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Research Article

Multi-criteria approach to adjust demand forecast for products: application of analytic hierarchy process

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Abstract

Paper aims: Investigate whether the results of time series models can be adjusted with the AHP method towards a more assertive forecast.

Originality: Considering demand forecasting as a complex decision-making situation, this research investigated the use of the AHP as a complement to traditional forecasting methods.

Research method: This applied research employed, as main procedures, literature review and mathematical modeling.

Main findings: Two models were proposed that presented satisfactory results: model I reduced the forecast error by 16% in January, 25% in February, 37% in March, 3% in April, and 7% in May; model II reduced it by 17% in January, 21% in February, 29% in March, 2% in April, and 5% in May.

Implications for theory and practice: We conclude that the AHP has the potential to correct the results of time series in the textile industry by allowing the incorporation of quantitative and qualitative variables.

Keywords

Demand forecasting. Analytic hierarchy process. Textile industry.

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1. Introduction

Demand forecasting is related to anticipating future levels of demand for a company's products and/or services. According to Werner & Ribeiro (2006), forecasting is fundamental for structuring the company to determine the quantity of goods or services it will produce so that it can predict and meet the consumer market's demand. With that in mind, Pellegrini & Fogliatto (2001) consider that demand forecasting plays an important role in the strategic planning of production, sales, and finances of organizations in general. For Werner & Ribeiro (2006), reliable forecasts require the use of various methods and the largest amount of available information. Based on these definitions, one infers the importance and extent to which demand forecasting is a determining factor for the company's performance in the market as a whole.

The company analyzed is a textile industry with an average portfolio of 812 models per collection, supplying products to more than 30 thousand stores in Brazil, besides exporting to such countries as Saudi Arabia, Argentina, Bolivia, Canada, Chile, Costa Rica, El Salvador, Slovenia, Guatemala, Japan, Lebanon, Libya, Paraguay, Peru, Portugal, Suriname, Uruguay, and Venezuela. For its production and purchase planning, it uses time series techniques to forecast demand from the billing history (simple moving average, weighted moving average, simple exponential smoothing, double exponential smoothing, and triple exponential smoothing). However, due to the particularities of the industry (seasonality, fashion trends, product life cycle, and marketing and sales actions) associated with the effects of the Covid-19 Pandemic, the inaccurate results of these techniques made it difficult for the PPC (Production Planning and Control) to make decisions, causing excess or shortage of finished product and raw material inventory.

Multicriteria Decision Methods (MCDA) support important decisions by breaking down, or decomposing, a complex problem into criteria, sub-criteria and alternatives. Thus, they allow decision makers to understand and evaluate forecast results (Dodgson et al., 2009). In the context in which demand forecasting is complex, especially in the textile industry, multicriteria methods can support the forecasting process, allowing it to encompass more information, unlike the time series, which considers only past history. The Analytic Hierarchy Process (the AHP) is a multi-criteria decision support method developed by the mathematician Thomas Lorie Saaty, being used worldwide for complex decisions in various areas. Dyer & Forman (1991) suggest that the AHP can be used as an expert opinion tool for selecting the most appropriate forecasting method or technique, and for combining the results of several forecasting techniques to produce a single forecast.

This research was developed to investigate the suitability of the AHP to adjust the demand forecast of a textile company considering quantitative and qualitative data, i.e., historical data and expert opinion. The research question posed is: is the AHP effective in improving the forecasting results of traditional time series methods in the textile industry? The aim of this paper is to investigate whether the results of time series models for forecasting demand for textile products can be adjusted with the AHP method..

This paper is structured as follows. Section 2 (Theoretical framework) presents a brief background of demand forecasting and the AHP method. Section 3 (Research Method) presents the classification and operational procedures of the research. Section 4 presents the results, while Section 5 concludes the paper.

2. Theoretical framework

2.1. Demand forecasting

According to Pellegrini & Fogliatto (2001), demand forecasts can be prepared using quantitative or qualitative methods, or a combination of both. For Krajewski & Ritzman (1999), qualitative methods are based on expert opinions, which rely on the judgments of specialized professionals with experience in the market. The qualitative forecast methods are: (1) Market Research: it aims to assess the demand for a product or service directly with end consumers, it is usually used for long-term demand forecasts and for new products (Schneider & Gupta, 2016); (2) Delphi Method: it seeks the opinion of a set of experts from different fields with the purpose of providing various views and considering different factors (Hsu & Sandford, 2007); (3) Analogy: based on the historical data of a similar product, the demand forecast of the new product is performed (Pandey et al., 2015); (4) Scenario Simulation: from the opinion of experts, it is sought to build different future scenarios and, for each of them, estimate the behavior of sales (Schoemaker, 1993); and (5) Sales team survey: it aims to collect information, such as estimated sales by product and/or service for each region and/or sector of operation of the company (Silva, 2019).

For Lee et al. (2008), quantitative forecasting methods are based on a wide variety of statistical methods, with different characteristics and complexity levels, and are divided into: time series projection and correlation and regression. Time series projection forecasting methods are: (1) Moving Average: it is suitable only for short-term forecasts and for irregular historical data, where the time series pattern does not show trend and seasonality (Makridakis et al., 1998); (2) Simple Exponential Smoothing: it assumes that demand oscillates around a constant plateau or base demand, i.e., starting from an initial value, the base is corrected each period as new demand data are incorporated into the historical series (Koehler et al., 2001); (3) Exponential smoothing with trend (or holt method): a second variable is added that reflects the growth of the demand forecast from one period to another (Pellegrini & Fogliatto, 2000); and (4) Exponential smoothing with trend and seasonality (or winter method): it is necessary to remove the seasonality from the series, then calculate the level and trend in the same way as in the exponential smoothing model with trend (Pellegrini & Fogliatto, 2000). (For more details regarding mathematical formulas/deductions, see the references: Koehler et al. (2001) and Pellegrini & Fogliatto (2000)).

For Hair et al. (2005), the regression analysis method consists in studying the correlation between a response variable and one or more independent variables. The main linear regression methods are: (1) simple linear regression: wherein there is a dependent variable, an independent variable and linear behavior; (2) curvilinear regression: non- linear behavior; and (3) multiple regression: wherein two or more independent variables affect the dependent variable. (For more details regarding mathematical formulas/deductions, see Hair et al. (2005)).

After defining the forecast technique and implementing the model, it is necessary to monitor the performance of the forecasts and confirm their validity given the current dynamics of the data. This is done by calculating and monitoring the forecast error, which is the difference between the actual value of demand and the value forecast by the model for a given period (Tubino, 2017).

2.2. The AHP method

According to Saaty & Vargas (2001), the Analytic Hierarchy Process (AHP) is a Multicriteria Decision Method (MCDA) designed to support complex situations, through a hierarchical structure composed of an objective, criteria and/or sub-criteria and/or alternatives. In the process of hierarchical analysis, the decision maker makes pairwise judgments between elements at a given level and those at the next level using a scale of his own (Saaty scale) in order to determine priorities and, finally, order the alternatives. The three principles for solving decision problems with the AHP are presented below, based on Saaty (1987) and Ishizaka & Nemery (2013):

1. Decomposition: the simplest form used to structure a decision problem is a hierarchy, which consists of at least three levels: (1) decision objective; (2) criteria (in more complex hierarchies, more levels can be added, which are called subcriteria) and (3) alternatives. In order to build a hierarchy, it is important to consider the environment surrounding the problem, identify the attributes that contribute to the solution, and who are the participants associated with the problem. Saaty (1980) mentions that there is no standard procedure for raising criteria and objectives and suggests using brainstorming with experts and/or literature consultations to help elucidate the criteria and objectives.

2. Comparative judgments: pairwise comparisons of the relative importance of the elements of a given level in relation to the level above, according to the AHP Fundamental Scale proposed by Thomas Saaty (Chart 1). According to Costa & Belderrain (2009), although decision makers evaluate the same criteria and associate them to different weights, the information processing interaction can be obtained in a globalized manner. By attributing to the criteria weights that represent a consensus of value for the group by means of an open discussion, each decision maker can analyze the problem separately, according to their specific point of view and interest, and then aggregate the information.

Chart 1. AHP fundamental scale.

Degree of Importance	Definition	Brief Explanation
1	Equally important	The elements contribute equally to the objective, criterion, and subcriterion.
2	Weakly or slightly more important	
3	Moderate importance	Experience and judgment moderately favor one element over the other.
4	Moderate to strong importance	
5	Strong importance.	Experience and judgment strongly favor one element over the other.
6	Strong to very strong importance	
7	Very strong importance	One element is very strongly favored over the other.
8	Very, very strong importance	
9	Extreme	The evidence favoring one element over the other is of the highest possible order of assertion.

Source: The author, based on Saaty (1980).

The judgments made in comparisons (Equation 1 and 2) are computed in decision matrices of order n, reciprocal and positive (n equals the number of compared elements). In the decision matrix A, the eigenvector and the maximum eigenvalue (λmax) that express the priority value (W) of the compared elements are computed. W belongs to an interval scale, because it is obtained from judgments about the ratios between the elements of matrix A - a ratio scale is a set of numbers whose ratios do not change when multiplied by a constant positive number (Saaty, 1980). W and λmax can be obtained by:

In which:

$$W\left(A_j\right)=\frac{a_v}{\sum_{i-1}^{m} a_v}\sum_{j=1}^{m} \qquad j=1,\ldots,n, \tag{1}$$

So that:

$$\sum_{i=1}^{n} W_i\left(A_j\right)=1 \qquad j=1,\ldots,n \tag{2}$$

$$Aw = {}_{max}{}^{x\,w} \tag{3}$$

Chart 2 below shows the format of a decision matrix as an example.

The third step " Consistency Check", consists of analyzing the consistency of the judgment given by the decision maker in matrices of order n ≥3. Decision matrices are considered of acceptable consistency if the CR (Consistency Ratio) is less than 10% (or 0.1). The Consistency Index (CI) of the decision matrix is calculated based on Equation 4 below.

$$CI = \frac{\left(\lambda_{max} - n\right)}{\left(n-1\right)} \tag{4}$$

In which:

$\lambda_{max} - n$ = consistency indicator

Chart 2. Example of a decision matrix.

1	a_{12}	a_{13}	...	a_{1n}
$1/a_{12}$	1	a_{23}	...	a_{2n}
$1/a_{13}$	$1/a_{23}$	1	...	a_{3n}
⋮	⋮	⋮	...	⋮
$1/a_{1n}$	$1/a_{2n}$	$1/a_{3n}$	...	1

Source: The author, based on Costa & Belderrain (2009).

After calculating the CI, the Random Index (RI) previously calculated for square matrices of order n must be found. Table 1 shows the RI values.

And then the Consistency Ratio (CR) is found, by Equation 5 below.

$$RC = \frac{IC}{IR} \tag{5}$$

Table 1. RI values.

n	1	2	3	4	5	6	7	8	9	10
IR	0.00	0.00	0.52	0.89	1.11	1.25	1.35	1.40	1.45	1.49

Source: The author, based on Saaty (1980).

3. Priority synthesis: three types of priorities must be calculated: (1) the criteria priorities - importance of each criterion in relation to the main objective; (2) the local alternatives priorities - importance of an alternative in relation to a specific criterion; and (3) global alternatives priorities - the criteria priorities and the local alternatives priorities are intermediate results used to calculate the global alternatives priorities. Thus, the priorities of global alternatives rank the alternatives relative to all criteria and hence to the overall goal. The priorities only make sense if they are derived from consistent matrices, so it is important to perform consistency checking. For Saaty & Vargas (2001), priorities are derived based on peer evaluations, using judgment or proportions of measures from a scale.

According to Ishizaka & Nemery (2013), the last step in the decision process is to perform sensitivity analysis – which entails input data perturbation to analyze results. Since a decision can affect several people, the AHP can be applied to a group of several experts aiming to reduce the bias usually present in the judgment of a single decision maker. The three most used ways to combine the group preferences are: (1) through consensus, used when there is a synergistic group and not a set of individuals- in this way, the judgment is agreed upon by all parties, determining a single value for each entry in the comparison matrix, (2) AIJ individual aggregation of judgments: by means of the geometric mean between the Saaty scale values assigned by each decision maker during the individual evaluations between the elements of a given matrix of paired comparisons to obtain the group priorities (3) AIP individual aggregation of priorities: each decision maker performs his/her pairwise comparisons between the elements of all hierarchical levels of the problem to obtain the final individual priorities. Then, the group priorities are calculated by means of normalized geometric mean or arithmetic mean (Ishizaka & Nemery, 2013). (For more details regarding mathematical formulas/deductions, see Saaty (1987) and Ishizaka & Nemery (2013)).

2.3. The AHP in demand forecasting

A bibliographic search was conducted in December 2019 and April 2021, in the Web of Science and Scopus bases, with the following keywords: "demand forecasting" and "Analytic Hierarchy Process", and thirty-four articles were found without limiting the period. Sixteen of those articles were disregarded; four of them for being unavailable for reading, and twelve articles for not fitting the research theme, given that the research focus was not demand forecasting.

The eighteen articles found demonstrate that the AHP method has already been applied in several areas and situations related to demand forecasting. The AHP contributed to improve the process or the forecast calculation, with all articles reporting good results, despite being used in problematic situations and with distinct objectives. The articles found are presented in Chart 3, in chronological order of publication, and with the following information: authors, year of publication, article title, and brief contextualization of the research. After analyzing the articles, it was possible to conclude that:

- 66.67% of the forecast studies applied the AHP in some stage of the demand forecast study as a support for decision making. One can highlight that the AHP was used for: identification, weighting and prioritization of information, product classification, and for the selection of the best forecasting model. The main applications of AHP were forecasting for: travel, water, electric power, traffic, underground space development, resources needed for chemical fires, spare parts and printers.
- 33.33% of the studies used the AHP effectively to calculate/adjust the demand forecast, of which the application in hotel and electric energy stands out. Thus, it can be seen that few demand forecast research studies were developed using the AHP to adjust/calculate the demand forecast, the focus of this study. Below are those articles that were the basis for our research.

Korpela & Tuominen (1996) used the AHP to forecast demand for strategic stock products (products to be sold to other industries). The problem was structured as from the identification of 5 criteria (and their respective sub-criteria) considered to have an impact on demand forecasting, the proposition of 3 scenarios associated with the sub-criteria, and demand growth rates (range) as decision alternatives in the model. From the synthesis of the model results, the authors calculated an average factor for the correction of the demand forecast (scenario probability multiplied by the arithmetic mean of the upper and lower limits of the range of growth rates).

Lee et al. (1996) used the AHP to estimate the demand for a new (high value-added) electronic product from market segmentation. Peer-to-peer comparisons were conducted to determine the relative purchasing power among groups of buyers (multiple criteria related to age and gender) for a given existing product and for the new product. A projection of potential purchasing power for the new product was estimated from a coefficient of variation between the two models. The authors state that the results with the AHP for the existing product were very close to the estimated and actual demand. Thus, they concluded that the AHP can be of great value when one does not have enough data to use traditional quantitative methods.

Yüksel (2007) proposed the integration of the AHP with time series to adjust, correct distortions of demand forecast for a 5-star hotel in Turkey. The author selected the time series model with the lowest error for 148 monthly forecast data on the hotel's demand. Using the AHP, he built a hierarchy containing 7 criteria affecting demand (collected from expert opinions), 3 possible scenarios for hotel demand, and levels (in percent) for demand correction associated with the scenarios, all from expert opinion. The result pointed to a more likely correction between -10% and 10% from the results from the time series model. According to the author, this yielded a higher accuracy with regard to the actual demand.

Chart 3. Article presentation. Source: the authors.

Reference	Title	Background
Banai-Kashani, 1984	Travel demand (modal split) estimation by hierarchical measurement	The authors developed a procedure to forecast travel demand and used the AHP in this process.
Lee et al., 1996	A model for estimating the potential demand of high touch product	The authors conducted a study on demand forecasting for a new product and used the AHP to evaluate the process of identifying the buying power of the existing product and the newly developed product with respect to each customer group.
Korpela & Tuominen, 1996	Inventory forecasting with a multiple criteria decision tool	The authors developed a hierarchy for demand forecasting using a multi-criteria approach.
Yüksel, 2007	An integrated forecasting approach to hotel demand	The authors developed a study for demand forecasting for the hotel industry and used the AHP to adjust the forecast.
Li & Kuo, 2008	The inventory management system for automobile spare parts in a central warehouse	The authors conducted research on stock management of automobile spare parts in a central warehouse, and developed a decision support system based on the AHP and fuzzy neural network.
Panagopoulos et al., 2012	Mapping Urban Water Demands Using Multi-Criteria Analysis and GIS	The authors conducted a study on water demand forecasting and used the AHP to evaluate the weighting factor for urban growth mapping.
Shih et al., 2012	A forecasting decision on the sales volume of printers in Taiwan: An exploitation of the Analytic Network Process	The authors developed a study on printer sales forecasting using the ANP (Analytic Network Process) method.
Rodrigues et al., 2015	Demand Forecasting Process of Innovation Using the Method Analytic Hierarchy Process	The authors developed an electricity demand forecasting study and used the AHP to adjust the demand forecast.
Fradinata et al., 2017	Comparison of hybrid ANN models: A case study of instant noodle industry in Indonesia	The authors developed new forecasting methods integrating artificial neural networks with the AHP, and with the Monte Carlo (MC) simulation method, which is an independent random probability production process.
Prasad & Raturi, 2017	Grid electricity for the Fiji islands: Future supply options and assessment of demand trends	The authors conducted a study on electricity forecasting and used the AHP to decide the best demand-forecasting model.
Wu et al., 2018	Research on Quantitative Demand of Underground Space Development for Urban Rail Transit Station Areas: A Case Study of Metro Line 1 in Xuzhou, China	The authors carried out research on forecasting and planning the development of underground space in railway transport stations, and the used the AHP as a weighted indicator scale.
Xu et al., 2019	Research on dynamic prediction method for traffic demand based on trip generation analysis	The authors studied dynamic forecasting for traffic demand based on trip generation analysis and used the AHP to evaluate the influence of factors.
Antosz & Ratnayake, 2019	Spare parts' criticality assessment and prioritization for enhancing manufacturing systems' availability and reliability	The authors developed an empirical system, which allows the performance of a criticality analysis, considering the perspective of the spare parts management system, adopting factors related to logistics and maintenance, and used the AHP to prioritize the spare parts within the selected group.
Zhou et al., 2020	An assessment model of fire resources demand for storage of hazardous chemicals	The authors developed a model to predict the demand of resources needed in accidental fires in hazardous chemical warehouses, using Fuzzy Analysis and the AHP.
Taylan et al., 2020	Assessment of Energy Systems Using Extended Fuzzy AHP, Fuzzy VIKOR, and TOPSIS Approaches to Manage Non-Cooperative Opinions	The authors developed a process to predict the most suitable energy systems for investment in a given region, using and integrating Fuzzy AHP, Fuzzy VIKOR, and Fuzzy TOPSIS methods.
Alalawin et al., 2021	Forecasting vehicle's spare parts price and demand	The authors developed a model to predict the demand and price of spare parts, using Linear Regression and the AHP.
Fu et al., 2020	Research on optimization method of VR task scenario resources driven by user cognitive needs	The authors developed a model for predicting cognitive load based on mapping user cognitive behavior and system design feature elements under multi-perception channels of Virtual Reality (VR) system, using QFD-CNN (Quality Function and Convolution Neural Network) methods and the AHP.
Chen et al., 2021	Forecast of flood disaster emergency material demand based on IACO-BP algorithm	The authors developed a model to predict the demand of emergency supplies in flood disaster by means of IACO-BP algorithm and used the AHP to comprehensively discuss the transportation time, and other indicators, so as to integrate the advantages and disadvantages of the circulation path in the disaster area.

Rodrigues et al. (2015) presented a model to adjust the demand forecast for electricity, from time series and through the AHP. To this end, the AHP prioritization algorithm was applied, obtaining the weights of factors and sub-factors. The adjustment indices were calculated using the final weight of the sub-factors and the arbitrated variation given by analysts for each factor. The authors concluded that the adjustment of forecasts based on the AHP is flexible and capable of dealing with tangible and intangible factors. Also, they suggested that a careful, efficient treatment of the qualitative factors can contribute to obtaining satisfactory results to reduce forecast uncertainties. Hence, future scenarios can be established with higher probability of occurrence.

Xu et al. (2019) presented a "dynamic" method to forecast traffic demand based on trip generation analysis. Combined with classical demand forecasting method, they used the AHP to evaluate and determine the influence of factors. The dynamic changes of trip characteristics and the main influencing factors of trip formation of future residents were analyzed. The predicted results compared with traditional forecasting results show that the development of land use, transportation, and travel choice under the influence of certain dynamic changes have occurred in traffic generation and provide a theoretical basis for urban traffic management and forecasting methods.

Zhou et al. (2020) developed a model to predict the demand for resources needed in accidental fires of hazardous chemical warehouses. Fuzzy AHP is used to investigate the actual combat coefficient of foam. When determining the weight of each factor influencing foam fire extinguishing efficiency, one of the main obstacles is to quantify the weights of various indicators, so an expert consultancy participated in the AHP step. Using the fire resource demand prediction model, the actual combat coefficient of tank foam demand was calculated. It was then possible to help firefighters to distribute firefighting equipment and maximize the performance of firefighting equipment.

3. Research method

This research is of applied nature, and combines the following approaches: qualitative (model building) and quantitative (solution and analysis of model results). Bertrand & Fransoo (2002) define quantitative research in production engineering as the research where a problem can be modeled which presents variables whose relationships are causal and quantitative. As for the objectives, the research is classified as exploratory, aiming at a greater knowledge about the subject studied. The procedures used were bibliographic research and mathematical modeling. Within the context of Operations Research, the Modeling and Simulation method helps in the construction of models aimed at representing and solving complex problems in real systems. These models are quantitative in nature and seek to absorb the main characteristics in the real system (Bertrand & Fransoo, 2002; Chwif & Medina, 2015). After presenting the characteristics/methodological framework of this research, the operational procedures are addressed in detail, i.e., the steps that were taken during the research.

3.1. Operational procedures of the research

Step 1 consisted of defining the object of study. In order to do that, it was necessary to consult the departments involved in the forecasting process, and analyze the sales history of the last five years. Also, the products with the largest fluctuation in demand and and of greatest interest to the company (the best-selling product) were identified to apply the proposed method. In step 2, the specialists were chosen. They are professionals with experience in the area, essential to conduct the research. According to the diagram of Ackermann & Eden (2011), the "players", "subjects", "regulators" and "crowd" are all stakeholders involved. They have high degree of interest and power, high degree of interest and low power, high degree of power and low interest and low degree of interest and power, respectively. In step 3, semi-structured brainstorming was performed with the experts; for the identification of internal and external factors that, in their view, affect the demand for the defined products. Brainstorming is a technique to create alternatives for complex decisions. Keeney (2012) proposed value-focused brainstorming, consisting of four steps: 1) Introduce the problem to be solved: the statement of the problem to be solved defines the purpose of brainstorming; 2) Identify the objectives to solve the problem: the set of objectives for a brainstorming session can be provided by the individual or organization facing the problem; 3) Generate alternative solutions individually: identify the set of objectives separately with each participant; and 4) Collectively generate alternative solutions: all objectives are combined and organized, and the group can add missing objectives.

In step 4, the AHP was applied with the decision makers in 3 steps: Step 1: Decomposition: based on the internal and external factors that affect demand forecast, the problem was structured and the AHP hierarchy was built; Step 2: Judgments: individual and structured interviews were conducted with the experts aiming at assigning weights to the factors; and Step 3: Synthesis of priorities: algebraic development, a process carried out with the aid of the Super Decisions software. Step 5 consisted in identifying the best time series model and its respective forecast result for the products studied through MAD (Mean Absolute Deviation), based on calculations from the system used by the company's (PPC).

Stage 6 proceeded the adjustment of the forecast in three steps: 1) calculation of an arbitrated variation to determine the demand growth rates for 4 possible scenarios (high and low growth and high and low decline); 2) assignment of arbitrated variation values to internal and external factors (criteria and sub-criteria) of the model by the specialists, according to the scenarios; and 3) obtaining the forecast adjustment percentage: sum of the multiplication of the AHP final result (criteria and sub-criteria weight) by the respective arbitrated variations assigned. The forecast adjustment percentage was obtained in two ways: by means of the individual preferences of the experts (model I), or by group preferences (model II). The last step was a sensitivity analysis, which aims to verify how the weight of internal and external factors can impact the forecast results. Figure 1 shows the application steps of this research.

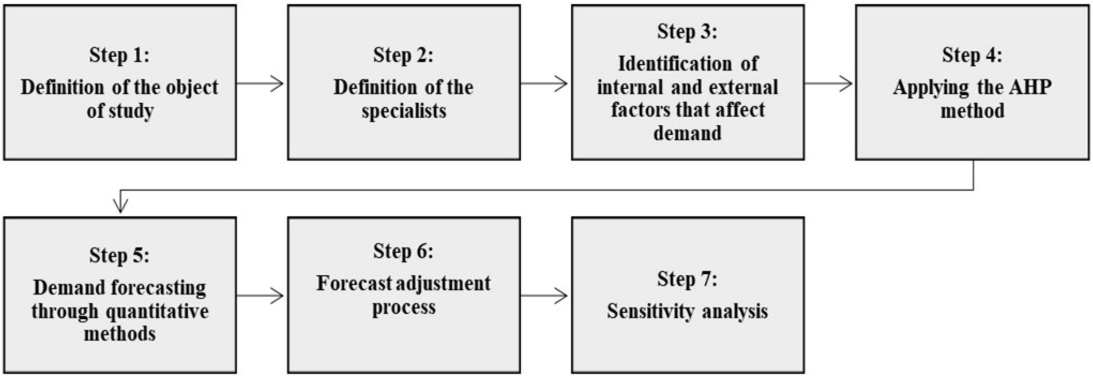

Figure 1. Application steps. Source: the authors.

4. Results and discussions

4.1. Definition of the study object

Company Z is a Brazilian industry in the textile segment that has been in business for 100 years. It occupies an area of 90 thousand square meters and employs 5 thousand employees. It offers an average portfolio of 812 models per collection, serving more than 30 stores in the Brazilian territory, as well as exporting to countries in South America, North America, Europe, Asia and Africa.

As company Z has a wide product portfolio, one product was chosen for the application of the proposed method, which in this study shall be called “B”. This choice was defined by means of initial conversations with the commercial area, the PPC, and with the company directors, with the intent of identifying the product of greatest interest to apply the method. Moreover, the sales history of the last five years was analyzed, aiming to identify the product with the greatest variation in demand. Figure 2 shows the sales history for the last 5 years for the month of December for product B.

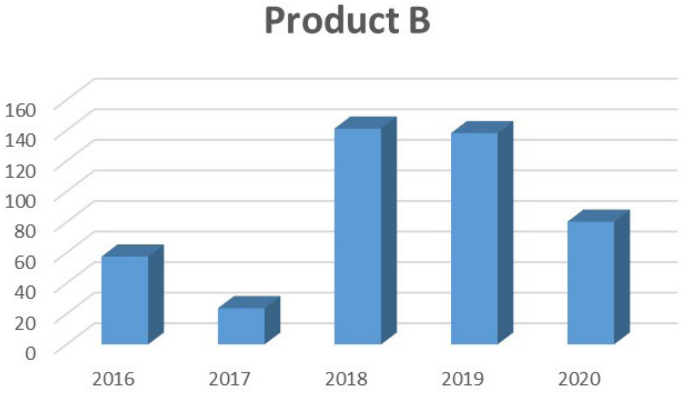

Figure 2. Product B – sales history (in units). Source: the author

In December 2017, product B had a -59% drop. In 2018, there was a surprising high growth of 495%, and in 2019 and 2020 there was a drop of -2% and -42%, respectively. The company's top management believes that these oscillations are influenced by competitors' actions and the promotional actions carried out to leverage sales in some periods, considering that quality and price are factors that impact the sale of this product.

4.2. Definition object of the specialists

Considering the departments with a high degree of interest, knowledge and decision-making power in the demand forecasting process, thirteen specialists were selected: (1) Superintendent Director, (2) Commercial and Marketing Director, (3) PPC Manager, (4) PPC Coordinator, (5) PPC Analyst, (6) Sales Administrative Manager, (7) Sales Manager - Magazines, (8) Sales Manager - Retail, (9) Sales Analyst, (10) Sales Assistant, (11) Production Manager, (12) Franchise Manager, and (13) Market Intelligence Analyst.

4.3. Definition of internal and external factors

Individual brainstorming was conducted with the 13 experts. The problem was presented through this question, "What internal and external factors affect demand forecasting?" Initially, 16 internal factors and 22 external factors were collected. After the tabulation of the results by the facilitator, the factors were reviewed in their meanings and organized into a final list containing 10 internal factors and 12 external factors, which was presented to the experts for validation (Chart 4).

Chart 4. Final list of external and internal factors validated by the experts. Source: the authors.

Internal factors	External factors
Product Technology	Seasonality
Promotional Actions	Commemorative Dates
Marketing Activities	Exchange Variation
Product Quality	Fashion Trends
Sales Price	Economy
Punctuality in delivery	Competition
Sales Team Motivation	Unexpected events
Prompt Delivery	Unemployment Level
Customer Relationship	Inflation
Customer Relationship Strengthening	Seasons / Weather
	Customer loss and gain
	Franchise Renovations/ Inaugurations

4.4. Application of the AHP

4.4.1. Step 1 – decomposition

To formulate a decision problem, it is first necessary to define the objective, the criteria and sub-criteria, and the alternatives for solving the problem. Then, the problem must be represented in a hierarchy. The objective is to "adjust the demand forecast"; the criteria and sub-criteria were defined through brainstorming with specialists, which are presented in Chart 4. The alternatives are the possible scenarios and growth rates related to the demand, which in this case will not compose the problem hierarchy. Figure 3 presents the problem hierarchy, which comprises four levels:

- Level 0 – the objective of the problem: to adjust the demand forecast;
- Level 1 – the criteria subdivision (internal and external);
- Level 2 – internal criteria (sales and product) and external criteria (seasonality, fashion trends, unexpected events, competition, loss and gain of customers, economic indicators, reform and opening of franchises);
- Level 3 – these are the subcriteria related to level 2; only the criteria sales (promotional actions, marketing actions, team motivation, relationship with the customer, customer strengthening, and punctuality in delivery),

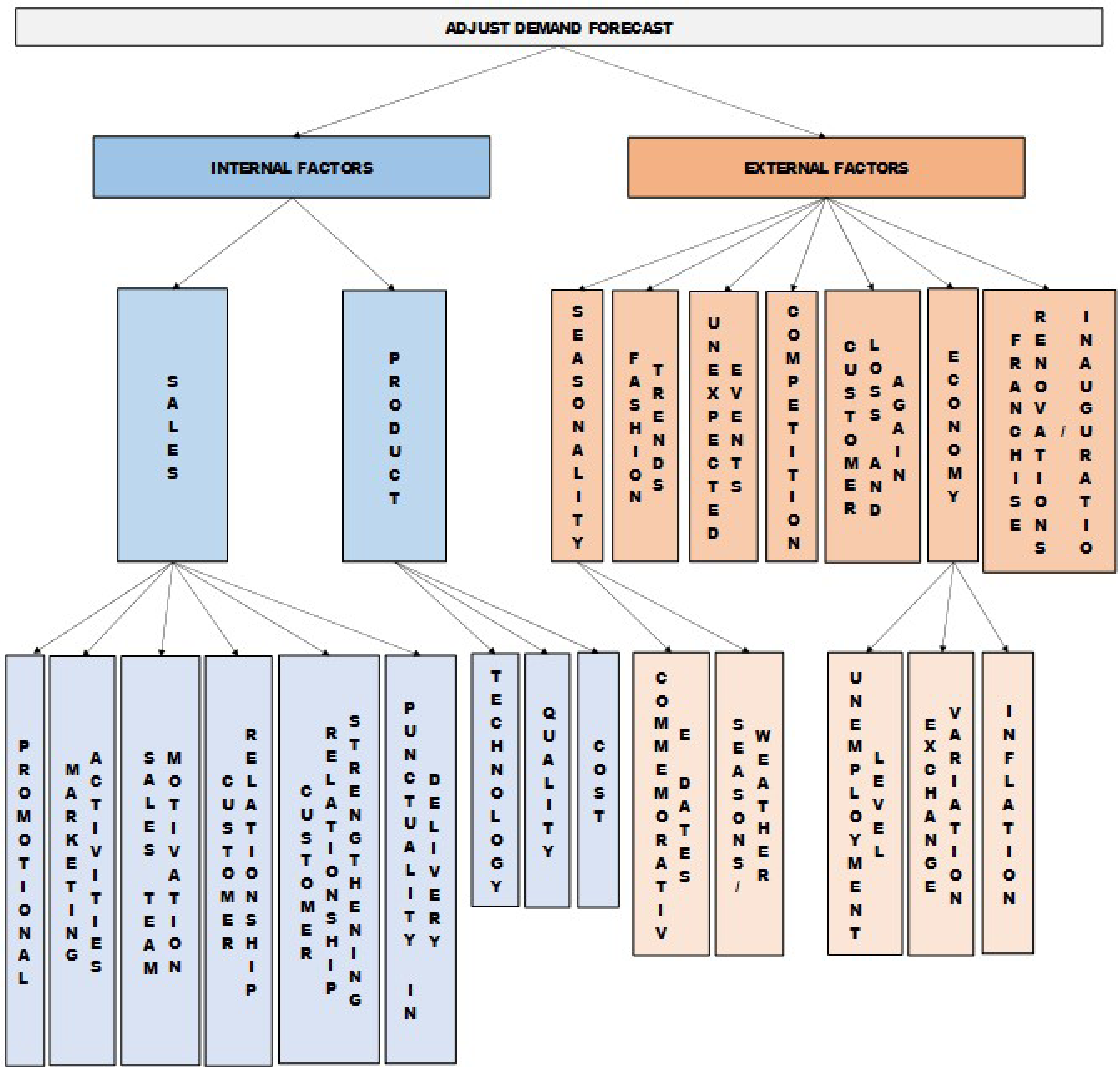

Figure 3. Problem hierarchy. Source: the author.

product (technology, quality and cost), seasonality (commemorative dates and seasons and weather) and economy (unemployment level, exchange rate variation and inflation) have subcriteria.

4.4.2. Step 2 – judgments

Of the thirteen specialists who participated in the brainstorming, five were considered as decision makers (E1 - sales analyst, E2 - PPC coordinator, E3 - general commercial manager, E4 - retail sales manager, and E5 - superintendent director) able to perform the “pairwise comparisons”. This process was performed in the software “Super Decisions®”. In order to do that, a structured individual interview was conducted with each decision maker.

4.4.3. Step 3 – priorities synthesis

This step consists of the whole algebraic process of the AHP method, which results in a ranking of priorities. This process was performed in the “Super Decisions®” software. Table 2 presents the priority ranking of each

Table 2. Expert priority ranking. Source: the authors.

Name	E1	E2	E3	E4	E5
Sales					
Marketing Actions	1.67%	5.11%	1.70%	2.41%	3.03%
Promotional Actions	2.10%	2.84%	2.35%	2.12%	1.51%
Strengthening Channels	2.62%	4.87%	2.63%	1.72%	3.03%
Team Motivation	2.96%	6.04%	2.63%	2.28%	3.03%
On-Time Delivery	4,69%	7.24%	4.71%	5.58%	3.03%
Customer Relationship	2.62%	7.24%	2.63%	2.56%	3.03%
Seasonality					
Commemorative Dates	6.57%	3.58%	6.91%	3.78%	3.66%
Seasons of the Year	2.19%	1.79%	2.30%	3.78%	1.83%
Products					
Cost	5.56%	8.66%	5.56%	5.56%	3.33%
Quality	5.56%	10.92%	5.56%	5.56%	6.67%
Technology	5.56%	13.75%	5.56%	5.56%	6.67%
Economic Indicators					
Inflation	4.82%	0.58%	4.07%	3.99%	4.01%
Unemployment Level	4.82%	1.46%	4.07%	3.99%	4.01%
Exchange rate variation	4.82%	0.92%	4.07%	3.99%	4.01%
Competition	8.08%	2.43%	10.92%	11.98%	12.03%
Unexpected Events	14.46%	7.98%	12.21%	11.98%	12.03%
Openings and Renovations Franchises	6.07%	6.55%	6.17%	5.03%	7.57%
Customer Gains and Losses	9.88%	3.62%	10.92%	11.98%	12.03%
Fashion Trends	4.96%	4.41%	5.03%	6.16%	5.48%

expert obtained in the "Super Decisions" software. The consistency index (CI) was calculated, and when an inconsistency above 0.1 was detected, the decision makers were asked to review their judgments.

4.5. Demand forecasting through quantitative methods

Company Z performs demand forecasting considering the billing history of each product. It compares all temporal series models (simple moving average, weighted moving average, simple exponential smoothing, double exponential smoothing, and triple exponential smoothing) through MAD (mean absolute deviation) to select the most appropriate one for the product in question, and the forecast is determined by the model that presents the smallest margin of error. MAD (mean absolute deviation) is the only metric used by company Z, so other metrics present in the literature were not addressed in this study.

Thus, PPC calculated the demand forecast for product B (Table 3) considering the billing horizon of the last five years. The model that presented the smallest error margin was "triple exponential smoothing".

Table 3. Demand forecast – quantitative methods. Source: the authors.

Month	Forecast
January	286,003
February	397,900
March	320,000
April	218,202
May	445,003

4.6. Demand forecast adjustment process

To adjust the demand forecast with the AHP, the first step was to evaluate the forecast error margins to determine the "arbitrated variation". Thus, the margins of error of 2020 forecasts for product B were calculated, to then calculate the arbitrated variation. To do this, we obtained the average percentage of the 3 months with greater errors for more, and the average percentage of the 3 months with lesser errors for less, as well as the averages for the quarters with intermediate percentages (for less and for more), as presented in Table 4.

Table 4. Arbitrated variations of output B. Source: the authors.

Month	Error margin 2020	Arbitrated Variation	Scenarios
January	-69%		
February	-56%	-53%	High decline
March	-33%		
April	-24%		
May	-11%	-14%	Low decline
June	-7%		
July	-3%		
August	19%	17%	Low growth
September	36%		
October	37%		
November	86%	70%	High growth
December	89%		

The arbitrated variations (VA) are the demand growth rates established for the possible scenarios: high growth (70%), low growth (17%), high decline (-53) and low decline (-14%).

Next, the specialists were consulted to classify the factors according to the possible demand growth rates (high growth (70%), low growth (17%), high decline (-53%) and low decline (-14%)), that is by the arbitrated variation (VA). This process was done monthly, with the same priority ranking obtained with the method, alternating only the demand scenario from one month to the next. Table 5 presents the arbitrated demand variations for each specialist for January.

Table 5. Classification arbitrated variation – january. Source: the authors.

Name	E1	VA	E2	VA	E3	VA	E4	VA	E5	VA
Sales										
Marketing Actions	1.67%	17%	5.11%	-14%	1.70%	70%	2.41%	17%	3.03%	17%
Promotional Actions	2.10%	17%	2.84%	-14%	2.35%	17%	2.12%	17%	1.51%	17%
Strengthening of Channels	2.62%	17%	4.87%	70%	2.63%	70%	1.72%	17%	3.03%	17%
Team Motivation	2.96%	17%	6.04%	70%	2.63%	17%	2.28%	70%	3.03%	70%
On-Time Delivery	4.69%	-14%	7.24%	-14%	4.71%	-14%	5.58%	-14%	3.03%	-14%
Customer Relationship	2.62%	17%	7.24%	70%	2.63%	70%	2.56%	70%	3.03%	70%
Seasonality										
Commemorative Dates	6.57%	17%	3.58%	17%	6.91%	17%	3.78%	17%	3.66%	17%
Seasons of the Year	2.19%	17%	1.79%	17%	2.30%	17%	3.78%	17%	1.83%	17%
Products										
Cost	5.56%	-14%	8.66%	-14%	5.56%	-14%	5.56%	-14%	3.33%	-14%
Quality	5.56%	70%	10.92%	17%	5.56%	70%	5.56%	70%	6.67%	70%
Technology	5.56%	17%	13.75%	17%	5.56%	70%	5.56%	17%	6.67%	17%
Economic Indicators										
Inflation	4.82%	-14%	0.58%	17%	4.07%	-14%	3.99%	-14%	4.01%	-14%
Unemployment Level	4.82%	-14%	1.46%	-14%	4.07%	-14%	3.99%	-14%	4.01%	-14%
Exchange rate variation	4.82%	-14%	0.92%	17%	4.07%	-14%	3.99%	-14%	4.01%	-14%
Competition	8.08%	17%	2.43%	-14%	10.92%	17%	11.98%	70%	12.03%	17%
Unexpected Events	14.46%	70%	7.98%	-53%	12.21%	17%	11.98%	17%	12.03%	70%
Openings and Renovations Franchises	6.07%	17%	6.55%	17%	6.17%	17%	5.03%	-14%	7.57%	-14%
Customer Gains and Losses	9.88%	17%	3.62%	17%	10.92%	17%	11.98%	17%	12.03%	17%
Fashion Trends	4.96%	17%	4.41%	17%	5.03%	17%	6.16%	17%	5.48%	17%

The prediction adjustment percentage was determined by multiplying the priority percentage of each factor by the arbitrated variation (VA). The final result was obtained by adding these values, as exemplified in Table 6, which shows the adjustment percentage obtained with expert E1 for January through individual preferences. The forecast adjustment percentage can be obtained in two ways: by means of the individual preferences of the experts (model I), or by the preferences of the group (model II). Table 6 presents the percentages of

Table 6. Adjustment percentages – model I. Source: the authours.

Month	E1	E2	E3	E4	E5
January	19.95%	12.43%	19.62%	20.13%	22.07%
February	-6.15%	10.23%	2.81%	-0.51%	-21.52%
March	-7.96%	11.35%	-5.02%	-6.10%	-19.46%
April	-1.19%	16.71%	3.37%	-0.21%	-3.28%
May	-0.37%	8.99%	3.37%	0.62%	-5.77%

adjustment considering the individual preferences. The adjustment percentages were inserted in the initial forecast presented in subsection 4.5; Table 7 presents the adjusted forecasts of model I, which considers the experts' individual preferences. In January, the initial forecast had a margin of error of -27% in relation to the actual sales. With the adjustment provided by the proposed method, it was possible to reduce the forecast error given by quantitative methods

Table 7. Adjusted forecast – model i. Source: the authors.

Expert	Initial forecast (IF)	Adjustment percentage (AP)	Adjusted forecast (AF)	Sales in the Period (SP)	Error margin (IF / SP)	Error margin (AF / SP)
			January			
E1	286,003	20%	343,204	392,486	-27%	-12.56%
E2	286,003	12%	320,323	392,486	-27%	-18.39%
E3	286,003	20%	343,204	392,486	-27%	-12.56%
E4	286,003	20%	343,204	392,486	-27%	-12.56%
E5	286,003	22%	348,924	392,486	-27%	-11.10%
			February			
E1	397,900	-6%	374,026	343,810	16%	8.79%
E2	397,900	10%	437,690	343,810	16%	27.31%
E3	397,900	3%	409,837	343,810	16%	19.20%
E4	397,900	-1%	393,921	343,810	16%	14.58%
E5	397,900	-22%	310,362	343,810	16%	-9.73%
			March			
E1	320,000	-8%	294,400	165,124	94%	78.29%
E2	320,000	11%	355,200	165,124	94%	115.11%
E3	320,000	-5%	304,000	165,124	94%	84.10%
E4	320,000	-6%	300,800	165,124	94%	82.17%
E5	320,000	-19%	259,200	165,124	94%	56.97%
			April			
E1	218,202	-1%	216,020	211,054	3%	2.35%
E2	218,202	17%	255,296	211,054	3%	20.96%
E3	218,202	3%	224,748	211,054	3%	6.49%
E4	218,202	0%	218,202	211,054	3%	3.39%
E5	218,202	-3%	211,656	211,054	3%	0.29%
			May			
E1	445,003	0%	445,003	379,624	17%	17.22%
E2	445,003	9%	485,053	379,624	17%	27.7%
E3	445,003	3%	458,353	379,624	17%	20.74%
E4	445,003	1%	449,453	379,624	17%	18.39%
E5	445,003	-6%	418,303	379,624	17%	10.19%

by 16% (difference between the error margins of the initial forecast (IF) and the adjusted forecast (AF)), considering the smallest margin of error obtained with expert "E5". In February, the initial forecast was 16% higher than the actual sales. With the adjustment provided by the proposed method, the forecast error could be reduced by 25%, considering the smallest margin of error obtained with expert "E5". It is worth noting that the experts "E2" and "E3" obtained a margin of error higher than the initial forecast. In March, the initial forecast was 94% higher than the actual sales. The adjustment provided by the method reduced the forecast error by 37% using the smallest margin obtained with "E5" expert. In April, the initial forecast was 3% higher than the actual sales. The error was reduced with the adjustment provided by the method by 3% considering the smallest margin with expert “E5”. Experts “E2” and “E3” obtained a margin of error larger than the initial forecast.

The initial forecast in May was 17% higher than the actual sales. The adjustment provided by the method allowed for a reduction of 7% In the error, considering the smallest margin with expert “E5”. Experts “E2”, “E3” and “E4” obtained a margin of error larger than the initial forecast.

The sensitivity analysis was performed to verify how the weight of internal and external factors can impact the forecast results. The degree of importance given by each specialist to the “internal criteria” when compared to the “external criteria” was varied between 1/9 and 9. For the “E1” expert in January, February, March and May, the increase in the importance degree from 1/8 to 9 did not show improvements in the results. The latter were kept at 346,710, 349,817 and 278,428. With specialists “E2” and “E3”, in January the increase in the degree of importance from 1/8 to 9 showed improvements in the results. In February, March, April and May, the increase in the degree of importance from 1/8 to 9 did not improve the results, which were kept at 361,293, 318,572, 236,310 and 476,185 with “E2” and 370,244, 288,686, 217,371 and 443,319 with “E3”. With the expert “E4” in January the increase in the degree of importance from 1/8 to 9 improved the results. In February, March and May, the increase in the degree of importance from 1/8 to 9 did not improve the results, kept at 371.994, 288,625 and 427,694. In April and May, the increase in the degree of importance from 1/8 to 1/5 improved the results. Finally, with specialist “E5” in January, February, April and May the increase in the degree of importance from 1/8 to 9, 1/8 to 1, 1/8 to 1/2 and 1/8 to 1/5 respectively, improved the results. As for March, the increase in the degree of importance from 1/8 to 9, did not bring improvements, with the result at 208,388 being kept.

In another analysis, the preferences of the group of experts were combined through the geometric mean of the individual evaluations, as shown in Table 8. After calculating the geometric mean, the values were normalized.

Table 8. Ranking of group priorities – model II. Source: the authors.

Name	E1	E2	E3	E4	E5	Geometric Average	Normalized Result
Sales							
Marketing Actions	1.67%	5.11%	1.70%	2.41%	3.03%	2.54%	2.71%
Promotional Actions	2.10%	2.84%	2.35%	2.12%	1.51%	2.14%	2.28%
Strengthening of Channels	2.62%	4.87%	2.63%	1.72%	3.03%	2.81%	2.99%
Team Motivation	2.96%	6.04%	2.63%	2.28%	3.03%	3.18%	3.39%
On-Time Delivery	4.69%	7.24%	4.71%	5.58%	3.03%	4.86%	5.17%
Customer Relationship	2.62%	7.24%	2.63%	2.56%	3.03%	3.29%	3.51%
Seasonality							
Commemorative Dates	6.57%	3.58%	6.91%	3.78%	3.66%	4.68%	4.99%
Seasons of the Year	2.19%	1.79%	2.30%	3.78%	1.83%	2.29%	2.43%
Products							
Cost	5.56%	8.66%	5.56%	5.56%	3.33%	5.48%	5.84%
Quality	5.56%	10.92%	5.56%	5.56%	6.67%	6.59%	7.03%
Technology	5.56%	13.75%	5.56%	5.56%	6.67%	6.91%	7.36%
Economic Indicators							
Inflation	4.82%	0.58%	4.07%	3.99%	4.01%	2.83%	3.02%
Unemployment Level	4.82%	1.46%	4.07%	3.99%	4.01%	3.41%	3.63%
Exchange rate variation	4.82%	0.92%	4.07%	3.99%	4.01%	3.11%	3.31%
Competition	8.08%	2.43%	10.92%	11.98%	12.03%	7.91%	8.43%
Unexpected Events	14.46%	7.98%	12.21%	11.98%	12.03%	11,52%	12.28%
Openings and Renovations Franchises	6.07%	6.55%	6.17%	5.03%	7.57%	6.22%	6.63%
Customer Gains and Losses	9.88%	3.62%	10.92%	11.98%	12.03%	8.91%	9.50%
Fashion Trends	4.96%	4.41%	5.03%	6.16%	5.48%	5.18%	5.51%
	100.00%	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**93.87%**	**100.00%**

Then, the demand scenario (VA) rankings given by each expert were multiplied by the group’s priority ranking. Table 9 presents the forecast adjustment percentages considering the group preferences (model II). Table 10 presents the adjusted forecasts of model II, which considers the priority ranking of the expert group.

With the second model, the adjustment for January reduced the forecast error by 17%, considering the smallest margin of error with specialist “E3”. In February, the adjustment reduced the forecast error by 21%,

Table 9. Adjustment percentage – model II. Source: the authors.

Month	E1	E2	E3	E4	E5
January	20.73%	4.95%	23.00%	20.29%	22.33%
February	-1.30%	0.75%	7.48%	1.51%	-17.90%
March	-4.40%	5.63%	-3.51%	-4.40%	-15.40%
April	2.61%	12.02%	4.53%	0.56%	-1.97%
May	3.50%	12.02%	4.53%	1.45%	-3.93%

Table 10. Adjusted forecast – model II. Source: the authors.

Expert	Initial forecast (IF)	Adjustment percentage (AP)	Adjusted forecast (AF)	Sales in the Period (SP)	Error margin (PI / VOP)	Error margin (PA / VOP)
			January			
E1	286,003	21%	346,064	392,486	-27%	-11.83%
E2	286,003	5%	300,303	392,486	-27%	-23.49%
E3	286,003	23%	351,784	392,486	-27%	-10.37%
E4	286,003	20%	343,204	392,486	-27%	-12.56%
E5	286,003	22%	348,924	392,486	-27%	-11.10%
			February			
E1	397,900	-1%	393,921	343,810	16%	14.58%
E2	397,900	1%	401,879	343,810	16%	16.89%
E3	397,900	7%	425,753	343,810	16%	23.83%
E4	397,900	2%	405,858	343,810	16%	18.05%
E5	397,900	-18%	326,278	343,810	16%	-5.10%
			March			
E1	320,000	-4%	307,200	165,124	94%	86.04%
E2	320,000	6%	339,200	165,124	94%	105.42%
E3	320,000	-4%	307,200	165,124	94%	86.04%
E4	320,000	-4%	307,200	165,124	94%	86.04%
E5	320,000	-15%	272,000	165,124	94%	64.72%
			April			
E1	218,202	3%	224,748	211,054	3%	6.49%
E2	218,202	12%	244,386	211,054	3%	15.79%
E3	218,202	5%	229,112	211,054	3%	8.56%
E4	218,202	1%	220,384	211,054	3%	4.42%
E5	218,202	-2%	213,838	211,054	3%	1.32%
			May			
E1	445,003	4%	462,803	379,624	17%	21.91%
E2	445,003	12%	498,403	379,624	17%	31.29%
E3	445,003	5%	467,253	379,624	17%	23.08%
E4	445,003	1%	449,453	379,624	17%	18.39%
E5	445,003	-4%	427,203	379,624	17%	12.53%

considering that expert “E5” had an error margin of -5% in relation to the actual sale. It is worth pointing out that specialists “E2”, “E3” and “E4” had a margin of error larger than the initial forecast. In March, the proposed method reduced the forecast error by 29%, considering the smallest margin of error obtained with “E5” expert, and “E2” had a margin of error larger than the initial forecast. In April, the proposed method reduced the forecast error by 2%, considering the smallest margin of error obtained with expert “E5”. The other experts had a larger error margin than the initial forecast. In May, the proposed method reduced the forecast error by 5%, considering the smallest margin of error obtained with “E5” expert, while the other experts had a larger margin of error than the initial forecast.

Both models result in a different forecast for each specialist, requiring a final evaluation by PPC and those involved in the forecasting process for decision making. It was possible to perform the AHP method application process through a consensus when there is a synergic group, where the judgment is agreed upon jointly. Then, a single value for each entry in the comparison matrix is determined, resulting in a single forecast.

In this study, it was decided not to apply the AHP through consensus due to the influence that the "high decision power" experts could cause on the "lower decision power" experts. This could distort the results.

The first and second models had similar results: in January, the difference in error reduction between the models was only 1%; in February, it was 4%; in March, 8%; in April, 1%; and in May, 2%. This shows that both are effective. It is worth noting that in January model II was more assertive, while in February, March, April and May model I was more assertive.

The expert "E2" (PPC coordinator) had the lowest accuracy, while "E1" (sales analyst) and "E5" (superintendent director) had the most assertive results. Specialists "E3" (general commercial manager) and "E4" (retail sales manager) also had good results, much more accurate than "E2". This demonstrates that the commercial area is the most suitable for the forecast adjustment process because it has an external view of the market, unlike PPC, which only has an internal view of the company.

5. Conclusion

In a context of uncertainty due to the particularities of the sector (seasonality, fashion trends, product life cycle, and marketing and sales actions) associated with the effects of the Covid-19 Pandemic, the time series methods did not present good demand forecast results for the company studied, generating excess inventory in some moments and lack of products in others, making it difficult for the PPC (Production Planning and Control) decision making process. This research aimed to adjust the demand forecast method, from a historical series starting point, by means of the AHP method. To this end, a bibliographical review was conducted on the Web of Science and Scopus databases. The results allowed us to verify that there is still a gap when it comes to exploring the AHP as a tool for forecasting. This motivated us to apply it in the textile industry, which is strongly influenced by variations due to fashion trends, product life cycle, and marketing and sales actions. This study proposed 6 steps to adjust the demand forecast through the AHP: (1) defining the object of study, (2) defining the experts, (3) defining the internal and external factors affecting demand, (4) applying the AHP method, (5) forecasting through quantitative methods, and (6) forecasting the adjustment process.

The results of the two models were satisfactory since the proposed method reduced the forecast error of quantitative methods by 16% in January; 25% in February; 37% in March; 3% in April; 7% in May for model I; 17% in January; 21% in February; 29% in March; 2% in April; and 5% in May for model II. Considering that demand forecasting is the basis for all strategic and planning decisions of a company, one can conclude that the accuracy obtained with the AHP-based forecast adjustment method contributes to better customer service, higher profits, and lower losses. The results presented showed that the strategy followed in this study can be a good way to perform forecasting, as the AHP-based forecast adjustment method has a flexible and systematic structure that contributes to obtaining satisfactory results that allow for a reduction in forecasting uncertainties.

The limitation of this study was related to the fact that the topic was still little explored. In view of the scenario of uncertainty inherent to the forecasting process and the effectiveness of the AHP method in complex problems, further research is suggested with the objective of ratifying the AHP method as an adequate tool for forecast adjustment. As a suggestion for future reasearch, we recommend the application of the proposed method in other areas to identify/evaluate the validity period of the priority ranking given by the AHP method. We also suggest that the arbitrated variation be determined by specialists in the commercial area, with the purpose of testing a new model. This suggestion arose because in this study the arbitrated variation was determined based on historical sales and forecast.

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