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Article

Demand forecast using the Holt-Winters method: Application in a restaurant in Brazil

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Abstract

The Holt-Winters method produces accurate forecasts and is easy to implement. This study evaluated the suitability of the Holt-Winters method for demand forecasting at an Asian cuisine restaurant, located in Petrolina, PE. The method was chosen because of the behavior of the demand, its low implementation cost, and adaptability to different types of time series. A survey of the sales share of each item on the restaurant's menu was initially carried out to identify the best-selling items and establish an equation that relates this sales share to the demand forecast for each product. Next, a comparison between the additive and multiplicative variants of the Holt-Winters method was conducted to analyze which was the most appropriate for the data. The results showed that the greatest sales share came from promotional and special combos (representing, together, 81% of sales), and the equation for forecasting product demand was also established. Furthermore, the additive model was found to be the most appropriate, yielding the lowest error metrics.

Keywords: Delivery. Demand forecast. Holt-Winters.

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Previsão de demanda utilizando o método de Holt-Winters: aplicação em um restaurante brasileiro

Resumo

O método de Holt-Winters é uma técnica que estabelece previsões precisas, além de ser de fácil implementação. Desse modo, este trabalho teve como objetivo avaliar a adequação do referido método na análise de previsão de demanda de um restaurante de comida oriental, situado em Petrolina-PE. A escolha do método se deu em função do comportamento da demanda apresentada, além do baixo custo de execução e adaptabilidade aos diversos tipos de série temporal. Para isso, foi feito inicialmente um levantamento da representatividade de vendas de cada item do cardápio do restaurante, de modo a entender quais itens são os mais consumidos e estabelecer uma equação que relacione essa representatividade de vendas com a previsão de demanda de cada produto. Na sequência, foi feito um comparativo entre os dois métodos de Winters para analisar qual era o mais adequado aos dados. Como resultados, obteve-se que a maior representatividade era dos combos promocionais e especiais (representando, juntos, 81% das vendas), e foi estabelecida também a equação para a previsão de demanda dos produtos. Além disso, concluiu-se que o método aditivo era o mais adequado aos dados, obtendo as menores medidas de erro.

Palavras-chave: *Delivery*. Previsão de demanda. Holt-Winters.

Pronóstico de la demanda utilizando el método de Holt-Winters: aplicación en un restaurante brasileño

Resumen

El método Holt-Winters es una técnica que establece predicciones precisas, además de ser fácil de implementar. Así, este trabajo tuvo como objetivo evaluar la idoneidad de dicho método en el análisis del pronóstico de demanda de un restaurante de comida oriental, ubicado en Petrolina-PE. El método fue elegido con base en el comportamiento de la demanda presentada, además del bajo costo de ejecución y adaptabilidad a diferentes tipos de series de tiempo. Para ello, inicialmente se realizó un estudio sobre la representatividad de ventas de cada artículo del menú del restaurante, con el fin de conocer cuáles son los artículos más vendidos y establecer una ecuación que relacione esta representatividad de ventas con el pronóstico de demanda de cada producto. A continuación, se realizó una comparación entre los dos métodos de Winters para analizar cuál era el más apropiado para los datos. Como resultado, se encontró que la mayor representatividad provino de los combos promocionales y especiales (en conjunto representan el 81% de las ventas), y también se estableció la ecuación para pronosticar la demanda de los producto. Además, se concluyó que el método aditivo fue el más apropiado para los datos, obteniendo las medidas de error más bajas.

Palabras clave: Delivery. Pronóstico de demanda. Holt-Winters.

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INTRODUTION

As a consequence of modern life, in which individuals increasingly seek to optimize their time, the practice of eating octside the home has become progressively more common. According to Queiroz (2015), the growth of oct-of-home food consumption is a global characteristic of the evolution of eating behavior, and Brazil is no exception to this trend.

With particular emphasis on delivery services, it is through this channel that oct-of-home dining has gained a new dynamic. Through mobile applications, a wide range of restaurants offering diverse cuisines can now be accessed, with meals delivered directly to customers within increasingly shorter time frames. Moreover, this market has grown steadily over the years and has become progressively more profitable (Souza, 2021).

The preference for delivery during the pandemic scenario is Uniterstandable, as "people feel safer placing an order via Rappi and avoiding large gatherings," the company stated in a communiqué to Reuters (Calais, 2020). In this pandemic context, in which restrictive measures and commercial closures were imposed to contain the spread of the virus, frequently patronized oriental restaurants were required to adapt to operating exclusively through delivery—and were also successful in this new format.

From this perspective, Basseto (2015) argues that demand forecasting is an effective method that enables the integration of the entire production process, minimizing inventory-related costs. For Tubino (2007), demand forecasting is the most important variable in defining a system, particularly for the functions performed by Production Planning and Control (PPC), since forecasting provides information regarding the future sales value of an item or group of items (Moreira, 2011). Such information is used to plan production in advance, thereby reducing inventory levels, financial costs, and delivery times, while increasing predictability and customer satisfaction (Cavalheiro, 2003; Santos *et al*., 2021).

Recognizing the importance of demand forecasting in companies, particularly in restaurants, there appears to be a lack of application of sophisticated forecasting models in this type of business. According to Cecatto and Belfiore (2015) and Purificação *et al.* (2017), most companies supplying food products do not employ sophisticated forecasting models; 93.8% of those surveyed rely on historical analysis, moving averages, or market analysis. The appropriate application of forecasting methods is essential for effective planning, given that food products are perishable and demand is subject to seasonality. Furthermore, forecasting assists restaurants in mayntaining the consistency of their menus.

In light of this context, the following research question was formulated to guide the study: Is the Holt-Winters method suitable for analyzing demand forecasting in a restaurant septing? Therefore, the objective of this study was to evaluate the adequacy of the Holt-Winters method for forecasting demand in a Brazilian restaurant of oriental origin.

LITERATURE REVIEW

According to Kotler (1991), product demand refers to the total volume that would be purchased by a given group of consumers within a specific geographic area, over a defined period of time, Uniter particular market conditions and a specified marketing program. Estimating and forecasting this volume is not a simple task, as demand for goods and services can vary considerably (Krajewski; Ritzman; Malhotra, 2009). Moreover, several factors may influence demand, such as product price,

consumer income, preferences and expectations, as well as the prices of related goods (Santos, 2020; Sobral; Silva; Santos, 2025).

Despite such variability in demand behavior, when historical sales data for a specific item, product family, or service are analyzed, certain patterns can be identified. According to Martins and Laugeni (2005), demand behavior exhibits several common patterns of variation, including

- **Mean (stationary)**: fluctuations occur aroUnit a constant value;
- **Linear trend**: demand increases or decreases in a linear manner;
- **Nonlinear trend**: demand increases or decreases nonlinearly, for example, following a second-degree equation;
- **Seasonal (periodic)**: demand rises or falls during specific periods, such as particular days of the week, months, or specific times of the year.

For the purpose of analyzing demand behavior, data may be compiled over different time intervals—daily, weekly, monthly, among others—depending on data availability and until a discernible behavioral pattern can be identified. Therefore, analyzing demand behavior is essential for identifying consumption patterns, detecting the presence or absence of trend and seasonality, and supporting the selection of the most appropriate forecasting method to ensure the highest possible level of accuracy.

Demand Forecasting

In the competitive and dynamic environment in which companies operate, several methods support managerial decision-making; among them are forecasts regarding the expected behavior of demand. Demand forecasting plays a fUnitamental role, guiding production planning, sales, financial management, and marketing activities within an organization (Santos, 2020; Lima *et al.*, 2025).

Demand forecasting is a highly important tool for companies, as it constitutes the starting point for effective planning across multiple organizational areas (Souza; Silva, 2017). Despite its relevance, because it involves projections, forecasting does not yield exact results. As Stevenson (2001) argues, forecasts are rarely perfect due to the inherent difficulty of anticipating the full sep of factors that may influence future octcomes.

One factor that directly affects forecasting accuracy is the planning horizon. According to Fernandes and Godinho Filho (2010), as the planning horizon increases, forecast accuracy tends to decrease. Long-term forecasts are generally more uncertain than medium-term forecasts, which, in turn, are more uncertain than short-term forecasts. Therefore, organizations that respond more rapidly to market changes benefit from more accurate forecasts, as they require shorter planning horizons (Santos *et al.*, 2017). It is also important to emphasize that, for demand forecasting to achieve its intended purpose successfully, several conditions must be met (Corrêa *et al.*, 2001):

1. The ability to analyze historical data, identifying specific patterns in consumer behavior and eliminating anomalies that could lead to forecasting errors.
2. In-depth knowledge of the products, including how their characteristics, applications, and life cycle stage affect demand.

3. Consideration of relevant events, with proper documentation of their impacts on demand, since the recurrence of such events may facilitate the forecasting process.

According to Moreira (2011) and Soares *et al.* (2022), forecasting methods can be classified according to various criteria; however, the most common classification is based on the type of approach employed—that is, the tools and conceptual foUnitations Uniterlying the forecast. Uniter this criterion, forecasting methods are generally divided into qualitative and quantitative approaches.

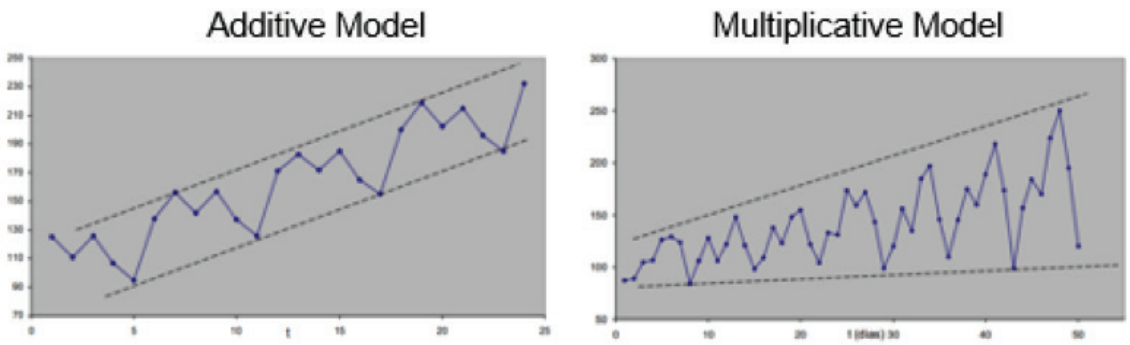
Holt-Winters Method

The Holt-Winters method is an extension of the Holt model developed by Winter and is Uniterstood as an exponential smoothing method that incorporates an additional equation to adjust forecasts for seasonality (Makridakis; Wheelwright; Hyndman, 1998). It is therefore an appropriate model for time series that exhibit both trend and seasonality, based on the assumption that certain series contain a seasonal component in addition to level and trend, which capture recurring characteristics observed at regular time intervals.

According to Morettin and Toloi (1987), this model comprises procedures based on three equations with three distinct smoothing constants, each associated with one of the standard components of the series: level, trend, and seasonality. Winter proposed forecasting procedures for such series by considering two types of seasonal effects: additive and multiplicative (Alves *et al.*, 2019). Figure 1 illustrates the components of both the additive and multiplicative models.

FIGURE 1

Components of the Additive and Multiplicative Models



Source: Lobo (2007).

The additive model is employed in the modeling of data in which the amplitude of the seasonal cycle is independent of the local level of the series, that is, it remayns constant over time. In contrast, the multiplicative model is used when the amplitude of the seasonal cycle varies proportionally with the level of the series over time (Alves *et al.*, 2019). Table 1 presents the equations for both models.

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TABLE 1

Equations of the Additive and Multiplicative Models

Equations	Additive Holt-Winters	Multiplicative Holt-Winters
Level	$Lt = \alpha(Zt-St-s)+(1-\alpha)(Lt-1+Tt-1)$ (1)	$Lt = \alpha(Zt/St-s)+(1-\alpha)(Lt-1+Tt-1)$ (2)
Trend	$Tt = \beta(Lt-Lt-1)+(1-\beta)Tt-1$ (3)	$Tt = \beta(Lt - Lt-1) + (1-\beta)Tt-1$ (4)
Seasonality	$St = \gamma(Zt-Lt)+(1-\gamma)St-S$ (5)	$St = \gamma(Zt/Lt)+ (1-\gamma)St-s$ (6)
Forecast	$\hat{z}t+k = Lt+KTt+St-s+k$ (7)	$\hat{z}t+k = (Lt+KTt)St-s+k$ (8)

Source: Elaborated by the authors.

Where: Lt is the level component; Tt, the trend component; St, the seasonal component; $\hat{z}t+k$, the forecast for k periods ahead; Zt, the actual observed value at time t; k, the number of future periods to be forecasted; α, the smoothing constant for level estimation ($0 \leq \alpha \leq 1$); β, the smoothing constant for trend estimation ($0 \leq \beta \leq 1$); and γ, the smoothing constant for seasonal estimation ($0 \leq \gamma \leq 1$).

Equations (1), (2), (3), (4), (5), and (6) are used to estimate the level, trend, and seasonality components, respectively, in the additive and multiplicative models. It can be observed that only the trend equation is identical in both models. The level equations (1) and (2), the seasonality equations (5) and (6), and the forecast equations for kkk periods ahead (7) and (8) present subtle differences, such as the use of addition and subtraction operations in the additive model, and division and multiplication operations in the multiplicative model.

In recent years, several methodologies have approached the Holt-Winters method in conjunction with quantitative statistical and mathematical techniques. This trend arises from the need to evaluate forecasting performance in the presence of unpredictable factors and to develop robust forecasting algorithms using real-world data (Kumar; Khedlekar, S.; Khedlekar, U., 2024).

The application of this technique across various contexts is further justified by the need to capture demand fluctuations while accounting for seasonality, market trends, and cyclical patterns. Moreover, marketing and economic factors can be incorporated with greater emphasis (Kumar; Khedlekar, S.; Khedlekar, U., 2024).

It is also noteworthy that some studies have demonstrated the effectiveness of the Holt-Winters method when integrated with demand forecasting models based on neural networks, for example. In such cases, this hybrid approach has been shown to octperform traditional methods in terms of accuracy and stability. This combination highlights the relevance of integrating Holt-Winters with other advanced methodologies to enhance forecasting performance (Chen; Du, 2024; Gao; Xu; Li, 2022; Kumar; Khedlekar, S.; Khedlekar, U., 2024; Maia; Carvalho, 2011).

After applying the forecasting methods, it is necessary to determine which model is most appropriate for the data Uniter study. This identification is carried oct through the analysis of the forecasting errors to which the methods are subject.

Forecast Error Measures

Forecast accuracy is characterized by the degree of proximity between the forecasted values and the actual demand. The smaller the errors, the closer the forecasting model is to the real data and, consequently, the greater its accuracy. Some commonly used error measurement metrics are presented below.

- **Mean Absolute Percentage Error (MAPE):** MAPE is calculated as the average percentage of the absolute difference between the forecast error and the actual observed value. According to Lewis (1997), MAPE is one of the most widely used error measures for evaluating forecasting methods, as shown in Equation (9).

$$MAPE = \sum[(A(t) - F(t)) / A(t)] / N \quad (9)$$

Where: A(t) represents the actual demand in period *t*; F(t) denotes the forecast for period *t*; and N is the number of forecast periods considered.

- **Mean Absolute Deviation (MAD)**: MAD is calculated as the average of the absolute differences between actual demand and forecasted demand over the observed periods. According to Mentzer and Bienstock (1998), it is expressed as shown in Equation (10) below:

$$MAD = \sum[A(t) - F(t)] / N \quad (10)$$

Where: A(t) represents the actual demand in period *t*; F(t) denotes the forecast for period *t*; and N is the number of forecast periods considered. Thus, if the MAD is small, the observed data closely follow the forecasts of the dependent variable, indicating that the model provides accurate predictions. Therefore, error measures are indispensable, as they enable the assessment of the reliability of the results obtained through the application of the selected forecasting method.

In the present study, demand forecasts will be developed using the Holt-Winters method, also known as Triple Exponential Smoothing, with a comparative analysis between the additive and multiplicative models. This method is based on time series analysis; that is, by using historical daily sales data, the components of the series will be examined and forecasts will be generated. To verify the reliability of the results, the error measures employed will be MAD and MAPE—both widely used and relatively straightforward to implement and interpret.

METHODOLOGY

With regard to its objectives, this research is classified as exploratory, as it seeks to provide greater familiarity with the problem and to clarify it. The study was structured into four phases. In the first phase, the research theme, the object of study, as well as the research problem and objectives were defined. In the second phase, a literature review was conducted in order to gather relevant sources and provide a theoretical foUnitation for the study.

The third phase consisted of analyzing the sales representativeness of combo meals in relation to other items on the menu. This analysis indicated that promotional and special combos were the best-selling items, thereby requiring more effective demand management. Based on this assessment of sales representativeness and the prices of each combo, the procedure for applying the restaurant's weekly sales forecast to the demand forecast of the company's products was established, as expressed in Equation (11).

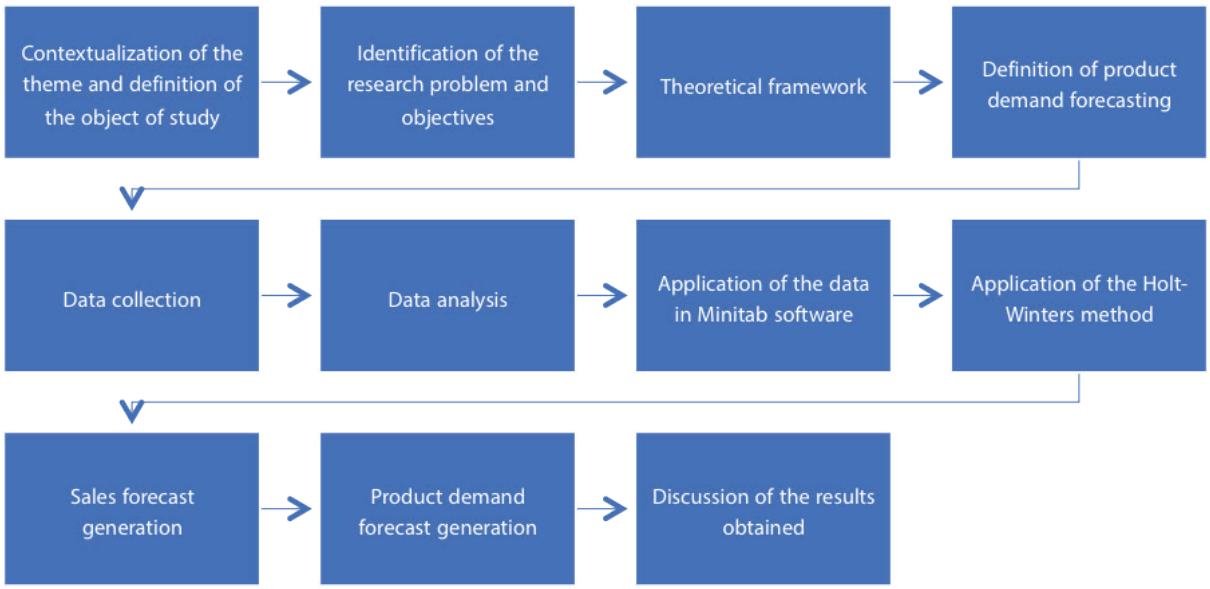
Subsequently, daily revenue data from the restaurant were collected for the period from April 2020 to October 2021. The data were organized using Microsoft Excel® 2013, and an analysis of demand behavior was carried oct to verify the suitability of the selected forecasting method. After this stage, the data were entered into Minitab® 21.1 software, and the additive and multiplicative Holt-Winters methods were applied.

The fourth and final phase involved generating the actual sales forecasts and, based on the error measures employed, determining which Holt-Winters model exhibited the best performance. To validate its adequacy in comparison with other demand forecasting methods, a comparative analysis was conducted using the moving average method, simple exponential smoothing, and double exponential smoothing, based on the error measures MAPE and MAD. Finally, groUnited in the weekly sales forecast, the demand forecast for each combo was obtained and the results were discussed.

In summary, the research phases and the actions Unitertaken in each of them are presented in Figure 2.

FIGURE 2

Research Stages



Source: Elaborated by the authors.

It is worth noting that adhering to this sequence of steps was essential for achieving satisfactory progress in the work and accomplishing the proposed objectives, which demonstrates that the steps were aligned and interdependent. Furthermore, it should be emphasized that the research steps described here can serve as a foUnitation for other authors to follow as a reference in the application of this type of technique—specifically within the gastronomic sector.

RESULTS

Company profile

Established in the city of Petrolina-PE, the company Uniter study began its operations on November 29, 2018. Its organizational structure comprises chefs, kitchen assistants, sushimans, sushiman assistants, packers, delivery staff, cashiers, and a general manager, totaling 20 employees. A distinguishing feature of the restaurant's structure is the use of sushi machines to assist in product preparation. The company owns a sushi rolling machine, which produces the base for uramakis and makimonos, as well as a machine for making rice balls for nigiris.

The company's sales channels include two delivery applications and WhatsApp, integrated through the Totvs system, whereby the customer places an order via WhatsApp and the cashier inputs the order into Totvs. The restaurant delivers both within Petrolina-PE and Juazeiro-BA, thus handling a high volume of weekly orders. The average weekly order volume for each sales channel is presented in Box 1.

BOX 1

Weekly Order Volume

Applications	Number of Orders
App 1	1100
App 2	200
Totvs	250
Total	1550

Source: Elaborated by the authors.

To determine the restaurant's average weekly orders, the weekly number of orders for each sales channel was recorded from April 2020 to October 2021, after which an average per application was calculated.

Both delivery applications serve both cities; however, the Totvs system operates only in Petrolina-PE, covering 165 neighborhoods. Application 1 delivers to 226 neighborhoods across both cities, while Application 2 delivers to only 77 neighborhoods across the two cities—hence the significantly lower order volume for the latter. Additionally, Application 1 consistently provides sales incentives to the restaurant through discount coupons and free delivery options for customers, which considerably boosts sales on this platform.

The restaurant's menu consists of five promotional combos—hereafter referred to as A, B, C, D, and E—and two special combos—referred to as X and Y. In addition, the menu includes four types of appetizers (beef pastel with cream cheese, cheese pastel, spring rolls, and cheese rolls) and Chinese cuisine dishes (yakisoba, chop suey rice, and kung pao chicken). The menu also features 14 types of beverages.

Each promotional combo consists of 40 sushi pieces and is priced at R$ 42. The special combos contain 30 sushi pieces each and are priced at R$ 74. The mayn difference between promotional and special combos is the amount of salmon used in the pieces. Due to its higher cost, the special combos contain pieces with a greater quantity of salmon. The composition of the promotional combos is shown in Box 2.

BOX 2

Composition of the Promotional Combos

Combo	Combo Items	Total
A	15 Hot Rolls, 15 Hot Philadelphia, and 10 Special Hot Rolls	40
B	10 Dragons, 5 Kani Uramakis, 5 Salmon Nigiris, 10 Hot Rolls, 10 Hot Philadelphia	40
C	5 Salmon Nigiris, 5 Breaded Kani Nigiris, 10 Salmon Pâté Makimonos, 10 Kani Uramakis, and 10 Salmon Skin Uramakis	40
D	5 Salmon Nigiris, 5 Breaded Kani Nigiris, 10 Hot Philadelphia, 10 Kani Uramakis, and 10 Salmon Skin Uramakis	40
E	10 Kani Uramakis, 10 Hot Rolls, 10 Hot Philadelphia, and 10 Breaded Kani Nigiris	40

Source: Elaborated by the authors.

The composition of the special combos is presented in Box 3.

BOX 3

Composition of the Special Combos

Special Combos	Items	Total
X	5 Salmon Sashimis, 5 Salmon Nigiris, 10 Salmon Uramakis, and 10 Salmon Makimonos	30
Y	5 Salmon Sashimis, 5 Salmon Nigiris, 5 Salmon Uramakis, 5 Salmon Makimonos, and 10 Hot Philadelphia	30

Source: Elaborated by the authors.

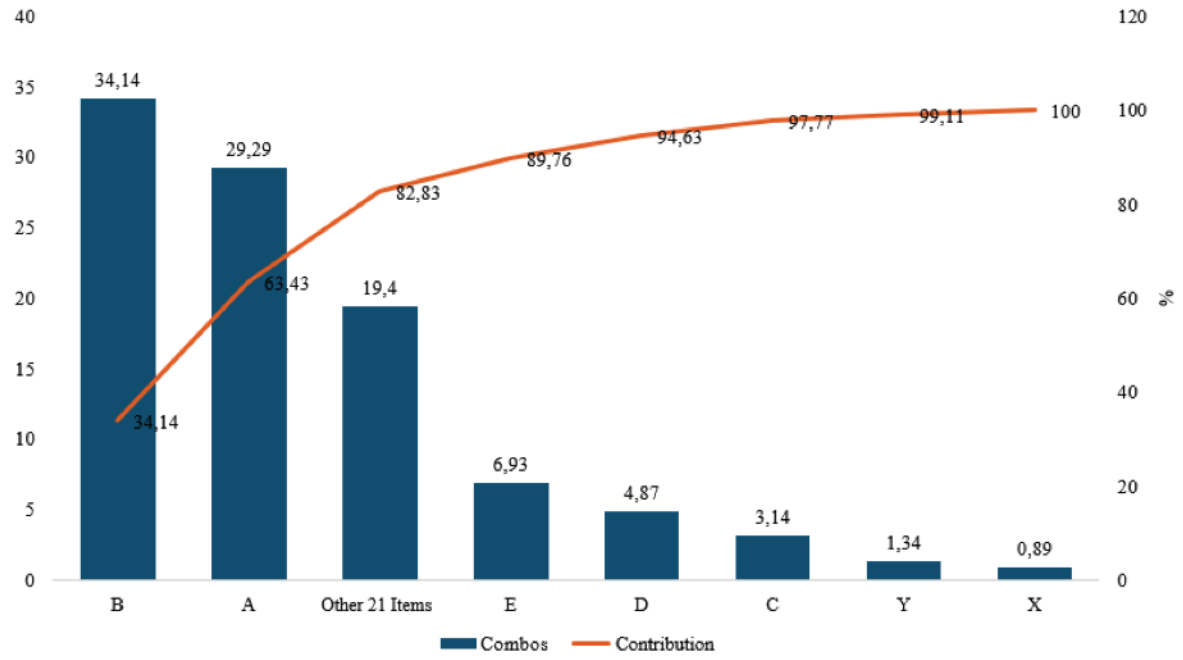
As observed in Boxes 2 and 3, the promotional combos are mostly composed of pieces in which the predominant proteins are salmon pâté, salmon fat, and salmon skin, as well as kani, which reduces the cost of these pieces and makes the combo more affordable. In contrast, the special combos feature salmon fillet as the sole predominant protein in their pieces, making them more expensive. The Hot Philadelphia included in Combo Y is made with salmon fillet, unlike the Hot Philadelphia in the promotional combos, which is made with salmon fat.

Definition of Product Demand Forecast

It is important to highlight that the company Uniter analysis does not possess historical sales data for each menu item; rather, it has data regarding the relationship between weekly revenue and the sales proportion of each item relative to that revenue—information provided through the company's sales channels. A preliminary analysis of these relationships reveals the prominence of the combos compared to other menu items, as shown in Figure 3.

FIGURE 3

Sales Contribution of Menu Items



Source: Elaborated by the authors.

Thus, of the 28 items available on the menu, the seven combos (A, B, C, D, E, X, and Y) account for 80.60% of sales, meaning that 25% of the items correspond to 81% of total revenue. Furthermore, Combos A and B alone represent 63.43% of the restaurant's revenue.

This highlights the significance of the seven combos on the menu for the company and the need for enhanced management of these products. Demand forecasting plays a crucial role in this management, as it provides a clearer Uniterstanding of the quantity sold for each item, enabling more precise control over production volumes. Accordingly, it was necessary to develop a method for forecasting the demand for these items based on projected weekly sales.

Knowing that the selling price of each promotional combo is R$ 42 and each special combo is R$ 74, and based on the forecasted weekly sales and the percentage contribution of each product, the demand for each item could be estimated. The relationship between weekly sales forecasts and the demand forecast for each item can be expressed by Equation (11), Elaborated by the authors:

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$$\text{Demand Forecast for Each Item} = \frac{Percentage\ x\ PV}{P} \quad (11)$$

In the equation, the percentage refers to the sales contribution of the item to the weekly revenue; PV denotes the forecasted sales for a given week; and P represents the price of the combo. Thus, the demand forecast for each item is calculated on a weekly basis. This relationship will be applied later, once the restaurant's weekly sales forecast has been determined.

Analysis of Demand Behavior

Before initiating the demand forecasting process, it was essential to Uniterstand the behavior of demand in previous periods to determine whether the proposed method was suitable for the data analyzed. In this sense, this approach provided a way to detect the presence or absence of components such as trend and seasonality within the data.

This investigation was only meaningful after presenting the collected data—serving, therefore, as the starting point—with the daily revenue time series of the restaurant from April 2020 to October 2021, considering that the restaurant operates from Tuesday to SUnitay. Observing the data provided insights into the consumption habits of the restaurant's customers. There is daily variation in demand, with peaks occurring throughoct the series. This variation initially indicated seasonality related to the days of the week: sales are lower at the beginning of the week, from Tuesday to Thursday, and increase considerably on weekends, from Friday to SUnitay. However, a more detailed analysis was necessary to confirm this seasonality.

The sales peak observed in June of both 2020 and 2021 is due to Valentine's Day in Brazil (June 12), the day of the year with the highest sales for the restaurant. A decrease in sales was also noted, particularly from July 2021 onward, which may indicate the presence of a trend in the analyzed data. In addition to analyzing the daily data from the time series, it was also important to examine the data on a weekly basis. Accordingly, the daily data were consolidated so that demand behavior could be observed over the course of the weeks. To generate a data sample that provided meaningful insights for the analyses, it was necessary to establish a criterion defining how the weeks of the month would be consolidated. Box 4 specifies the groupings performed.

BOX 4

Criterion for consolidating daily data into weeks of the month

Week	Days
1	01-06
2	08-13
3	15-20
4	22-27
5	Remayning

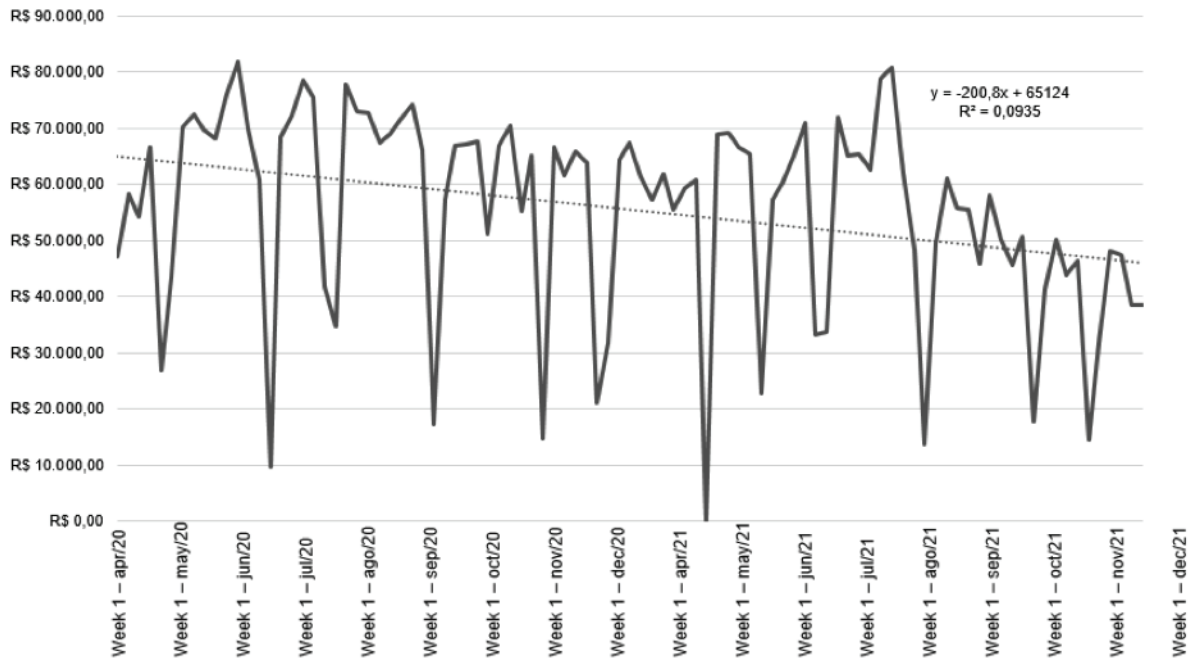
Source: Elaborated by the authors.

This criterion was applied to all months in which the first day falls on a Tuesday. Since the restaurant does not operate on Mondays, a typical week spans from Tuesday to SUnitay; however, this rule may vary depending on the day of the week on which the month begins. If the month starts on a Monday, the week is counted from Tuesday to SUnitay, resulting in a week of fewer than six days.

Thus, the first four weeks of each month were generally composed of the same sep of days, providing an analytical advantage in observing weekly demand patterns. Since months do not have the same number of days, a fifth week was created to account for these differences and to allow the other weeks to average six days each. With these considerations, the weekly demand curve was generated, as illustrated in Figure 4.

FIGURE 4

Weekly Sales History from April 2020 to October 2021



Source: Elaborated by the authors.

Similarly to the observations made regarding daily demand behavior, analyzing the data on a weekly basis also suggested the potential presence of seasonality, now at the weekly level. To support whether the conclusions drawn from the graphical analysis were consistent, numerical data were collected regarding the contribution of each day of the week and each week of the month to the restaurant's total revenue, considering the entire available historical series, as shown in Table 2.

TABLE 2

Demand Contribution by Day of the Week and Week of the Month

Day	Week					TOTAL
	1	2	3	4	5	
Tuesday	0,78%	2,43%	2,61%	2,27%	2,26%	10,35%*
Wednesday	1,51%	2,67%	2,55%	2,68%	2,31%	11,72%
Thursday	2,31%	3,01%	2,64%	2,36%	1,70%	12,02%
Friday	3,78%	4,81%	4,67%	4,68%	2,45%	20,39%
Saturday	4,99%	5,41%	5,23%	5,22%	2,42%	23,27%**
Sunday	5,22%	5,14%	5,05%	4,99%	1,86%	22,26%
TOTAL	18,59%	23,47%**	22,75%	22,20%	13%*	100%

Note: *lowest values; **highest values.

Source: Elaborated by the authors.

Thus, it was observed that the day with the highest sales contribution during the week is Saturday, followed by SUnitay and Friday. Tuesday had the lowest sales contribution. This pattern is characteristic of this type of business.

Regarding the weeks of the month, the second week was the top performer in sales, while the fifth week had the lowest sales, which was predictable, as this week only included a few days. The higher sales in the second week can be explained by consumers having more disposable income at the beginning of the month, in addition to most credit card bills already being septled, making consumers more willing to spend. The lower sales contribution in the first week can be attributed to it not consistently containing six full days in all months. Therefore, the presence of seasonality in the analyzed data series was confirmed.

Moreover, the negative slope of the trend line and the significant R^2 value confirmed a negative demand trend. This decline in sales can be explained by the restaurant mayntaining the same product lineup since the beginning of the pandemic, withoct introducing new items, offering little flexibility, and no customization options for the products. Thus, it became evident that the analyzed data exhibited both trend and seasonal characteristics, justifying the choice of the Holt-Winters method for this study.

Sales Forecast

The Holt-Winters method was applied to the weekly revenue data from April 2020 to October 2021, totaling 95 observations. The forecast horizon was sep to 60 weeks, equivalent to one year, generating forecasts for all weeks from November 2021 to October 2022. This forecast period was selected because the restaurant planned to continue operating solely in delivery mode during this time; after this period, the plan was to resume in-person service, which could potentially alter delivery demand

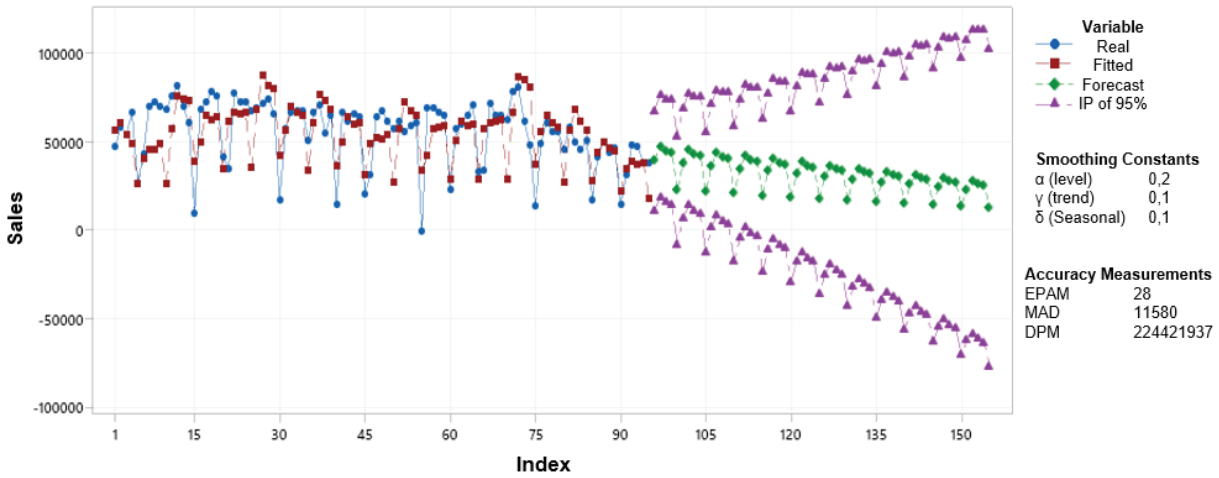
patterns, necessitating further analysis. Both the multiplicative and additive Holt-Winters methods were applied.

Multiplicative Holt-Winters

Using a seasonal length of 5 weeks and smoothing constants $\alpha = 0.2$, $\gamma = 0.1$, and $\delta = 0.1$, the exponential smoothing graph shown in Figure 5 was obtained. These smoothing constants were determined through multiple trial combinations until the lowest MAPE and MAD values were achieved.

FIGURE 5

Exponential Smoothing Using the Multiplicative Holt-Winters Method



Source: Elaborated by the authors.

As observed, the fit and forecast measures obtained with the method were close to the actual demand values. Regarding the error measures obtained, these are presented in Table 3.

TABLE 3

Error Measures for the Multiplicative Holt-Winters Method

Accuracy Measures	
MAPE	28%
MAD	R$ 11.580

Source: Elaborated by the authors.

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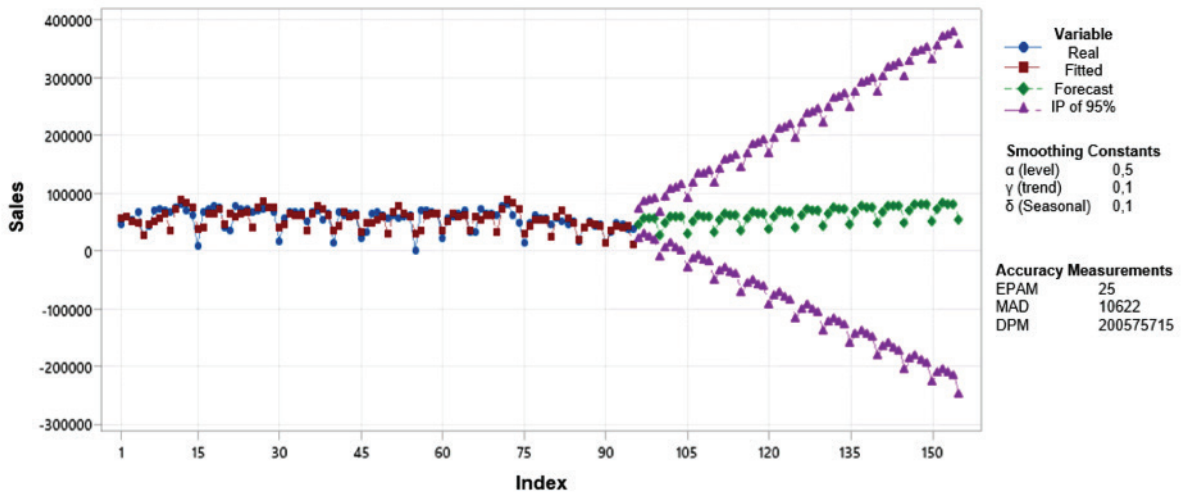
Thus, the mean absolute error totaled R$ 11,580, corresponding to a mean absolute percentage error of 28%. Subsequently, the additive model was implemented, and the results are presented below.

Additive Holt-Winters

Using the same seasonal length of 5 weeks and smoothing constants $\alpha = 0.5$, $\gamma = 0.1$, and $\delta = 0.1$, the exponential smoothing graph shown in Figure 6 was obtained. As before, these smoothing constants were determined in the software through multiple trial combinations until the lowest MAPE and MAD values were achieved.

FIGURE 6

Exponential Smoothing Using the Additive Holt-Winters Method



Source: Elaborated by the authors.

A closer alignment of the fit and forecasts with actual demand (degree of accuracy) can be observed compared to the multiplicative method; however, this analysis can only be confirmed through a comparison of the error measures. Thus, the MAPE and MAD error measures for the additive model are presented in Table 4.

TABLE 4

Error Measures for the Additive Holt-Winters Method

Accuracy Measures	
MAPE	25%
MAD	R$ 10,622

Source: Elaborated by the authors.

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Thus, the mean absolute error totaled R$ 10,622, corresponding to a mean absolute percentage error of 25%. When comparing the error measures of the multiplicative and additive methods, it was observed that the measures are quite similar; however, the additive method exhibited slightly lower error values. This indicates that the amplitude of seasonal variation remayns relatively constant throughoct the series, favoring the forecasts generated by the additive model. Therefore, the method selected to establish the demand forecasts for the company Uniter study was the additive method, and the weekly forecasts obtained using this method are presented in Table 5.

TABLE 5

Sales Forecasts

Forecast								
Period		FORECAST	Period		FORECAST	Period		FORECAST
nov/21	1 WEEK	R$ 47.351,00	mar/22	1 WEEK	R$ 56.850,70	jul/22	1 WEEK	R$ 66.350,40
	2 WEEK	R$ 58.053,30		2 WEEK	R$ 67.553,00		2 WEEK	R$ 77.052,70
	3 WEEK	R$ 55.778,30		3 WEEK	R$ 65.278,00		3 WEEK	R$ 74.777,70
	4 WEEK	R$ 55.722,10		4 WEEK	R$ 65.221,80		4 WEEK	R$ 74.721,50
	5 WEEK	R$ 28.475,70		5 WEEK	R$ 37.975,40		5 WEEK	R$ 47.475,10
dec/21	1 WEEK	R$ 49.725,90	apr/22	1 WEEK	R$ 59.225,60	ago/22	1 WEEK	R$ 68.725,30
	2 WEEK	R$ 60.428,20		2 WEEK	R$ 69.927,90		2 WEEK	R$ 79.427,60
	3 WEEK	R$ 58.153,20		3 WEEK	R$ 67.652,90		3 WEEK	R$ 77.152,60
	4 WEEK	R$ 58.097,10		4 WEEK	R$ 67.596,80		4 WEEK	R$ 77.096,50
	5 WEEK	R$ 30.850,60		5 WEEK	R$ 40.350,40		5 WEEK	R$ 49.850,10
jan/22	1 WEEK	R$ 52.100,90	may/22	1 WEEK	R$ 61.600,60	sep/22	1 WEEK	R$ 71.100,30
	2 WEEK	R$ 62.803,10		2 WEEK	R$ 72.302,80		2 WEEK	R$ 81.802,50
	3 WEEK	R$ 60.528,20		3 WEEK	R$ 70.027,90		3 WEEK	R$ 79.527,60
	4 WEEK	R$ 60.472,00		4 WEEK	R$ 69.971,70		4 WEEK	R$ 79.471,40
	5 WEEK	R$ 33.225,60		5 WEEK	R$ 42.725,30		5 WEEK	R$ 52.225,00
feb/22	1 WEEK	R$ 54.475,80	jun/22	1 WEEK	R$ 63.975,50	oct/22	1 WEEK	R$ 73.475,20
	2 WEEK	R$ 65.178,10		2 WEEK	R$ 74.677,80		2 WEEK	R$ 84.177,50
	3 WEEK	R$ 62.903,10		3 WEEK	R$ 72.402,80		3 WEEK	R$ 81.902,50
	4 WEEK	R$ 62.846,90		4 WEEK	R$ 72.346,60		4 WEEK	R$ 81.846,30
	5 WEEK	R$ 35.600,50		5 WEEK	R$ 45.100,20		5 WEEK	R$ 54.599,90

Source: Elaborated by the authors.

It is important to highlight that the software allowed forecasts to be generated for periods longer than 60 weeks, which is relevant in case the restaurant changes its strategy regarding delivery-only operations. To assess how closely the forecasts presented in Table 5 matched the restaurant's actual sales, weekly revenue data from November 2021 to February 2022—the last month with available revenue data—were collected. This comparison is presented in Table 6.

TABLE 6

Comparison of Forecasted and Actual Demand

Moth	Week	Forecast	Actual Demand
nov/21	1	R$ 47.351,00	R$ 47.511,50
	2	R$ 58.053,30	R$ 48.083,70
	3	R$ 55.778,30	R$ 53.122,40
	4	R$ 55.722,10	R$ 47.237,10
	5	R$ 28.475,70	R$ 5.045,60
dec/21	1	R$ 49.725,90	R$ 39.901,80
	2	R$ 60.428,20	R$ 55.151,20
	3	R$ 58.153,20	R$ 49.423,06
	4	R$ 58.097,10	R$ 48.017,20
	5	R$ 30.850,60	R$ 26.491,20
jan/22	1	R$ 52.100,90	R$ 13.822,78
	2	R$ 62.803,10	R$ 55.991,78
	3	R$ 60.528,20	R$ 50.771,40
	4	R$ 60.472,00	R$ 56.883,60
	5	R$ 33.225,60	R$ 43.204,44
feb/22	1	R$ 54.475,80	R$ 48.286,00
	2	R$ 65.178,10	R$ 57.279,60
	3	R$ 62.903,10	R$ 56.451,20
	4	R$ 62.846,90	R$ 54.614,39
	5	R$ 35.600,50	R$ 0,00

Source: Elaborated by the authors.

A close alignment between the actual demand data and the forecast was observed, with a maximum difference of approximately R$ 10,000. The significant discrepancy in the fifth week of November is explained by the fact that this week contained only one day (November 30), as well as in the first week of January, when the restaurant was closed on January 1 due to New Year's Day, a public holiday in Brazil.

The last week of February had zero actual demand because it included only one day (February 28) and fell on a Monday. This comparison also showed that, in general, the forecasts tend to overestimate demand, which is advantageous for the company as it helps prevent stockocts and, consequently, lost sales. However, it is important to carefully analyze production quantities to avoid excessive waste, taking this overestimation into account.

Although the preliminary data analysis already indicated the Holt-Winters method as suitable for demand forecasting due to the presence of trend and seasonality, it was important to validate this by comparing it with other forecasting methods. Accordingly, in addition to the previously demonstrated Holt-Winters methods, the software applied the moving average method, simple exponential smoothing, and double exponential smoothing—commonly used in demand forecasting. Forecasts for the next 60 weeks were generated using all methods.

For the moving average analysis, a window length of five was applied, meaning that the program used five consecutive weeks to calculate the moving average. For simple exponential smoothing, $\alpha = 0.07$ was used, while for double exponential smoothing, $\alpha = 0.1$ and $\beta = 0.1$ were applied. The α constant in the simple exponential smoothing method was determined using the ARIMA (AutoRegressive Integrated Moving Average) model, which identified $\alpha = 0.07$ as optimal, yielding the lowest MAPE and MAD values. For double exponential smoothing, the constants were obtained through iterative trials until the lowest MAPE and MAD values were foUnit. Unlike simple exponential smoothing, where ARIMA defined the optimal constant, in double exponential smoothing the ARIMA-derived constants did not result in the lowest error measures.

Thus, the comparison of the lowest error measures obtained with each method is presented in Table 7.

TABLE 7

Error Measures for Each Method

Method	MAPE	MAD
Moving Average	43%	13822
Simple Exponential Smoothing	40%	12763
Double Exponential Smoothing	41%	13486
Multiplicative Holt-Winters	28%	11580
Additive Holt-Winters	25%	10622

Source: Elaborated by the authors.

Therefore, the triple exponential smoothing method, or Holt-Winters method—both additive and multiplicative—yielded the lowest error measures compared to the other methods, particularly the additive model, highlighting its suitability for the analyzed data.

Product Demand Forecast

After performing the weekly sales forecasts and using Equation (11) defined earlier, it was possible to obtain demand forecasts for each combo individually. As previously described, the restaurant's menu divides combos into promotional and special categories. The promotional combos are priced at R$ 42, while the special combos are priced at R$ 74. Additionally, each combo has a specific sales contribution, as shown in Tables 8 and 9.

TABLE 8

Price and Sales Contribution of Promotional Combos

Promotional Combos	Sales Contribution (%)	Value (R$)
A	29,29%	42,00
B	34,14%	42,00
C	3,14%	42,00
D	4,87%	42,00
E	6,93%	42,00

Source: Elaborated by the authors.

TABLE 9

Value and Sales Contribution of Special Combos

Special Combos	Sales Contribution (%)	Value (R$)
X	0,89%	74,00
Y	1,34%	74,00

Source: Elaborated by the authors.

Thus, the demand forecast was applied to Combo A. Based on this combo's sales contribution to weekly revenue (29.29%), its price (R$ 42), and using the sales forecasts presented in Table 9, the demand forecasts for Combo A were obtained for the five weeks of each month over the next 12 months, totaling 60 weeks, as shown in Table 10.

TABLE 10

Demand Forecast for Combo A

COMBO A					
Period	Demand Forecast	Period	Demand Forecast	Period	Demand Forecast
	330		396		463
	405		471		537
nov/21	389	mar/22	455	jul/22	521
	389		455		521
	199		265		331
	347		413		479
	421		488		554
dec/21	406	apr/22	472	ago/22	538
	405		471		538
	215		281		348
	363		430		496
	438		504		570
jan/22	422	may/22	488	sep/22	555
	422		488		554
	232		298		364
	380		446		512
	455		521		587
feb/22	439	jun/22	505	oct/22	571
	438		505		571
	248		315		381

Source: Elaborated by the authors.

As observed in Table 10, the demand forecast for Combo A indicates an average of 420 units in the first week of each month, 496 units in the second week, 480 units in the third week, 480 units in the fourth week, and 290 units in the last week of each month. As expected, the second week — the week with the highest sales — shows the highest forecasted quantity, while the last week — the week with the lowest sales — shows the lowest forecasted quantity. The same procedure was applied to the other promotional combos, and the resulting forecasts are presented in Table 11.

TABLE 11

Demand Forecast for Promotional Combos

	B	C	D	E
Period	Demand Forecast	Demand Forecast	Demand Forecast	Demand Forecast
	385	35	55	78
	472	43	67	96
nov/21	453	42	65	92
	453	42	65	92
	231	21	33	47
	404	37	58	82
	491	45	70	100
dec/21	473	43	67	96
	472	43	67	96
	251	23	36	51
	424	39	60	86
	510	47	73	104
jan/22	492	45	70	100
	492	45	70	100
	270	25	39	55
	443	41	63	90
	530	49	76	108
feb/22	511	47	73	104
	511	47	73	104
	289	27	41	59
	462	43	66	94
	549	51	78	111
mar/22	531	49	76	108
	530	49	76	108
	309	28	44	63
	481	44	69	98
	568	52	81	115
apr/22	550	51	78	112
	549	51	78	112
	328	30	47	67
	501	46	71	102
	588	54	84	119
	569	52	81	116
	569	52	81	115
	347	32	50	70

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	B	C	D	E
Period	Demand Forecast	Demand Forecast	Demand Forecast	Demand Forecast
	520	48	74	106
	607	56	87	123
jun/22	589	54	84	119
	588	54	84	119
	367	34	52	74
	539	50	77	109
	626	58	89	127
jul/22	608	56	87	123
	607	56	87	123
	386	35	55	78
	559	51	80	113
	646	59	92	131
ago/22	627	58	89	127
	627	58	89	127
	405	37	58	82
	578	53	82	117
	665	61	95	135
sep/22	646	59	92	131
	646	59	92	131
	425	39	61	86
	597	55	85	121
	684	63	98	139
oct/22	666	61	95	135
	665	61	95	135
	444	41	63	90

Source: Elaborated by the authors.

As done previously, the average forecasts for each week and for each of Combos B, C, D, and E can be seen in Table 12.

TABLE 12

Average Forecasts for Promotional Combos

FORECAST	COMBOS			
	B (UNIT)	C (UNIT)	D (UNIT)	E (UNIT)
1 WEEK	491	45	70	100
2 WEEK	578	53	82	117
3 WEEK	560	51	80	114
4 WEEK	559	51	80	113
5 WEEK	338	31	48	69

Source: Elaborated by the authors.

As observed with Combo A, the average forecasts for the other promotional combos are highest in the second week and lowest in the last week of each month. Furthermore, when comparing the forecasts of all promotional combos, it is evident that Combo B has the highest forecasted demand, followed by Combos A, E, D, and lastly, Combo C—consistent with the sales contribution of these products.

The same procedure was applied to the two special combos; however, the selling price used was R$ 74. A portion of the forecasts for products X and Y is presented in Table 13, while the remayning forecasts are included in Appendix A.

TABLE 13

Demand Forecast for Special Combos

	X	Y
Period	Demand Forecast (Unit)	Demand Forecast (Unit)
nov/21	6	9
	7	11
	7	10
	7	10
	3	5
dec/21	6	9
	7	11
	7	11
	7	11
	4	6

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	X	Y
Period	Demand Forecast (Unit)	Demand Forecast (Unit)
jan/22	6	9
	8	11
	7	11
	7	11
	4	6
feb/22	7	10
	8	12
	8	11
	8	11
	4	6
mar/22	7	10
	8	12
	8	12
	8	12
	5	7
apr/22	7	11
	8	13
	8	12
	8	12
	5	7

Source: Elaborated by the authors.

As done with the promotional combos, the weekly average forecasts for the special combos are presented in Table 14.

TABLE 14

Average Forecasts for Special Combos

Forecast	Combos	
	X (UNIT)	Y (UNIT)
1 WEEK	7	11
2 WEEK	9	13
3 WEEK	8	12
4 WEEK	8	12
5 WEEK	5	8

Source: Elaborated by the authors.

Analyzing Table 14, the same pattern observed for the promotional combos is evident: the average forecasts are highest in the second week of the month and lowest in the fifth week. Furthermore, Combo Y exhibits higher forecasted values than Combo X, which is also explained by the sales contribution of these items. Despite the overall relevance of all combos compared to other menu items, Combos A and B stand oct, as reflected in their sales contributions. Therefore, the restaurant should prioritize these products, improving production and inventory management to ensure that they are neither unavailable nor compromised in quality.

Based on the weekly demand forecasts for each combo and taking into account the observed demand patterns across the days of the week—lower sales on Tuesdays, followed by Wednesdays and Thursdays, and higher sales on weekends, particularly Saturdays—the company can establish daily demand forecasts, thereby determining how much of each product should be produced on a daily basis.

FINAL CONSIDERATIONS

The present study sought to apply a demand forecasting method that best suited the sales profile and products of the aforementioned company. Following a preliminary analysis of the data, the Holt-Winters method was foUnit to be appropriate for the time series Uniter investigation, a finding that was confirmed through comparison with other demand forecasting methods. Furthermore, when comparing the additive and multiplicative approaches, the additive Holt-Winters model demonstrated superior performance, exhibiting a better fit to the time series.

Some limitations were encountered in forecasting the demand for each combo due to the restaurant's lack of historical sales data for individual items. However, based on the weekly sales forecasts obtained through the Winters method, combined with information regarding the sales share of each combo and their respective prices, it was possible to estimate the weekly demand forecasts for each item using Equation (11), as developed in this study.

In this regard, it can be concluded that the objective of the study was achieved, and the research problem—namely, whether the Holt-Winters method is suitable for analyzing the demand forecasting of the company Uniter study—was successfully addressed, as highly accurate forecasts were obtained. The most significant contributions of this research include: (i) the development of an equation to estimate the demand forecast for each product, establishing a relationship between the forecasted weekly revenue and the forecasted demand for each combo; (ii) the analysis of demand behavior, an essential step in determining the suitability of the Holt-Winters method for the data analyzed; and (iii) the confirmation of the presence of trend and seasonality in the historical time series.

As suggestions for future research within the company, it is recommended that a more in-depth analysis of product profit margins be conducted, since high sales volumes do not necessarily correspond to high profitability. Such analysis would enable the company to prioritize products that yield greater financial returns. Another recommendation is the continuous monitoring of these forecasts, particularly as the restaurant intends to resume its all-you-can-eat service format, which may alter delivery demand patterns. Additionally, a specific demand forecasting analysis for the all-you-can-eat service is suggested.

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DATA AVAILABILITY

All datasets supporting the results of this study are included within the article.

APPENDIX A

Demand Forecast for Special Combos

	X	Y
Period	Demand Forecast (Unit)	Demand Forecast (Unit)
nov/21	6	9
	7	11
	7	10
	7	10
	3	5
dec/21	6	9
	7	11
	7	11
	7	11
	4	6
jan/22	6	9
	8	11
	7	11
	7	11
	4	6
feb/22	7	10
	8	12
	8	11
	8	11
	4	6
mar/22	7	10
	8	12
	8	12
	8	12
	5	7
apr/22	7	11
	8	13
	8	12
	8	12
	5	7
may/22	7	11
	9	13
	8	13
	8	13
	5	8

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	X	Y
Period	Demand Forecast (Unit)	Demand Forecast (Unit)
jun/22	8	12
	9	14
	9	13
	9	13
	5	8
jul/22	8	12
	9	14
	9	14
	9	14
	6	9
ago/22	8	12
	10	14
	9	14
	9	14
	6	9
sep/22	9	13
	10	15
	10	14
	10	14
	6	9
oct/22	9	13
	10	15
	10	15
	10	15
	7	10

Source: Elaborated by the authors.