Descriptive and Predictive Model of Sales Using Business Intelligence and Time Series Analysis in an Awards Production Company

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Abstract

In small and medium-sized enterprises, sales data is often stored without being strategically leveraged to support business and operational decision-making. The lack of Business Intelligence tools makes it difficult to analyze sales behavior, identify trends, and forecast future demand. Therefore, the objective of this research was to develop a predictive sales model using Business Intelligence techniques and time series analysis to support data-driven planning and decision-making. The methodology took a quantitative approach and was carried out in two phases: a descriptive phase, based on data cleaning, transformation, and visualization using Power BI, and a predictive phase, focused on applying ARIMA models and Holt's double smoothing to estimate future sales. Among the main results, it was found that the products with the highest sales share were the Irregular Shield Pin, Medal, Acrylic Trophy, Recognition Plaque, and Regular Shield Pin. Additionally, significant changes in sales behavior were identified during certain periods of the year. The Holt model yielded better results for products with more stable trends, while ARIMA was better suited for products with more pronounced variations, such as the Medal. Additionally, an interactive dashboard was built to centralize and dynamically visualize business information.

Keywords

Predictive, Business Intelligence, Big Data, Sales, Machine Learning, Dashboard, Power BI

1. Introduction

In small and medium-sized businesses (SMBs), transactional sales data is often stored without being strategically leveraged, limiting its value for decision-making. One way to generate value is through descriptive and predictive analysis that allows this data to be turned into a strategic tool to identify patterns, anticipate future scenarios and strengthen business competitiveness [1].

In the company studied, the absence of a Business Intelligence (BI) tool makes it difficult to monitor sales and define performance indicators, generating loss of commercial opportunities. Similar experiences, such as that of the real estate agency Assessorial Sweet Home where CRISP-DM and the ARIMA model predicted sales that show the value of analytics to anticipate trends and optimize decisions [2].

Therefore, this work aims to develop a predictive sales model for a product of a recognition company, using time series analysis and BI techniques, to anticipate its future behavior and support decision-making. As a result, a Power BI dashboard for descriptive analysis was built, allowing indicators to be consulted, compared, optimized, and strategic planning to be supported. This research is based on the exploration of other sources that have already implemented predictive models such as the study by Perdomo Sauceda [3].

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It should be noted that both analyses are useful to improve the way in which the company uses its information to foresee changes in sales, organize resources and make clear decisions. It is hoped that this project will help strengthen internal processes by fostering a work culture in which data analysis is part of the day-to-day and serves to drive the company's growth and continuous improvement.

2. Related Jobs

This section presents research articles related to the application of predictive models and BI in sales within companies in the productive sector. The analysis of these studies allows us to identify various business problems and the methodological strategies used to address them through prediction and data analysis.

A study by Villachica Pérez et al. [4] focused on the development of a predictive model based on Machine Learning to record sales transactions and optimize decision-making in SMEs. Their contribution was the use of data management modules to make predictions. The results showed that SMEs lack data management and data analysis systems and that the model developed improves their sales management.

González Ramírez et al. [5] they conducted research focused on predicting trends using time series. Its main contribution was the analysis of time series as a statistical tool to identify patterns and generate sales forecasts. The most relevant findings evidenced the existence of seasonal behavior in the data and highlighted the importance of understanding sales history to project future values. Likewise, it was demonstrated that the ARIMA model is an effective technique for the prediction of historical trends.

Perdomo Sauceda [3] conducted a study to forecast sales revenues in the company Prilacentro, in the aquaculture sector, comparing the Random Forest and exponential smoothing methods in Power BI. The results showed that exponential smoothing achieved an accuracy of 83.04% in sales and 81.31% in quantities, surpassing traditional linear models. This work made it possible to anticipate decreases in sales, improve inventory control by reducing overstocking and the creation of an area focused on data analytics to support decision-making.

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Additionally, in the research of Sepúlveda Calle et al. [6] it is mentioned that the ARIMA model is useful for predicting future values based on past values through the identification of historical patterns of time series.

A review of the background is essential to guide the development of the project, as it allows us to understand how different authors have applied predictive models and BI tools to anticipate sales in various types of companies. From this reading, it was possible to identify the techniques with the best results, such as ARIMA, Holt and neural networks, as well as the importance of using historical data to improve planning and strategic decision-making.

Through this background analysis, it was possible to recognize gaps in previous studies, especially the lack of comparison between different methods applied to specific production contexts. Taking this into account, it is possible to lay the foundations of the model and the way of applying it that can be the beginning of the completion of this gap.

3. Methodology

The project was developed with a quantitative and predictive approach, based on the analysis of historical sales data from a recognition company. From this data, we sought to understand the behavior of sales to support decision-making in the company. To do this, Business Intelligence tools and time series analysis techniques were used to study sales trends and estimate their future behavior through a double Exponential Smoothing model.

To know the development of the project, Figure 1 presents the phases and detailed activities. In phase 1, a descriptive analysis of the information will be carried out and in phase 2, the predictive analysis of the same. The graph is as follows:

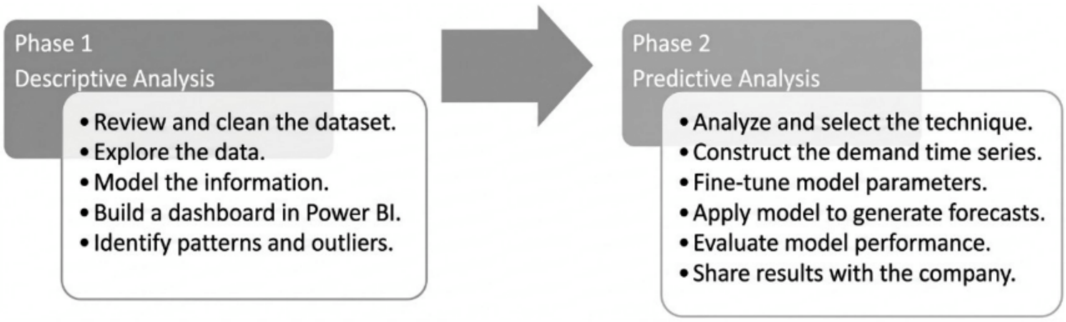

Figure 1: Project methodology, source: Authors.

Below are the detail of the phases and the activities within them:

3.1. Phase 1: Descriptive Analysis

In the descriptive phase, an exploratory analysis of historical sales data corresponding to a period of 12 months was carried out, which made it possible to understand the commercial behavior of the company, identify the 5 best-selling products and prepare the information for the construction of a predictive model. The identification of the top 5 was intended to characterize the products of greatest commercial relevance; however, the selection of products for the predictive phase was made later, considering, in addition to the sales volume, availability and behavior of their time series.

For the imputation of the data, the sales dataset for the year 2025 was reviewed and filtered, identifying inconsistent records, null values, typing errors and standardization problems. Subsequently, an exploratory data analysis was performed, which uses numerical and visual summarization to explore data in search of unanticipated patterns [7]. The above, supported by the construction of a correlation matrix that is an arrangement in rows and columns of correlation coefficients where each cell represents the linear association between pairs of variables [8]. This analysis made it possible to identify relationships between them and recognize those with the greatest influence on demand.

Finally, with the data filtered and analyzed, a star-shaped dimensional model was structured, which allows the data to be organized efficiently and facilitates the analysis of the information. Based on the model, a dashboard was developed in Power BI that integrates key indicators, allowing the identification of trends, patterns and atypical data that serve as the basis for the development of the predictive phase.

3.2. Phase 2: Predictive Analytics

In this phase, a predictive analysis of the company's sales information was performed. First, the appropriate model was selected for the information, the prediction of demand by product, which allows projecting the sales trend based on the analysis of historical behavior [9]. Secondly, the time series of demand of the top 5 best-selling products was built on a notebook, on the Databricks platform, since according to Rahmer et al. [10] it helps in predicting future data for a variable from the use of historical patterns. Third, simple exponential smoothing was applied as an exploratory technique to reduce the fluctuations of the series and facilitate the identification of their behavior patterns [11]. As a fourth step, a forecast of the demand for a product was generated, using the most appropriate model, HOLT or ARIMA, according to the behavior of the time series of the product, to estimate the number of products that could be demanded in the near future [6]. Fifth, the model was evaluated using the confidence interval and the MAE, WMAPE and MAPE metrics, which according to Vallejo Huanga [11] are used to measure and determine the performance of the forecast. Finally, the results obtained in the descriptive and predictive stage were socialized with the company.

4. Results

This section presents the results obtained from the application of the previously described method. First, an approach was made with the directors of the recognition company to understand their context and needs. In this meeting, it was identified that the company needed to have updated and easily accessible information that would allow it to visualize the current behavior of its sales, as well as to make a projection of its future behavior.

From this approach, the company provided the dataset used for the analysis, which contained the daily sales record for 2025 in an Excel workbook (3,455 records). In this file, the information was organized by months. The first phase of the project, corresponding to the descriptive analysis, was divided into five activities:

Initially, the homogeneity of the column structure was verified and the information for all the months was consolidated into a single table. A review was carried out on this unified dataset using Excel filtering tools, which allowed detecting and correcting inconsistencies such as misspelled dates and empty fields.

For the treatment of these errors, communication was established with the company to validate the possible solutions, and it was agreed that the missing dates would be assigned to the first day of the corresponding month. This to avoid imputations with unobserved information. However, it is recognized that this design choice introduces artificial demand peaks at the beginning of each month, altering the actual daily variability of the time series. This pragmatic simplification constitutes an accepted limitation in daily high-frequency modeling. For the empty boxes in the description fields, statistical techniques were not used, since they are categorical variables. Instead, empty records would be grouped under the categories "other" and "other work."

Once the data was cleaned and cleansed, the Exploratory Data Analysis (EDA) was developed to identify patterns, trends, relationships between variables and the behavior of the most representative products in sales. They are presented in Table 1 below:

Table 1
Data Dictionary.

Variable	**Data type**	**Description**
CANT. (Quantity)	Integer Numeric	Number of units of products sold in each order that determines the sales volume
UNIT PRICE	Decimal numeric	Value of a single unit of products that directly influences the order total
TOTAL, ORDER ($)	Decimal numeric	Total Purchase Value (Quantity × Unit Price) Key Revenue Variable
SEASON TICKET 1	Decimal numeric	First partial payment made by the customer indicating down payment behavior
SEASON TICKET 2	Decimal numeric	Second partial payment from the customer
OUTSTANDING BALANCE	Decimal numeric	Remaining value payable after credits that measures portfolio and financial risk
GROUPED OP	Categorical (numerically coded)	Order/order identifier or grouping that allows you to segment or group data

As part of this analysis, a correlation matrix was constructed that included the variables. This evidenced a strong positive relationship (0.95) between the total order and the outstanding balance, indicating that the higher the value of sales, the accounts receivable also increases. Additionally, the above is also evidenced by the correlation between the number of units sold and the outstanding balance (0.79). In contrast, the unit price showed low correlations with the other variables, especially with the quantity sold (-0.02) and the total order (0.23), which suggests that price has a limited influence on the behavior of demand.

From this, it was possible to conclude that the most influential variables in the behavior of sales are the quantity, the total of the order and the outstanding balance. Figure 2 shows the correlation matrix described.

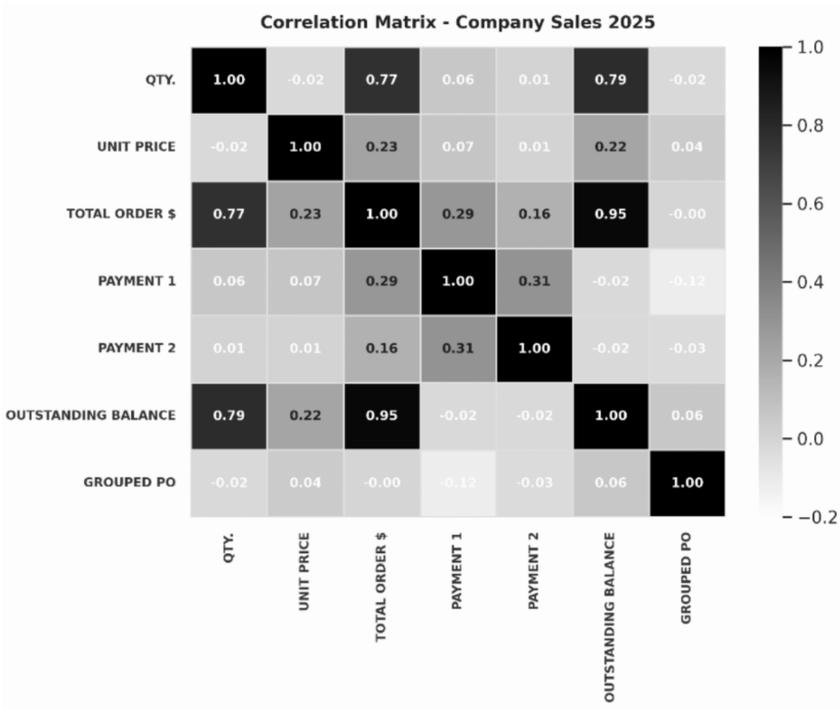

Figure 2: Project correlation matrix, source: Own authorship.

The measures of central tendency presented in Table 2 show that most of the orders correspond to purchases of lower value and low volume, represented by a median of 2 units and $\$116,000$. In contrast to the mean (25.67 units and 488,569), which is higher because there are outliers. This difference shows a bias in the distribution, so in this case the use of the median is more representative.

Table 2
Central tendency measures.

Statistician	ID	OP	Date of order	Delivery date	Quantity	Unit price	Total order	Outstanding balance
n	3.455	3.455	3.455	3.455	3.455	3.455	3.455	758
Media	1.728	6.392	5/07/2025	12/07/2025	25,68	73.911	418.857	164.811
Minimum	1	2.472	4/01/2025	11/01/2025	0	0	0	0
25th Percentile	864,5	5.766	4/04/2025	11/04/2025	1	11.667	45.000	18.000
Medium	1.728	6.391	11/07/2025	17/07/2025	2	26.180	116.000	50.000
75th Percentile	2.591,50	7.001,50	2/10/2025	10/10/2025	11	95.000	292.500	180.000
Maximum	3.455	7.711	25/12/2025	22/12/2025	9.485	10.547.600	45.053.750	3.700.000
Standard deviation	997,52	721,05	—	—	190,5	247.549	1.369.137	327.274

The data model was structured under a star-type dimensional approach, with a table of facts in the center that concentrates the transactional information of sales: quantities sold, value of orders, credits, outstanding balances and associated dates. From this central table, various dimensions are articulated: products, customers, salespeople, payment method, order status, product technique and time, as well as operational tables of production orders and records. They are all linked to the fact table by identifiers, forming a structure that allows information to be analyzed from multiple perspectives, improves performance in Power BI and facilitates the construction of clearer visualizations. This organization can be seen in Figure 3.

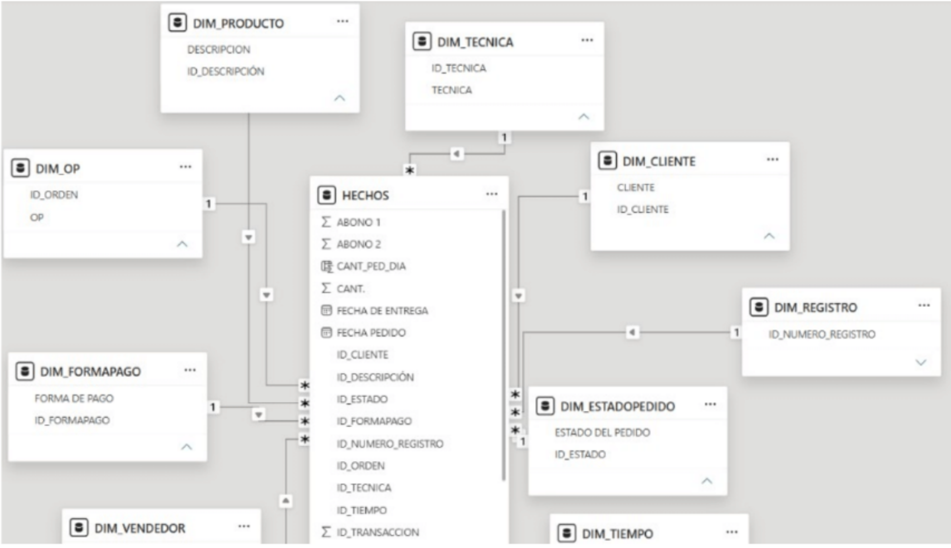

Figure 3: Dimensional model in star in Power BI, source: Own authorship.

The modeling allowed the data to be structured in an organized and coherent way, serving as the basis for the construction of the dashboard and the predictive model. From this model, an interactive dashboard was developed in Power BI that dynamically visualizes the behavior of sales. The tool has a main menu (Figure 4) that functions as a navigation point to the different sections of the analysis.

Figure 4: Sales dashboard. Source: Own elaboration.

The summary panel presents general indicators such as total sales, number of orders, portfolio value and best-selling product, accompanied by graphs of sales by product, evolution over time and portfolio by customer. The products section allows you to analyze the best sellers and units by technique, while the customer section shows the buying behavior, the main customers and the performance of the sellers. Additionally, correlation graphs were included between variables such as quantity sold, total order and outstanding balance, useful to identify patterns within the commercial process. Horizontal bar graphs were used to compare and rank products according to their sales volume, making it easier to read the categories. The vertical bars allowed comparing aggregate values between categories and periods. Line charts were used to identify trends, fluctuations, and time patterns in sales. Finally, the mosaic graph allowed the distribution and relationship between categorical variables to be analyzed.

The dashboard includes interactive filters in each section and a simple navigation interface that requires no technical knowledge, making it a practical tool for transforming data into visual insights, identifying trends, and supporting data-driven decision-making.

Then, an outlier analysis was performed using a time series with the variables "ORDER DATE" and "TOTAL ORDERED", activating anomaly detection in Power BI with a sensitivity level of 95%. In Figure 5, 9 outlier peaks outside the expected range were identified. This ended the descriptive analysis phase, whose deliverable was the dashboard in Power BI.

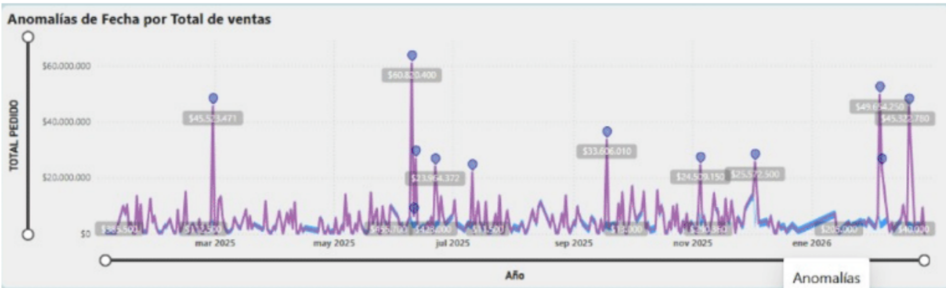

Figure 5: Time series of anomalies. Source: Own elaboration.

At this point, the predictive analysis phase began, aimed at protecting the future behavior of demand. Since the data correspond to historical records ordered in time, it was determined to work with time series models. The prediction focused on demand per product, based on the five best-selling products.

For each of these products, an independent dataset was built on separate notebooks within Databricks. The variables used were the date of sale and the daily quantity sold. Since there were multiple records per day, sales were grouped by date to obtain a single daily value per product. Finally, the time series was plotted, and monthly visualizations were generated to facilitate the analysis of demand behavior.

Figure 6 shows the monthly behavior of the irregular shield pin, medal, acrylic trophy, recognition plaque and regular shield pin in 2025. It shows atypical data on specific dates that generate noise for the development of the forecast.

Simple Exponential Smoothing was applied to reduce fluctuations and make it easier to identify the trend. From the analysis of the five products, the three with the most stable temporal behavior were selected: Regular Shield Pin, Medal and Irregular Shield Pin (Figure 7). The Acrylic Trophy and the Recognition Plaque presented greater variability, so they were not included in the predictive modeling and opportunities for future analysis are considered.

Based on the exploratory analysis, the level of demand, variability and trend of each series were evaluated. The selection of the models was based on indicators such as the mean, the standard deviation and the coefficient of variation, complemented by graphical analysis. According to these characteristics, Holt's exponential double smoothing method was selected for the Irregular Shield Pin and the Regular Shield Pin, due to the presence of trend, while for the Medal ARIMA was selected for the observed temporal dependence characteristics.

The Irregular Shield Pin was selected to develop the final forecast due to its commercial relevance within the products analyzed and the fact that it presented a significant sales volume during the study

Figure 6: Time series of top 5 products. Source: Own elaboration.

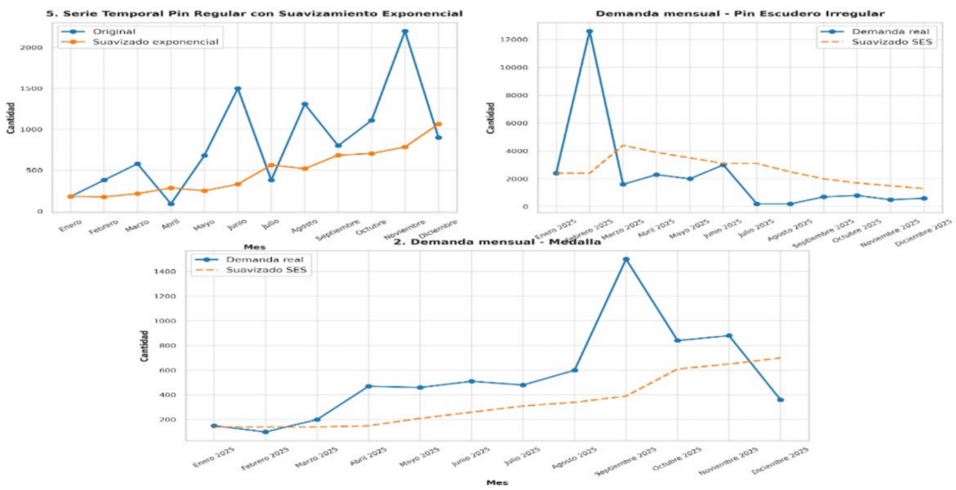

Figure 7: Simple Exponential Smoothing - three products. Source: Own elaboration.

period. Likewise, its time series allowed identifying changes in the level of demand and a trend that can be modeled using Holt's exponential double smoothing method. To evaluate the behavior of the forecast, the MAE, MAPE and WMAPE metrics were used, together with a prediction interval of 95%, to quantify the error of the estimates and the uncertainty associated with the projections.

Figure 8 shows the behavior and variability of the analyzed product data along with its confidence interval.

The model is close to the general trend and although the Irregular Shield Pin product series presents an irregular behavior with marked changes, these allow us to identify a stable trend towards the end of the period. However, the presence of outliers affects the accuracy of the model by limiting the ability to obtain highly reliable predictions. In this case, the confidence interval was constructed from the

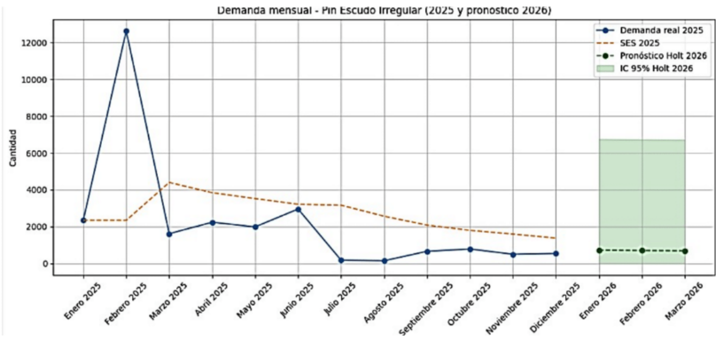

Figure 8: Predictive model with Irregular Shield Pin confidence interval. Source: Own elaboration.

standard deviation of the residuals of the Holt model, which allowed us to visualize the uncertainty of the forecast for the first three months of 2026. Figure 9 shows a graph where with the smoothed data of 2025 together with the forecast and confidence interval of 2026, however, it adds a new element and that is the line of real sales data of 2026 with the same simple smoothing applied.

Figure 9 compares the forecast with the actual data of 2026 allowing this model to be evaluated and it is observed that the actual data remains in the projected range, a little higher than the central estimate. Although it managed to partially represent the trend of the series, even so, its capacity presents limitations for its application in business environments.

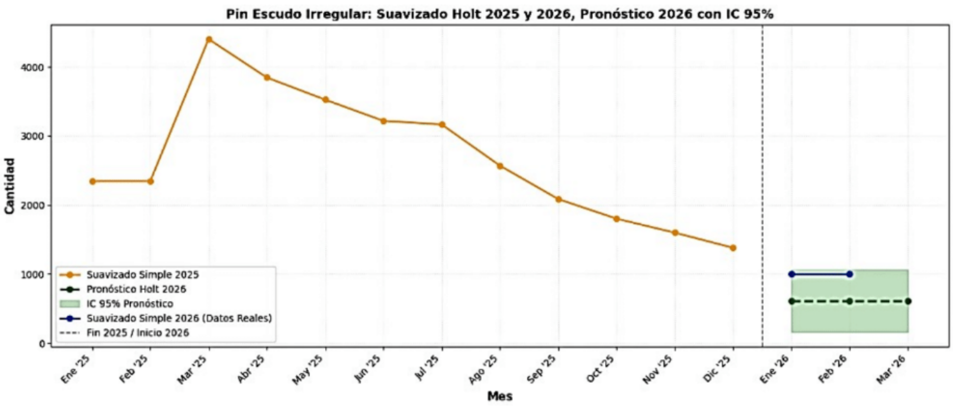

Figure 9: Predictive model with real data 2026 Pin Irregular shield. Source: Own elaboration.

Three metrics were used to evaluate the model: the MAE, average of the absolute error of 703.67, which indicates that on average there is a difference of about 704 units between what the model predicts and the real value; MAPE, an error in percentage of 50.57%, which shows that the model is wrong in more than half of the real value; and the WMAPE, a percentage error taking into account the weight of the most important data, of 53.43%, which confirms that the error is still high. Overall, these metrics show that the model is not accurate and that its predictions should be taken with caution.

This analysis identifies limitations related mainly to the amount of data available and the variability of the series, which suggests the need to incorporate a broader history or evaluate more robust models that allow improving the accuracy of the forecast in this type of products.

Considering the results obtained in the data transformation, the socialization of the project with the tools was carried out with the manager and the company's partners. These made it possible to identify patterns of variability in customers, sales behavior and products with better performance, facilitating strategic decision-making aimed at strengthening and growing the company.

5. Discussion

The results obtained allowed to meet the general objective of the project, focused on the construction of a predictive sales model through Business Intelligence techniques and time series analysis. Through the development of the dashboard in Power BI and the predictive model, it was possible to understand the historical behavior of sales and generate projections useful for decision-making.

In the descriptive phase, it was identified that the products with the highest concentration of sales were Irregular Shield Pin, Medal, Acrylic Trophy, Recognition Plaque and Regular Shield Pin, evidencing that a large part of the company's commercial behavior depends on them. This finding is consistent with what was stated by Villachica Pérez et al., [4] who highlighted that SMEs lack data management and analysis systems and that their implementation improves sales management. Likewise, during the exploratory analysis, inconsistencies were found in the dataset, such as incorrect dates, empty cells and differences in the structure of the files, so it was necessary to carry out a cleaning process to ensure a reliable database suitable for analysis.

Regarding predictive modeling, the Holt model was the most suitable for the Irregular Shield Pin due to its tendency towards stabilization, while for the Medal ARIMA was selected due to fluctuations in its demand, a result that coincides with Xu et al., [12][14] who concluded that ARIMA offers high accuracy in the short term for series with marked variations. This finding demonstrates the importance of selecting models according to the characteristics of each time series, especially in contexts with limited historical data. Additionally, nine anomalies were identified in sales behavior, eight upper and one lower, mainly concentrated after the middle of the year, suggesting periods of high demand associated with commercial or corporate factors, a pattern consistent with the findings of González Ramírez et al., [5] who highlighted the importance of understanding sales history to identify seasonality and project future values.

The results are in line with Boada [13], who points out that in business environments of high uncertainty it is not possible to obtain completely accurate forecasts, and that models must be adjusted as more information becomes available. In this regard, both projects prioritized the generation of estimates consistent with the way in which the data behave. The project also demonstrated the need to expand the historical data to strengthen the predictive capacity of the models and confirmed the importance of having centralized, updated and visually accessible information to support the present and future management of the company.

The MAPE obtained should not only be interpreted as a statistical limitation of the model, but also as an indicator of risk in decision-making. Its value suggests that predictions should be used with caution and complemented by expert judgment, business rules, or more flexible inventory control systems, such as safety inventories or dynamic replenishment policies. It also highlights the need to improve the quality and quantity of historical data, since the availability of only 12 months of information limits the model's ability to capture seasonal patterns or long-term trends.

The research developed a predictive model focused on the five products with the highest sales, carrying out a specific analysis of the Irregular Shield Pin product to estimate its commercial behavior during January and February 2026. From this, different lines of future research arise, including the comparison between the trend of this product and the general sales behavior of the company and the analysis of some possible patterns of seasonality in sales. Likewise, it is considered pertinent to incorporate some external variables that could influence the behavior of sales to improve the explanatory capacity of the model. Finally, the monthly fluctuations in demand and the identification of products with the greatest impact on revenues, through analyses such as the Pareto principle, represent relevant opportunities to deepen the predictive study of sales in companies.

The study evidenced the limitations of working with only 12 months of historical information, which made it difficult to identify seasonal patterns and improve the accuracy of the projections, reflected in the MAPE of 50.57% of the Irregular Shield Pin. In this sense, López & Cadena [2] pointed out that the use of real-time data and the comparison between different models are key aspects to improve the reliability of predictions. It is also pertinent to analyze other variables related to price, customer behavior and external market factors that were not contemplated in this research.

On the other hand, although there are studies on ARIMA, exponential smoothing and Machine Learning in sectors such as retail, e-commerce and the food industry, such as those developed by Morsi, no research was found applied to companies with similar productive characteristics, which limited the direct comparison, but highlights the value of the project as a contribution to organizations with reduced volumes of data.

Finally, the models used are not universal and their effectiveness depends on factors such as variability, seasonality and volume of data, so it is essential to carry out a prior exploratory analysis to select the most appropriate methodology according to the context of the organization.

6. Conclusion

The research fulfilled the objective of developing a descriptive and predictive sales model for the company, through time series analysis and Business Intelligence techniques. Based on the processing of the information for the year 2025, an interactive dashboard was designed in Power BI that made it possible to visualize key indicators such as sales, pending portfolio and commercial behavior of customers.

Among the main findings, the products with the greatest strategic relevance were identified, such as Irregular Shield Pin, Medal and Regular Shield Pin, in addition to significant relationships between commercial variables, especially between total orders, outstanding balance and revenue. Likewise, the exploratory analysis made it possible to detect anomalies and variations in demand useful for analyzing customer behaviors, orders and their traceability.

In the predictive component, time series models such as Holt and ARIMA were applied, selecting the Irregular Shield Pin product from among the first three, since it is the product with the highest sales, and has a high scalability potential, its behavior is fluctuating, which represents strong peaks that through Holt's model it was possible to obtain a projection for the year 2026 that can help decision-making, planning and inventory, considering thatfor Holt's method, the presence of seasonal patterns in the series was previously evaluated. Because the Holt method models level and trend, but does not explicitly incorporate a seasonal component, it was verified that the series did not present a sufficiently marked seasonal pattern to justify the use of a Holt-Winters model.

As a main contribution, the project integrated tools such as Power BI, Python and Databricks into an analytical and predictive solution for a small company in the recognition sector, demonstrating that it is possible to create functional models even with little historical data. However, when evaluating the model, an MAPE of 50.57% was obtained, which means that the predictions have a high margin of error. For this reason, although the model can serve as a support for analysis and decision-making, its results should be interpreted with caution.

Finally, it is recommended to expand the historical data used in the model, incorporating information from various periods and seasons that allow identifying more solid and consistent behavior patterns in sales. It would also be pertinent to include external variables that may influence demand, such as market trends, commercial seasons, advertising campaigns, economic behavior, special dates and customer-related factors, to enrich the analysis and increase the explanatory capacity of the predictive model.

Similarly, for future work, it is suggested to evaluate and compare different Machine Learning techniques and algorithms, as well as to carry out optimization processes that improve the accuracy of the predictions. Finally, future research could extend the analysis to a greater number of products, customer segments, or financial variables, thereby strengthening the company's analytical capacity, business planning, and competitiveness.

Declaration on Generative AI

During the preparation of this paper, the last author used Gemini Notebook LM in order to verify information and enhance the text. After using this tool, the editing was done by the last author as needed, and he takes full responsibility for the final content.

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