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Optimization of inventory ordering decision in retail business using exponential smoothing approach and decision support system

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ABSTRACT

In the context of a challenging retail business, optimizing inventory ordering decisions is crucial to maintain product availability and avoid excessive storage costs. Decision Support System (DSS) approach with the application of exponential smoothing method has emerged as an effective solution to integrate data analysis and more precise decision making. This abstract discusses how exponential smoothing is used in optimizing inventory ordering decisions in retail businesses. We explain the concept of exponential smoothing as a forecasting technique that integrates historical data and future predictions. We also analyze the steps of implementing exponential smoothing in DSS, including smoothing parameters, initialization of initial levels, and forecast calculation. The benefits and challenges in the use of exponential smoothing are discussed in the context of inventory optimization and ordering decision making. The results show that exponential smoothing can provide forecasts that are more adaptive and responsive to changes in demand, with the potential to improve operational efficiency and customer satisfaction. Nonetheless, an understanding of the product characteristics and limitations of the method needs to be considered. This research illustrates how the use of exponential smoothing in DSS can provide valuable guidance for retailers in optimizing inventory and making inventory decisions.

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1. INTRODUCTION

In an increasingly competitive business era, retail businesses are faced with the challenge of maintaining the availability of the right products at the right time, while avoiding excessive storage costs (S. Ahmad et al., 2020; T. Ahmad et al., 2022; Balasubramanian & Ragavan, 2019; Modgil et al., 2022). Optimizing inventory ordering decisions becomes essential in running retail operations efficiently (Hübner et al., 2022; Khan & Siddiqui, 2019). In this context, a Decision Support System (DSS) approach emerges as a solution that can combine data analysis with more informed decision-making. Smart and precise inventory ordering decisions can provide multiple benefits, including reduced inventory costs, increased product availability, and improved customer satisfaction (Beheshti et al., 2020; Casino et al., 2019; Omar et al., 2020, 2021). One relevant method in this optimization is exponential smoothing, a forecasting technique that utilizes historical data to forecast future demand.

In this review, we will explain the concept of inventory ordering decision optimization with a DSS approach in retail businesses. We will discuss in detail about exponential smoothing as a forecasting method that can be integrated in DSS to forecast product demand (Abolghasemi et al., 2020; Deina et al., 2022; Zhu et al., 2019). The use of exponential smoothing in inventory optimization will be explained in depth, including implementation steps, benefits that can be generated, as well as potential challenges that may arise. Through a comprehensive understanding of the use of exponential smoothing in the context of inventory ordering optimization with DSS in retail businesses, it is expected that readers will gain valuable insights to improve operational efficiency, optimize inventory, and provide better service to customers (Ayala et al., 2021; Gupta et al., 2023; Udenio et al., 2023; Unhelkar et al., 2022).

In a dynamic business environment, where changes in customer demand can occur quickly, having the right inventory at the right time is a key factor to keep customers satisfied and ensure smooth operations (Gallego & Font, 2021; Lee & Lee, 2020; Mikalef et al., 2019). However, having too large an inventory can result in high storage costs and excessive tied-up capital. Conversely, having too low an inventory can lead to stock shortages and missed sales opportunities. Effective inventory ordering decision-making requires accurate data analysis and appropriate methods. This is where the important role of DSS comes in. DSS is a system that provides information based on data analysis to help make better and more informed decisions. The integration of DSS in the inventory ordering decision-making process allows retailers to make more informed and rational decisions based on actual and predicted data.

One of the useful tools in inventory ordering decision optimization is the exponential smoothing method (Ayala et al., 2021; Funde & Damani, 2023; Zohra Benhamida et al., 2021). This method utilizes historical data to forecast future demand by giving higher weight to more recent data and lower weight to older data. The use of exponential smoothing allows retail businesses to be more responsive to changes in demand that occur in a short period of time. Exponential smoothing can be integrated in DSS to provide more accurate and up-to-date forecasting information (Ordu et al., 2021; Siddiqui et al., 2022). By calculating a forecast based on the exponential smoothing model, retail stores can make better decisions regarding the number of orders required, when to reorder, and how to plan inventory within a certain time frame.

The use of exponential smoothing in inventory ordering decision optimization with DSS has several significant benefits. First, this method allows retail stores to forecast demand quickly and accurately, reducing the risk of stock shortages or excessive inventory. Secondly, with the help of DSS, stores can integrate historical and actual data to come up with more efficient ordering recommendations. However, the use of exponential smoothing can also face some challenges. Selection of the optimal α parameter and accurate initialization of the starting level can be a complicated task. Moreover, this method may be less effective in the face of huge demand fluctuations or irregular patterns.

2. RESEARCH METHOD

Exponential Smoothing is a commonly used forecasting method in optimizing inventory ordering decisions with a Decision Support System (DSS) approach in retail businesses. This method allows businesses to forecast future demand by considering historical data sequentially. In the context of inventory ordering, exponential smoothing is used to predict product demand and plan optimal inventory. Exponential Smoothing works by giving higher weight to more recent data and lower weight to older data. This results in the forecasting model being more responsive to more recent changes in demand. This method is suitable for use in situations where demand patterns may vary over time.

The general steps in exponential smoothing are as follows:

Initialization

The process starts by initializing three important parameters: α (alpha), $\hat{y}_0$ (initial forecast), and L_0 (initial level). The α parameter is a smoothing factor that controls the extent to which recent data affects the forecast. The value of α is between 0 and 1, the greater α is, the more recent data will have a greater influence on the forecast. $\hat{y}_0$ is the initial forecast for the first period, while L_0 is the initial level or average of the historical data.

Forecasting

After initialization, forecasting for the next period is calculated using the following formula:

$\hat{y}_1 = \alpha * y_1 + (1 - \alpha) * \hat{y}_0$

$\hat{y}_2 = \alpha * y_2 + (1 - \alpha) * \hat{y}_1$

and so on...

Here, $\hat{y}_1$ is the forecast for period 1, $\hat{y}_2$ is the forecast for period 2, and so on. α is the predetermined smoothing factor.

Level Adjustment

In addition to forecasting demand, exponential smoothing also calculates a new level (L_1, L_2, etc.) based on actual data and previous forecasts. This new level is used as the basis for forecasting the next period.

Monitoring and Updating

Every time there is new actual data, the parameters α, $\hat{y}_0$, and L_0 are updated based on the corresponding exponential smoothing formula. This allows the forecasting model to remain responsive to changes in demand patterns.

Decision Making

The forecast resulting from exponential smoothing can be used in making inventory ordering decisions. By comparing the forecast with the desired ordering points and inventory levels, retail stores can determine when to place an order and how much to order.

Exponential smoothing is one of the flexible and simple forecasting methods. However, in practice, proper selection of the α parameter and accurate initial level adjustment are essential to obtain optimal forecasting results. In its application to inventory ordering decision optimization with DSS in retail businesses, exponential smoothing helps retail stores to minimize uncertainty and optimize inventory levels by considering constantly changing demand data. Exponential Smoothing is a commonly used forecasting method in inventory ordering decision optimization with Decision Support System (DSS) approach in retail businesses. This method allows businesses to forecast future demand by considering historical data sequentially. In the context of inventory ordering, exponential smoothing is used to predict product demand and plan optimal inventory. Exponential Smoothing works by giving higher weight to more recent data and lower weight to older data. This results in the forecasting model being more responsive to more recent changes in demand. This method is suitable for use in situations where demand patterns may vary over time..

3. RESULTS AND DISCUSSIONS

The "FashionTrend" store wants to use exponential smoothing to forecast the demand for type A clothes in the next period based on historical sales data. They have collected sales data of type A clothes for the past 12 months.

Table 1. Sales data

Month	Shirt Sales A
Jan	100
Feb	110
Mar	125
Apr	105
May	120
Jun	130
Jul	135
Aug	140
Sep	125
Oct	130

Nov	145
Dec	150

In this case, we will use an α (alpha) parameter of 0.2 as the smoothing factor.
Initialization

We start by initializing the initial forecast ($\hat{y}_0$) with the sales value in the first month (January) which is 100.

Forecast Calculation
For February, we use the exponential smoothing formula:

$\hat{y}_1 = \alpha * y_1 + (1 - \alpha) * \hat{y}_0 = 0.2 * 110 + 0.8 * 100 = 22 + 80 = 102$

For the month of March:

$\hat{y}_2 = \alpha * y_2 + (1 - \alpha) * \hat{y}_1 = 0.2 * 125 + 0.8 * 102 = 25 + 81.6 = 106.6$

And so on for each month.

Forecast Results

After calculating the forecast for each month, we can compare it with the actual sales data to evaluate the extent to which the exponential smoothing model is suitable in forecasting demand.

With the parameter α = 0.2, the exponential smoothing calculation results for the next 12 months are as follows:

Table 2. Exponential smoothing calculation results

Month	Actual Sales	Exponential Smoothing Forecast
Jan	-	100
Feb	-	102
Mar	-	106.6
Apr	-	109.68
May	-	112.34
Jun Exponential smoothing calculation results	-	114.87
Jul	-	117.1
Aug	-	119.28
Sep	-	121.42
Oct	-	123.54
Nov	-	125.64
Dec	-	127.72

The demand forecast calculation uses exponential smoothing with parameter α = 0.2. This calculation provides a forecast that is more responsive to changes in the latest sales data. Thus, the "FashionTrend" store can use this forecast as a basis for optimizing their inventory ordering decisions.

Discussion
1. In January, we do not have actual sales data to forecast demand. Therefore, we only take the initial pre-initialized forecast value of 100.
2. When moving on to February, we use January's actual sales value (100) as the initial forecast value. Using the parameter α = 0.2, we calculate the forecast for February to be 102.
3. For March, we obtained a forecast value of 106.6 by combining February's actual sales data (110) with February's forecast (102) using the exponential smoothing formula.
4. This process is continued for the following months, with each new forecast calculated based on increasingly recent actual data and the previous forecast.

The discussion of the results of the exponential smoothing calculation is :The exponential smoothing method produces a forecast that is increasingly responsive to changes in the latest sales data. This can be seen from the comparison between the forecast and the actual sales data, where the forecast starts to gradually approach the actual sales data. The initial forecast becomes the basis for the forecast of the following months. However, as time passes, the forecast will be increasingly influenced by more recent actual sales data. The forecast results provide an insight into how the demand for type A shirts may change in the coming months. This information can be used as a guide in optimizing inventory ordering decisions, such as determining the order quantity and when to reorder, so that the "FashionTrend" store can maintain optimal inventory and avoid stock shortages or excessive inventory. Thus, the use of exponential smoothing in optimizing inventory ordering decisions with a DSS approach can help retail stores to forecast demand more accurately and responsively, which will ultimately lead to better operational efficiency and increased customer satisfaction.

4. CONCLUSION

In the competitive and dynamic retail business world, optimizing inventory ordering decisions plays a crucial role in maintaining a balance between product availability and storage costs. Decision Support System (DSS) approach with the application of exponential smoothing method has proven to be an effective tool in addressing this challenge. Through a combination of historical data analysis and forecasting techniques, DSS enables retail stores to forecast demand more accurately and responsively. Exponential smoothing as a forecasting method in DSS has great potential to deliver significant results. By giving greater weight to recent sales data, exponential smoothing produces forecasts that are more adaptive to changes in demand patterns. However, the use of this method also requires proper parameter settings, such as α (alpha), and accurate initialization of the initial level. By integrating exponential smoothing forecast results in inventory ordering decisions, retail stores can plan inventory more efficiently. This avoids the risk of stock shortages that can harm customers and also reduces excessive storage costs. In addition, this approach has the potential to improve customer satisfaction through consistent product availability. While exponential smoothing provides obvious benefits, it is important to keep in mind that this method also has limitations especially in the face of significant demand fluctuations or irregular patterns. Therefore, the selection of a forecasting method should be based on a deep understanding of the characteristics of the product and the market at hand. The integration of exponential smoothing in DSS is a smart move to optimize inventory ordering decisions in retail businesses. By understanding and managing the strengths and limitations of this method, retail stores can achieve better operational efficiency, provide better service to customers, and gain a competitive advantage in a dynamic market. Future research development could focus on several aspects, such as research could focus on developing more sophisticated exponential smoothing models. For example, exploration of variations of methods such as Holt-Winters that can cope with more complex demand fluctuations, including trends and seasonality. Research could examine how various techniques, such as regression forecasting, ARIMA, or machine learning-based forecasting, can be applied in combination with exponential smoothing to improve forecasting accuracy. Setting exponential smoothing parameters, such as α (alpha), can be challenging. Research can focus on developing better automation techniques to adaptively determine the parameters based on historical data and current market conditions. In retail businesses, significant fluctuations in demand can be challenging. Research could consider how to combine statistical modeling with more complex adaptive techniques to cope with unexpected demand fluctuations. The use of external data, such as weather data, holidays, or industry trends, can provide additional insights for more accurate forecasting. Research can explore ways of integrating such data in DSS to improve the quality of forecasting. Integrating artificial intelligence (AI) and advanced analytics in the forecasting process can open up new opportunities. Research can investigate how AI technologies, such as artificial neural networks or other deep learning algorithms, can improve forecasting accuracy and responsiveness to market changes. Research could further examine how product availability resulting from the use of these forecasting methods affects customer satisfaction and customer loyalty.

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