Degree work in application mode

[201020] Design of a digital platform with demand forecasting and costing system for the improvement of a retailer's performance indicators

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Abstract

To have an accurate demand forecast and to manage resources is crucial for retailers' strategy. They must make decisions such as the amount of product to order from distribution centers and what products they sell to consumers. The management of their businesses and their sales are affected by many variables such as weather, seasonality, consumers taste and availability of the products they order, among many others. In this project these factors will be considered in a retailer from Crem Helado, the most important ice cream selling company in Colombia, in order to build a strategy that will contribute to the administration of the business. The impact of this project is that it can be highly applicable and extrapolated to other retailers. The methodology to build this strategy is to establish a model that can predict the behavior of the demand, to applicate a costing system to manage resources and *drivers* and to integrate both models into a digital platform that adapts to the retailer's situation, and facilitates decision making throughout a functional, reliable, and usable software that seeks for the improvement of KPIs (Key Performance Indicators).

Key Words: Retailer, Demand Prediction, Costing System, Strategy, Digital Platform, KPIs.

1. Justification and problem statement

Retailer's sales are affected by a variety of conditions such as product availability, weather, seasonality, the existence of alternative products, discounts, and advertising (Raju, Kang, Moroz, Clement, et al 2015). In fact, this is evidence of the challenge of selling in a volatile environment and it also highlights the retailer's necessity of generating a sales strategy that supports operating under unfavorable market conditions. In most cases, these conditions cannot be modified and require adaptation. In that regard, the strategy is successful when every part of the supply chain is coordinated because lead time delivery is reduced, there is less inventory and there is less reprocessing (Hung, Eldridge, 2019).

Substantial support for the strategy to improve the performance of the supply chain, is its ability to generate demand forecasts (Eksoz, Mansouri, Bourlakis, 2014). The authors highlight the importance of information between all parts of the supply system because if its delivery isn´t precise, forecasts will be highly affected. Wholesalers deliver the product to the final consumer or those who market it. For this purpose, the data they handle is of the highest importance. Syntetos, Babai, et al (2010) applied Exponential Smoothing methods and an SKU (Stock Keeping Unit) classification method according to their inventory turnover. This substantially improved their business in terms of inventory control, lead time delivery, product availability, which resulted in a positive impact on business's profitability.

Considering food industry's relevance for every economy, a costing tool that provides accurate information is crucial to support decision-making and outline strategies that improve the performance of people, resources, and activities of a company (Dwivedi, Chakraborty, 2016). The application of an activity-based costing method is a useful tool to manage costs. With this method, the values of direct and indirect costs are classified. The ABC method applied by these authors was successful in a food processing company in Bihar, India by achieving effectiveness in cost control. Considering the previous evidence, a proper costing management contributes to the sales strategy by managing costs for accurate decision making.

The ice cream market is a significant part of food industry's ecosystem. With the use of the database Passport (2020), which provides demographic data, socio-economic studies, and research of various industries, the following table was built to illustrate the growth of ice cream sales in Colombia:

Geography	Category	Data type	Units	2014	2015	2016	2017	2018	2019
Colombia	Ice cream and frozen desserts	Sales volume	Billons of COP	1,281	1,347	1,402	1,410	1,448	1,527

Table 1. Ice cream sales growth in Colombia. Source: Passport. Euromonitor International (2020). The Authors.

As a result, the ice cream sales in Colombia have increased over the past six years. The sale volumes indicate that there is a tangible opportunity to reach a market that is growing. Currently, in Colombia there are about 350 dairy producers in the market and in terms of consumption, ice cream has a share of 8.7%. An average Colombian can consume around 1.4 liters of ice cream annually, which explains the annual growth in this market of 3.1% (La República, 2019). Additionally, in an analysis form Sectorial (2019) it is established that the ice cream industry in Colombia is generating 98,000 tons of product and $900,000 COP million per capita. The foregoing points out the importance of the ice cream industry for the country. The company that has the most relevance in the ice cream market in Colombia is Crem Helado, a brand from Meals S.A.S, with a history of more than 70 years. The brand has consolidated the market with a 41.2% share (La República, 2019).

According to the Integrated Management Report of Nutresa (2018), in Meals' supply chain, raw materials are collected in each of the 30 plants they hold in Colombia. With the collected inputs, ice cream references of the Crem Helado's brand are produced, such as: Chococono, Artesanal, Jumbo, Vaso Hobby Sundae , Heladino, Boom, Chocolisto, Jet, Tosh, Sinfonía, Polet, Bocatto, and Aloha, among other references (Crem Helado, 2020). The finished products arrive at each of the 85 Meals' Distribution Centers in the country and they store the ice cream references and supply authorized retailers, supermarkets, and small neighborhood stores with product orders. Distributors deliver the products to retailers and they are responsible for marketing it to customers. The dynamics of neighborhood stores and supermarkets is the direct sale of ice cream references. The following image illustrates the interaction of the links in Meals' supply chain:

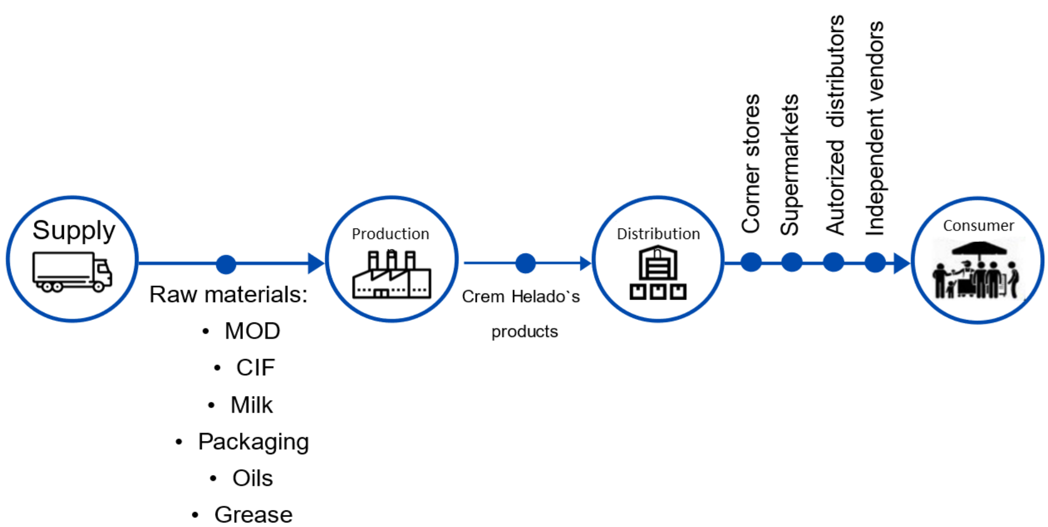
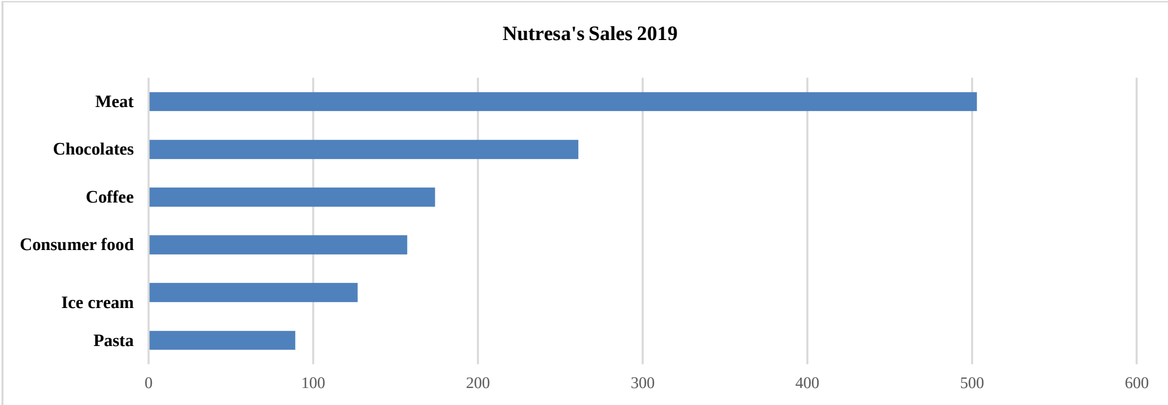


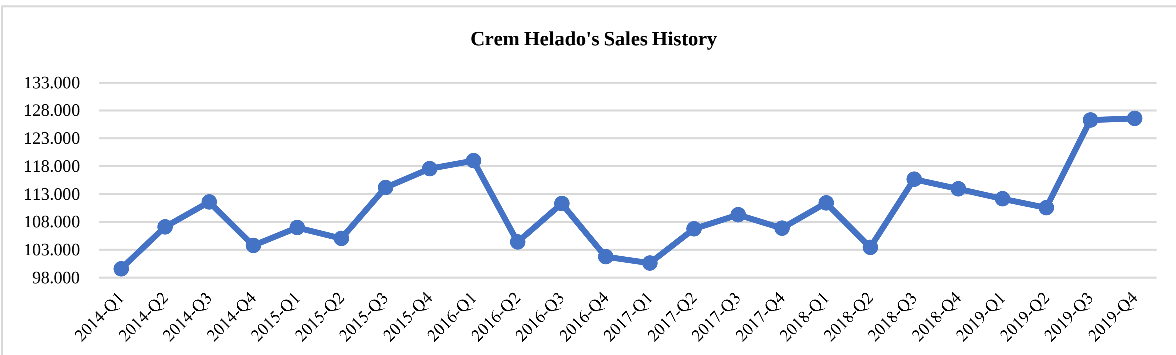
Diagram 1. Meals supply chain. Source: Nutresa Integrated Report (2018). The Authors.

Retailers, neighborhood stores, and supermarkets are crucial sections of Meals' supply chain because they possess the main contact with the customer. For this reason, the strategies that are carried out in these channels will directly impact the ice cream sales. This can be visualized in the graph built with the information of sales results per business unit from Nutresa (2019). The sales of Crem Helado are 8.1% of the company's profit, with a total of 126 billion (COP), which acknowledges the significance of this business branch for the company.



Graph 1. Nutresa 2019 sales. Source: Nutresa results presentation (2019). The Authors.

According to Mario Alberto Niño, president of Meals, although ice creams do not generate the highest percentage of sales for Nutresa, they are one of the most profitable business branches (La República, 2019). The following graph was built considering the historical sales results of Nutresa until 2019:



Graph 2. Crem Helado's sales volume. Sourse: Nutresa. (2019). The Authors.

The preceding graph shows an increase in sales which rose to 126 billion (COP). This corresponds to a percentage increase of 11% compared to the last quarter of 2018, which is a notable increase. The graph also registers that sales reached the highest peak in the last 5 years. Undoubtedly this supports the statement of Crem Helado's president: although Crem Helado is not Nutresa's largest business, it has a sizable profit margin. In addition to this, it is import for Nutresa to expand its market. In their Integrated Management Report, it is established that part of the company's vision is to strengthen their distribution channels with technology and innovation in other to reach more costumers (Nutresa 2019).

The importance of sales channels with direct interaction with costumers is evident in the fact that Nutresa is investing resources to develop strategies to train their authorized marketers[1] in indicators, sales methods, and numerical analysis (Nutresa 2019), which are one of Meals' main sales channels. The project to be developed focuses on the Crem Helado ice cream retailer in El Restrepo, a neighborhood in the city of Bogotá, which stores product from the Meals' Distribution Centers in industrial refrigerators, sales the product in its main location and supplies the independent Crem Helad's vendors of the area.

In conversations with Crem Helado's retailer there are several factors that are affecting sales, such as communication, availability, and management. Assertive communication between the links of the supply chain is not taking place in an adequate way, since the ice cream references requested from the Meals' distribution centers do not correspond to what customers demand. In addition to the above, the costing system is not clearly defined either, because although there is a financial model, there are costs and drivers that are not being considered when making strategic and operational decisions.

Acknowledging what was mentioned earlier about the several factors that impact sales, the development of this project is relevant because there are difficulties that are affecting Crem Helado's retailer sales performance. In conversations with the retailer, it has been established that sales were affected by internal policies of the company because in many cases the product

[1] In this project, the figure of *Authorized Marketer* that Crem Helado uses is equivalent to the figure of *Retailer*.

is not available because a demand forecasting model has not been implemented. The fact that a costing system has not been defined, results in costs and drivers that are not being considered when making strategic and operational decisions.

According to Crem Helado's retailer factors such as weather, seasonality, and availability of independent vendors are also affecting sales. There are moments of the year in which consumption of ice cream is higher and the company should have in its strategy elements that support decision-making according to the season. Finally, there is a large dependence on ice cream cart vendors to market the product, but there are times when, due to their free will, they do not commercialize ice cream in the area.

For these reasons, the proposed project is the design of a method that articulates two main elements: effective management of demand planning, keeping in mind the particularities of the Meals' supply chain for the retail sector, and a costing system that provides better administration of resources. The method will be applied in Crem Helado's retailer and will be supported by a platform that allows better strategic and operational decision-making, consequently aiming for an increase in sales.

2. Literature review

In food industry it is crucial to make an adequate sales forecast because costs must be considered. For example, in the case where there is a need to meet the demand at all costs, the retailer tends to "overstock", and obtains a higher inventory cost. The opposite situation can also occur when the retailer is not able to respond to consumer demand, which results in missing costs. In this sense, forecasting's role is important because it seeks to obtain a balance between supply and demand, thus leading to better cost management, an effective sales strategy, and a higher consumer satisfaction. Some elements affect forecasting management (construction, analysis, and decision making) and therefore it is important to take them into account.

Regarding the elements that affect forecasting, especially in the case of ice cream sales, one of the most relevant is the weather, since it has been proven that it affects sales. Stulec, Petljak et al, (2019) demonstrate that there is an important correlation between weather and sales in the soft drinks and ice cream market. The authors prove that in sunny day sales are higher and lower on a rainy day. The research results show a positive trend in the summer and a negative trend in the winter with a very strong correlation between weather and sales. Nevertheless, this correlation diverges depending on the seasons, since there are seasons where it is stronger than others.

Several forecasting methods have been applied in the food industry. This applies to both retailers and wholesalers. Goodness, Balcilar et al, (2015) applied various forecasting methods at a food company in South Africa. They argue that the demand for emerging economies present high volatility, which implies that both linear and non-linear models can be applied, taking into consideration the effect seasons have. Based on an investigation by Da Veiga, Pereira, et al (2014), this high volatility obligates the retailer to respond according to the behavior of the demand. Their research contrasted Simple, Double, and Triple Exponential Smoothing methods with ARIMA (Autoregressive Integrated Moving Average) models. They applied the techniques on a food company in Curitiba, Brazil. They measured the errors (MAPE) of each model. In their case, Double Exponential Smoothing provided higher accuracy in contrast to ARIMA models, since their data had a trend.

When there are high volumes of food demand data, digital tools such as machine learning are used to gather accurate forecasts. A state-of-the-art investigation of the application of machine learning forecasting techniques was developed to forecast fast-moving inventory goods, such as beverages, and ice creams (Tarallo, Akabane, et al, 2019). The investigation used a report from Nielsen, one of the most important data analysis companies in the world. The report indicates that machine learning is useful for generating accurate forecasts when food demand has a seasonal pattern, in contrast to other traditional forecasting models. Due to the degree of precision, speed, and applicability of machine learning methods, the results were adequate for wholesalers and retailers in terms of product availability, inventory management, and consumer satisfaction.

Evaluating the significance of generating reliable forecasts with different models and highlighting the use of digital tools as a resourceful way to achieve this end, precise management of information must be contemplated, which can be presented through a digital platform. Among the available digital solutions to integrate information there are apps and web portals. Mekha, Dullayachai, et al (2017) applied these tools to carry out a comprehensive analysis of a food production system. They developed a digital platform containing 4 modules: the first for traceability of inputs and raw materials, the second for financial management, the third integrating the costs of each batch, and the last for the presentation of results. The implementation of the platform implied better cost and inventory management.

A digital platform requires appropriate information to determine a sales strategy that could benefit the business owner. In the case of retailers, inventory control is essential because the stock product generates costs. At the International Conference on Engineering and Systems Management, a study was carried out to determine the optimal product order quantity and its relationship with inventory levels (X. Sheng and C. Xin, 2019). The study displayed that inventory levels, seasonality, demand, selling price, and stocking cost, among others, were related to inventory levels and had financial impact. A non-linear mathematical model to determine the optimal product order was proposed to increase profits and minimize inventory costs. Once the mathematical model was applied in the fresh food field, it was discovered that it is beneficial to maintain a product slack to attract customers, increase profit, and anticipate changes in demand.

Supply chains have costs that are associated with the resource consumption of the different links that are part of the operation. The food supply chain is not an exception and costing systems improve control and decision making. In this market, it is common to apply an Activity Costing method (ABC). Kabinlapat and Sutthachai (2017) implemented a study that regarded controlling and lowering food production costs using an Activity Costing method. They identified that the main problems in the application of this system are the collection of data and the identification of activity and cost drivers. The outcome of the research evidenced significant differences in comparison to the non-application of the costing system since there was an improvement in the control of unit costs.

The life cycle of products plays a fundamental role when planning production, distribution, and sales. Edwards, Burn, Crossin, et al (2018) carried out a study in which the life cycle costs were taken into consideration. In the study, a costing method named LCC (Live Cycle Costing) was implemented and it incorporated the impact that food waste had on environmental and social indicators. The research helped the government making better decisions regarding public policies to avoid wastage costs.

The sales strategy to be developed in this research must consider the market it will address: the ice cream market. Silva, Rodríguez and Marques (2014) developed a study about the perception of consumers towards different ice cream references. Consumers' expectations were analyzed considering their socio-demographic characteristics. The study found that older people had a greater preference for healthy ice cream. Additionally, the idea that seasonality affects ice cream demand was strengthened, since, according to the data, consumers are more likely to buy the product in the summer.

An accurate demand estimation and an appropriate management of resources could have a positive impact on the performance and profitability of the business. These models will be incorporated in a digital platform that includes an arrangement of functions, modules, and graphical interface. These elements will have an impact on the use of the platform. The cognitive experience, the satisfaction in terms of functionalities and the confidence that the user has when using the digital platform, are factors that directly influence how frequently a user interacts with a digital platform (Molinillo, Navarro, García, et al, 2019). Therefore, the platform to be developed must consider these elements that improve the user's experience.

3. Objectives

Design a demand estimation and cost management system based on a case study developed in a Crem Helado retailer through a digital platform seeking to improve the performance of sales indicators.

Specific objectives:

- Develop a demand estimation model integrated into a digital platform for a Crem Helado's authorized marketer.
- Design a costing system in the platform that allows mitigating the costs and drivers associated with the processes that impact the financial management of the authorized marketer, measured with key performance indicators (KPIs).
- Implement the digital platform in the authorized marketer.
- Measure the implementation's performance in the case study company.

4. Methodology

4.1 Development of the demand estimation model

To build the demand estimation model, the first step was to collect the data from the retailer. The retailer uses Nutresa's platform to make orders and register sales. The available collected data was framed in a time window from 2015 to this date and the authors had to download and organize the information regarding the different ice cream references and consolidated in one data-frame. This included quantities, taxes, sold units, invoices, among other details. After gathering the data, a cleansing process was performed to eliminate the information that was not relevant which included invoices, discontinued products, repeated values, and other elements that did not add value to the project.

After performing the cleansing process, the next step was to perform a statistical analysis and preparation of the data. Since there is a restriction of time in this project, it is not possible to apply the methodology to all the ice cream references. For this reason, in conversations with the retailer, it was stablished that the ice cream references to consider in this project would be classified by types or product brands, because according to the retailer, these are the most important references. To establish if those ice cream brands were important for the case study company, the historic data of all the ordered references by the retailer from 2015 to 2019 was collected and a series of Pareto charts were constructed to organize the references in order of importance.

After determining the references to analyze, it was decided to develop the demand estimation models using Python language because its flexibility and usability. Python provides several libraries that allow visualization, organization, and analysis of data. The programming language can be applied in several software such as PyCharm, Anaconda Navigator, Spyder and Google Colab, among others (Castillo, Llebot, 2020). The sales data used in a monthly frequency since the records of the ice cream demand did not have a daily or weekly basis. It is important to consider the Time Series Definition from the book *Forecasting: Principles and Practice*: "Anything that is observed over time is a time series (Hyndman and Athanasopoulos, pg, 13, 2018). For this reason, it was decided to consolidate available data and apply a monthly frequency for the demand of each ice cream reference.

Colab, from Google, was chosen as the programming software in which the code of the forecasting models was constructed. It includes the many libraries, more than one user can program at the same time, does not require installation, works in all operating systems, it is open sourced and there is a vast community of developers and programmers that facilitate the experience of programming in the platform. The only requirement is to have a Google account. The programing language of Colab is Python. It was decided to upload the demand of the ice cream references in GitHub[2] because this would make them available every time it was necessary to program in Colab.

The purpose of using Colab is to determine a quantity of ice cream references to support the decision-making process. In order to achieve this goal, the code was built with the following structure: the selection of the necessary Python libraries, taking the product brands sales from GitHub, the visualization and analysis of the product brands, the application of the forecasting models, the calculation of error measurements, the selection of the forecasting model that had a lower error measurement and the automatic placement of the generated forecasts in a Google Sheets file that integrates the costing model, which will be explained in the following section.

The libraries from Python are an important section of the code because they provide the tools that are necessary to make it work. Pandas, Numpy, Matplotlib, Prophet, Statmodels, Math and Sklearn where the most relevant libraries in the code. Pandas was used to import the ice cream demands from GitHub and to manipulate the data. Matplotlib was used to analyze the behavior due to its visualization tools. Numpy generated arrays that were used to build Data frames. Prophet was used to build one of the forecasting models. Statmodels was implemented to apply an ARIMA model and to generate forecast errors. Math provided the calculation tools and Sklearn offered the possibility of calculating errors (Data Flair, 2020).

The visualization analysis section is where the behavior of the demand is analyzed with several Python tools that include descriptive analysis, density plots, and decomposition of the data. The decomposition was performed with Decompose tool, which identifies trend and seasonality, removes both and the result is a residual. If the residual still has trend and seasonality, this means that it could not capture all the information from the data and therefore, it cannot be used since there are several random values. If the residual has neither trend nor seasonality, this means that all the information was captured, and the data can be used for forecasting process. This tool removes trend and seasonality by differencing the past values. To remove trend, the difference is obtained by subtracting the value of one period with the next. In the case of differencing to obtain seasonality it is necessary to difference by cycles (Brownlee, 2017, p. 107).

[2] GitHub: It is an open-sourced repository that programmers and developers use to store their codes, data, and projects. The platform was created by Lunix founder, Matthew McCullough. One of its many characteristics is that it stores files online and makes it possible to import them using Python, which results in having the data available all the time and not having to upload the data in Python every time the file is opened (Finleey, 2012).

To suggest the inventory policies for the retailer and to analyze the behavior of the demand, it must be ensured that demand behavior is stationary. The inventory models are continuous inventory policies and assume stationarity. Taking this into account, the stationarity of the data was measured with the Augmented Dickey-Fuller test, also known as unit root test. This test uses an autoregressive model to capture the information of the values of the data and applies a unit root test that determines whether the data is stationary or not with two hypotheses: H_0 (Null Hypothesis)-Suggests that the time series data has a unit root, which means that the data is not stationary and H_1 (Alternate Hypothesis)-Rejects the null hypothesis and assumes that the time series data is stationary. The test uses a p-value. If the p-value is lower than 0.05, the Null hypothesis is rejected, and the data is assumed to be stationary (Brownlee, 2017, p. 140).

Another important component of the analysis of data of the ice cream brands was the autocorrelation tool that Python provides. Autocorrelation means that the future values depend on the past values, which basically means that past values can be used to forecast future values. In this regard it was important to determine if the time series data had correlation with itself before preforming the forecasts. The tool to determine this correlation was the autocorrelation, which is integrated in the code. If the correlation is close to 1 or -1, it means that there is a strong correlation between the values of the data. If the correlation is close to zero, it means that correlation levels are low, and it is not possible to predict the future values using the past data (Brownlee, 2017, p. 187).

After preforming the analysis of the data, the following step was the development of the forecasting models in Colab. The applied forecasting models were ARIMA[3] and Facebook Prophet[4]. To forecast in Python, it is necessary to establish a *training* and *testing* data. The *training* data is the quantity of information that the algorithm needs to predict future values and the *testing* data is the information that the algorithm need to evaluate its performance (contrast predicted values with real values and calculate error measures) (Brownlee, 2017, p. 146). Considering this fact, the *training* data consists of the ice cream sales starting on january of 2015 until december of 2019. The *testing* data consists of the ice cream sales from january of 2020 until november of 2020. This *training* and *testing* data were proposed because the implementation of the digital platform was on december of 2020 and therefore, the forecasts of the analyzed brands were for this month. Regarding the ARIMA model, a FOR cycle was used to find the *p, d* and *q* values that would minimize the error and with respect to the Facebook Prophet model, it automatically generated the forecast, the visualization of the forecasts and their contrast with the ice cream demand and identified trend and seasonality.

The next step after the forecasting with ARIMA and Facebook Prophet in Python was the evaluation of the performance of the forecasts to determine which of them would be the most suitable model for each of the ice cream brands. The forecast errors[5] that were used were MAE, MSE and MAPE. A conditional was built to select and forecast the demand of november and december with the method that had the smallest MAPE or MAE value, or the smallest error. After selecting the best forecasting model, the predicted demand is exported to a Google Sheets file that contains the costing system.

Parallel to generation of the forecasts in Colab and to ensure that the forecasts from Colab would work for the retailer, other forecasting alternatives were evaluated using Excel with a similar method as the one in Colab. The considered models were the Moving Average, Weighted Moving Average and Simple, Double and Triple Exponential Smoothing. The behavior of the demand was also analyzed by visualization techniques. Excel's *Solver* was used to establish the parameters of the forecasting models that guaranteed a lower forecast error measurement. In a similar methodology used in the Python algorithm, the forecast that had the lowest error (MAPE) was selected as the model to generate the forecasts. These generated forecasts were also placed in the costing model file. The authors established that the maximum tolerable variation of MAPE was 40% because according to the retailer, a larger variability of the forecast would imply a financial impact. The following folder contains the forecasts from Excel: Excel's forecasts (Annexed # 1).

3 ARIMA: The name ARIMA stands for Autoregressive Integrated Moving Average (AR-I-MA). Autoregressive (AR), means that that the past values have a regression with the future values, which means that the past values can be used to forecast the future values. The Integrated(I) part is referred to the use of the differencing method to make the data Stationary to be used in the model. Moving Average (MA) is referred to forecasting future values using several past values. The number of past values to be used is *Moving Average Window*. The ARIMA model has three parameters: *p, d and q*. Each of them represents what was mentioned earlier (Brownlee, 2017, p. 208).

4 Facebook Prophet: Is an open-sourced forecasting tool developed by Facebook that Works in either Python or R. This forecasting method incorporates Simple, Double and Triple Exponential Smoothing techniques and ARIMA. It automatically detects trend and seasonality and forecasts using a procedure called *Additive Regression*, which is mainly used for hourly, daily or weekly observations with a few months of history. The additive model is a non-parametric model which uses a one-dimensional smoother that builds a restricted class of regression models. This model performs a core analysis to address different variants of the case in question. This tool identifies the trend of the curve and automatically detects trend changes by selecting the change points of the data using Fourier series for annual data. Finally, a MAPE optimization is generated for parameters with extremes in less than one second. It is fully automatic and provides visualization techniques to measure the accuracy of the forecasts and automatically calculates performance measurements. It is a very strong and precise forecasting method. (Taylor and Letham, 2017)

5 Error Measures: They are an indicator of how accurate or precise the forecasts are in contrast to the real values. There are different types of Error Measures that include MAPE, MAE, RMSE and MSE (Vendeput, 2019).

It is relevant to make the distinctions of the forecast methods in Colab with respect to the methods in Excel. In order to forecast in Colab, which uses Python language, it is necessary to establish the *training* and *testing* data that was mentioned previously. This *training* data is the input the models need to forecast. The generated forecasts are evaluated in the time window framed by the *testing* data that includes the error measures that evaluate the performance of the forecasts. The methodology used in Excel was different. There was a definition of the parameters of the forecasting models and Excel's *Solver* optimized these parameters in order to generate the forecasts that minimize the error. In this regard, the methods are not comparable and therefore their error measures are not either. The selection of the forecasts would depend on the retailer's experience and the MAPE of 40% could provide additional criteria to make that selection.

4.2. Design of the costing system and definition of KPIs

The second objective is the design of the costing system that allows the mitigation of the costs associated with the financial management of the retailer. For the development of this objective, one important step was the gathering of the information regarding fixed and variable costs of the retailer. The fixed costs include rent, public services bills, taxes, loans, and salaries. The variable costs in this case are the costs of the ice cream references that are purchased by the retailer in Nutresa's platform. The designed costing system is integrated with an inventory model.

The software used for the costing system was Google Sheets since Google Colab can export data to Google Sheets because one of the inputs of the costing system are the forecasts that are exported from Google Colab. The link between the forecasts and the costing system is that in order to evaluate the impact of placing an order taking the forecasts into account, it is important to evaluate its impact in inventory and costs. Regarding inventory management, two inventory policies were proposed to the retailer for each of the product brands: Ss and QR[6]. For each of the product brands, it was evaluated which of the inventory policies had lower costs.

The first step of the model was to consider the Pareto charts and the brands that were chosen by the retailer because they represented about 80% of each years' sales. The definition of the annual demand was denoted with lambda (λ). It was found by organizing the unit demand of each ice cream reference per year by applying a smoothing factor of 5% to 2015, 8% to 2016, 12% to 2017, 15% to 2018, 20% to 2019, and 40% to 2020. It was organized in that way because market tendencies and references change over the years and the most recent sales data has a priority over the whole data. By applying the factor for each years' demand and adding these results, the annual demand (λ) was obtained for each ice cream reference.

Following the definition of the lambda, the next step was the definition of the ordering cost (k), the unit cost (c), and the holding cost (h) of each ice cream brand. The ordering cost (k) was calculated considering the average time utilized when placing an order, which is about 20 min. The unit cost (c) was obtained from Meals' digital platform, which retailers use to place orders. The holding cost was calculated with information given by the retailer and according to an annual interest rate (I %) of 13% each year.

These variables were used to calculate a theorical order quantity (Q) that ensured a minimum cost. For its calculation, the average weekly orders placed by the retailer and the time that it takes Meals to place supply the retailer with product or cycle time (T) were considered. The cycle time (T) has an average of 12 hours. Additionally, to comply with the retailer's capacity restrictions the inventory capacity was considered and was estimated by measuring the volume of each ice cream refrigerator. One of the challenges was that ice creams are delivered in boxes and there were 14 different sizes of boxes which vary depending on the product the retailer orders. For this reason, with the use of the historic placed orders on Meals' platform since 2015, there was an estimation of an average box size. In order to calculate it, there was approximation of the frequency and volume of each box and these values were weighed, resulting in the standard box, which ensured that the suggested order from the forecasting models would never exceed the inventory capacity.

Afterward, this standard box size was employed to estimate the maximum storage capacity of the refrigerators. In this case, acknowledging that there are 14 sizes of boxes, a maximum of 80% of capacity was assigned to each refrigerator. The information of the placed orders in the implementation of the project was the necessary input to ensure that this capacity would never be exceeded. Identifying the number of boxes that could be stored by reference and brand and the information from Meals digital platform, the limit of possible units per box was calculated.

5. QR and Ss Inventory Policies: Both inventory policies assume that the demand has a stationary behavior. With respect to the QR policy, the R is the amount of product that indicates that it is necessary to place an order and the Q is the quantity of product to order. In the Ss policy, the "S" references the necessary inventory level to reach and the "s" indicates the amount of that requires a new order. (Nahmias, S.,2007).

The following step was the theorical modeling of the Ss and QR policies proposed for each ice cream brand to generate the daily suggested orders for the retailer. The information to build those inventory policies were the monthly placed orders from 2018 to 2019. The calculated theorical order quantity (Q) was applied to the model and if this quantity exceeded the inventory capacity, a maximum Q was contemplated. The models also required minimum of units that would indicate the necessity to place an order (R for the QR model and s for the Ss model). This information was given by the retailer for each ice cream brand. The lead-time employed for this model is the average of 12 hours that Meals takes to supply the retailer with product. After this process, the policies were evaluated in terms of costs for each reference in an inventory model. This model contained the result of applying the QR and Ss models and the forecast from Python. The model also contained the daily sales, the daily placed orders, and the daily inventory levels. The previous would be collected from a digital platform and its development will be explained later.

The theorical modeling of the continuous inventory policies (QR and Ss) was developed considering portions of the data that had stationary behavior, respecting the assumptions of the policies. The goal of applying these policies was to calculate a theorical alert of when it was necessary to place an order during the month. The policy (QR or Ss) that would determine the placement of orders chosen depending on its cost. These theorical distribution of each brand was placed in the designed inventory model that was proposed for the retailer.

After determining the theorical distribution of the suggested orders, the monthly forecasts generated form Google Colab were uniformly distributed in a daily frequency (for december of 2020). The previous procedure was proposed considering that the sales records that were necessary to generate the forecasts of each brand did not have a daily frequency (these data had a discontinuous frequency during the month) and therefore it was necessary to consolidate the sales data in a monthly frequency in order to apply Time Series Forecasting. The sales data are not recorded daily because Meals demands retailers to register sales at least three times a week. In other words, there is an assumption that the monthly forecasts would distribute uniformly for each day of the month because the sales records did not have a daily frequency.

To give an example of how the monthly forecast were distributed in a daily frequency, if a month has 31 days and the forecast is 3100 units for one brand, the daily forecast of every day of the month would be 100 units and this value would be calibrated depending on the orders placed by the retailer (The QR and Ss would suggest when it is necessary to place them). In this regard, the suggested order of the first day would be 100 units. If the retailer ordered 500 units on the third day, the next suggested order would be 92 units because that monthly forecast of 3100 units would be reduced to 2600 units. Those 2600 units would be distributed again during the remaining days of the month (28 remaining days). This monthly forecast would be consumed by the number of units placed by the retailer and in this sense, it will be adjusted to the remaining Net Requirement of each month as well as the remaining days of each month. The idea is that the retailer places the monthly forecast that is estimated from Google Colab. The model is flexible because it is adjusted with the orders placed by the retailer.

In order to evaluate the importance of the forecasts, the maximum MAPE of 40% discussed with the retailer, was taken as reference to measure how the forecasts would perform if the real sales had a 40% increase or a 40% decrease. If sales increased by this percentage, this would mean that the forecasts are underestimating the monthly demand and the contrary situation would mean that the forecasts are overestimating the monthly demand. The previous scenarios would represent a financial impact for the retailer that was measured in inventory costs (h), missing costs (p), income, and revenue.

This inventory model registers the retailer's placed orders and daily sales and automatically readjusted the daily suggested orders. The suggested orders also considered the restriction of the inventory capacity and the inventory levels. To obtain those levels, the authors counted all inventories of the analyzed products in the location of the case study. These values constituted the initial inventory levels placed in the inventory model. The inventories of each product were obtained by subtracting the daily sales and the daily orders placed by the retailer. This meant that it was not necessary to come back to the case study. The estimated suggested orders guaranteed that the inventory capacity would never be exceeded and that the demand could be supplied.

The suggested orders were initially presented to the retailer in a maximum and a minimum value. The minimum value was the number of units that would not exceed the inventory capacity restriction. The maximum value was the suggested order that the inventory model delivered and constituted the quantity that was necessary to meet the demand. If the suggested order was bigger than the inventory capacity, the suggested order was the necessary units that were needed to cover the inventory capacity and, in this case, the suggested order was only one value, rather than a range.

Contributing to the financial analysis of the forecasts that were proposed to the retailer, there was an evaluation that consisted of generating situations in which each brand had a different variation, rather than applying a 40% variation to each brand. The analysis was performed taking three scenarios into account: the first scenario was based on the real orders that were placed by the retailer considering the suggestions (the range) provided by the inventory model as well as the retailer´s criteria, the second scenario was the theorical situation in which the retailer ordered the exact quantities of the suggested orders[7], and the third scenario was a theorical situation in which the retailer orders the exact quantities of the suggested orders considering a security stock.

The security stock (SS) was implemented to respond to the variability of the demand and was calculated with the maximum delivery time (MDT), the normal delivery time (NDT), and the average demand (AV) of each of the evaluated brands. What was stated previously resulted in the following equation: $SS = (MDT - NDT) \times AD$ (EAE Business School, 2020). The normal and maximum delivery times Meals takes to supply the product to the case study company were provided by the retailer.

The analysis of the impact of the three scenarios that were previously described in terms of variability of the demand were made considering the Variation Coefficient proposed by Hamndy Taha, which is constructed placing the standard deviation of the demand on the numerator and the average demand on the numerator (Taha, 2012). This coefficient allows the calculation of the dispersion of the data around the mean under the assumption that this dispersion is the variability of the demand. The coefficient was applied to the demand of each brand to obtain their variation.

The Variation Coefficient and the real data of the demand of december of 2020 for each brand were used to calculate an upper and a lower bound to the demand of each brand. The upper bound was the theorical situation in which the demand increased by the Taha's coefficient and the lower bound was the opposite situation. The analysis was performed in a simulation of how the inventory model would respond to these variations financially, and in this regard, it was necessary to estimate the costs of the system.

Activity Based Costing was chosen as the method due to its applicability to identify costs and drivers in an accurate way. After gathering the information regarding the costs, the retailer evidenced the principal activities that impacted the performance on business. The activities included placing orders, storing the product in refrigerators, and selling ice cream to the public, which can be in the business itself, and through ice cream vendors that supply the product around the area. The identified cost drivers were the number of ice cream references to purchase from Meals and the number of connected refrigerators. The number of connected refrigerators impacts the electric bill of the retailer and if there are too many unsold references, it is necessary to connect more refrigerators. This results in a higher electric service bill. Each cost driver was divided by its cost to identify its rate, which establishes its importance.

The costing model gathered the previously described inputs from the inventory model and added a missing cost (p), which was calculated as the opportunity cost by subtracting sales price minus the unit price. The missing cost is a sale that was not preformed. This costing model required the daily sales, daily shortages, daily orders, and daily inventory. The daily income, the holding costs (h), the ordering cost (k), and the unit cost (c) were placed in the costing model so that the retailer could use this information to make decisions.

The KPIs that would evaluate the business performance with the use of the digital platform were formulated in the Costing System file. To create business intelligence dashboards with the calculated indicators, there are several software platforms that can be found in the market, including Power BI, from Microsoft. In the case of this case, Tableau was the platform used to graph the KPIs since it easily integrates with Google Sheets data. Among the several alternatives that Tableau has to offer, there is Tableau Public, an open-sourced software. Using this tool, it was possible to take the indicators from Google Sheets and create graphs and dashboards. The suggested order for each product family, which was part of the inventory model in the costing system was also assembled into a dashboard in Tableau Public. After generating those dashboards, they were saved and sent to an online repository from Tableau Public. Those dashboards were exported to the digital platform using the HTML language of the dashboard, which is enabled by Tableau to export dashboards to other websites.

The developed digital platform contained a series of modules that are associated with the placement of orders with the support of the inventory and forecasting models, a section to register sales, and indicators that reflect inventory levels, cost

7 In the second scenario and the third one, rather than a range, the suggested order was one single value.

of missing products, product orders, income, and indicators that are associated with the performance of the forecasting models.

For the development of the digital platform, it was necessary to create an account on Colombia Hosting, a service that provides domain and hosting for the development of digital platforms. This platform provides data bases, hosting, corporate emails, design tools, 10 GB to store website information, and a domain. After acquiring the services of this platform, the logo of the digital solution was developed. As it was mentioned before, Colombia Hosting provides web design tools, and for this case, Constructor Plus was the software where the modules of the platform were designed. Taking elements of UX and UI into account, the modules of the platform were designed, and this included selecting the appropriate color pallet and the distribution that made the experience of using the platform comfortable and usable for the retailer.

The digital platform is divided in four sections that can be accessed and visualized in a menu: Home, Sales Registration, Suggested Orders, and the Business Indicators section. The sales data that was recorded in the Sales Registration module was the input for the costing and inventory models that were developed in Google Sheets. This module allowed the retailer to register sales and missing products. The Suggested Orders module took the information provided by the inventory policy and the forecasting model. This section is linked with Nutresa's digital platform where retailers place orders. The last section is where the retailer can visualize the business indicators. They were designed using Tableau and their development will be explained in the following section.

The design also contemplated using the official pictures of Crem Helado's ice cream references to build a collage that would make the platform attractive. This ice cream references are sold in the case study company. Since these images are the company´s property, it is important to clarify that they were properly referenced on the website. The restriction of the retailer, not being able to access a computer in the location of the case study company was also contemplated and therefore, the platform was designed smartphone and desktop friendly.

There are several interactions between the different tools that were used for the development of this project. The following sequence (Diagram 2) display the main interactions: (1) The sales information downloaded from Nutresa's was saved as a CSV and uploaded to GitHub. (2) The forecasting model in Colab uses the ice cream sales from GitHub and generates the forecasts. The forecasting model in Excel directly takes the ice cream sales. The forecasts of both models are placed in the costing model. (3) The costing model in Google Sheets allocates the inventory policies and the KPIs. The KPIs are sent to Tableau Public. (4) Tableau public takes the Google Sheets file and generates the business intelligence dashboards that are used for the KPIs and the suggested product order. (5) The digital platform receives the dashboards and projects the information to the retailer. It also allows the retailer to register sales and missing products. The sales information of the sales and missing products is sent to the forecasting model and the cycle starts again.

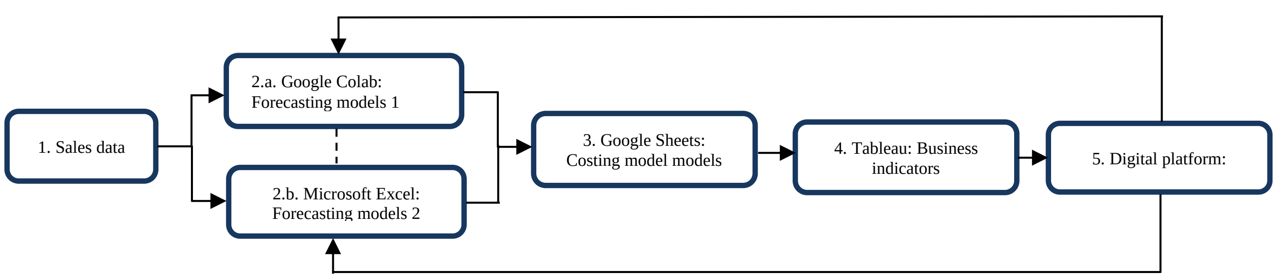


Diagram 2. Information cycle of the project (2020). The Authors.

4.3. Implementation of the digital platform

For the implementation of the platform, the retailer agreed to place orders using the platform during december of 2020. This process included the introduction of the digital platform, the placing orders considering the suggested quantity of each brand. The retailer was illustrated on how to use the modules of the digital platform: home page, sales, and missing products registration, suggested product, and indicators modules. The information about the suggested orders of each brand was used to place orders on Meals' platform. Sessions of four days a week were carried out with the retailer, to evaluate the perception and user experience of working with the digital platform. The retailer was instructed to place the daily sales and missing products. The information from the placed orders was downloaded from Meals' platform. This information was an input for the costing and inventory models which were adjusted taking this information into account.

It was necessary to evaluate the retailer's experience with the digital platform. Elements such as usability, functionality, and the perception the retailer had about the platform were evaluated through a semi-structured interview. It included the visualization of information in the modules, the availability of relevant information for decision making as well as the benefits for the retailer during the implementation period. The insights of this interview would result in possible adjustments as well as a final survey that would be released in the final stage of the project. The following activity was to support the retailer in the use of the platform.

This survey had different types of questions such as simple and multiple choice, and Likert scales. These scales were used to identify the level of agreement of the retailer's perception of the digital platform in the format of asking from 1 to 5, being 1 the lowest value and 5 the highest. The questions included accessibility, the information presented in the modules, the perception of the retailer concerning functionality and the main benefits to the business's needs. In terms of the positive impact of implementing the digital platform, the retailer was asked of the possibility of recommending it to future retailers. Regarding user experience, the questions provided quantitative results of the platform's accessibility, usability, and effectiveness for the retailer. The survey consisted of 9 questions and contemplated the insights of the previous interview. In this regard, this constitutes a 360º evaluation.

Each question was assigned a percentage related to the characteristics of ISO 9126 so that each one can be weighted, determining the strengths of the application and the improvements to be made. Each question had a score that ranged from 1 to 5. This score was multiplied with the values found in table 1. The assignment of the weighting of the questions was made with respect to the relationship of each characteristic with what was posed in the question, so that the greater the relationship between the characteristic and the question, the greater the percentage value. The conducted survey can be consulted in the following link: Evaluation of the digital platform (Annexed # 2). To obtain the results, the value that was obtained in the survey was multiplied by its percentage for each of the characteristics and afterward the total values were added.

Questions	Functionality	Relatability	Usability	Efficiency	Maintainability	Portability
	Do the functions and properties satisfy the explicit and implicit needs?	Can it maintain the level of performance, under certain conditions and for a certain time?	Is the software easy to use and easy to learn?	Is it fast and minimalist in terms of resource usage?	Is it easy to modify and verify?	Is it easy to transfer from one environment to another?
Question 1	5%	5%	15%	25%	20%	20%
Question 2	15%	5%	20%	5%	4%	12%
Question 3	6%	20%	10%	7%	5%	15%
Question 4	18%	12%	12%	8%	20%	19%
Question 5	8%	10%	12%	6%	8%	5%
Question 6	15%	5%	16%	20%	9%	11%
Question 7	11%	5%	5%	5%	15%	5%
Question 8	10%	13%	5%	9%	4%	5%
Question 9	12%	25%	5%	15%	15%	8%

Table 1. Question weighting table. Source: Abud, M.A, (2012). The Authors.

4.4. Measurement of the implementation in the case study company

Regarding the measurement of the digital platform in the case study company, the initial step was the collection of all the required information to calculate the KPIs. The idea was to measure their values before (november 2020) and after (december 2020) the implementation of the digital platform. The results of the KPIs would evaluate how the retailer was impacted after using the digital platform. To implement the platform there was a recollection of daily sales, placed orders and initial values of inventory levels. That information was recorded in second week of november of 2020. This information was directly recorded from the retailer and by the last week of november of 2020, it was recorded with the respective modules in the digital platform.

The main reason for establishing the comparison of the implementation of KPIs for november of 2020 with respect to december of 2020, rather than comparing december of 2020 with respect to december of 2019, was the drastic social and economic transformation that the country suffered due to the sanitary situation of COVID-19. In addition to this, there was an atypical situation that was characterized by mobility restrictions that, according to the retailer, had a negative impact on the company.

According to DANE, there was a 1.61% increase in the Consumer Price Index (CPI) and despite this increase in the cost of living, there was a 9.5% drop in GDP for the third quarter of 2020 in comparison to the third quarter of 2019 (DANE, 2021). This had a high impact on the average income of Colombian citizens. In addition to this, there was a 3.9% increase on unemployment levels by comparing december of 2020 to december of 2019 (DANE, 2020). Taking these factors into account, it can be assumed that in general terms, the purchasing power of Colombian citizens was negatively affected which can be reflected in the negative financial impact the case study company suffered.

For the previous reasons, it was decided to compare the month of december of 2020 with november of 2020. The comparisons were made in this manner because the conditions were similar in the periods where the analysis was performed. The results of the Augmented Dickey-Fuller test also demonstrate that even though there are brands that have clear trends and seasonality, there are some brands that present stationary behavior, which makes this an appropriate comparison.

The KPIs were discussed with the retailer and there was a definition of the most relevant and useful to measure the implementation. They were classified in Financial Indicators, Inventory Indicators, and Forecasting Indicators because the main impact of the digital platform would be in those areas. The following tables were built considering the characteristics of the indicators: Name[8], Objective[9], Formula[10], Period[11], and the Responsible[12]:

Name	Goal	Formula	Period	Responsible
Sales Revenue (*SR*)	It is a simple, but necessary indicator for the retailer. It evaluates the sales of each ice cream reference by multiplying the amount of sold units by the price.	$SR = \#\ of\ units \times Sales\ price$	Daily, Weekly, and Monthly	The retailer
Sales Cost (*SC*)	To sell references, the case study company must purchase them from Meals. This indicator represents the cost of selling an ice cream reference for the case study company.	$SC = \#\ of\ units \times Purchase\ price$	Daily, Weekly, and Monthly	The retailer
Profit (P)	This indicator establishes how the case study company is generating profit after selling each of the ice cream references, considering the costs.	$P = SR - SC$	Daily, Weekly, and Monthly	The retailer
Gross Margin (*GM*)	This indicator measures the proportion of money that is left after selling products. It is important because it calculates how the company can grow performing its business activity.	$GM = \frac{SR}{SC}$	Weekly, and Monthly	The retailer
Sales growth (*SG*)	This indicator represents how the sales are growing from one time period compared to a previous time period.	$SR = \frac{SR_t - SR_{t-1}}{SR_{t-1}} \times 100$	Monthly	The retailer
Return of investment (*ROI*)	This calculates the number of times the retailer is generating revenue after incurring in the cost of purchasing ice cream units. The indicator was calculated for each of the product brands and as an overall of all the product brands.	$ROI = \frac{SR - SC}{SC}$	Monthly	The retailer

Table 2. Financial KPIs. Source: Scoro (2020). The Authors.

In terms of inventory indicators, the following table are the KPIs that the US Postal Service (USPS) has suggested KPI's that can improve the inventory management process. As well as with the financial indicators, they were discussed with the retailer, and the most relevant ones for the business were selected. The following table was constructed based on USPS suggested inventory KPI's that were introduced to the case study company:

Name	Goal	Formula	Period	Responsible
Average inventory (*AI*)	It is an estimation of the inventory that is on hand on a given time period. To keep this indicator under control, the company should avoid having big spikes or drops in inventory.	$AI = \frac{Inventory_{t1} + Inventory_{\ t2}}{period}$	Monthly	The retailer
Inventory Rotation (*IR*)	It is defined as the number of times the inventory has been sold and replaced in a known time period. If the value is small, the company is either having low sales or a big stock.	$IT = \frac{Sales}{Average\ inventory}$	Monthly	The retailer
Product orders (*PO*)	This indicator calculates the number of placed orders of a product in a period. It is necessary to keep track of those orders to evaluate how the retailer is following the proposed inventory policy.	$PO = \#\ of\ product\ orders$	Daily, Weekly, and Monthly	The retailer
Brand importance (*BI*)	It calculates the importance each brand has in terms of sales and it was proposed to prioritize the brands that represent a higher revenue for the retailer.	$BI = \frac{Revenue}{Total\ sales\ revenue}$	Monthly	The retailer

Table 3. Inventory KPIs. Source: USPS Delivers (2020). The Authors

8. Name: It is the name of the KPI as well as its abbreviation.
9. Objective: It is the description of what the indicator measures and why.
10. Formula: It is the mathematical expression of how the indicator is calculated.
11. Period: It is the time period the indicator measures, which can be daily, weekly, or monthly, in this case.
12. Responsible: It is the person that is responsible of the management and control of the indicator.

The next KPIs are the forecasting indicators. The indicators were proposed with an absolute value because it was not in the project's interest to penalize a forecast that underestimated or overestimated sales. The purpose was to penalize forecast that did not estimate sales or orders in a correct manner. They measure the level in which the retailer used the forecast to place orders as well as how the forecast managed to approach the december's sales. The following table contains the proposed forecasting KPIs:

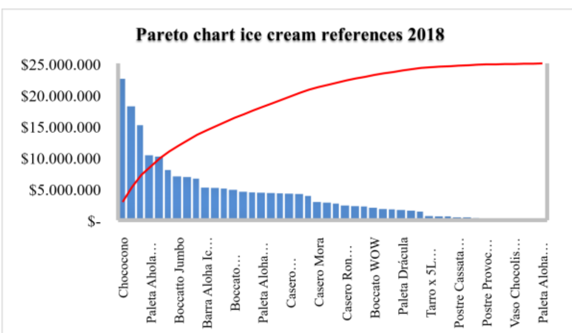
Name	Goal	Formula	Period	Responsible
Forecast and Sales Gap (*FSG*)	This KPI measures the level in which the forecast that came from the estimation model managed to predict sales. If the level is high, it means that the forecast is either overestimating or underestimating sales.	$FSG = \frac{\lvert Forecasts - Sales \rvert}{Sales}$	Monthly	The retailer
Forecast and Orders Gap (*FOG*)	This KPI measures how the retailer used the forecasts presented in the digital platform as information to place orders of each of the ice cream brands. If the level is high, it means that the retailer did not use the forecast as a reference to place orders.	$FOG = \frac{\lvert Forecasts - Orders \rvert}{Orders}$	Monthly	The retailer

Table 4. Forecasting KPIs (2020). The Authors.

5. Results

5.1 Development of the demand estimation model

The selected ice cream brands to focus the implementation of the project were Artesanal, Chococono, Barra Aloha, Casero, Paleta Aloha, Paleta Chocolisto, Vaso Chocolisto, Vaso Heladino, Vaso Hobby Vaso Hobby Sundae , Polet, and Bocatto. The following Pareto Charts of 2018 and 2019 indicate that those ice cream brands are relevant because they are always in the top 10 most purchased ice cream references, although it is worth mentioning that their position in the chart vary from one year to the next, which can be explained by the fact that Meals changes brands and strategies according to the market's tendencies an this results in supplying different volumes of product according to this and cancelling certain products. The charts also reveal that Chococono is always the most purchased reference by the retailer. The Pareto Charts of the years 2015 to 2019 can be found in the following link: Pareto Charts (Annexed # 3).



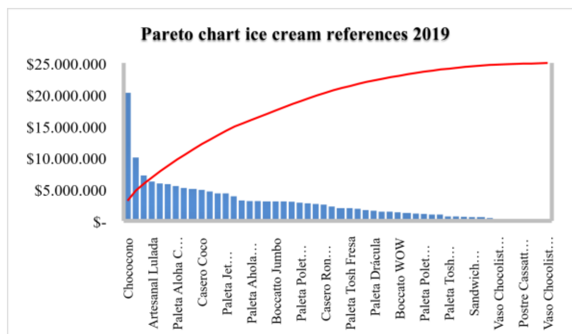


Diagram 3 and 4. Information cycle of the project (2020). The Authors.

The construction of the estimation model was described before, and the following link contains the development of the code in Google Colab: Estimation model (Annexed # 4). The result of this estimation model are the forecasts of each ice cream brand for december of 2020, which are sent to the costing model in Google Sheets file. Google Colab provides several tools to analyze data, which were used in this section. The following sequence demonstrates logical structure and the elements of the demand estimation model:

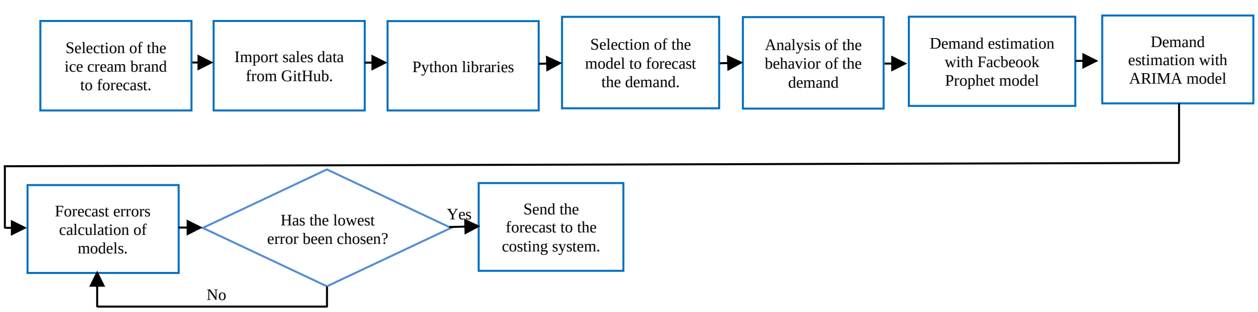
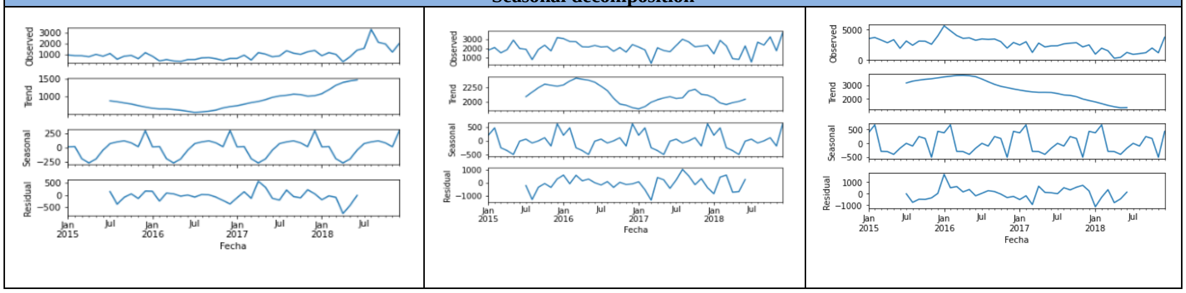


Diagram 6. Structure of fore forecasting model (2020). The Authors.

The results of the analysis of the sales data include the analysis of the demand, the application of the Augmented Dickey-Fuller test, Seasonal Decomposition, Autocorrelation Plots, Histograms, Density Plots, Statistical data, a Facebook Prophet analysis of trend and seasonality. These results can be observed in the following link: Sales analysis results (Annexed # 5) An initial step to analyze the behavior and quality of the time-series data of the ice cream sales was the use of Python's Seasonal decomposition tool for each of the selected ice cream brands. The decomposition of the demand by trend and seasonality enables the possibility of determining which references tend to decline or increase in sales, and their monthly behavior. The seasonal decomposition tool captured the trend and seasonality of the ice cream brands. The residual of the of the sales data has a random behavior and this is a sign that it is reliable to work with that data. The following graphs are the result of the seasonal decomposition of Artesanal, Casero, and Paleta Aloha brands. This illustrates how the analysis was performed for all sales data.

Seasonal decomposition



Graphs 3, 4 and 5. Seasonal decomposition of Artesanal, Casero and Paleta Aloha (Respectively). Source: Statsmodels. Python. (2020). The Authors.

The graphs show that the tool helped to determine the behavior of the sales data successfully. In the case of these three product brands, there is a seasonal behavior, and the tool was able to capture the trend and seasonality adequately because the residual data has random behavior. In the case of Paleta Aloha, the result of the residual is very similar to the data. The observed data show a decrease in sales from Paleta Aloha, while Artesanal is showing an increase in sales. Casero presents a stationary behavior with a tendency to decline in sales.

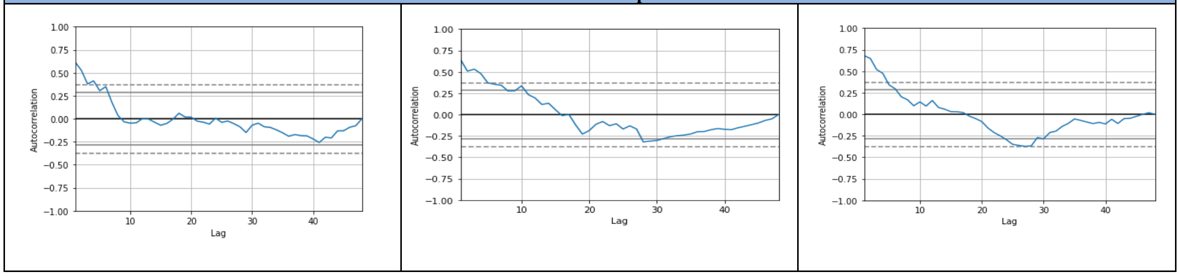
After performing the Augmented Dickey fuller test, the Null Hypothesis of the brands not being stationary can be rejected in the case of Polet, Chococono, Casero Barra Aloha, and Vaso Chocolisto because the p-value is less than 0,05 in the case of these brands, which means that they have a stationary behavior and therefore the forecasting models would capture their trend and seasonality. The other references do not have a stationary behavior because the p-value is more than 0,05 and as it can be observed in the Seasonal Decomposition of ice cream Brands like Artesanal, there is a clear trend, which is a clear signal of a non-stationary behavior.

Augmented Dickey-Fuller test Results		
Ice cream brands	**P-value**	**Demand Behavior**
Bocatto	0,06	Non-Stationary
Polet	0	Sationary
Artesanal	0,054	Non-Stationary
Chococono	0	Sationary
Casero	0,003	Sationary
Barra Aloha	0	Sationary
Paleta Aloha	0,335	Non-Sationary
Paleta Chocolisto	0,807	Non-Stationary
Vaso Chocolisto	0,011	Sationary
Vaso Hobby Sundae	0,614	Non-Stationary
Vaso Heladino	0,061	Non-Stationary

Table 5. Augmented Dickey-Fuller test Results. (2020). The Authors.

As it was mentioned earlier, in autocorrelation plots, a value that is close to 1 or -1 indicates that there is a strong autocorrelation between the values. The brands that presented a higher correlation coefficients were Paleta Chocolisto, Paleta Aloha and Bocatto with values of 0.65, 0.7, and 0.6 respectively (Sales analysis figure 4). This rest of the ice cream brands present lower autocorrelation, ranging between 0.25 and -0.25 which is also an indication that there is a low dependency between past and future values that can be explained by the effects of trend and seasonality.

Autocorrelation plots



Graphs 6, 7 and 8. Autocorrelation plots of Bocatto, Paleta Chocolisto and Paleta Aloha (Respectivly). Source: Statsmodels. Python (2020). The Authors.

Paleta Chocolisto, Paleta Aloha and Bocatto have higher values because they presented an initial stationary behavior therefore resulting in that there is a dependency between past values and future values. This is not the case for references like Casero and Heladino, which in this case present a low correlation (less than 0.25) which shows that the dependency between past values and future values is low.

The graphical information of the sales analysis can be consulted on the following link, wich contains histograms, density plots and the descriptive information: Sales analysis figures 5, 6 and 7. The values of each percentile can provide information of the distribution of sales during the period in which they were analyzed. The ice cream brand that presents the largest sales volume is Chococono with a mean of 2695 and the highest maximum value (7642), followed by Paleta Aloha, Vaso Chocolisto and Artesanal. The high standard deviation of brands like Paleta Chocolisto can be explained by the fact that according to the retailer, that product went to market in 2016, its sales have tendency to increase and has a Non-Stationary behavior.

As it was mentioned before, the code in Colab selects the model that has the lowest forecast error measurement and predicts the demand for december with that method. MAPE was the chosen performance error measure because it shows the size of the error in percentage and therefore delivers sufficient information to make decisions. The following table summarizes the error measures form Colab, the results of MAPE and, the selected forecasting method:

Selected forecasting model and error measures					
Ice cream brand	**Selected Method**	**Colab's MAPE**	**Excel's forecast**	**Colab's Forecast**	**Total sales december 2019**
Bocatto	Facebook Prophet	0,29	1024	555	587
Polet	Facebook Prophet	0,30	334	209	535
Artesanal	Facebook Prophet	0,26	2493	3454	3514
Chococono	Facebook Prophet	0,25	1243	4979	4147
Casero	Facebook Prophet	0,19	2518	2338	2670
Barra Aloha	Facebook Prophet	0,39	239	970	1901
Paleta Aloha	Holt Winters	0,41	3065	3399	2954
Paleta Chocolisto	Facebook Prophet	0,32	1410	1278	1742
Vaso Chocolisto	Facebook Prophet	0,22	1243	1169	1150
Vaso Hobby Sundae	Holt Winters	0,49	247	206	265
Vaso Heladino	Facebook Prophet	0,30	120	545	600

Table 6. Selected forecasting models and error measures. (2020). The Authors.

In the majority of situations Facebook Prophet was chosen as the best forecasting model because it presented a lower error measurement than ARIMA. However, as it can be observed in the table, Paleta Aloha and Vaso Hobby Sundae presented a considerable error measure that could have a negative financial impact for the retailer because of the high uncertainty that the error measure reflects. In the case of this brands, the retailer was also provided with the forecasts from Excel. The criteria the retailer followed to choose the forecasts that could be used to place orders was also based on the historic data of each brand and in the case of those brands, in addition to their high MAPE, the historic sales played a heavy role on the retailer´s decision to choose the forecasts from Excel. The sales data from december of 2019 of Paleta Aloha and Vaso Hobby Sundae presented values that were very similar to Excel's forecasts (2945 and 245, respectively).

5.2 Design of the costing system and definition of KPIs

The costing system is where the information from the forecasting model and the inventory model converges and where the performance indicators are generated and sent to Tableau and therefore, the result of the design of the costing system is precisely how all the elements of that system interact to provide the retailer information that is relevant to make decisions. The costing system developed in Google Sheets can be consulted in the next link: Costing system (Annexed # 6) The design includes receiving the forecasts from Google Colab, applying the forecasting models of QR and Ss to the historic orders of the selected brands, the distribution of the monthly forecast in according to the forecasting models and the Net Requirement calculation.

The costing system contemplates the daily recording of sales, placed orders, inventories, and missing products using the digital platform that was developed in this project. This information is stored, and the respective calculations are made to generate the costs and incomes indicators. The daily suggested product orders automatically adjust to the day, the order quantity, and the inventory capacity. Tableau Public allows the possibility of working with Google's cloud and therefore, taking the daily product orders and making them available in the digital platform through a dashboard. In addition to this, the diagram that can be observed here is the graphical representation of the design of the costing system, which includes the logical connections that are made.

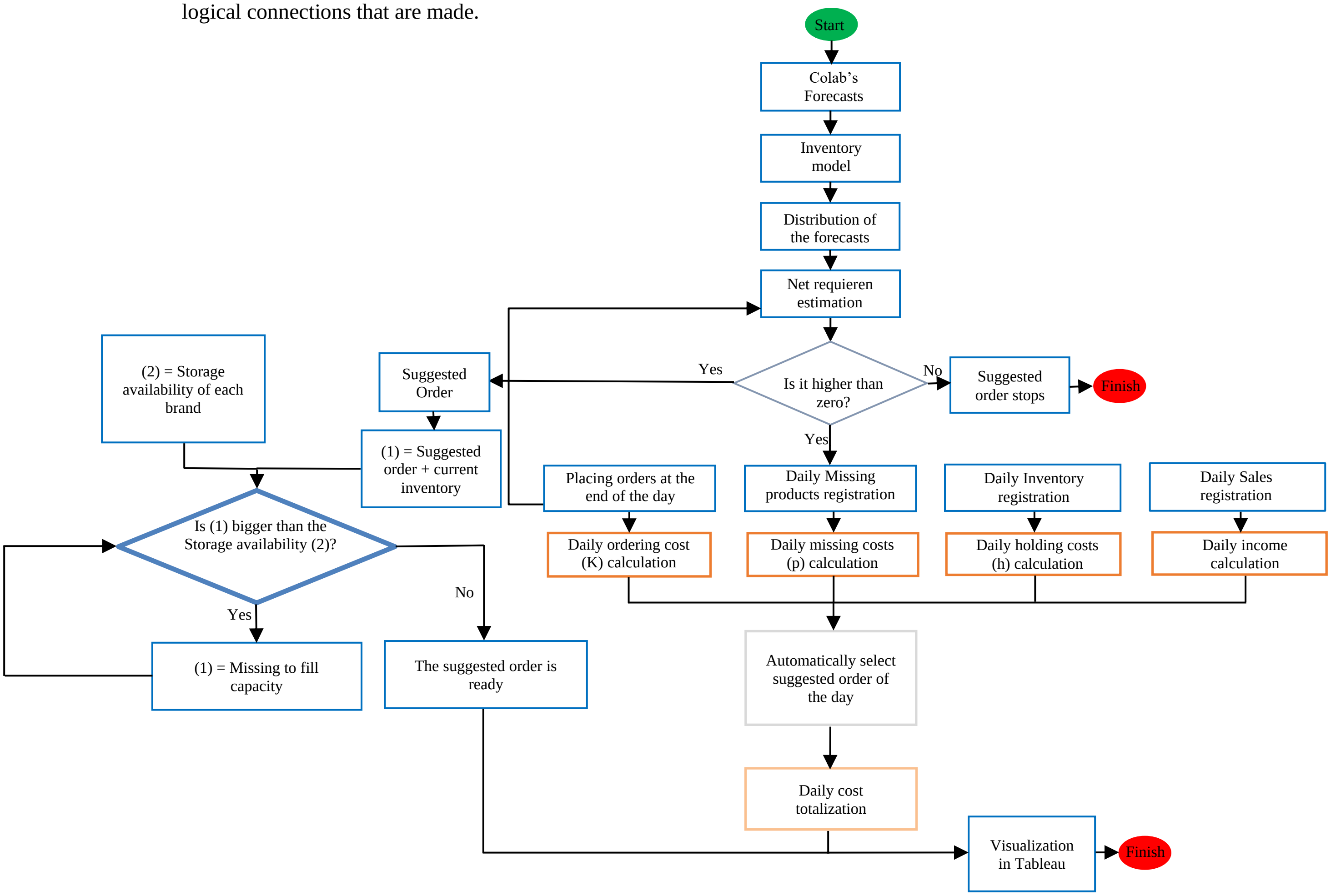


Diagram 7. Design of the costing model. (2020). The Authors.

The following table is the result of the application of the inventory policies to the historic daily orders the retailer made from 2018 to 2019:

Results of inventory policies								
Ice cream Brand	**Cost of policy**	**Inventory Policy**	**Q**	**R**	**S**	**s**	**# of missing units**	**# of orders**
Bocatto	$ 411.758	QR	132	18	132	18	1411	86
Polet	$ 1.055.045	QR	48	7	48	7	38475	236
Artesanal	$ 253.392	QR	582	50	725	50	45	19
Chococono	$ 1.159.944	QR	903	106	1488	106	3953	72
Casero	$ 182.859	Ss	200	14	200	14	945	47
Barra Aloha	$ 47.381	Ss	120	14	120	14	606	75
Paleta Aloha	$ 220.474	Ss	240	18	240	18	1003	49
Paleta Chocolisto	$ 153.906	QR	600	34	600	34	167	19
Vaso Chocolisto	$ 114.081	QR	156	6	180	6	439	73
Vaso Hobby Sundae	$ 285.213	Ss	112	12	112	12	2343	104
Vaso Heladino	$ 346.446	Ss	72	11	72	11	7388	165

Table 7. Results of inventory policies (2020). The Authors

The previous table illustrates that references with a higher number of orders such as Polet and Chococono, represent higher costs for the case study company. The number of missing units could be explained by the fact that the low inventory of certain brands requires a higher frequency of product orders, and this has a high financial impact for the company. Products that have a higher demand, eventually have higher product order quantities (Q).

The next table contains unit, ordering, holding, and missing costs as well as the calculated demand and the sales price of each brand:

Estimated costs						
Ice cream Brand	**Unit costs (c) COP**	**Ordering costs (k) COP**	**Holding costs (h) COP**	**Missing costs (p) COP**	**Demand (λ) units**	**Sales price COP**
Bocatto	$ 1.988	$ 1.400	$ 258	$ 1.012	6616	$ 3.000
Polet	$ 1.902	$ 1.400	$ 247	$ 1.098	2411	$ 3.000
Artesanal	$ 1.136	$ 1.400	$ 148	$ 564	17872	$ 1.700
Chococono	$ 1.003	$ 1.400	$ 130	$ 497	37946	$ 1.500
Casero	$ 672	$ 1.400	$ 87	$ 328	4870	$ 1.000
Barra Aloha	$ 294	$ 1.400	$ 38	$ 206	4934	$ 500
Paleta Aloha	$ 1.100	$ 1.400	$ 105	$ 100	6355	$ 1.200
Paleta Chocolisto	$ 672	$ 1.400	$ 87	$ 328	12082	$ 1.000
Vaso Chocolisto	$ 500	$ 1.400	$ 224	$ 300	1952	$ 800
Vaso Hobby Sundae	$ 1.467	$ 1.400	$ 191	$ 33	4208	$ 1.500
Vaso Heladino	$ 1.100	$ 1.400	$ 191	$ 1.100	3908	$ 2.200

Table 8. Estimated Costs. (2020). The Authors.

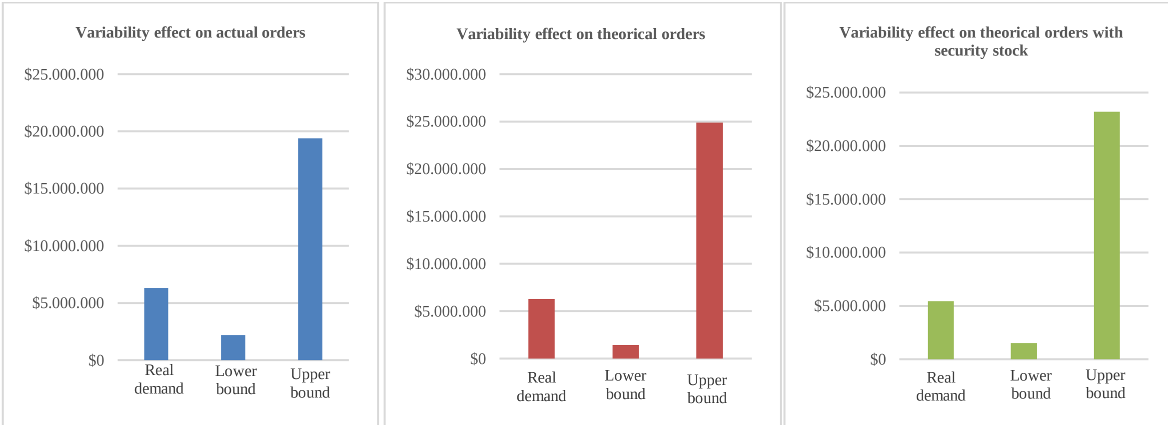
Table 9 displays the financial impact of underestimating and overestimating the demand by 40%. The purpose of this table was to measure the importance of the forecasts taking a variation of sales into account.

Brand	**Overestimated theorical demand**				**Underestimated theorical demand**			
	Missing costs (p) COP	**Holding costs (h) COP**	**Income**	**Profit**	**Missing costs (p) COP**	**Holding costs (h) COP**	**Income**	**Profit**
Artesanal	$ 146.608,80	$ 279.447,65	$ 4.607.000,00	$ 2.079.133,00	$ -	$ 1.155.850,62	$ 1.975.400,00	-$ 552.467,00
Paleta Chocolisto	$ -	$ 329.078,40	$ 970.000,00	$ 2.320,00	$ -	$ 532.873,60	$ 418.000,00	-$ 549.680,00
Chococono	$ 730.851,64	$ 196.050,90	$ 8.293.500,00	$ 4.417.289,76	$ -	$ 1.428.834,23	$ 3.550.500,00	-$ 325.710,24
Vaso Heladino	$ 122.100,00	$ 22.256,67	$ 840.400,00	$ 602.800,00	$ -	$ 103.620,00	$ 360.800,00	$ 123.200,00
Polet	$ -	$ 149.624,00	$ 1.065.000,00	$ 334.632,00	$ -	$ 357.449,20	$ 465.000,00	-$ 265.368,00
Bocatto	$ -	$ 1.017.238,87	$ 1.122.000,00	-$ 472.239,66	$ -	$ 1.252.597,94	$ 492.000,00	-$ 1.102.239,66
Vaso Vaso Hobby Sundae	$ 7.425,00	$ 28.557,60	$ 991.500,00	$ 498.584,58	$ -	$ 203.472,90	$ 421.500,00	-$ 71.415,42
Casero	$ 248.084,04	$ 185.930,24	$ 4.123.000,00	$ 2.156.581,00	$ -	$ 918.536,16	$ 1.767.000,00	-$ 199.419,00
Paleta Aloha	$ 909.000,00	$ 126.510,00	$ 8.520.600,00	$ 5.842.200,00	$ 16.200,00	$ 377.070,00	$ 3.638.800,00	$ 960.400,00
Vaso Chocolisto	$ 517.500,00	$ 7.366,67	$ 1.776.000,00	$ 1.686.000,00	$ 101.100,00	$ 32.883,33	$ 665.600,00	$ 575.600,00
Barra Aloha	$ 167.890,00	$ 32.369,40	$ 803.000,00	$ 648.650,00	$ -	$ 113.523,20	$ 301.000,00	$ 146.650,00
Total	$ 2.849.459,48	$ 2.374.430,40	$ 33.112.000,00	$ 17.795.950,68	$ 117.300,00	$ 6.476.711,19	$ 14.055.600,00	-$ 1.260.449,32

Table 9. Financial impact of the variations of the demand. (2020). The Authors

As it can be observed on Table 9, there would have been a positive financial impact if the demand was overestimated, meaning the value of the demand would have been 40% higher. This would represent a higher value of missing costs (p), impacting the levels of service of the case study company and therefore a higher rotation of inventory, which can be observed in the values of holding costs (h), which would have been lower by 63,33% than the values of underestimating the demand. Despite having lower levels of service by overestimating the demand, the company's income and profit would have been higher. If the demand is underestimated by 40%, there would not have been a profit for the case study company and references would have been a longer time in inventories, which can be observed in the holding cost (h) value. The previous implies that considering the forecasts that were generated, it is more expensive of the case study company to have forecasts that are higher than the demand if there is a variation of 40%.

The financial and inventory impact of the suggested orders was evaluated considering the variability of the demand for each brand. The evaluation was focused on the effects this variability would have on inventories, specifically on missing costs (p) and holding costs (h). The following link contains the analysis of the impact of variability has on suggested orders: Impact of the variability of the demand (Annexed # 7). The impact was evaluated in three scenarios, as it was previously described: the impact on the real orders placed by the retailer, the impact of what would have happened if the retailer placed the suggested orders and the impact of what would have happened if the retailer had placed the suggested orders considering a security stock. The impact was measured considering the real sales data and an upper and lower bound of that same sales data, which can be translated into the theorical situation of the forecasts having to respond to lower sales or their response to a higher number of sales. The following graphs indicate the overall financial impact of the three scenarios:



Graphs 9, 10 and 11. Impact of variability on the suggested orders (2020). The Authors.

As it can be observed on the previous graphs, if the retailer had followed the suggested orders exactly and had considered a security stock for each brand, this would have had a positive impact on inventories and costs considering the fact that by taking the real demand for december, the performance of the overall costs ($Total\ costs = missing\ costs(p) + holding\ costs(h)$) was better in the third situation, with a value of $5,454,854 COP, by contrast to the second situation with a value of $6,297,568 COP and the first situation with a value of $6,312,418 COP.

The scenario where the retailer ordered the exact values of the suggested orders performed better in the case where the demand would have had a negative variation (lower bound), with a value of $1,441,451 COP. This can be explained by the fact that orders would have been much lower in this situation. The best performance of having a higher demand due to a positive variability (upper bound) was in the case of the real orders placed by the retailer, but it reflects the retailer tended to overstock, which has an impact on costs and inventories.

The effect of the security stock can be observed in the cases of each brand, by instance in the case where there is a theorical increase on the demand Vaso Chocolisto has cost of $6.378.421 COP on the real scenario, $3.695.368 COP on the second scenario and $3.381.671 COP on the third scenario, which constitutes an estimated 10% reduction in costs with respect to the second situation and an estimated 89% reduction with respect to the real situation. After analysing the three situations, it is clear that if the demand would have had a positive variability, the retailer would have had a negative impact in terms of inventories and costs, due to the fact that the missing costs would have risen in a considerable way. The file that contains the analysis of the impact the suggested order has considering the variability of the demand can be consulted on the following link: Analysis of the variability of the demand.

The digital platform that was designed and developed to be implemented in the case study company can be consulted in the following link: Digital platform.

5.3 Implementation of the digital platform

Regarding the implementation of the digital platform, the retailer's perception had to be evaluated through a semi-structured interview. The transcription of the semi-structured interview was designed to evaluate the retailer's perception of the platform can be consulted on the next the following link: Perception of the digital platform (Annexed 8). The answers provided by the retailer display that the retailer trusted the forecasts that were presented in the digital platform. This can be evidenced by the fact that the word "accuracy" in relationship with the forecast is very repeated throughout the interview. The retailer also evidenced that the platform provided relevant information to make decisions, which is presented in the indicator's module.

Another element that can be manifested in the retailer's answers is that there was a negative impact on the business in 2020, which resulted on lower influx of people through the year in the case study company and therefore sales were affected. With respect the process of relying on the forecast, the retailer expressed that in an early stage of the implementation the values presented in the suggested orders were perceived as very high or very low, and that with time, and by seeing the sales by comparison to the forecasts, the level of trust increased.

In terms of the perception towards the benefit of the digital platform as a business model, the retailer expressed that since the daily suggested orders of the analyzed brands took the forecasts, the previous placed orders, and the inventory levels into account, it was not necessary to manage large inventories of references that did not have a good rotation, and in the retailer's view this resulted in costs reductions.

Even though the retailer expressed that the platform was functional, the suggested orders were accurate, and that its implementation was beneficial, it mentioned that it was very demanding register of information because of the level of detail that was required, which included the daily sales, the inventory levels, the daily orders, and the missing products of each selected brand.

After performing the interview, a survey was conducted to evaluate the design and functionalities of the digital platform. The following table are the results of the survey that measured how the retailer's needs were met following the characteristics of standard ISO 9126:

Question weighting table							
Questions	**Functionality**	**Relatability**	**Usability**	**Efficiency**	**Maintainability**	**Portability**	**Score**
Question 1	0,25	0,25	0,75	1,25	1,00	1,00	5,00
Question 2	0,75	0,25	1,00	0,25	0,25	0,60	5,00
Question 3	0,30	1,00	0,50	0,35	0,25	0,75	5,00
Question 4	0,90	0,60	0,60	0,40	1,00	0,95	5,00
Question 5	0,40	0,50	0,60	0,30	0,40	0,25	5,00
Question 6	0,60	0,20	0,64	0,80	0,36	0,44	4,00
Question 7	0,55	0,25	0,25	0,25	0,75	0,25	5,00
Question 8	0,50	0,65	0,25	0,45	0,20	0,25	5,00
Question 9	0,60	1,25	0,25	0,75	0,75	0,40	5,00
TOTAL	4,85	4,95	4,84	4,80	4,96	4,89	88%

Table 10. Question weighting table (2020). The Authors.

With the results of the previous table, the following table was built to have an overall result of the scores of applying the standard to evaluate the digital platform:

Overall results of the functionalities of the platform				
Characteristics	**Description**	**Percentage**	**Score**	**Total**
Functionality	Do the functions and properties satisfy the explicit and implicit needs?	15%	4,85	0,7228
Reliability	Can it maintain the level of performance, under certain conditions and for a certain time?	10%	4,95	0,4895
Usability	Is the software easy to use and easy to learn?	25%	4,84	1,21
Efficiency	Is it fast and minimalist in terms of resource usage?	10%	4,80	0,48
Maintainability	Is it easy to modify and verify?	15%	4,91	0,7365
Portability	Is it easy to transfer from one environment to another?	25%	4,89	1,2225
TOTAL		100%	29,24	4,86

Table 11. Overall results of the functionalities of the platform (2020). The Authors.

The obtained results demonstrate that the platform met the needs of the retailer in terms of the characteristics of the standard in a satisfying manner. The characteristic that required a greater level of improvement is the efficiency of the platform, which can be corrected with a design that is more minimalistic and clearer for the retailer. Since the indicators part of the platform is where the relevant information is presented to the retailer, it is critical that there is a high level of efficiency in this module.

5.4 Measurement of the implementation of digital platform

As it was mentioned earlier, the KPIs were measured before the implementation of the digital platform (november 2020) and after its implementation (december 2020). These values were calculated with the ice cream brands that were selected for the development of this project. The tables than can be observed in this part contain the measured KPIs and are a tool to evaluate the impact of the implementation of the digital platform by the retailer. There is an evident improvement in the indicators after the implementation, although it is important to mention that over the year 2020 there was a negative impact in the business (due to Covid-19 and public policies deployed to decrease the spread of the virus) and there were several variables that influenced the improvement of the december's indicators, such as a correlation between climate and sales and a larger influx of people purchasing in the case study company.

The following table corresponds to the Return on Investment (ROI), the Gross Margin, and the Inventory Rotation measured in november and december of 2020:

ROI, Gross Margin, and Inventory Rotation			
Months	ROI	Gross Margin	Inventory Rotation
november 2020	12,67%	11,24%	3,105
december 2020	35,17%	26,02%	5,469

Table 12. ROI, Gross Margin, and Inventory Rotation (2020). The Authors.

As it can be observed in the previous table there was a 254% increase in the Return of investment of the selected ice cream brands, which means for every $100 COP that was invested in purchasing the selected brands, there was a return of $135,17 COP during december. There was a 231% increase in Gross Margin, which means that for every COP that was sold during december, $26 COP were generated. The improvement in inventory rotation can be explained by the fact that the implementation of the digital platform could guarantee that the references that had a higher demand were sold and this has a very clear relationship with the forecasting model.

The following table corresponds to the KPIs of november and december of 2020 of the sales revenues, the sales costs, the average inventories, and the order quantities of each ice cream brand as well as the totalized result of the performance of the KPIs of these brands. There was a significant increase in the sales of some brands and in some cases, it is more than double. This can be explained by the fact that brands like Artesanal have a non-stationary behavior, which means that they present trend and seasonality, and the forecasting models were able to capture this behavior. Brands like Vaso Chocolisto have a Stationary behavior and do not present a large variation in sales.

Financial and inventory KPIs 1								
Ice cream brands	november 2020				december 2020			
	Revenue	Sales Cost	Average inventory	Order Quantity	Revenue	Sales Cost	Average inventory	Order Quantity
Artesanal	$ 1.401.621	$ 1.762.945	349	1500	$ 3.291.200	$ 2.527.867	386	2225
Barra Aloha	$ 255.000	$ 91.241	225	300	$ 502.000	$ 154.350	442	525
Casero	$ 1.537.241	$ 1.133.603	589	1630	$ 2.945.000	$ 1.966.419	462	2925
Chococono	$ 3.258.621	$ 2.814.383	385	2712	$ 5.922.000	$ 3.876.210	337	3864
Paleta Ahola	$ 255.000	$ 91.241	225	904	$ 502.000	$ 154.350	442	2976
Paleta Chocolisto	$ 651.724	$ 542.234	154	780	$ 694.000	$ 967.680	492	1440
Vaso Chocolisto	$ 521.379	$ 341.379	297	660	$ 555.200	$ 90.000	189	180
Vaso Heladino	$ 261.724	$ 13.655	65	12	$ 600.600	$ 237.600	17	216
Vaso Hobby Sundae	$ 406.552	$ 291.377	71	192	$ 706.500	$ 492.912	18	336
Polet	$ 462.414	$ 377.777	31	192	$ 765.000	$ 730.368	97	384
Bocatto	$ 422.069	$ 913.031	38	444	$ 807.000	$ 1.594.240	413	802
TOTAL	$ 9.433.345	$ 8.372.866	2429	9326	$ 17.290.500	$ 12.791.996	3295	15873

Table 13. Financial and inventory KPIs 1. (2020). The Authors.

The previous table show an increase in sales costs by contrasting december and november and the explanation of this is that a higher demand of ice cream requires the retailer to purchase more references. This situation can be reflected in the increase of average inventories of december with respect to november. If the demand of one month is lower because of variables such as weather, this has a negative impact in the demand of each ice cream and therefore, the retailer purchases lower number of references. Taking this situation into account, the forecasting models projected an increase on december's demand and by integrating them in the costing system with the inventory models, it delivered the daily orders for the retailer. An increase in the number of orders increases in the average inventories.

The next table displays the values of each brand's profit, sales, average inventories, and importance in both november and december of 2020. There is a lower profit in the brands of november that can be explained with the Inventory Rotation indicator. The references in november had a lower rotation and therefore, remained a longer time in the refrigerators which derives in purchasing references that are not being sold. There is a clear increase in sales volumes and the references of december portray a higher inventory cost since the retailer placed a higher number of orders to supply the demand. In terms of the importance of each brand with respect to sales, there was a shift from some brands to others, but it was tenuous, which can be explained by the fact that these are indeed the most important brands for the retailer and therefore they are the ones that are more frequently ordered from Meals. Chococono is the brand that shows a higher profit and remains the most popular brand for the customers of the case study company.

Financial and inventory KPIs 2								
Ice cream brands	november 2020				december 2020			
	Profit	Sales	Average Inventory costs	Brand importance	Profit	Sales	Average Inventory costs	Brand importance
Artesanal	-$ 361.324	825	$ 3.965	10,82%	$ 763.333	1936	$ 4.385	10,63%
Barra Aloha	$ 163.759	535	$ 662	7,01%	$ 347.650	1004	$ 1.299	5,51%
Casero	$ 403.638	1536	$ 3.960	20,14%	$ 978.581	2945	$ 3.106	16,16%

Chococono	$ 444.238	2214	$ 3.862	29,03%	$ 2.045.790	3948	$ 3.381	21,67%
Paleta Ahola	$ 163.759	405	$ 1.812	5,31%	$ 347.650	5532	$ 3.560	30,36%
Paleta Chocolisto	$ 109.490	657	$ 1.035	8,61%	-$ 273.680	694	$ 3.306	3,81%
Vaso Chocolisto	$ 180.000	743	$ 5.127	9,74%	$ 465.200	894	$ 3.262	4,91%
Vaso Heladino	$ 248.069	125	$ 954	1,64%	$ 363.000	273	$ 249	1,50%
Vaso Hobby Sundae	$ 115.175	275	$ 1.042	3,61%	$ 213.588	471	$ 264	2,58%
Polet	$ 84.637	158	$ 590	2,07%	$ 34.632	255	$ 1.845	1,40%
Bocatto	-$ 490.962	154	$ 755	2,02%	-$ 787.240	269	$ 8.210	1,48%
TOTAL	$ 1.060.478	7627	$ 23.764	100,00%	$ 4.498.504	18221	$ 32.867	100,00%

Table 14. Financial and inventory KPIs 2. (2020). The Authors.

To evaluate the impact of the implementation of the digital platform there was a comparison of the Sales Growth KPI from november of 2019 to december of 2019 with respect to its value from november of 2020 to december of 2020 (the month where the platform was implemented). The following table displays the revenues of each year's months and the Sales Growth indicator:

Sales contrast between 2019 with 2020				
Months	**Revenue 2019**	**Revenue 2020**	**Sales Growth 2019**	**Sales Growth 2020**
november	$ 28.751.140	$ 9.433.345	-13,71%	83,29%
december	$ 24.808.462	$ 17.290.500		

Table 15. Sales contrast between 2019 with 2020. (2020). The Authors

The ice cream brands that were analyzed in 2020 were also examined for 2019. 2019 was a year in which the finances of the company were not as affected as they were in 2020 and therefore the revenue of these brands was much higher in those months by comparison to their 2020 values. Taking this into consideration, these brands showed a decrease in sales during 2019 of -13,71%. There was a drastic 83,29% increase in sales for those brands in november of 2020 with respect to december of 2020 and this is an indication that there is a benefit on implementing a business model that contains a forecasting system, rather than relying only on intuition and knowledge of the market.

The impact of the digital platform was also on the degree in which the daily forecasts presented in the digital platform were considered to place orders as well as the level in which the sales matched the forecasts. In most cases there was an acceptable performance of the forecasts by comparison to sales. The forecasts of references such as Bocatto had a considerable gap between forecasts and sales. Another element that can be observed in the table is that the retailer trusted the daily forecasts presented in the digital platform in a good percentage during the implementation. This can be evidenced by the fact that the sales forecast of most brands presents a gap that is lower than 30% in most cases, although it can be acknowledged that for the retailer to fully rely on the forecasts, there is a process of adapting to the digital platform. An example of the retailer not fully relying in the daily orders is the large gap between the forecast and the orders of Vaso Chocolisto. The following table displays december's forecasts, december's sales, and the placed orders of each brand during this month:

Forecasts performance in terms of placed orders and sales					
Brand	**december's Forecast**	**december's sales**	**Orders**	**Forecast Sales Gap**	**Forecast Orders Gap**
Artesanal	2493	1936	2225	28,77%	12,04%
Chococono	4979	3948	3864	26,12%	28,86%
Barra Aloha	970	1004	525	3,39%	84,76%
Casero	2518	2945	2925	14,50%	13,91%
Paleta Aloha	3065	5532	2976	44,60%	2,99%
Paleta Chocolisto	1278	694	1440	84,15%	11,25%
Vaso Chocolisto	1169	1388	180	15,78%	549,44%
Vaso Heladino	247	273	216	9,52%	14,35%
Vaso Hobby Sundae	239	471	336	49,26%	28,87%
Polet	209	255	384	18,04%	45,57%
Bocatto	555	269	802	106,32%	30,80%

Table 16. Forecasts performance in terms of placed orders and sales. (2020). The Authors

In most cases there was an acceptable performance of the forecasts by comparison to sales. The forecasts of references such as Bocatto had a considerable gap between forecasts and sales. Another element that can be observed in the table is that the retailer trusted the daily forecasts presented in the digital platform in a good percentage during the implementation. This can be evidenced by the fact that the sales forecast of most brands presents a gap that is lower than 30% in most cases, although it can be acknowledged that for the retailer to fully rely on the forecasts, there is a process of adapting to the digital platform. An example of the retailer not fully relying in the daily orders is the large gap between the forecast and the orders of Vaso Chocolisto.

In addition to the positive impact of implementing the digital platform as a business management tool, there was a social impact, that can be measured through 3 of the 17 Sustainable Development Goals proposed by United Nations (UN): Economic Growth (Goal number 8), Industry and Infrastructure (Goal number 9), and Responsible Consumption and production (Goal number 12):

According to the UN, poverty and employment numbers of 2018 reached their best records in history, but despite this, a large percentage of the world population does not have a stable employment situation. 61% of the world's labor force had informal jobs in 2016, which is more than 2 billion people. This makes them vulnerable to worldwide events such as an economic crisis. In addition to this, more than 700 million people around the world work under situations of extreme or moderate poverty for the year 2018 (United Nations, 2021). Economic growth challenges require solutions that can increase productivity and technological development hence making companies able to create more jobs because of higher incomes. In this sense, the results of the financial KPIs show that this digital platform can be beneficial for retailers, and by a process of constant improvement, it can potentially adapt to other retailers and small independent marketers that do not have access to digital management systems, such as an ERP (Enterprice Resource planning). A proper business management with a tool that facilitates decision making, translates into greater productivity because less resources generate a higher revenue.

Innovation can be defined as helping organizations grow by improving turnover, profit, knowledge, and efficiency and this implies making changes to something that was established and introducing something new to improve processes, services, or products from an organization (Sullivan, 2009). The UN establishes that innovation is a necessary tool to face several world's challenges (United Nations, 2021). In this regard it is evident that this project took elements and tools and integrated them into a digital management system that contributed to the case study company in terms of knowledge, by making the business information available in KPIs and improved processes such placing orders, supported by an estimation model and a costing system and therefore, there was an innovative process that translated into a benefit for the retailer.

The United Nations sustain the level of consumption needs of a large part of the population is so large, that the current resources are not going to be able to satisfy the demand. Despite this fact, people and companies are wasting resources that could be used properly (United Nations, 2021). By granting the retailer the possibility of ordering only what is necessary, taking the forecasts and inventory levels into account, energy and resources are used better to fulfill the business's goals.

6. Conclusions and recommendations

6.1 Conclusions

- As the results show, the ice cream families that present a greater amount of sales volume tend to have a lower value of p-value in contrast to the ones that had lower sales. The three brands had a p-value lower than 0,05 or near (in the case of Artesanal that had a p-value of 0,054, which is close to a stationary behavior). Regarding the Aloha brand which had a p-value of 0.33, it reflected a clear seasonality and trend. It is important to mention that Meals constantly uses this brand for sales contests during random times of the year and in the case of 2020's december there was an active contest of this brand, which triggered sales during this month in comparison to previous ones.

- There is a clear relationship between Colab's forecasts' MAPE and the profitability of the references since lower values of error in certain references tended to have higher profitability. This can give a general overview that unexpected changes in order quantities and demand can generate a larger gap between forecasts and sales as well as forecasts and orders. Even though this gap was larger in some cases, there is a clear benefit in implementing forecasting models rather than not having one implemented, which can be seen in the retailer's perception and with the financial impact of the platform as a business management tool.

- Since the behavior of most brands was not stationary, there were considerable variations over the year, there are restrictions that must adapt to those changes. A suitable way to manage inventories, taking these restrictions into account was the designed dynamic inventory model integrated in the costing system. This model took the QR and Ss policies only as a reference to distribute the forecast in each month. It would not have been as beneficial to only rely on the QR and Ss policies these policies since they assume stationarity. The suggested orders adapted to the reality of the business by considering orders, sales, forecasts, and storage capacity, which allowed to suggest orders that considered this information thus helping the retailer make proper ordering decisions, such as not ordering large volumes of references that would not have an acceptable inventory rotation.

- The interview and the survey that were carried out, as well as the gap between forecasts and orders (which serve as a measure for the retailer's trust on the suggested orders) indicate that even though in most cases there was a high level of trust in the information of suggested orders, there are a few brands that present a large gap between orders and forecasts. The positive economic impact on the examined brands after the implementation of this platform could be a first step for the retailer to fully trust the platform as a business tool as well as a larger period to implement the platform.

- The measurement of the implementation consisted of evaluating the use of the platform in december of 2020 by contrast to not using the platform in november of 2020 using KPIs. Based on the KPIs, which it is possible to indicate that the use of the platform as a business management system was useful from a decision standpoint. The effects of the implementation were higher suggested orders, by comparison to the previous period, which increased average inventories as well as purchasing costs. This was not a negative outcome, since there was an increase in income, which is reflected in indicators such as Return on Investment (ROI) and Inventory Rotation. The implementation of this digital tool had a generally positive impact on business dynamics.

- It was an adequate decision to use Google services for the development of the system that resulted in the digital platform. Google Colab, where the forecasting models were generated using Python language, sent the forecasts to Google Sheets, where the costing system was designed. Google Sheets files are easily read by Tableau Public and the indicators can be generated in real time. Tableau public allows dashboards to be presented in other websites with HTML language. This evidences that the flow of information did not require additional costs and that the communication between the tools that composed the system was smooth.

6.2 Recommendations

- Brands that have a demand that has a constant behavior are easier to forecast and could consequently have more effective methods to increase their sales, such as positioning the brand in consumer's habits rather than relying on specific promotions contests. This could translate into better demand planning, reduction in the elasticity of the demand, and lower values of errors between forecasts and sales.

- It is recommended for the retailer to apply QR and Ss inventory policies for Polet, Chococono, Casero Barra Aloha and Vaso Chocolisto, since those brands have a stationary behavior, and this respects the theorical assumptions of the continuous inventory models. This could derive the retailer losing costs by ordering only when is necessary and in guaranteeing that the demand is satisfied by measuring two service levels: The proportion of the inventory that can cover the demand and the number periods where there are no missing products.

- Taking the results into consideration, it could be useful to collect the historical information on the demand from different Crem Helado's authorized marketers from different locations in the city and this implies different socio-economic conditions. This could nourish the analysis because if the behavior of these brands is similar. It would be beneficial for Meals since there could be better production planning, better investment in resources, and proper inventory management.

- Given the financial impact weather could have on retailers, it is recommended to analyze the behavior of rainfall, temperature, and sales to carry out statistical tests that could determine the correlation between these variables. If there is a correlation, this opens the possibility of integrating weather to the forecasting model and this could provide criteria to generate forecasts that adapt to the situation of each retailer. This could avoid incurring in additional costs during rainy seasons or take advantage of situations where there is good weather to increase sales, given the seasonal effects that ice cream has.

- The retailer evidenced that the recollection of information of all the analyzed brands was a demanding task. A higher level of automation, by for example using a QR code in certain ice creams to register sales and missing products and later sending this information to a data base that is input of the forecasting model and the costing system could make the retailer's task easier as well as the accuracy of information. Making this process easier for retailers could increase the number of people that use the platform for business management.

7. References

[1] R. J. Hyndman and G. Athanasopoulos, "Forecasting: Principles and Practice," *Princ. Optim. Des.*, p. 504, 2018, [Online]. Available: https://otexts.com/fpp2/.

[2] I. Stulec, K. Petljak, and D. Naletina, “Weather impact on retail sales: How can weather derivatives help with adverse weather deviations?,” *J. Retail. Consum. Serv.*, vol. 49, pp. 1–10, Jul. 2019, doi: 10.1016/j.jretconser.2019.02.025.

[3] J. C. F. Ehrenthal, D. Honhon, and T. Van Woensel, “Demand seasonality in retail inventory management,” *Eur. J. Oper. Res.*, vol. 238, no. 2, pp. 527–539, 2014, doi: 10.1016/j.ejor.2014.03.030.

[4] USPS Delivers, “KPIs to Improve Inventory Management Process | USPS Delivers,” 2020. https://www.uspsdelivers.com/10-kpis-that-can-help-improve-your-inventory-management-process/#identifier_0_174 (accessed Nov. 22, 2020).

[5] G. Nutresa, “Informe integrado,” p. 154, 2019.

[6] J. Edwards, S. Burn, E. Crossin, and M. Othman, “Life cycle costing of municipal food waste management systems: The effect of environmental externalities and transfer costs using local government case studies,” *Resour. Conserv. Recycl.*, vol. 138, no. July, pp. 118–129, 2018, doi: 10.1016/j.resconrec.2018.06.018.

[7] website.com, “What is a domain name? - Domain Names - Beginner’s Guide | Website.com,” Oct. 02, 2020. https://www.website.com/beginnerguide/domainnames/8/1/What-is-a-domain-name?.ws (accessed Nov. 03, 2020).

[8] F. Badorf and K. Hoberg, “The impact of daily weather on retail sales: An empirical study in brick-and-mortar stores,” *J. Retail. Consum. Serv.*, vol. 52, no. March 2019, p. 101921, 2020, doi: 10.1016/j.jretconser.2019.101921.

[9] L. Wen, K. Zhou, and S. Yang, “Load demand forecasting of residential buildings using a deep learning model,” *Electr. Power Syst. Res.*, vol. 179, no. november 2019, p. 106073, 2020, doi: 10.1016/j.epsr.2019.106073.

[10] CFI, “Cost Driver - Know the Significance of Cost Drivers in Cost Accounting,” 202. https://corporatefinanceinstitute.com/resources/knowledge/accounting/cost-driver/ (accessed Nov. 03, 2020).

[11] Passport, “Statistics Redesign | Passport,” *Ice Cream and Frozen Desserts* , 2019. https://www-portal-euromonitor-com.ezproxy.javeriana.edu.co/portal/statisticsevolution/index (accessed Nov. 03, 2020).

[12] ISOTOOLS, “KPIs Indicadores.” https://www.isotools.org/soluciones/procesos/kpis-indicadores/ (accessed Nov. 03, 2020).

[13] Grupo Nutresa, “Resultados trimestrales - Grupo Nutresa,” *Ventas en Valor y Volumen*, 2019. https://gruponutresa.com/inversionistas/resultados-y-publicaciones/resultados-trimestrales/#2019-4 (accessed Nov. 03, 2020).

[14] Expert System, “What is Machine Learning? A definition - Expert System,” May 06, 2020. https://expertsystem.com/machine-learning-definition/ (accessed Nov. 05, 2020).

[15] X. Sheng and C. Xin, “Ordering strategy for fresh food with nonlinear holding cost and inventory -dependent demand,” Sep. 2019, doi: 10.1109/IESM45758.2019.8948141.

[16] J. I. Escavy, M. J. Herrero, L. Trigos, and E. Sanz-Pérez, “Demographic vs economic variables in the modelling and forecasting of the demand of aggregates: The case of the Spanish market (1995–2016),” *Resour. Policy*, vol. 65, no. September 2019, 2020, doi: 10.1016/j.resourpol.2019.101537

[17] N. Vandeout, “Forecast KPI: RMSE, MAE, MAPE & Bias | by Nicolas Vandeput | Towards Data Science,” May 2019. https://towardsdatascience.com/forecast-kpi-rmse-mae-mape-bias-cdc5703d242d (accessed Nov. 03, 2020).

[18] J. Brownlee, *Introduction to Time Series Forecasting With Python: How to Prepare Data and ... - Jason Brownlee - Google Libros*, 1st ed., vol. 1. 2020

[19] A. Uzialko, “Business to Business: What Is B2B? - businessnewsdaily.com,” Jun. 23, 2020. https://www.businessnewsdaily.com/5000-what-is-b2b.html (accessed Nov. 04, 2020).

[20] J. Aschemann-Witzel *et al.*, “Key characteristics and success factors of supply chain initiatives tackling consumer-related food waste – A multiple case study,” *J. Clean. Prod.*, vol. 155, pp. 33–45, 2017, doi: 10.1016/j.jclepro.2016.11.173.

[21] Y. Raju, P. S. Kang, A. Moroz, R. Clement, A. Hopwell, and A. Duffy, “Investigating the Demand for Short-shelf Life Food Products for SME Wholesalers,” vol. 9, no. 6, pp. 2051–2055, 2015.

[22] M. Gumani, Y. Korke, P. Shah, S. Udmale, V. Sambhe, and S. Bhirud, “Forecasting of sales by using fusion of machine learning techniques,” *2017 Int. Conf. Data Manag. Anal. Innov. ICDMAI 2017*, pp. 93–101, 2017, doi: 10.1109/ICDMAI.2017.8073492.

[23] Microsoft, “Qué es Power BI | Microsoft Power BI.” https://powerbi.microsoft.com/es-es/what-is-power-bi/ (accessed Nov. 03, 2020).

[24] El Economista, “Modelo de coste ABC: qué es - Diccionario de Economía - elEconomista.es.” https://www.eleconomista.es/diccionario-de-economia/modelo-de-coste-abc (accessed Nov. 03, 2020).

[25] S. Nahmias, *Análisis de la producción y las operaciones*, 7th ed., vol. 51, no. 1. Mexico City, 2007.

[26] V. Kotu and B. Deshpande, *Data Science Concepts and Practice*, vol. 2, no. C. 2019.

[27] C. Scott, H. Lundgren, and P. Thompson, *Guide to Supply Chain Management*. 2011.

[28] E. J. Flies, B. W. Brook, L. Blomqvist, and J. C. Buettel, “Forecasting future global food demand: A systematic review and meta-analysis of model complexity,” *Environ. Int.*, vol. 120, pp. 93–103, Nov. 2018, doi: 10.1016/j.envint.2018.07.019.

[29] Abud Figueroa María Antonieta, “Calidad en la Industria del Software . La Norma ISO-25000,” *Calid. en la Ind. del Software. La Norma ISO-9126*, p. 255, 2012, [Online]. Available: javier8a.com/itc/bd1/Normas iso 9126.pdf.

[30] Forbes, “What Is A Minimum Viable Product, And Why Do Companies Need Them?,” Feb. 27, 2018. https://www.forbes.com/sites/quora/2018/02/27/what-is-a-minimum-viable-product-and-why-do-companies-need-them/?sh=298fa1c2382c (accessed Nov. 03, 2020).

[31] “Business Intelligence.” https://www.microstrategy.com/en/business-intelligence (accessed Nov. 03, 2020).

[32] L. Meazzini, “Everything you need to know about Time Series | by Luis Meazzini | Towards Data Science,” *The most complete introduction to Time Series analysis you can find*, Jan. 20, 2020. https://towardsdatascience.com/everything-you-need-to-know-about-time-series-5fa1834d5b18 (accessed Nov. 03, 2020)

[33] G. Nutresa, “Grupo Nutresa,” pp. 1–28, 2019, [Online]. Available: https://www.gruponutresa.com/wp-content/uploads/2016/03/Estructura-Organizacional.pdf%0Ahttp://www.elempleo.com/sitios-empresariales/colombia/grupo-nutresa/mision.asp

[34] G. C. Aye, M. Balcilar, R. Gupta, and A. Majumdar, “Forecasting aggregate retail sales: The case of South Africa,” *Int. J. Prod. Econ.*, vol. 160, pp. 66–79, Feb. 2015, doi: 10.1016/j.ijpe.2014.09.033.

[35] D. Romero, P. Gaiardelli, D. Powell, T. Wuest, and M. Thürer, “Rethinking jidoka systems under automation & learning perspectives in the digital lean manufacturing world,” *IFAC-PapersOnLine*, vol. 52, no. 13, pp. 899–903, 2019, doi: 10.1016/j.ifacol.2019.11.309.

[36] R. Estévez, “¿En qué consiste el análisis de costes del ciclo de vida? - ecointeligencia - cambia a un estilo de vida sostenible!,” Jul. 28, 2016. https://www.ecointeligencia.com/2016/07/lcc-analisis-costes-ciclo-vida/ (accessed Nov. 03, 2020).

[37] E. Tarallo, G. K. Akabane, C. I. Shimabukuro, J. Mello, and D. Amancio, “Machine learning in predicting demand for fast-moving consumer goods: An exploratory research,” *IFAC-PapersOnLine*, vol. 52, no. 13, pp. 737–742, Sep. 2019, doi: 10.1016/j.ifacol.2019.11.203.

[38] PORTAFOLIO, “Helados: una industria que seduce a grandes y chicos | Negocios | Portafolio,” Feb. 13, 2019. https://www.portafolio.co/negocios/helados-una-industria-que-seduce-a-grandes-y-chicos-526211 (accessed Nov. 03, 2020).

[39] V. M. Da Silva, V. P. R. Minim, M. A. M. Ferreira, P. H. de P. Souza, L. E. da S. Moraes, and L. A. Ô. Minim, “Study of the perception of consumers in relation to different ice cream concepts,” *Food Qual. Prefer.*, vol. 36, pp. 161–168, Sep. 2014, doi: 10.1016/j.foodqual.2014.04.008.

[40] S. Reyes, “¿Qué es estacionalidad? - MacroConcept Analytica,” Nov. 2017. https://www.analytica.com.do/2017/11/que-es-estacionalidad/ (accessed Nov. 04, 2020).

[41] P. A. Vargas Rubio, “La marca Crem Helado vende más de 1,8 millones de helados cada día en el país,” Jun. 14, 2019. https://www.larepublica.co/empresas/la-marca-crem-helado-vende-mas-de-18-millones-de-helados-cada-dia-en-el-pais-2873705 (accessed Nov. 04, 2020).

[42] “Tiempo Bogotá - meteoblue.” https://www.meteoblue.com/es/tiempo/semana/bogotá_colombia_3688689 (accessed Nov. 03, 2020).

[43] Python.org, “What is Python? Executive Summary | Python.org.” https://www.python.org/doc/essays/blurb/ (accessed Nov. 05, 2020).

[44] A. T. Sarmiento and O. C. Soto, “New product forecasting demand by using neural networks and similar product analysis,” *Dyna*, vol. 81, no. 186, p. 311, 2014, doi: 10.15446/dyna.v81n186.45223.

[45] Expert System, “What is Machine Learning? A definition - Expert System,” May 06, 2020. https://expertsystem.com/machine-learning-definition/ (accessed Nov. 04, 2020).

[46] namecheap.com, “What is web hosting? Beginners, listen up.,” 2020. https://www.namecheap.com/hosting/what-is-web-hosting-definition/ (accessed Nov. 03, 2020).

[47] S. Ma, R. Fildes, and T. Huang, “Demand forecasting with high dimensional data: The case of SKU retail sales forecasting with intra- and inter-category promotional information,” *Eur. J. Oper. Res.*, vol. 249, no. 1, pp. 245–257, Feb. 2016, doi: 10.1016/j.ejor.2015.08.029.

[48] M. S. AL-Musaylh, R. C. Deo, J. F. Adamowski, and Y. Li, “Short-term electricity demand forecasting using machine learning methods enriched with ground-based climate and ECMWF Reanalysis atmospheric predictors in southeast Queensland, Australia,” *Renew. Sustain. Energy Rev.*, vol. 113, no. February 2019, p. 109293, 2019, doi: 10.1016/j.rser.2019.109293.

[49] D. Li, X. Wang, H. K. Chan, and R. Manzini, “Sustainable food supply chain management,” *Int. J. Prod. Econ.*, vol. 152, pp. 1–8, 2014, doi: 10.1016/j.ijpe.2014.04.003.

[50] Sectorial, “Colombia Produce 98.000 Toneladas de Helado Anual,” Mar. 15, 2019. https://www.sectorial.co/informativa-lacteo/item/213443-colombia-produce-98-000-toneladas-de-helado-anual (accessed Nov. 04, 2020).

[51] “Python Pandas Tutorial - Learn Pandas in Python (Advance) - DataFlair,” *Data Flair*. https://data-flair.training/blogs/pandas-tutorial/ (accessed Dec. 04, 2020).

[52] A. A. Syntetos *et al.*, “Forecasting and stock control: A study in a wholesaling context,” *Int. J. Prod. Econ.*, vol. 127, no. 1, pp. 103–111, 2010, Accessed: Nov. 04, 2020. [Online]. Available: https://econpapers.repec.org/RePEc:eee:proeco:v:127:y:2010:i:1:p:103-111.

[53] J. Vermorel, “Definición de unidad de mantenimiento de existencias (SKU),” Aug. 2013. https://www.lokad.com/es/definicion-unidad-de-mantenimiento-de-existencias-(sku) (accessed Nov. 04, 2020).

[54] “Getting started with VBA in Office | Microsoft Docs,” Aug. 14, 2019. https://docs.microsoft.com/en-us/office/vba/library-reference/concepts/getting-started-with-vba-in-office (accessed Nov. 03, 2020).

[55] GitHub, “Hello World · GitHub Guides,” 2016. https://guides.github.com/activities/hello-world/ (accessed Nov. 05, 2020).

[56] Grupo Nutresa, “Abastecimiento responsable,” 2019.

[57] R. Castaño, “¿Qué es el diseño UX/UI?,” 2018. https://www.neoland.es/blog/que-es-el-ux-ui-design (accessed Nov. 03, 2020).

[58] R. M. Yetkin Özbük and A. Coşkun, “Factors affecting food waste at the downstream entities of the supply chain: A critical review,” *J. Clean. Prod.*, vol. 244, 2020, doi: 10.1016/j.jclepro.2019.118628.

[59] La República, “Un colombiano gastó $29.128 en helados durante el último año, según Euromonitor,” Mar. 04, 2019. https://www.larepublica.co/consumo/un-colombiano-gasto-29128-en-helados-durante-el-ultimo-ano-2835187 (accessed Nov. 03, 2020)

[60] J. Brownlee, “How to Decompose Time Series Data into Trend and Seasonality,” *Machine Learning Mastery*, Jan. 30, 2017. https://machinelearningmastery.com/decompose-time-series-data-trend-seasonality/ (accessed Dec. 04, 2020).

[61] S. H. Goh and S. Eldridge, “Sales and Operations Planning: The effect of coordination mechanisms on supply chain performance,” *Int. J. Prod. Econ.*, vol. 214, no. February, pp. 80–94, 2019, doi: 10.1016/j.ijpe.2019.03.027.

[62] K. Karlson, “29 Financial KPIs for Your Financial KPI Dashboard | Scoro,” 2020. https://www.scoro.com/blog/financial-kpis-for-financial-kpi-dashboard/ (accessed Nov. 22, 2020).

[63] R. Dwivedi and S. Chakraborty, “Adoption of an activity based costing model in an Indian steel plant,” *Bus. Theory Pract.*, vol. 17, no. 4, pp. 289–298, 2016, doi: 10.3846/btp.17.10864.

[64] S. Molinillo, A. Navarro-García, R. Anaya-Sánchez, and A. Japutra, “The impact of affective and cognitive app experiences on loyalty towards retailers,” *J. Retail. Consum. Serv.*, vol. 54, p. 101948, May 2020, doi: 10.1016/j.jretconser.2019.101948.

[65] P. Mekha, K. Dullayachai, and A. Changkamanon, “Stock recording and cost analyzing system for chicken farm,” in *2nd Joint International Conference on Digital Arts, Media and Technology 2017: Digital Economy for Sustainable Growth, ICDAMT 2017*, Apr. 2017, pp. 432–436, doi: 10.1109/ICDAMT.2017.7905007.

[66] P. Kabinlapat and S. Sutthachai, “An application of activity-based costing in the chicken processing industry: A case of joint products,” *Int. Food Agribus. Manag. Rev.*, vol. 20, no. 1, pp. 85–97, 2017, doi: 10.22434/IFAMR2016.0017.

[67] J. M. Desharnais, A. Abran, and W. Suryn, “Identification and analysis of attributes and base measures within ISO 9126,” *Softw. Qual. J.*, vol. 19, no. 2, pp. 447–460, 2011, doi: 10.1007/s11219-010-9124-5.

[68] IBM, “What is supply chain management | IBM.” https://www.ibm.com/topics/supply-chain-management (accessed Nov. 05, 2020).

[69] Crem Helado, “Crem Helado | Productos,” 2020. https://www.cremhelado.com.co/productos (accessed Nov. 03, 2020).

[70] C. L. Lorente, “LibGuides: Research Data Services: Data Types & File Formats,” *Oregon State Univ.*, Accessed: Nov. 05, 2020. [Online]. Available: https://guides.library.oregonstate.edu/research-data-services/data-management-types-formats.

[71] Gerencie.com, “Rotación de inventarios | Gerencie.com,” Sep. 25, 2020. https://www.gerencie.com/rotacion-de-inventarios.html (accessed Nov. 22, 2020).

[72] J. Vermorel, “Lead time,” Oct. 2020. https://www.lokad.com/lead-time (accessed Nov. 04, 2020).

[73] J. P. Usuga Cadavid, S. Lamouri, B. Grabot, R. Pellerin, and A. Fortin, “Machine learning applied in production planning and control: a state-of-the-art in the era of industry 4.0,” *J. Intell. Manuf.*, vol. 31, no. 6, pp. 1531–1558, 2020, doi: 10.1007/s10845-019-01531-7.

[74] S. Taylor and B. Letham, “Prophet: forecasting at scale - Facebook Research,” *Facebook*, Feb. 23, 2017. https://research.fb.com/blog/2017/02/prophet-forecasting-at-scale/ (accessed Dec. 07, 2020).

[75] C. Eksoz, S. A. Mansouri, and M. Bourlakis, “Collaborative forecasting in the food supply chain: A conceptual framework,” *Int. J. Prod. Econ.*, vol. 158, pp. 120–135, 2014, doi: 10.1016/j.ijpe.2014.07.031.

[76] Crem Helado, “Politica integral de Gestión.” p. 1, 2016, [Online]. Available: https://www.cremhelado.com.co/politica-integral-gestion.pdf.

[77] R. Zhong, X. Xu, and L. Wang, “Food supply chain management: systems, implementations, and future research,” *Ind. Manag. Data Syst.*, vol. 117, no. 9, pp. 2085–2114, 2017, doi: 10.1108/IMDS-09-2016-0391.

[78] United Nations Development Program, Sustainable Development Goals, [Online]. Available: https://www.undp.org/content/undp/es/home/sustainable-development-goals.html

[79] Grupo Nutresa, “Informe Integrado.” . 2018, [Online]. Available: http://informe2018.gruponutresa.com/pdf/informeintegrado2018gruponutresa.pdf

[80] UNIVERSITY, K., 2021. Libguides: SPSS Tutorials: Pearson Correlation. [online] Libguides.library.kent.edu. Available at: <https://libguides.library.kent.edu/spss/pearsoncorr>

[81] O'Sullivan, D. and Dooley, L., 2009. Applying Innovation. Thousand Oaks, California: Sage Publications.

[82] DANE. (2021). Indicadores coyunturales. Bogotá: Gobierno de Colombia. Retrieved from https://www.dane.gov.co/files/ses/ses_2021/Indicadores_Coyunturales_29_01_21.pdf

[83] Empleo y desempleo. (2021). Retrieved 3 February 2021, from https://www.dane.gov.co/index.php/estadisticas-por-tema/mercado-laboral/empleo-y-desempleo#:~:text=Para%20el%202020%2C%20la%20tasa,2019%20(10%2C5%25).&text=Finalmente%2C%20la%20tasa%20de%20ocupaci%C3%B3n%20fue%2049%2C8%25%2C,2019%20(56%2C6%25).

[84] Cálculo de stock de seguridad: fórmula y consejos de gestión. (2020). Retrieved 7 February 2021, from https://retos-operaciones-logistica.eae.es/calculo-del-stock-de-seguridad-la-formula/

[85] Taha, H. (2012). Investigación de operaciones (9a. ed.). Distrito Federal: Pearson Educación.