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Original Article

Demand Forecasting for the Furniture Industry with Multivariate Time Series Models

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Abstract

Demand forecasting is important for businesses to prepare for potential adverse situations in the future. Time series models are a useful and reliable tool for demand forecasting. These models enable businesses to improve planning and decision-making by providing more accurate and consistent demand forecasts. This study aims to forecast the monthly door sales quantities of a business in the furniture industry using various multivariate time series methods. The variable set includes the U.S. dollar exchange rate, inflation, and interest rates. The models considered and compared are ARIMA-SARIMAX, Multiple Linear Regression, and Holt-Winters. Analyses are conducted using real-life sales data from the years 2005 to 2019. Data on the dollar exchange rate, inflation, and interest rates were obtained from the Central Bank of Türkiye. By incorporating these variables, the study aims to enhance the accuracy and reliability of the predictions, providing valuable insights for the industry. Results show that ARIMA-SARIMAX produces more accurate forecasts compared to Holt-Winters and Multiple Linear Regression. It is observed that time series models accounting for seasonality and trend factors provide better forecast results in the furniture industry. The findings highlight the importance of advanced forecasting methods in maintaining a competitive advantage. This approach not only supports strategic planning but also helps optimize inventory levels.

Keywords: Furniture Industry, Demand Forecasting, Holt-Winters, ARIMA-SARIMAX, Multiple Linear Regression

Mobilya Sektörü için Çok Değişkenli Zaman Serisi Modelleri ile Talep Tahmini

Özet

Talep tahmini, işletmelerin gelecekte ortaya çıkabilecek olumsuz durumlara hazırlıklı olmaları açısından önem taşımaktadır. Zaman serisi modelleri, talep tahmini için yararlı ve güvenilir bir araçtır. Bu modeller, daha doğru ve tutarlı talep tahminleri sunarak işletmelerin planlama ve karar alma süreçlerini iyileştirmelerine olanak sağlar. Bu çalışmanın amacı, mobilya sektöründe faaliyet gösteren bir işletmenin aylık kapı satış miktarlarını çeşitli çok değişkenli zaman serisi yöntemleri kullanarak tahmin etmektir. Değişken setinde Amerikan doları döviz kuru, enflasyon ve faiz oranları yer almaktadır. Çalışmada ele alınan ve karşılaştırılan modeller ARIMA-SARIMAX, Çoklu Doğrusal Regresyon ve Holt-Winters yöntemleridir. Analizler, 2005-2019 yılları arasındaki gerçek satış verileri kullanılarak gerçekleştirilmiştir. Dolar kuru, enflasyon ve faiz oranlarına ilişkin veriler Türkiye Cumhuriyet Merkez Bankası'ndan temin edilmiştir. Bu değişkenlerin modele dahil edilmesiyle, tahminlerin doğruluğunu ve güvenilirliğini artırmak ve sektöre değerli içgörüler sağlamak amaçlanmaktadır. Sonuçlar, ARIMA-SARIMAX modelinin Holt-Winters ve Çoklu Doğrusal Regresyon yöntemlerine kıyasla daha doğru tahminler ürettiğini göstermektedir. Zaman serisi modellerinin mevsimsellik ve trend faktörlerini dikkate almasının mobilya sektöründe daha başarılı tahmin sonuçları sağladığı gözlemlenmiştir. Bulgular, ileri düzey tahmin yöntemlerinin rekabet avantajının korunmasındaki önemini ortaya koymaktadır. Bu yaklaşım, yalnızca stratejik planlamayı desteklemekle kalmayıp, aynı zamanda stok seviyelerinin optimize edilmesine de katkı sağlamaktadır.

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Anahtar Kelimeler: Mobilya Sektörü, Talep Tahmini, Holt-Winters, ARIMA-SARIMAX, Çoklu Doğrusal Regresyon

1. INTRODUCTION

The furniture industry is a continuously evolving sector that plays a significant role in the global economy. This industry offers a variety of products that help consumers organize their living spaces and meet aesthetic needs. However, in this highly competitive environment, businesses need to implement effective strategies to succeed and grow. One of these strategies is making accurate demand forecasts.

Demand forecasting is a critically important process for determining future sales volumes. Accurate forecasts affect many operational decisions, such as production, inventory management, supply chain planning, and marketing strategies. Furthermore, with accurate demand forecasts, businesses can quickly adapt to increases or decreases in demand and gain a competitive advantage (Karahan, 2011).

Traditional methods often fall short in addressing data complexity in demand forecasting, leading to an inability to respond effectively to customer needs. These shortcomings result in problems such as unplanned production, high inventory costs, stock imbalances, and customer dissatisfaction. Disruptions in production reduce internal efficiency and weaken competitiveness. Additionally, poor forecasting negatively impacts marketing and sales effectiveness (Kaya, 2020).

This study aims to forecast demand in the furniture industry and evaluate the accuracy of different forecasting models. ARIMA, SARIMAX, Holt-Winters (HW), and Multiple Linear Regression (MLR) models are applied. Time series analysis is a powerful statistical method used to predict future trends, seasonality, and patterns based on past data (Akgül, 1994).

The main objective is to improve forecasting accuracy for a door-manufacturing furniture company in Alanya, enhancing production and sales efficiency. The goal is to accurately predict the company's future door sales using time series models such as ARIMA-SARIMAX, Holt-Winters, and MLR. The analytical capabilities of these models enable better management of inventory, production planning, and marketing strategies, which in turn enhances overall performance and competitiveness. This also contributes significantly to the company's long-term strategic goals.

This study contributes to the literature by being the first to focus on demand forecasting for door products in the furniture industry, applying ARIMA, SARIMAX, and multivariate regression models. Input variables include past door sales, inflation rate, exchange rate, and interest rate. These models allow for optimized inventory and production planning. With improved forecasts, companies in the sector can respond more effectively to customer demand, increase satisfaction, adapt quickly to market trends, and strengthen risk management by addressing uncertainties such as seasonal fluctuations and changing consumer behavior.

Model performance is evaluated using statistical metrics including Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R^2, achieving high accuracy. This supports enhanced operational efficiency and a more competitive and sustainable structure in the furniture industry. The findings may serve as a useful reference for manufacturers and support further academic research.

The remainder of this paper is structured as follows: Section 2 presents a literature review. Section 3 details the research methods. Section 4 explains the application process and presents the data. Section 5 discusses and analyzes the results. This structure ensures clarity and logical flow throughout the study.

2. LITERATURE REVIEW

Various studies on demand forecasting in companies from different sectors show that businesses actively utilize modern techniques to predict future customer demand. These studies share a common objective: to optimize production, inventory management, and sales strategies in order to increase customer satisfaction, strengthen market positioning, and ensure long-term sustainability. Literature reviews indicate that companies across diverse industries achieve successful outcomes by applying similar and effective forecasting techniques.

2.1 Demand Forecasting

Demand is defined as the measure of consumers' purchasing desires per unit of time at a specific price point (Tekin, 2009). Forecasting refers to determining future conditions using data from past periods (Türkay, 1995). Businesses conduct marketing research to understand market needs and adjust production planning accordingly, aiming to meet anticipated demand while achieving strategic goals.

2.2 Demand Forecasting Methods

Forecasting methods are categorized in different ways by various researchers. Shim (2009) places market research under quantitative methods, while Tanyaş and Baskak (2008) classify qualitative techniques under qualitative methods. An overview of forecasting methods is presented in Figure 1.

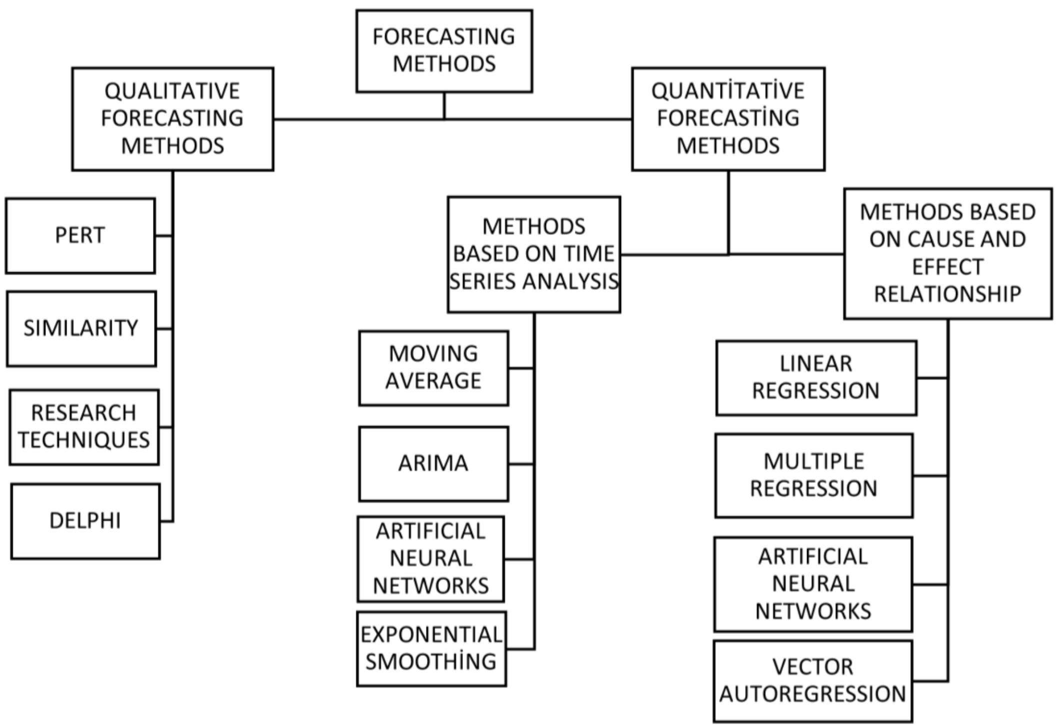

Figure 1. Forecasting methods (Aydın, 2012)

This study focuses on three major methods highlighted in the literature: ARIMA-SARIMAX, Multiple Linear Regression (MLR), and Holt-Winters (HW).

2.3 ARIMA-SARIMAX

A time series is a sequence of variable values recorded over time (Akgül, 1994). These values can be recorded at different or regular time intervals, covering various periods such as hourly, daily, weekly, monthly or yearly. Examples of time series data include stock prices, temperature, sales figures, population counts, and electricity consumption. Time series data can have different characteristics such as seasonality, trend, and stationarity.

There are various articles in the literature that include ARIMA or SARIMA. For example, Fattah et al. (2018) forecast demand in a food business using the ARIMA model. Using historical data, they find that the most suitable model to predict future demand is ARIMA (1, 0, 1). Extending the ARIMA model, Yücesan (2018) uses ARIMAX-ANN and SARIMAX-ANN hybrid models in the electronics sector to predict sales. It is stated that the use of these models is innovative and can improve forecast accuracy. In addition, Yücesan et al. (2018) also examine the performance of ARIMAX, ANN, and ANN-ARIMAX hybrid models for sales forecasting in the furniture sector. In their study, sales of various products at a furniture factory are forecasted. The authors state that the hybrid model provides higher accuracy compared to individual methods.

Other examples of the ARIMA model include Lin et al. (2019), who collect time series data in China's wooden furniture industry to study market supply and demand. They forecast market supply and demand using the ARIMA model and predict that the sector will face challenges such as oversupply and a declining domestic market share. Furthermore, Önen (2020) uses the ARIMA model to forecast aviation cargo demand in Türkiye. It is stated that the ARIMA model provides benefits at both micro and macro levels for logistics companies in terms of pricing, capacity management, and investment decisions. Additionally, Önen (2023) forecasts air passenger demand in Türkiye using ARIMA and ARIMAX models.

As for examples of SARIMA models, Alharbi et al. (2022) use the SARIMAX model to make forecasts in the electricity sector in Saudi Arabia. For a 30-year period from 2021 to 2050, their SARIMAX model, which includes seasonal and exogenous factors, demonstrates significantly better forecast accuracy compared to other time series techniques. Falatouri et al. (2022) use SARIMA in comparison with the LSTM model in retail supply chain management. They find that LSTM performs better for stable demand, while SARIMA performs better for seasonal products. They also find that the SARIMAX model shows superior performance in forecasting promotional products.

Further examples of SARIMA application include Nurtaş et al. (2024), who use the SARIMAX model in earthquake time series prediction. They state that successful results are achieved by using SARIMAX models, which demonstrates the effectiveness of the model in capturing the temporal patterns of seismic events. Another application example is provided by Cheng et al. (2024), who use LSTM and SARIMA to predict Bitcoin price and volatility. They conclude that LSTM, in their case, demonstrates superior performance.

2.4 Holt-Winters

The Holt-Winters (HW) forecasting method is a smoothing technique developed to forecast time series that include trend and seasonal effects. This method can be applied to the slope, mean level, and seasonal components of a series. The use of the HW method varies depending on the variance of the time series. If the variance of the data changes over time, the Multiplicative HW Method is preferred, whereas if the variance is constant, the Additive HW Method is used (Makridakis et al., 1997).

The HW method is often used in comparison with other forecasting methods. For example, Silva et al. (2014) compared ARIMA and HW models for forecasting dairy product time series. They find that the HW model outperforms the ARIMA model in their case. İmece and Beyca (2022) utilize Holt-Winters, Ridge Regression, Random Forest, and XGBoost models to accurately forecast demand. They find that ensemble models have lower error rates. Their study is an example showing that ensemble models may enhance accuracy in demand forecasting. Furthermore, Rumbe (2024) compares the Holt-Winters and Artificial Neural Networks (ANN) models in the tent manufacturing industry. The study shows the superior accuracy of ANN in the particular setting considered.

2.5 Multiple Linear Regression

Econometrically, when an analysis is conducted, it is observed that the bivariate (simple regression) model is often insufficient. This is because, in real-life analysis, it is usually not possible to explain a topic using a single variable. Multiple regression refers to a model with one dependent variable and multiple independent variables. The multiple regression model examines the impact of several independent variables on the dependent variable and aims to predict the dependent variable using these inputs (Polat, 2022).

Examples of related studies include Jiang et al. (2020), who use a hybrid regression model supported by a fruit fly optimization algorithm to predict electricity consumption. They report that their model achieves high prediction accuracy even with limited data. Nebati et al. (2021) also forecast electricity demand in Türkiye using regression analysis and time series techniques. Their predictions yield results similar to the actual data from the Turkish Statistical Institute (TSI).

Other application examples include Yüksel (2023), who conducts time series analyses in the retail sector. The study finds that, after testing various forecasting models, the CatBoost model provides the best performance. On the other hand, Yaneva and Kulina (2023) forecast furniture demand in Bulgaria using Machine Learning (ML) methods. They report achieving high accuracy in their demand predictions.

Table 1. Forecasting literature in the furniture sector

Author	**Year**	**Subject**	**Method**	**Parameter**
Ender Hazır Küçük Hüseyin Koç Şakir Esnaf	2016	Estimating Türkiye Furniture Sales Values with Artificial Intelligence Application	Artificial neural networks	Gross Domestic Product (GDP), Consumer Confidence Index, Real Sector Confidence Index, Investment Expenditures, Population, Housing Sales Values, Dollar
Melih Yücesan Erkan Çelik Muhammet Gül	2018	Performance comparison between ARIMAX, ANN and ARIMAX-ANN hybridization in sales forecasting for furniture industry	ANN, ARIMAX, ANN-ARIMAX Hybrid Model	Sales data of dining room, bedroom, youth room, living room set, and sofa products, economic indicators (inflation rate, exchange rate, etc.)
Meng Lin Zongli Zhang Yukun Cao	2019	Forecasting Supply and Demand of the Wooden Furniture Industry in China	ARIMA	Annual sales, Production value, Export and import data, such as time series data
Burçin Salttürk	2022	Prediction of Product Sales Quantities with Artificial Neural Networks: An Application in the Furniture Sector	Artificial-neural networks	Furniture industry production index, Dollar exchange rate, Average prices of products
P E Yaneva H N Kulina	2023	Furniture Market Demand Forecasting Using Machine Learning Approaches.	CART Ensemble, ANN (LSTM)	Store and online store traffic, Advertising and visitor data

The forecasting studies related to the furniture sector are summarized in Table 1. Literature shows that time series methods have been applied successful in furniture industry. Unlike these studies, the present research focuses on door production within the furniture sector, which is an area that is notably underrepresented.

This study compares demand forecasts using ARIMA-SARIMAX, MLR, and HW methods, addressing a topic that is generally overlooked in the industry. A forecasting model was developed using multiple variables, including past door sales volumes, exchange rates, inflation, and interest rates. The data set covers the years 2005 to 2019.

For the first time in the literature, a comprehensive time series forecasting approach has been applied to door production, and a comparison of different models has been conducted. The aim of this study is to make accurate predictions of door sales volumes using time series applications. These models provide businesses with more accurate and reliable demand forecasts, offering improved opportunities for planning and decision-making.

3. METHOD

In this section, the solution steps of the ARIMA-SARIMAX, MLR, and HW models are explained.

3.1 Data Collection

The data required for demand forecasting were obtained from the sales department of the company and relevant platforms. These data include historical door sales volumes, exchange rates, interest rates, and inflation figures.

The dataset for this study, consisting of historical door sales volumes, was analyzed using the time series analysis methods ARIMA-SARIMAX, followed by analyses using the HW and MLR methods. Finally, error rates were calculated for all methods, and a comparison was made.

3.2 Model Development

The aim of this study is to forecast demand for a company manufacturing doors in the furniture sector using the ARIMA-SARIMAX model. The application section elaborates on the process of translating the theoretical foundations of these techniques into a concrete application. As mentioned in previous sections, the literature reveals extensive use of time series and ANN models in demand forecasting studies. However, there is a lack of research on demand forecasting specifically for door quantities, making it a relatively unexplored area. Therefore, data from a door manufacturing company and the Central Bank were used for demand forecasting using ARIMA-SARIMAX, HW, and CDR applications.

Firstly, a detailed analysis of the door demand forecasting problem in the furniture sector was conducted, highlighting the limitations of existing solutions. The reasons for selecting the ARIMA-SARIMAX model were explained, and the impact of these techniques on demand forecasting accuracy was examined.

The methodology of the study, along with the datasets used and the data processing procedures, is explained in detail, including the training stages of the ARIMA-SARIMAX models. ARIMA-SARIMAX, HW, and MLR models were compared. The performance of the models was subjected to comprehensive evaluation, and the results obtained were analyzed in depth.

The application section also discusses the potential usage of the forecasts in the industry and evaluates the accuracy and reliability of these predictions. Finally, the theoretical and practical contributions of the study are presented, along with recommendations for future research.

3.2.1 Time Series-Based Prediction Models

Demand Forecasting with ARIMA and SARIMAX Methods

After a non-stationary time series is made stationary by applying differencing, the resulting stationary series is modeled using AutoRegressive Integrated Moving Average, or simply ARIMA models. When the series becomes stationary, the ARIMA model becomes an AR, MA, or ARMA model. The ARIMA model is generally represented as ARIMA(p, d, q)(P, D, Q):

p represents the order of non-seasonal AutoRegressive (AR) terms,

q represents the order of non-seasonal Moving Average (MA) terms,

d represents the degree of differencing at the non-seasonal level,

P represents the order of seasonal AR terms,

Q represents the order of seasonal MA terms,

D represents the degree of differencing at the seasonal level.

This model is used to forecast future values by first making the time series stationary and then identifying the autoregressive and moving average components (Ulutürk, 1994).

The SARIMAX model is a commonly used tool in time series analysis and is an extended version of the ARIMA and SARIMA models. In addition to modeling the intrinsic structure of the time series with ARIMA and seasonal components, SARIMAX also accounts for external regression effects (Valipour, 2015).

The model is trained on the dataset to learn the time series patterns, and then predictions are made on the test data. The predicted values are compared with the actual values.

Forecasting Demand with the Holt-Winters Method

To validate the time series-based forecasting models (ARIMA and SARIMAX), another time series forecasting model, the HW method, was constructed, and the forecasted values were compared.

The simple exponential smoothing method is determined by multiplying the difference between the actual and predicted values of the previous period by a correction factor α, which varies between [0,1] (Jacobs and Chase, 2010). In 1957, Charles Holt further developed this method by incorporating a linear trend factor β to capture the trend in the data (Chase, 2013). Later, in 1960, Peter Winters expanded Holt's approach by adding a seasonal component (γ) to the model, resulting in the method known as Holt-Winters (Siddiqui et al., 2021). In this study, statistical software was also used to determine the most appropriate constants for the dataset.

Demand Forecasting with Multiple Linear Regression

To validate the time series-based forecasting models (ARIMA and SARIMAX), another model, the MLR (Multiple Linear Regression) model, was developed, and the forecasted values were compared.

MLR is a regression analysis technique used to model the relationship between a dependent variable (the variable to be predicted) and multiple independent variables (predictor variables). Essentially, multiple regression is a statistical modeling method that examines the effects of a set of independent variables on a dependent variable.

4. APPLICATION

The purpose of this study is to enable demand forecasting for a company producing doors in the furniture sector using the ARIMA-SARIMAX model. The application section details the process of translating the theoretical foundations of these techniques into a practical application. As previously mentioned, the literature shows extensive use of time series and neural network models for demand forecasting. However, there is a lack of research specifically focused on demand forecasting for door quantities, making this an unexplored area. Therefore, data obtained from a door manufacturing company and the Central Bank were used for demand forecasting through the implementation of ARIMA-SARIMAX, HW, and MLR models.

Firstly, a detailed analysis of the door demand forecasting problem in the furniture sector was conducted, highlighting the limitations of existing solutions. The reasons for selecting the ARIMA-SARIMAX model were explained, and the impact of these techniques on the accuracy of demand forecasting was examined.

4.1 Data Collection and Preparation

This study aims to forecast monthly door sales and identify factors affecting door sales.

1. Exchange Rate (USD): The exchange rate indicates the value of one US dollar against the Turkish lira. The company purchases MDF both domestically and internationally in USD. Therefore, fluctuations in the exchange rate affect the door sales volume. Figure 2 below shows the monthly exchange rate changes from 2005 to 2019.

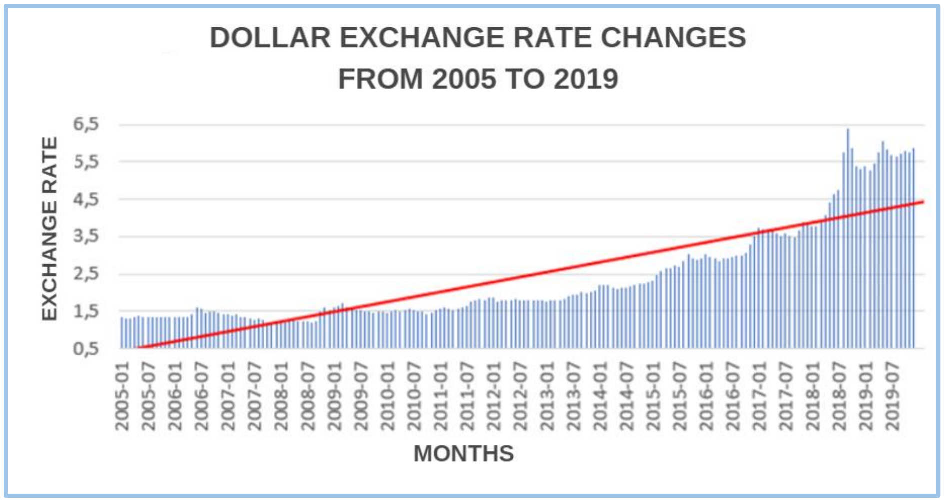

Figure 2. Monthly exchange rate changes from 2005 to 2019

2. Inflation: Inflation refers to a continuous increase in prices or a continuous decrease in the value of money. As implied by this definition, inflation affects the purchasing power of both suppliers and customers. Therefore, changes in inflation impact the quantity of door sales. Figure 3 below illustrates the monthly changes in inflation from 2005 to 2019. (Inflation amounts were obtained from the Central Bank data on the Consumer Price Index (CPI), which was recorded monthly. The percentage changes in CPI were converted into decimal expressions to create the graph.

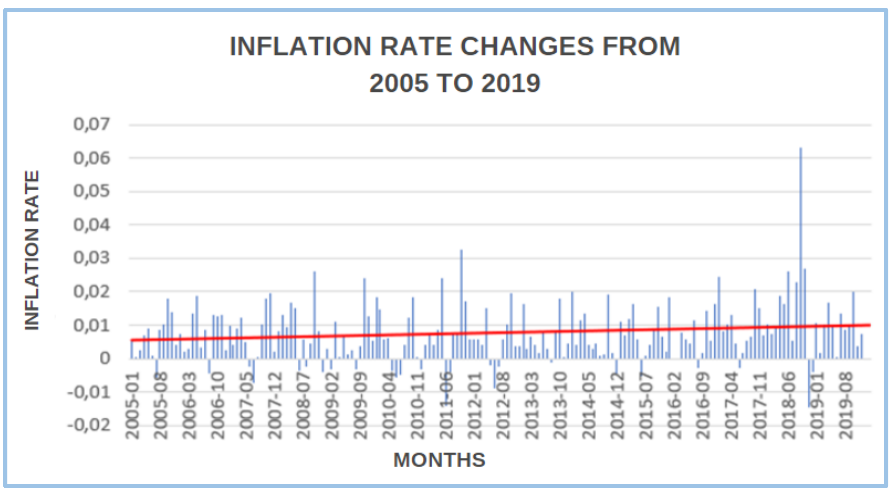

Figure 3. Monthly Changes in Consumer Price Index (CPI) from 2005 to 2019

3. Interest Rate: In the furniture sector, the interest rate is typically a significant factor influencing businesses' financing costs. This rate represents the additional cost a business incurs when obtaining loans or borrowing funds. Therefore, for a business in the furniture sector, interest rates are important in terms of loan repayments or borrowing costs. Additionally, interest rates can affect furniture purchases by consumers, especially in cases of consumer loans or installment payments, where interest rates play a significant role. Hence, interest rates in the furniture sector can impact both businesses' and consumers' financial decisions. Interest rate data were obtained from the Central Bank. Below is Figure 4, illustrating the monthly changes in interest rates between 2005 and 2019.

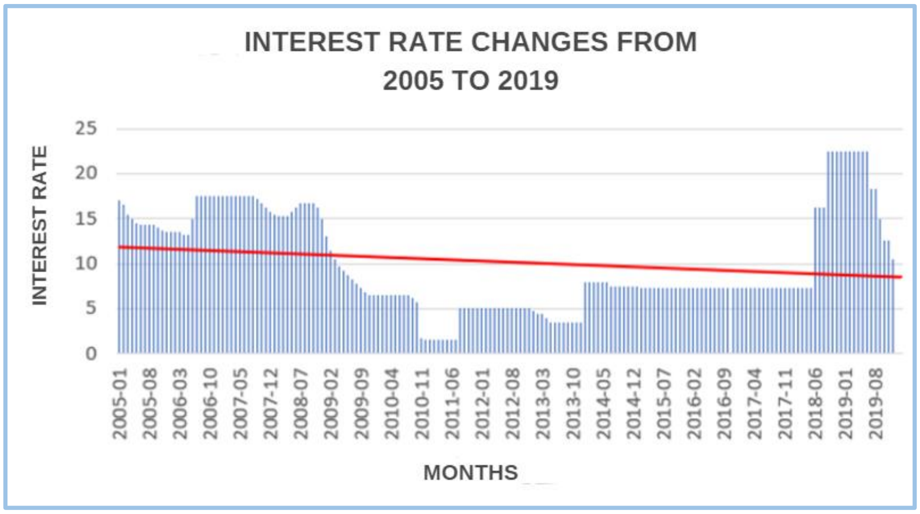

Figure 4. Monthly changes in interest rates between 2005 and 2019

4. Door Sales Quantity: Past door sales quantity is a crucial factor for implementing the ARIMA-SARIMAX model. Sales data were obtained from Has Yapı company. Figure 5 below illustrates the monthly changes in door sales quantity between 2005 and 2019.

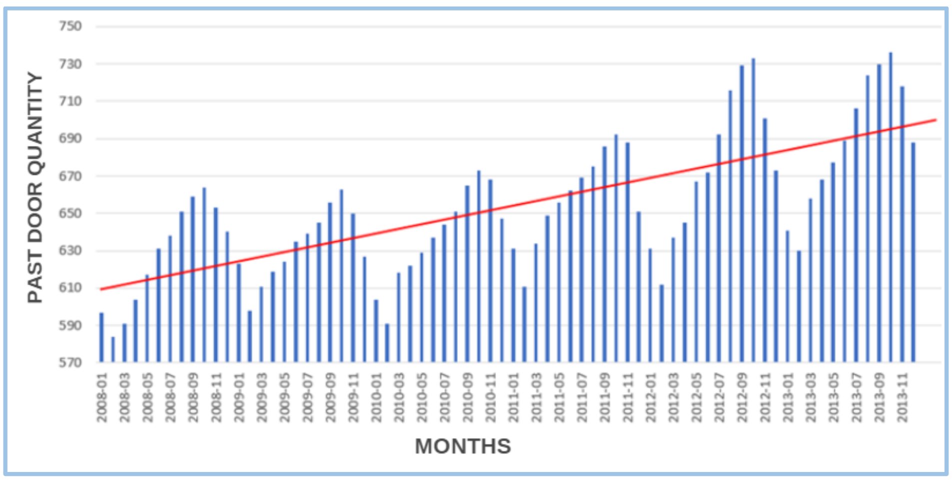

Figure 5. A segment of door sales quantity

In the demand forecasting study in the furniture sector, the reasons for using past sales volume, exchange rate, inflation, and interest rates as parameters can be briefly explained as follows:

Past door sales data play a crucial role in predicting future demand. These data reflect consumer behaviors and purchasing habits from previous periods. They provide insights into trends, seasonal variations, and other periodic effects.

The exchange rate, fluctuating due to its impact on production costs and prices, can directly influence consumer demand in the furniture sector, as some materials used in production are imported. Exchange rate volatility significantly affects pricing strategies and demand forecasts.

Inflation can directly impact furniture demand by affecting consumer confidence and purchasing power. Changes in inflation rates serve as a significant input for pricing strategies and demand forecasting models.

Interest rates influence the cost of borrowing and, consequently, consumers’ propensity for major expenditures. Low interest rates may encourage the use of consumer credit, potentially boosting demand.

The reasons for selecting these input variables are associated with their direct or indirect impacts on the furniture sector. Historical sales data serve as a fundamental source for understanding consumer behaviors and trends. Macroeconomic indicators such as exchange rates, inflation, and interest rates have significant effects on production costs, pricing strategies, and consumer spending. All of these variables are critical for enhancing the accuracy of demand forecasting models and supporting decision-making processes within the furniture sector.

4.2 Periodic Separation

Time series analysis is an important tool for understanding the characteristics of data. Seasonality, trend, and residual components are fundamental elements used to comprehend the dynamics of a dataset. In the 15-year data presented in Figure 6, changing trends over time, regularly repeating patterns (seasonality), and the uncertainty remaining after accounting for these patterns (residual components) can be observed.

The analysis identified an increasing trend in the dataset attributable to seasonality and trend. This analysis provides a valuable foundation for predicting the future behavior of the dataset and understanding past trends.

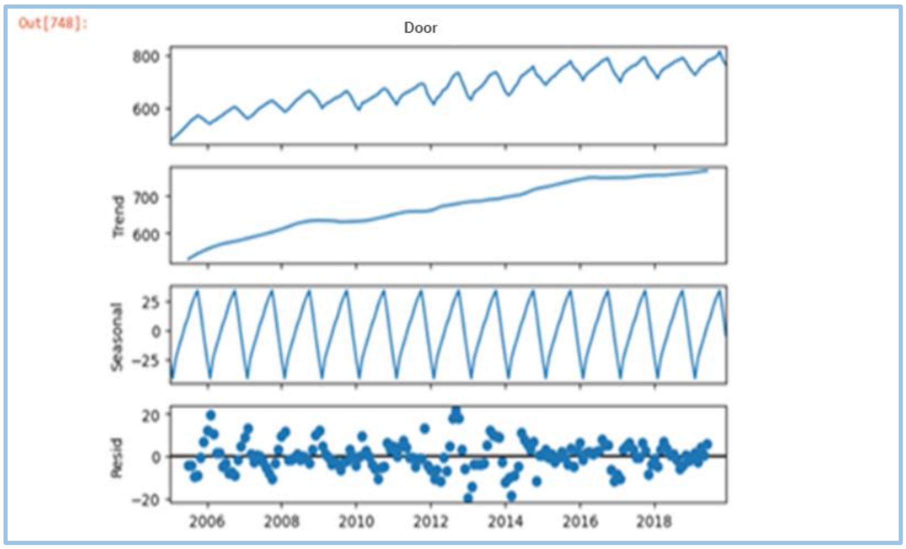

Figure 6. Seasonal decomposition

4.3 ARIMA-SARIMAX Model and Outputs

The performance metrics, including MSE, R^2, MAPE, and MAE, were examined as a result of the ARIMA-SARIMAX application. The obtained values are shown in Figure 7.

```
from sklearn.metrics import mean_squared_error
rmse = np.sqrt(mse)
print(f"SARIMA,(2,0,1),(5,1,0,12) RMSE: {rmse:.10f}")
```

```
SARIMA,(2,0,1),(5,1,0,12) RMSE: 5.1993934237
```

```
from sklearn.metrics import r2_score

r2 = r2_score(df_test[' Kapı  '], predictions)
print("R^2:", r2)
```

```
R^2: 0.9572964935907678
```

```
import numpy as np
mape = np.mean(np.abs((np.array(predictions) - np.array(df_test[' Kapı  '])) / np.array(predictions))) * 100
```

```
print("MAPE:", mape)
```

```
MAPE: 0.5087396582761672
```

```
from sklearn.metrics import mean_squared_error, mean_absolute_error
```

```
mae = mean_absolute_error(predictions,df_test[' Kapı  '])
```

```
print("MAE:", mae)
```

```
MAE: 3.9230746783722643
```

Figure 7. Evaluation result of ARIMA-SARIMAX performance

According to the results obtained from the demand forecasting application with ARIMA-SARIMAX, the RMSE value is 5.199, the R^2 value is 0.957, the MAPE value is 0.508, and the MAE value is 3.923.

As a result of the application, it was observed that the best parameter values are (2,0,1) and (5,1,0,12). Since the R^2 value is very close to 1, it can be said that the model fits the actual values very well. In other words, a large portion of the predicted values are very close to the real values. The low RMSE and MAE values indicate that the model's predictions are accurate.

The mathematical form of this model consists of the non-seasonal (2,0,1) ARIMA and seasonal (5,1,0,12) SARIMA components. The general form of the model is as follows:

$$(1 - \phi_1 L - \phi_2 L^2)(1 - \Phi_1 L^{12} - \Phi_2 L^{24} - \ldots - \Phi_5 L^{60})(1 - L^{12})Y_t = \beta X_t + (1 + \theta_1 L)\varepsilon_t \tag{1}$$

In this formula, Y_t represents the dependent variable predicted by the model, X_t represents the independent variables, L is the lag operator, ϕ_1 and ϕ_2 are the autoregressive parameters, and $\Phi_1,\ldots,\Phi_5$ are the seasonal autoregressive parameters. θ_1 accounts for the moving average term and improves the accuracy of the model's predictions by considering error terms. The seasonal differencing component $(1 - L^{12})$ adjusts for yearly recurring seasonal patterns, making the series more stationary.

The ARIMA-SARIMAX model used in the demand forecasting application exhibits a significant alignment between the actual values and the predictions depicted in Figure 8. This alignment underscores the successful utilization of the ARIMA-SARIMAX model in the demand forecasting process, as the predictions closely approximate the actual values. This indicates the model's ability to reliably and effectively forecast demand.

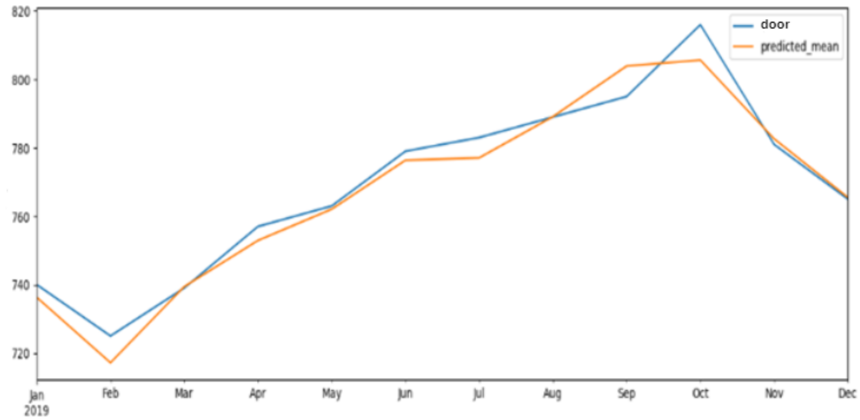

Figure 8. Real-Predicted value plot of time series analysis.

4.4 Holt-Winters Model and Its Outputs

The performance metrics including R^2, MAPE, MAE, and RMSE were evaluated for the Holt-Winters model. The obtained values are presented in Table 2.

Table 2. Performance evaluation results of Holt-Winters model

RMSE	R^2	MAE	MAPE
5.893	0.945	4.833	0.623

According to the results obtained from the Holt-Winters application, the R^2 value is 0.945, the MAPE value is 0.623%, the RMSE value is 5.893, and the MAE value is 4.833.

4.5 Multiple Linear Regression Model and Outputs

The performance metrics R^2, MAPE, MAE, and RMSE were also analyzed for the MLR application. The obtained values are presented in Table 3.

Table 3. Performance evaluation results of MLR

RMSE	R^2	MAE	MAPE
35.885	0.736	30.053	4.483

According to the results obtained from the MLR application, the R^2 value is 0.736, the MAPE value is 4.483%, the RMSE value is 35.885, and the MAE value is 30.053. The deviation of the MAE and RMSE values from 0 indicates that the model is exhibiting low performance. Additionally, the R^2 value being far from 1 may suggest that the model does not fit well with the actual values.

4.6 Comparison of Results

The comparison of the values obtained from the demand forecasting applications for door sales quantities is shown in Table 4.

Table 4. Comparison of application results

	RMSE	R^2	MAE	MAPE
ARIMA-SARIMAX	5.199	0.957	3.923	0.508
Holt-Winters	5.893	0.945	4.833	0.623
Multiple Linear Regression	35.885	0.736	30.053	4.483

When the obtained results are compared, it is observed that the ARIMA-SARIMAX application is the most successful, as it provides the lowest RMSE and MAE values, an acceptable MAPE value, and the R^2 value closest to 1.

5. SENSITIVITY ANALYSIS

The impact of economic parameters such as exchange rate, interest rate, and inflation on the performance of the ARIMA-SARIMAX model was analyzed. Performance changes were examined by removing each of these variables from the model.

5.1 Impact of Excluding the Interest Rate

In the ARIMA-SARIMAX model, which utilizes historical sales volumes, exchange rates, inflation, and interest rates, the model's performance was evaluated by excluding the interest rate variable from the dataset. The aim is to determine the importance of the interest rate for the model and assess its effect on prediction accuracy. The changes in the model's forecasting performance when the interest rate is removed are shown in Figure 9.

```
model=SARIMAX(df_training["Kapı"],order=(2,0,1),exog=df_training[['Enflasyon','Döviz']],seasonal_order=(5,1,0,12))
results=model.fit()
results.summary()
```

```
from sklearn.metrics import mean_squared_error
rmse = np.sqrt(mse)
print(f"SARIMA,(2,0,1),(5,1,0,12) RMSE: {rmse:.10f}")
```

```
SARIMA,(2,0,1),(5,1,0,12) RMSE: 5.6954282200
```

```
from sklearn.metrics import r2_score

r2 = r2_score(df_test['Kapı'], predictions)
print("R^2:", r2)
```

```
R^2: 0.9487597852600893
```

```
import numpy as np
mape = np.mean(np.abs((np.array(predictions) - np.array(df_test['Kapı'])) / np.array(predictions))) * 100
```

```
print("MAPE:", mape)
```

```
MAPE: 0.5775614153953483
```

```
from sklearn.metrics import mean_squared_error, mean_absolute_error
```

```
mae = mean_absolute_error(predictions,df_test['Kapı'])
```

```
print("MAE:", mae)
```

```
MAE: 4.447422898393209
```

Figure 9. Results obtained by removing the interest rate

When the interest rate is removed, RMSE, MAE, and MAPE values increase, while the R^2 value decreases. This is an undesirable outcome, indicating the importance of the interest rate variable for the model. Its removal negatively affects the model's performance. Therefore, including this variable is necessary to improve the accuracy of predictions.

5.2 Impact of Excluding the Inflation Rate

In the ARIMA-SARIMAX model, performance was also evaluated by removing the inflation rate and using the remaining dataset. The objective is to understand the effect of inflation on the model and assess its influence on predictive accuracy. The changes in the model's forecasting performance after removing the inflation rate are shown in Figure 10.

```
model=SARIMAX(df_training["Kapı"],order=(2,0,1),exog=df_training[['Döviz', 'Faiz Oranı']],seasonal_order=(5,1,0,12))
results=model.fit()
results.summary()
```

```
from sklearn.metrics import mean_squared_error
rmse = np.sqrt(mse)
print(f"SARIMA,(2,0,1),(5,1,0,12) RMSE: {rmse:.10f}")
```

```
SARIMA,(2,0,1),(5,1,0,12) RMSE: 9.8318313577
```

```
from sklearn.metrics import r2_score

r2 = r2_score(df_test['Kapı'], predictions)
print("R^2:", r2)
```

```
R^2: 0.8473042263062746
```

```
import numpy as np
mape = np.mean(np.abs((np.array(predictions) - np.array(df_test['Kapı'])) / np.array(predictions))) * 100
```

```
print("MAPE:", mape)
```

```
MAPE: 0.9972769230378202
```

```
from sklearn.metrics import mean_squared_error, mean_absolute_error
```

```
mae = mean_absolute_error(predictions,df_test['Kapı'])
```

```
print("MAE:", mae)
```

```
MAE: 7.832928266041345
```

Figure 10. Results obtained by removing the inflation rate

Removing the inflation rate results in increases in RMSE, MAE, and MAPE values, and a decrease in the R^2 value. These findings emphasize the critical role of inflation in model performance. Excluding this variable leads to reduced prediction accuracy and weaker overall model performance. Therefore, inflation is identified as an important parameter for improving forecasting accuracy.

5.3 Impact of Excluding the Exchange Rate

The impact of removing the exchange rate variable on model performance was assessed by using the remaining dataset. The change in forecasting accuracy was evaluated through error metrics, as shown in Figure 11.

```
start=len(df_training)
end=len(df_training)+len(df_test)-1
predictions = results.predict(start=start, end=end, exog=df_test[['Enflasyon','Faiz Oranı']], dynamic=False, typ="levels")
```

```
from sklearn.metrics import mean_squared_error
rmse = np.sqrt(mse)
print(f"SARIMA,(2,0,1),(5,1,0,12) RMSE: {rmse:.10f}")
```

```
SARIMA,(2,0,1),(5,1,0,12) RMSE: 5.9759930524
```

```
from sklearn.metrics import r2_score

r2 = r2_score(df_test['Kapı'], predictions)
print("R^2:", r2)
```

```
R^2: 0.9435871107213204
```

```
import numpy as np
mape = np.mean(np.abs((np.array(predictions) - np.array(df_test['Kapı'])) / np.array(predictions))) * 100
```

```
print("MAPE:", mape)
```

```
MAPE: 0.6049298520097501
```

```
from sklearn.metrics import mean_squared_error, mean_absolute_error
```

```
mae = mean_absolute_error(predictions,df_test['Kapı'])
```

```
print("MAE:", mae)
```

```
MAE: 4.696502137172
```

Figure 11. Results obtained by removing the exchange rate

When the exchange rate is removed, RMSE, MAE, and MAPE values increase, while the R^2 value decreases. These results highlight the significance of the exchange rate for model performance. Its exclusion adversely affects prediction accuracy. Hence, the exchange rate is an important parameter for enhancing model reliability.

5.4 Overall Evaluation

The analyses conducted provide insight into the impact of economic parameters on the performance of the ARIMA-SARIMAX model. The summary of the results is presented in Table 5.

Table 5. Overall evaluation of the analyses

	RMSE	R^2	MAE	MAPE
All variables	5.199	0.957	3.923	0.508
When the interest rate is removed	5.695	0.948	4.447	0.577
When inflation is removed	9.831	0.847	7.832	0.997
When exchange rate is removed	5.975	0.943	4.696	0.604

These results indicate that all three parameters are critical to model performance. When all variables are included, the model achieves the lowest RMSE, MAE, and MAPE values and the highest R^2 value. The low error values and the R^2 value close to 1 confirm the model's high predictive accuracy.

The analysis reveals that interest rate, inflation, and exchange rate have significant effects on the performance of the ARIMA-SARIMAX model. Among them, inflation has the greatest impact, while interest rate and exchange rate also contribute meaningfully. Therefore, including all these variables in the model is necessary to improve forecasting accuracy. Considering these economic parameters is essential to maintain the model's performance at its highest level.

6. CONCLUSION

In this study, demand forecasting for a company manufacturing doors in the furniture sector was carried out using the ARIMA-SARIMAX, Holt-Winters (HW) model, and Multiple Linear Regression (MLR) method. Initially, factors that could affect door sales quantities were identified. These factors were determined to be the dollar exchange rate, inflation, interest rate, and past door sales quantities. Data covering the period from 2005 to 2019 were utilized. Subsequently, demand forecasting models were developed using the ARIMA-SARIMAX, HW model, and MLR method. The performance of the developed models was evaluated using statistical metrics such as MAPE, MAE, R^2, and RMSE.

According to the results obtained, the HW and ARIMA-SARIMAX models are effective methods for forecasting door sales quantities. All three models produced statistically significant and highly accurate predictions. The ARIMA-SARIMAX model yielded a higher R^2 value compared to the HW and MLR methods, indicating better prediction performance. The MLR method, on the other hand, is a simpler and more interpretable model that requires less computational power compared to ARIMA-SARIMAX. While the HW model stands out for its ability to forecast seasonal data, ARIMA-SARIMAX models accurately capture the dynamics of time series data. Hence, it is recommended that future studies thoroughly examine and compare these methods.

However, it has been observed that both ARIMA and SARIMAX models have some limitations. While the ARIMA algorithm has a simpler structure, it struggles to forecast seasonal variables. In light of these limitations, it is recommended to use ARIMA and SARIMAX algorithms together for forecasting door sales quantities in the furniture sector. Additionally, different data preprocessing techniques and optimization algorithms can be employed to enhance the performance of both approaches.

Due to its simpler and more interpretable structure, the MLR method can be used for fast and straightforward predictions. It is believed that the findings obtained will be useful to companies producing doors in the furniture industry. These insights can help companies make more effective production and marketing plans.

In the sensitivity analysis conducted on the ARIMA-SARIMAX model, the effects of the interest rate, inflation, and exchange rate variables on model performance were examined. When each variable was removed from the model, increases in RMSE, MAE, and MAPE values and a decrease in the R^2 value were observed. Removing the interest rate decreased the model's prediction accuracy, while removing the inflation rate had the most significant negative impact on model performance. Similarly, the removal of the exchange rate also adversely affected performance. This analysis demonstrates that including all these economic parameters in the model is critical for enhancing prediction accuracy.

Furthermore, in this study, other factors that may affect door sales quantities could also be investigated. For instance, variables such as household income levels, population growth, housing market conditions, and furniture trends could impact door sales volumes. More comprehensive demand forecasting models could be developed using different datasets along with deep learning and machine learning algorithms. It is believed that such research efforts would contribute to making more accurate and reliable demand forecasts in the furniture sector.

The dataset can be expanded, and more complex models can be created using Artificial Neural Networks (ANN), which can also be applied in different sectors. In particular, findings obtained through expanded datasets and advanced ANN algorithms will significantly contribute to strategic decision-making processes in various industries, creating a competitive advantage.

As a result, the ARIMA-SARIMAX model can be used for forecasting door sales in the furniture sector. The ARIMA-SARIMAX algorithm provides better results in terms of prediction performance. Further research using different methods and datasets is needed to conduct more comprehensive studies.

This study has made several significant contributions to the furniture sector. These contributions include improving demand forecasts, optimizing production planning, increasing customer satisfaction, gaining competitive advantage, reducing risks, and supporting strategic decision-making. In particular, the accuracy of demand forecasts has increased thanks to the models and approaches developed, allowing for more efficient and effective planning of production processes. Furthermore, improved demand forecasts have enhanced inventory management, leading to increased customer satisfaction. This study has provided firms in the sector with a competitive advantage by enabling them to adapt more quickly to market conditions. Ultimately, minimizing risks and supporting strategic decision-making processes are among the most significant contributions of this study to the furniture sector.

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