

$$Y_t = \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \cdots + \varphi_p Y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} -, \ldots, -\theta_q \varepsilon_{t-q} \quad (1)$$

An ARIMA model can be extended into a seasonal ARIMA model, where there are additional parameters to account for time series with significant seasonal behavior (Wang et al., 2023).

To this end, SARIMA - an extension of the ARIMA model - is used to model the stochastic seasonal component that correlates with other non-seasonal components of the time series. This model includes three additional hyperparameters, which are used to specify autoregression (AR), differencing (I) and moving average (MA) terms, similar to those of ARIMA. However, in the case of the seasonal component, an extra parameter is included to take into account the seasonality period. The seasonal components are similar to the non-seasonal terms, but involve the inclusion of backshifts corresponding to the specified seasonal period (Chacón et al., 2023).

SARIMA has the ability to make the forecasting of univariate time series data that has trends and seasonality easier. By incorporating them as a feature in forecasting models, SARIMA is able to regulate the seasonality of time series and accommodate a number of patterns established in short-term datasets (Liu et al., 2021).

A notable advantage of SARIMA is the incorporation of time series and external factors, including seasonal and non-seasonal factors. As a result, SARIMA has a remarkable proficiency in predicting both long- and short-term data traffic flow. In addition, SARIMA effectively exploits the interrelationship within sequentially lagged relationships when building models (Wu et al., 2023).

The ARIMA model can be extended into a SARIMA model by including seasonal autoregressive, seasonal moving average and seasonal differencing operators (Arunraj & Ahrens, 2015). The SARIMA model is denoted as SARIMA (p, q, d) (P, Q, D) s, where 'p', 'q' and 'd' are the trend elements for autoregression, difference and moving average, respectively, as in the ARIMA model, and now with the corresponding seasonal terms, P, Q and D, in addition to the notation 's', which represents the number of time steps per seasonal period (Chacón et al., 2023).

According to Leite Coelho da Silva et al. (2022), following the contributions made by Box and Jenkins, the SARIMA multiplicative model is known as the Seasonal Autoregressive Integrated Moving Average model. This model incorporates several components, including level, trend and seasonality, which are derived from simple and seasonal operators, according to (Equation 2).

$$\phi(B)\Phi(B^s)\nabla^d\nabla_s^D Y_t = \theta(B)\Theta(B^s)\alpha_t \ (2)$$

In (Equation 2), the function $\phi(B)$ represents the simple autoregressive operator, which represent the relationship between a past value in the series and the current value, while $\Phi(B^s)$ represents the seasonal autoregressive operator, capturing relationships between seasonal past values. In addition, ∇^d denotes the simple differencing operator, used to remove trends from the series and make it stationary, and ∇^D_s represents the seasonal differencing operator, used to remove seasonal patterns from the series. The value of *s* corresponds to the periodicity of the seasonality (e.g. 12 for monthly data). After that, $\theta(B)$ represents the simple moving average operator, and $\Theta(B^s)$ denotes the seasonal moving average operator. Finally, α_t stands for the random noise (error).

According to Montgomery et al. (2015), the forecasting process involves the following steps: 1) problem definition; 2) data collection; 3) data analysis; 4) model selection and fitting; 5) model validation; 6) development of the forecasting model and 7) monitoring the model's performance. These steps are outlined in the following section. After that, the paper moves on to the analysis of results.

Therefore, in order to define the problem, this study used purely quantitative analysis, adopting time series analysis in an attempt to forecast the amount of expenditures by the HEI located in the south state of Minas Gerais, Brazil. As there are no precise amounts to be received each month or exact date, a forecasting model can help the manager of these financial resources.

The analysis covers the period from January 2021 to September 2023, with a monthly frequency, in which the values of expenses added up within the month were used, in Brazilian Real (R$). To collect the data, the Brazilian Federal Government's *Tesouro Gerencial* software was used, which allows for the extraction of data in the form of detailed reports.

The data was organized and added up to obtain monthly payment amounts, as well as annual and quarterly amounts. The data refers to payments of various kinds, such as suppliers (materials, services) and personnel costs. All the payments within the months analyzed were added together so that they were consolidated and then presented as a time series.

Table 1 shows the values expended, month by month and quarter by quarter, as well as the total overall and per year, and (Figure 2) shows the graph of the values spent by time, resulting in the time series.

Table 1. HEI's expenditure values, from January 2021 to September 2023.

Values expended (2021-2023)					
Year	Quarter	Month	Month count	Currency	Expenditures
	1	January	1	R$	5.281.205,49
	1	February	2	R$	17.042.000,49
	1	March	3	R$	16.632.268,97
	2	April	4	R$	16.917.191,93
	2	May	5	R$	17.003.649,02
2021	2	June	6	R$	17.121.426,07
	3	July	7	R$	22.670.452,97
	3	August	8	R$	17.871.625,76
	3	September	9	R$	19.324.470,53
	4	October	10	R$	17.421.867,87
	4	November	11	R$	24.433.285,64
	4	December	12	R$	24.223.586,52
	1	January	13	R$	5.399.529,65
	1	February	14	R$	17.463.484,31
	1	March	15	R$	17.370.458,26
	2	April	16	R$	18.134.461,76
	2	May	17	R$	18.873.035,53
2022	2	June	18	R$	18.818.573,80
	3	July	19	R$	24.501.527,19
	3	August	20	R$	18.751.666,57
	3	September	21	R$	18.898.494,72
	4	October	22	R$	19.070.279,19
	4	November	23	R$	24.673.520,40
	4	December	24	R$	27.952.669,46
	1	January	25	R$	5.416.230,45
	1	February	26	R$	17.910.883,83

	1	March	27	R$	17.821.344,37
	2	April	28	R$	18.678.806,37
2023	2	May	29	R$	17.714.777,10
	2	June	30	R$	18.730.183,04
	3	July	31	R$	26.701.539,97
	3	August	32	R$	22.168.613,61
	3	September	33	R$	21.519.494,83

Authors.

Upon examining the time series, when using the data collected (HEI's monthly payments), it is possible to see the seasonality and trend embedded in it. The trend analysis has been carried out using Minitab® software as seen in (Figure 2), which shows an upward trend.

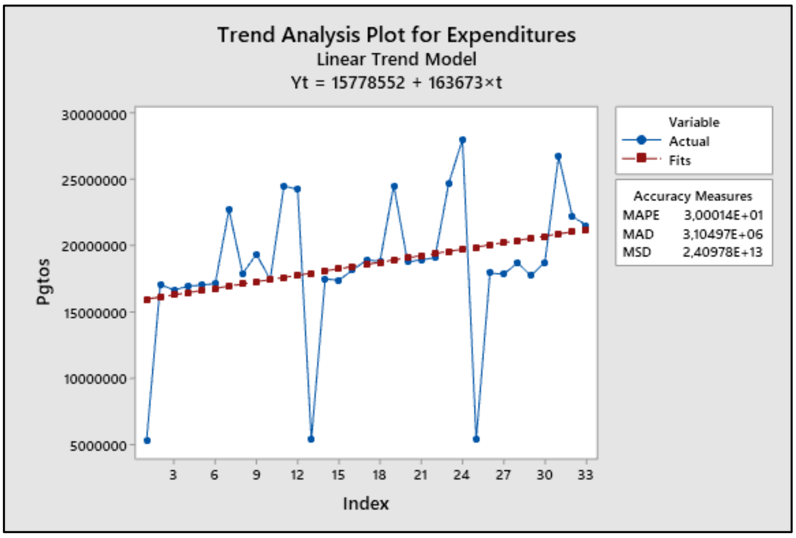

Figure 2. Time series and trend analysis of expenses from January 2021 to September 2023.

Authors.

The trend graph reveals an upward trend in the data. To further analyze this pattern, the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) graphs, shown in (Figure 3), were generated to highlight the correlations at lags 6 and 12.

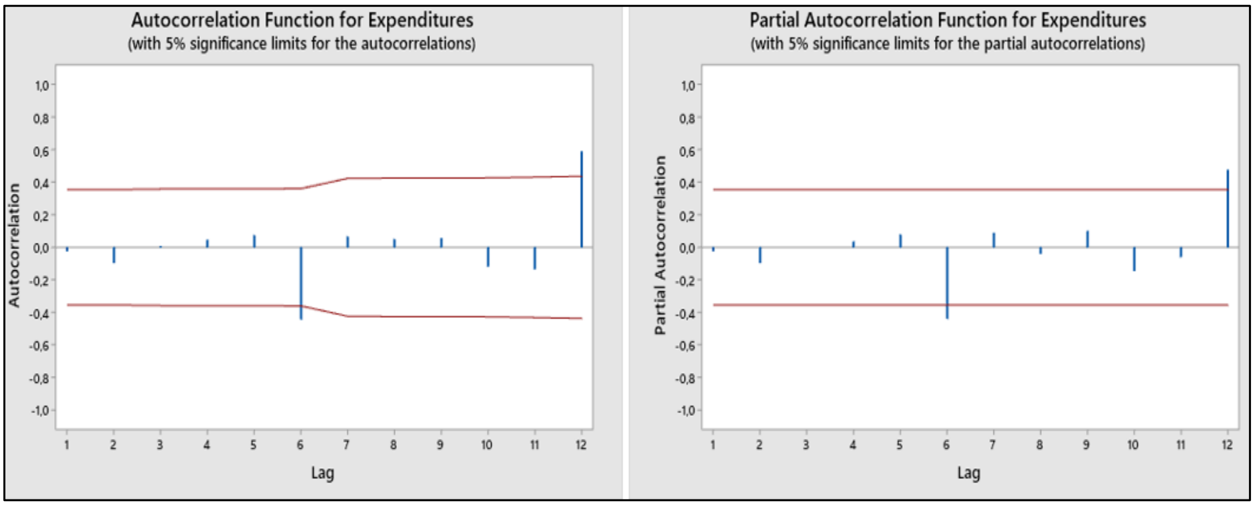

Figure 3. ACF and PACF of the amounts of expenses, from January 2021 to September 2023.

Authors.

To ensure stationarity, a first-order differencing was applied before calculating the ACF and PACF functions, as recommended in SARIMA modeling. Identifying the appropriate model involves analyzing the actual data representation, as well as studying the data stationary nature by observing the ACF and PACF graphs, as shown in (Figure 4).

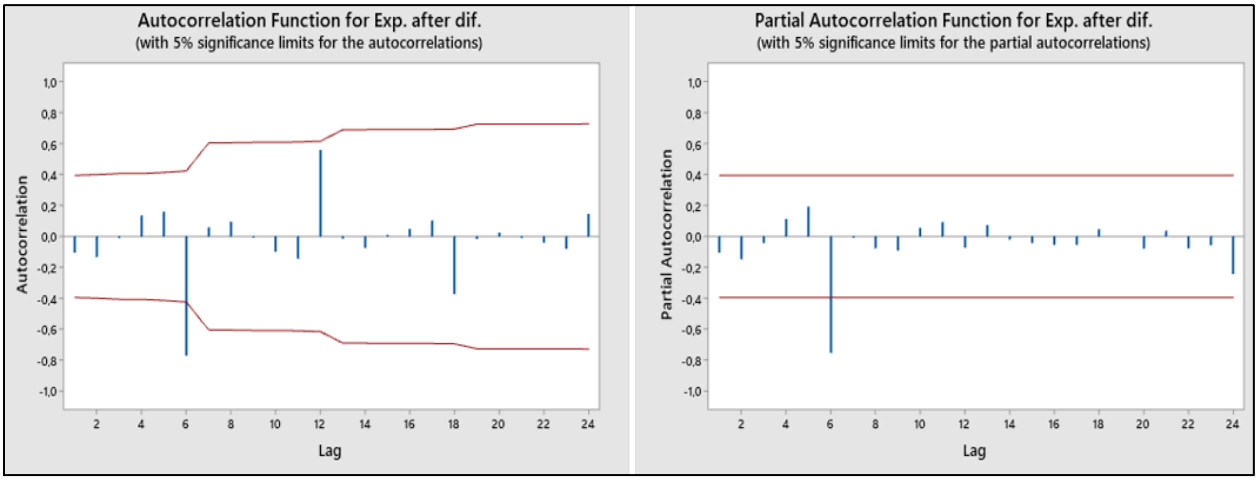

Figure 4. ACF and PACF of the amounts of expenses after differentiation, from January 2021 to September 2023.

Authors.

The graphs presented show significant autocorrelation and partial autocorrelation in lags 6 and 12, suggesting the presence of an autoregressive component in the data. This suggests the presence of seasonal patterns, given the limited number of observations (33 months), confirming seasonality of order 12 should be approached with caution. A pronounced peak at lag 6 suggests a possible short-term seasonal structure. To validate this hypothesis, the analysis was extended to include more lags and further tests were conducted to assess the suitability of the seasonal model.

Seasonality is observed in both the sixth and twelfth months of each year, during which peaks in expenditure occur. Fitting a SARIMA model to the data involves the following four-step iterative cycles: (a) identifying the SARIMA model structure (p, d, q) (P, D, Q); (b) estimating the unknown parameters; (c) performing goodness-of-fit tests on the estimated residuals; and (d) forecasting future results based on the known data. Fitting SARIMA models is a difficult task and involves human judgment on the ACF and PACF graphs (Choi, Yu, & Au, 2011).

This study focused on the decomposition effect to avoid the influences of human judgment in SARIMA modeling. A model selection algorithm was used, taking into account the candidate models based on the principle of parsimony, identifying by analysis of the ACF and PACF, in addition to the analysis of the time series itself. The necessary hyperparameters were run in the Minitab® software, and as a result, the SARIMA model (0, 1, 0) (1, 1, 0)12 showed the most favorable result, due to the Ljung-Box *portmanteau* tests with the highest p-value recorded (Makridakis et al., 1998). This is shown in (Table 2), along with the outcomes of the differencing procedures used to stabilize the time series.

Table 2. Ljung-Box *portmanteau* tests for the hyperparameters used.

Modified Box-Pierce (Ljung-Box) Chi-Square Statistic	
Statistics	Value
Lag	12
Chi-Square	7,06
DF	11
P-Value	0,79

Authors.

Results and discussion

Based on the calculations carried out using the Minitab® software, the results such as the p-value and the coefficient used by SARIMA are shown in (Table 3).

Table 3. Final Parameter Estimates used in the SARIMA model.

Final Estimates of Parameters			
Type	Coef	SE Coef	T-Value
SAR 12	0,996	0,151	6,59

Authors.

The high p-value in the Ljung-Box test (0.79) suggests that there is no statistical evidence to reject the null hypothesis that there is no significant residual autocorrelation. This is consistent with a good fit of the model to the data temporal characteristics. The forecasts results are shown in (Table 4) and the plot in (Figure 5):

Table 4. Forecasts, upper and lower limits (in Brazilian Reais).

Forecasts from period 33 (95% Limits)			
Period	Forecast	Lower Limit	Upper Limit
34	23.758.169	21.908.053	25.608.284
35	27.958.323	25.341.864	30.574.782
36	34.713.710	31.509.216	37.918.204
37	8.478.307	4.778.076	12.178.538
38	21.402.102	17.265.118	25.539.087
39	21.316.037	16.784.198	25.847.876
40	22.266.620	173.711.674	27.161.566
41	19.606.141	14.373.224	24.839.059
42	21.687.548	16.137.201	27.237.895
43	31.939.037	26.088.458	37.789.617
44	28.618.646	22.482.507	34.754.786
45	27.176.458	20.767.469	33.585.446

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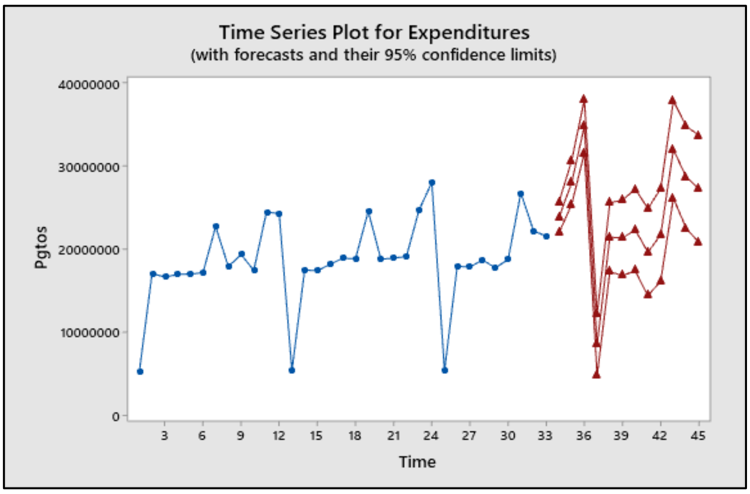

Figure 5. Forecasts plot using the SARIMA method.

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The ACF and PACF results (Figures 6) and (Figure 7) of the model's residuals show the resulting white noise, indicating that the model has been successful:

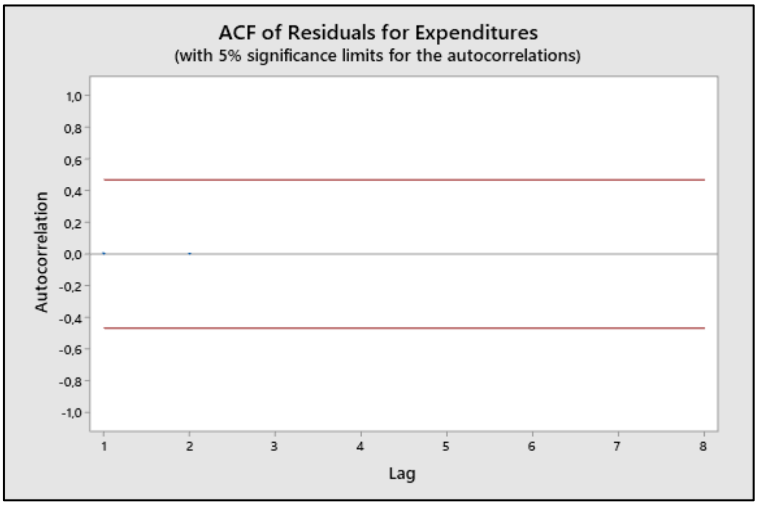

Figure 6. Model of ACF of residuals.

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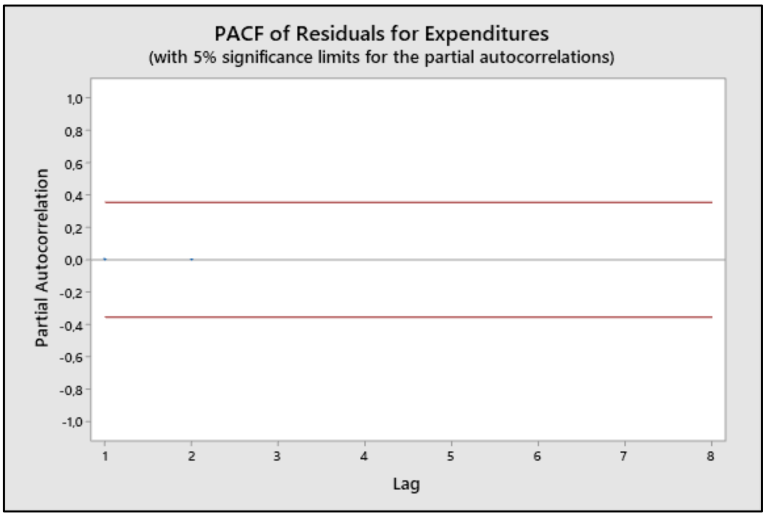

Figure 7. Model of PACF of residuals.
Authors.

The results clearly demonstrate that applying the SARIMA model to the public sector payment data from a Higher Education Institution (HEI) yielded positive outcomes. Using a sample of 33 data points ranging from January 2021 to September 2023, the model showed a chi-squared value of 7.06 and a corresponding p-value of 0.79 in the Ljung-Box test, meaning that there was no significant residual autocorrelation. These findings indicate a strong fit of the SARIMA model to the temporal dynamics of payment data. Overall, these results suggest a satisfactory SARIMA model performance in forecasting payments within the specified context, therefore validating its applicability for forecasting purposes in the public sector financial area.

To highlight the robustness of the model results, the Mean Absolute Percentage Error (MAPE) and RMSE (Root Mean Squared Error) were used, as they are popular measures of forecast accuracy (Kim & Kim, 2016). MAPE offers a clear measure of percentage error, while RMSE emphasizes the model's overall prediction accuracy by penalizing larger errors. According to Arunraj and Ahrens (2015), the formulas for the metrics are described below, where $\widehat{Y_t}$ is the forecast and *n* is the number of observations.

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{Y_t - \widehat{Y_t}}{Y_t}\right| \quad (3)$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(Y_t - \widehat{Y_t})^2}{n}} \quad (4)$$

The SARIMA model achieved an RMSE of 396 and a MAPE of 2.27, indicating a good performance. The relatively low RMSE suggests that the prediction errors are small, while the 2.27 MAPE indicates that the model's average prediction error is only 2.27%, demonstrating its accuracy and efficiency and that it can be used to better plan public resources expenditures.

The main focus of the discussion is the accuracy and precision demonstrated by the SARIMA model. The model's ability to capture patterns in expenditure data, including seasonality and time dependence, as well the observed trend, has contributed to its satisfactory forecasting performance. This accuracy is extremely important for public administrators, as it serves as a basis for making reliable decisions and capital management.

The importance of SARIMA model's success in forecasting expenditure is directly manifested in its ability to improve resource allocation. Public managers can rely on the model's forecasts to allocate funds strategically, ensuring that the budget is aligned with projected spending patterns. This supports the broader objective of optimizing resource use within the constraints of fiscal responsibility. However, it is also essential to acknowledge the model’s limitations, particularly in the face of external influences or unforeseen economic fluctuations. Addressing these weaknesses can help decision-makers interpret results more effectively and adapt their strategies accordingly.

Upon achieving successful forecasting, it becomes possible to identify and manage the impact of certain topics, including:

1. Resource optimization: Forecasting helps optimize resources allocation, enabling the finance department to plan and implement effective strategies.
2. Reduced planning cycles: With accurate forecasts, the time needed for planning can be reduced, increasing operational efficiency.
3. Alignment of finance and operations: Forecasting enables closer alignment between finance and operations, ensuring that financial decisions support operational objectives.
4. Empowering planners and decision-makers: Forecasting provides valuable information that can enable planners and decision-makers to make better choices and allocate workers efficiently.
5. Accuracy, quality and total transparency in dealing with data: Forecasting can improve the accuracy and quality of financial decisions and increase transparency in dealing with data, that is a Brazilian Government requirement.
6. Avoiding tax penalties and reaching deadlines: Accurate forecasting is a good tool for complying fiscal deadlines, reducing the possibility of incurring penalties. By making educated estimates of future financial allocation, managers can allocate their resources efficiently guaranteeing adherence to tax laws.

Conclusion

As far as practical implications are concerned, this paper's results had the potential of analyzing the educational system at an institutional level, especially in relation to the proper distribution of available financial resources within budgetary limits. Accurate forecasting of expenditures in higher education institutions is very important to ensure efficient and sustainable financial management. In an educational scenario where the demands for courses, resources and infrastructure are constantly growing, anticipating expenses becomes a fundamental decision-making tool. The ability to accurately predict financial needs allows institutions to allocate resources in a better way, avoiding budget surprises and guaranteeing the continuity and quality of educational services.

For public managers responsible for managing funds that come from the National Treasury, it is essential to have access to accurate and reliable information in order to make strategic decisions. In this context, forecasting models, such as SARIMA, have shown that it is an extremely useful tool in supporting decision-making. These models enable the anticipation of trends and financial behaviors, thereby facilitating more effective planning. By forecasting future events, it is possible to anticipate possible crises and take preventive measures to minimize their impact, as well as to avoid tax penalties. This capability is especially important in times of economic and political instability, when uncertainty is elevated. In short, forecasting makes it possible to anticipate trends, plan investments and manage risks more effectively, contributing to the country's sustainable development.

Revenue forecasts can support the budgeting process by helping ensure that planned expenditures do not exceed expected revenues, as well as helping predict the amount of work for staff involved in payment procedures, identifying trends in the workload, which increase when associated with seasonal patterns.

Among the multiple forecasting methods available, SARIMA has proven to be a robust choice for modeling and anticipating seasonal patterns and trends in HEI expenditures. By incorporating autoregressive, integrative and moving average components, SARIMA was effective in capturing seasonal variations. Its ability to deal with seasonal data, such as annual variations in spending and costs, makes it a good method for forecasting public spending. The proven efficiency of the SARIMA model in expenditure forecasting highlights the importance of forecasts for the public sector. They provide early and accurate insights into future spending patterns, enabling public managers to make informed and strategic decisions. This proactive approach not only improves day-to-day decision-making, but also contributes to the development of more resilient and adaptable public policies aligned with projected financial needs.

Furthermore, SARIMA's flexibility allows it to be adapted to different contexts and to accommodate the diversity of patterns observed in HEI expenditures. Its ability to simultaneously account for multiple factors makes it a good choice for modeling the complexity of the public education spending. By adopting SARIMA for expenditure forecasting, Higher Education Institutions invest in a sophisticated and accurate approach that is relatively low-cost to implement, leading to more strategic and sustainable spending decisions.

Finally, the incorporation of forecasting models such as the SARIMA method into the field of public administration serves as a valuable tool in the management of resources and future-oriented decision-making. The ability to anticipate future needs and trends enables managers to make more informed choices, optimize financial allocations and deal with risks more effectively. By taking advantage of SARIMA's predictive capabilities, public managers can manage the distribution of resources with a strategic and forward-thinking approach, thereby increasing the overall efficiency and impact of public services.

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