Customer-centric Approach to Determine Key Drivers of Sales Growth and Appropriate Inventory Management

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Abstract

A research is conducted on a Fast Moving Consumer Goods (FMCG) e-commerce store to determine factors that affect its sales growth. The research starts with applying the principles of customer-centric supply chain, outside-in process, and demand-driven network to analyze the key drivers of the sales growth. Multivariate forecasting and ABC classification methods are employed to predict the growth and provide recommendation for the safety stock levels of the 190 SKUs (Stock Keeping Unit) fall in the category A, B, and C. Seven major key drivers are identified. The size of the discount offered is found to be one of the most significant factors, while the people rating does not affect the sales growth. The key drivers in each category are found to be unique and tailoring the sales strategies according to the characteristics of the SKUs in each category is expected to improve their effectiveness. An ergonomic dashboard that applies human factors and user-centered design concepts is also proposed as a means to display critical information that support the store's demand forecasting and planning strategies

Keywords
E-commerce, multivariate forecasting, ABC classification, safety stock, ergonomic dashboard

1. Introduction
The Industrial Revolution 4.0 has spurred many industries to rush to find breakthroughs in managing their businesses (Nagy et al., 2018). The order of life in society has also undergone many changes with the increasing use of cyber physical systems, the internet of things, and networks. In Indonesia, President Joko Widodo has decided on Indonesia's participation in Industry 4.0 through the Make Indonesia 4.0 program, which is believed to bring a positive economic impact and employment opportunities (Ministry of Industry of the Republic of Indonesia, 2018). McKinsey & Company (2018) projects an exponential growth of e-commerce market share or 400% in 2022 compared to 2017. Today, many Fast Moving Customer Goods (FMCG) companies are increasingly expanding their business ventures in e-commerce platforms (Hartati, 2019; CNN Indonesia, 2020). Similarly, other business fields, such as banking, supply chains, food, hospitality, and transportation, show similar phenomenon. How to become superior in the increasingly tougher e-commerce competition?

Interactions and transactions that occur in e-commerce are characterized by speed and diversity. Epstein (2004) states, that one of the success keys in e-commerce is the ability to control costs over a long period of time, through adherence to traditional business principles and common sense, and not allowing easier and less-planned business practices, for example stock and demand control (Ren, Chan, & Siqin, 2019). Research of Liu et al. (2019) shows

that sales forecasting plays an important role in the e-commerce business world. Accurate and reliable sales predictions are very important in e-commerce business (Bandara et al., 2019), especially if a price war occurs (Hsieh, 2019). The Gartner Research Institute in 2017 published a study which showed that an increase in forecasting accuracy by 1% may be able to reduce about 3.9% of the total inventory load, and was able to reduce the order cycle time by 2.4% (The European Business Review, 2018). In addition, a proper inventory management also supports the company's performance to excel in competing (Gallmann & Belvedere, 2010).

PT XYZ is one of the largest companies in Indonesia that engage in consumer product goods, and currently starts managing more than 500 of its products for on-line transactions. Appropriate management of important factors, such as sales forecasting, safety stock recommendations, and the performance of products sold, plays an important role in being able to maintain sustainability and increase the competitiveness of PT XYZ in e-commerce. Monitoring of important information is also needed to support the smooth operation and improve the ability of PT XYZ to provide proactive responses. If this important information can be monitored easily and safely, then the level of error in translating the information received is also getting smaller (Hugo & Germain, 2017). This study aims to determine the key drivers of sales growth of e-commerce products from PT XYZ which are marketed in an online mall, and to recommend an ergonomic dashboard that contains important information to support store's demand forecasting and planning strategies.

2. Literature Review

2.1 Seller Service Level

PT XYZ aims to provide customer satisfaction and comfort in conducting online transactions, which are determined through a service ratio. This means, PT XYZ sets the service ratio as an indicator of the level of its customer satisfaction. The ability of companies to be able to fulfill every request that comes from customers, can improve company's performance (Gallmann & Belvedere, 2010), which is significantly determined by the performance of inventory management (Afolabi et al., 2017; Sohail & Sheikh, 2018; Elsayed & Wahba, 2016).

In running its business in the e-commerce sector, PT XYZ is listed on the platform of one of the largest online malls in Indonesia. This particular online Mall has established performance indicators for sellers, including PT XYZ - i.e., operational capability, human resource capacity, seller response speed, inventory management, seller order fulfillment performance (calculated through Non Fulfillment Rate or NFR minus the levels of unfulfilled orders, and Late Shipment Rate or LSR minus the late delivery rate), and the quality of product list from each seller. Sellers with a service ratio performance of below 90% will get a penalty. Therefore, it is important for PT XYZ to be able to fulfil the predetermined targets related to service ratio (the ratio of requests or demands that can be met or to get supply).

This study will use a customer-centric supply chain, demand driven, and attribute-based planning approach in determining the data that will be used to predict sales or demand based on key drivers that affect sales, including the selection of techniques to classify products based on SKUs. The results of this classification can be used to determine product priorities related to safety stock. By managing this information in a real time way, an integrated way and to be able to be accessed quickly in the form of an ergonomic dashboard, PT XYZ will receive operational support to be able to meet the targets related to demand and supply management.

2.2 Customer-Centric Supply Chain (CCSC) and Demand Driven

Customer-Centric Supply Chain (CCSC) can be defined as a supply chain where the customer becomes the focus or center of the supply chain. Starting from the procurement of raw materials, production (manufacturing), suppliers, to the distribution process (distribution), everything is carried out with due regard to customer feedback. This means, in the CCSC approach, real-time market reactions and customer information are integrated in the entire supply chain activities and processes. Data from customers becomes the driving force during the supply chain process in the CCSC concept (Melnyk & Stanton, 2017), while in the traditional supply chain process, data from customers does not necessarily get attention. New customers emerge upon receiving delivery at the final stage of the process (Chopra, 2019).

Customer-Centric Supply Chain is a strategic and effective supply chain model, because it focuses on key customers, value preposition, and capabilities. Amazon with its rapid growth to this day, is an example of the results

in supply chain management implementation with a customer-centric approach (Melnyk & Stanton, 2017). Companies that run supply chain processes centering on their customers will be able to recognize their main customers, and work together to improve customer satisfaction (Chaves et al., 2014), which will ultimately be able to further strengthen the company's competitive advantage, which needs to be continuously built, preserved, and maintained.

Demand driven supply chain (DDSC) has the concept that supply chain activation is carried out based on real demand from customers, or by predicted customer demand (Hull, 2005). According to Mendes (2011), in a DDSC company, the demand process occurs based on the customer's point of view, so that the existing demand tends to be closer to reality (real). This means, requests that will be included in the supply chain process are requests coming from the market or customers (market driven) and not from the target or marketing engineering (marketing driven).

The Customer-centric supply chain and demand driven supply chain both have a concept of demand shaping that is centered on the real market or customer. Both approaches can be used to complement each other, with the aim of producing better planning, with uniqueness that is in accordance with the wishes of the customer (attribute-based planning). Attribute-based planning is an important approach to produce better and more structured planning (Tolkach, King, & Pearlman, 2013).

In this study, demand shaping will include data that is estimated to influence the movement of market demand or sales, such as prices, promotions, sales / distributor incentives, and marketing campaigns. Attribute-based planning is the approach used to plan supply and demand based on SKUs (stock keeping units).

2.3 Demand Shaping and Forecasting

Demand shaping is the most optimal decision-making process, related to demand-and-supply, using demand-and-supply information availability (Richard, 2014). SAS (2014) records product pricing, product promotion, competitive pricing, competitive promotion, demand forecast, as data demand, while data such as Bill of Materials, inventory costs, production costs, logistics transit times, are categorized into data supply. Chase (2013) explains that the term demand shaping is often used to describe the relationship between customer or consumer demand with sales promotion and marketing events and / or price discounts, and then uses these influencing factors to estimate future demand (shape future demand). Chopra and Meindl (2013) emphasize the importance of accurate information as one of the main characteristics in conducting a forecast. Higher information distortion can occur alongside the distance that is built between the company and its customers (Li & Liu, 2013; Dominguez et al., 2015; Wang & Disney, 2016), which can ultimately increase errors or reduce the accuracy of forecast calculation. The ability to provide supply according to existing demand, can improve inventory costs and also increase service ratio.

The calculation techniques that can be used to solve the demand-shaping objective problems that have been set, for example, are maximizing gross margins or minimizing logistics costs. Hymanson (2013) mentions the possibility of using a combination of linear programming models. This research will use multiple regression models to predict sales or demand based on key drivers that affect sales.

2.4 Attribute-Based Planning and SKU Analysis

Attribute-based planning in this study is used to help categorize products based on their uniqueness or characteristics, which will then be grouped according to ABC classification. Thus, the product groups that need attention can be easily identified according to the characteristics of the product itself. This clustering method is chosen to consider the large number of product units or Stock Keeping Units (SKUs) that must be managed in PT XYZ's inventory.

Fisher and Vaidyanathan (2012) write in Harvard Business Review, that attribute based clustering can provide scientific input, especially for retailers, such as seeing the possibility to improve the variety of products sold by withdrawing slow-selling products or looking at potential demand for new products. Attribute-based planning is also said to be an approach used to improve accuracy and reduce biased forecasts (Snapp, 2013), to increase sales and the quality of operational planning (Logility, 2017), suitable for new or at the end of life cycle products., when there is not enough historical data to reliably describe demand or a lack of relevant data (Logility, 2019)

2.5 Ergonomic Dashboard

Relevant and accurate information is very important to produce the right strategic decisions (Gamble, Cassenti, & Buchler, 2018). In an increasingly competitive and global business competition, the information needed not only needs to be accurate, but also can be quickly made available in an integrated information system (Al-Mamary, Shamsuddin, & Aziati, 2013; Lurie & Swaminathan, 2009; Alkhaffaf, 2012). Various important information components are integrated in a display, using information technology, with the aim of making it easier for users to read the available information, known as the dashboard.

From an ergonomic standpoint, for a dashboard to function as an effective tool in the strategic decision-making process, it is necessary to fulfill important principles of display design, such as the principles of color, letter and number size, spatial, background, consistency, and meaning (Freivalds & Niebel, 2014; Guastello, 2014). In general, the dashboard of a motorized vehicle is the user interface that receives the most attention to meet the principles of ergonomics, because comfort and safety are the main criteria (Carvalho & Soares, 2012). Dashboards in the form of computer interfaces, which are commonly used to display information about the performance indicators of a business, have not received much attention to fulfill the important principle of ergonomics, which aims to reduce errors and increase productivity (Kroemer & Grandjean, 2009; MacKenzie, 2013). Research from Khan et.al (2012) shows that in general people are not aware of the implementation of the ergonomics principle as a safety factor, and even those who have related knowledge have not fully implemented those ergonomics principles to avoid health hazards.

Hugo and Germain (2017) state that each display of information must be designed to support a specific task or set of tasks. The ergonomic dashboard design in this study will be designed to contain important information to support store's demand forecasting and strategic planning. Ergonomic factors that will be used include visibility, distinguishability, interpretability, completeness, and standards (Guastello, 2014).

3. Project Framework

This study uses one dependent variable, namely sales, which is reflected by the quantity sold based on SKU. While the independent variables in this study consisted of eight variables, which are as follows:

1. Product, reflected by the unique name of the product (SKU);
2. Date, reflected by the occurrence date of sales transaction;
3. Promotion price, reflected by the promotional price applied to the products (SKU);
4. Regular price, reflected by the normal price applied to the product (SKU);
5. Ratings, reflected by assessment of products provided by customers, on a scale of one to five;
6. Quantity, reflected by the number of products in units marketed or sold;
7. Promotion depth, reflected by the percentage (%) of the amount of promotion applied to a product (SKU);
8. Month, reflected by the month the product was sold.

All these research variables, both dependent and independent variables, are derived from 547 Stock Keeping Units (SKUs) marketed by PT XYZ in an e-commerce platform, which is one of the largest online malls in Indonesia. Data collection is conducted once a week for 3 months. Of the 547 SKUs, there are 190 SKUs that have usable data as they have a minimum of 18 transactions, which are estimated as enough to be processed.

ABC classification is used to classify the 190 SKUs based on the level of importance, i.e. based on the contribution of each SKU to the total sales value. Classification A reflects the most valuable product (SKU), which contributes around 80% to 85% to the total sales value, or 5% to 10% of the total product. Category B reflects the products that have contributed about 15% to the total sales value, or 10% to 20% of total products. Category C reflects the products that have contributed about 5% to 10% to the total sales value, or 80% to 85% of total products. The calculation is done using Microsoft Excel. Each total sales value of 190 SKUs is listed and sorted by the total sales value, from the largest to the smallest value. Afterwards, the cumulative percentage (%) calculation is performed, before being classified into categories A, B, and C, based on the ABC criteria.

Based on the classification results based on ABC classification, exploration of sales growth key drivers are conducted using Multiple Regression Analysis, with Multiple Linear Regression calculation techniques. The level of significance was determined based on p-value ($p<0.05$) (Hair et al., 2014). From the significant key drivers of products that are in the ABC categories, A, B, and C, the magnitude of the impact of the key drivers (independent

variables) of each calculation group on sales (dependent variable) will then be determined. The calculation is done using Multiple Linear Regression, through Python 3.7 64-bit version. The coefficient of determination atau R^2 is used to see the proportion of variance in the dependent variable that can be predicted through the independent variable. To test the fit model (test of the goodness-of-fit) Root Mean Square Error (RMSE) is used (Tabachnick & Fidell, 2019).

Important information to support store's demand forecasting and planning strategies includes information related to sales performance, inventory, trends, overall ratings, and service level (Coyle et al., 2013; Simchi-Levi at al., 2009). This important information is contained in the form of an ergonomic dashboard, using the 64-bit version of Microsoft Power BI Desktop 2.78.5740.721. The dashboard display is set to fulfil the five criteria of an ergonomic display design (Guastello, 2014), with the following reflection:

1. The visibility factor is reflected through the display of a clear image and contains the main information on the display central location on the computer monitor (dashboard).
2. The distinguishability factor is reflected through the size, thickness, and distance of punctuation, so that the writing can be read clearly by the user.
3. The interpretability factor is reflected through a display that can be understood by the user and can help the user to make a decision to take further action.
4. The completeness factor is reflected through the availability of complete information needed by the user to do his work.
5. Standards are reflected through colors, images and terminology that are applied in the local work culture environment (users)

4. Calculation, Results, and Discussion

Based on the data that has been applied on all collected samples that can be used (190 SKUs), using the techniques mentioned in the methodology section, the explanations below are the results that can be delivered.

4.1 ABC Classification for SKU inventory

From all 190 SKUs grouped according to ABC classification calculation techniques, the results can be seen in Table 4.1.1, where there are 20 SKUs classified in category A with a contribution of 79.87% of the total sales value. Then, there are 23 SKUs that fall into category B with a contribution of 15.13% of the total sales value. The remaining 147 SKU fall into category C with a contribution of 5% of the total sales value.

Table 4.1.1
ABC Classification, N=190 SKU *(product)*

Category	Number of Product	% Number of Product	% Total Sales Value*	Total Sales Value* (in *Rupiah***)
A	20	10.53%	79.87%	4,913,530,800.00
B	23	12.11%	15.13%	930,524,400.00
C	147	77.37%	5.00%	307,870,030.00
Total	190	100.00%	100.00%	6,151,929,230.00

Note:
** Sales Record from January to March 2020*
*** Indonesian currency*

Based on the ABC classification results, PT XYZ needs to pay special attention to the overall SKUs that are in category A, which amounts to 20 SKUs (10.53%), because it has contributed 79.89% of the total sales value from January to March 2020, an equivalent to 4,913,530,800.00 *Rupiah* or equals to US $334,584.72 (with a rate of 1 *Rupiah* = 0.000068 US$).

Inventory management for category B products should receive less attention and time as compared to what can be given to category A products. The number of products in category B are 23 SKUs (12.11%), with a contribution of only around 15.13% of total sales value from January to March 2020, an equivalent to 930,524,400.00 *Rupiah* or equals to US $63,363.65 (with a rate of 1 *Rupiah* = 0.000068 US $).

The least attention and time, related to the restocking process, is given to category C products, which amounts to around 147 SKUs (77.37%) but only contributed 5% to the total sales value from January to March 2020, or valued at 307,870,030.00 *Rupiah* or an equivalent to USD 20,964.27 (with a rate of 1 *Rupiah* = 0.000068 US $).

4.2 Key Driver

Table 4.2.1 provides an overview of the calculation results in determining the key driver of sales, using multiple linear regression. In general, from the regression calculation results of the ABC category, with N = 190, the independent variable in the form of a product (SKU), promotion price, normal price, the amount of promotion applied, as well as the month when the sale transaction occurs, has a significance level with a value of $p<0.01$. This means that the independent variables are proven to be able to be accepted as key drivers of sales, with the possibility of acceptance error of less than 1%. On the other hand, the independent variables in the form of date of purchase and the number of products in units of sale (for example a pair, bundling), has a significance level with a value of $p<0.05$. This means, the two variables are also proven to be acceptable as the key drivers of sales, with the possibility of acceptance error of less than 5%. Rating variable that reflects the rating of the product given by the customer, has a significance level with a value of $p> 0.05$. This means that the rating variable has not been proven to be acceptable as a key driver of sales with the possibility of acceptance error of less than 5%. Thus, it can be said, that product variables, date, promotional price, normal price, quantity (the number of products in sales units, the amount of promotional prices, as well as the month of the transaction, proved to be acceptable as key drivers of sales for products of PT XYZ sold via e-commerce in an online mall.

Table 4.2.1
Significance Level of Sales Key Driver

Independent Variables (X)	**ABC Classification**			
	Category ABC	Category A	Category B	Category C
	P-value ($p<0.05$)* ($p<0.01$)**			
Product (SKU)	0.0000**	0.0055**	0.3756	0.0000**
Date	0.0233*	0.0957	0.0611	0.1704
Promotion Price	0.0000**	0.9250	0.1294	0.0171*
Regular Price	0.0000**	0.6287	0.0555	0.0072**
Rating	0.5987	0.7211	0.2381	0.4075
Quantity	0.0115*	0.2780	0.0608	0.0245*
Promotion Depth	0.0000**	0.0751	0.0006**	0.0008**
Month	0.0000**	0.0000**	0.0015**	0.2682

Note:
n for Category ABC is 190 SKU, n for Category A is 20 SKU, n for Category B is 23 SKU, n for Category C is 147 SKU

When a regression calculation to get more detailed results related to key drivers is conducted, differences between the key drivers of each category, both categories A, B, and C, are found. From Table 4.2.1 it can be seen that the key drivers that are proven to be significant for product categories A, are the product variable and month variable with a value of $p<0.01$. This means that for category A products, product variables and month variables are proven to be acceptable as key drivers from sales, with the possibility of acceptance errors less than 1%. Thus, it can be said that product variables and month variables are proven to be significantly accepted as key drivers of sales for category A products, while the other six variables are not proven to be accepted significantly as they have a probability of acceptance error greater than 5%.

The results of regression calculations to get key drivers to sales, from products included in category B (Table 4.2.1), show that the amount of the promotion (promotion depth) variable and month, can be accepted because they are proven significant with a value of $p<0.01$, and the with the possibility of acceptance error less than 1%. Thus, it can be said, that the promotion depth and month variable proved to be significantly accepted as the key drivers of sales for products in category B. Six other variables (product, date, promotion price, regular price, rating, and quantity) cannot be significantly accepted as they have a probability of acceptance error of more than 5%.

The results of regression calculations on products included in category C (Table 4.2.1), related to key drivers from sales, indicate that the product, regular price and promotion depth variables, are variables that have been proven to be significant with the value of $p<0.01$, thus they can be accepted as the key drivers from sales with the possibility of acceptance error of less than 1%. Promotion price and quantity variable are also proven significant with a value of $p<0.05$, thus it can be accepted as a key driver of sales, with the possibility of acceptance error of less than 5%. The other three variables (date, rating, and month) cannot be accepted because they have a probability of acceptance errors of more than 5%. Thus, it can be said, that the product, promotion price, regular price, quantity, and promotion depth variables are proven to be able to be significantly accepted as the key drivers of sales for category C products.

Table 4.2.2
Summary Key Driver for Sales

Category	Category ABC N=190	Category A N=20	Category B N=23	Category C N=147
Key Driver	Product (SKU)** Date* Promotion Price** Regular Price** Quantity* Promotion Depth** Month**	Product (SKU)** Month**	Promotion Depth** Month**	Product (SKU)** Promotion Price* Regular Price** Quantity* Promotion Depth**

Note:
*1. *p<0.5, **p<0.01*
2. Rating is a variable that is proven insignificant for all categories

From the description of the regression calculation results of all products (Category ABC), as well as of products according to the categorical division (Categories A, B, and C), it can be concluded that the variables that are proven to be significant and can be accepted as the key drivers of sales for product sold by PT XYZ via e-commerce in an online mall, is as tabulated in Table 4.2.2. Product assessments provided by customers after making a purchase transaction, evidently are not proven significant for all categories, both for general categories (Category ABC), and for specific categories (Category A, Category B, and Category C).

Based on the regression calculation results that has produced an acceptable key driver as it has been proven significant with the possibility of an acceptance error smaller than 5% ($p<0.05$) or smaller than 1% ($p<0.01$), then the calculation is continued to get the coefficient determinant (R^2), which can provide an estimation of how far the independent variable can predict the dependent variable. Prediction ability is categorized into three abilities (Moore

et al., 2017), which are strong predictive ability (R^2>0.7), moderate predictive ability (0.3<R^2<0.7), and weak predictive ability (R^2<0.3).

Table 4.2.3
The Goodness-of-Fit and R^2

Category	Category ABC N=190	Category A N=20	Category B N=23	Category C N=147
Key Driver	Product (SKU)** Date* Promotion Price** Regular Price** Quantity* Promotion Depth** Month**	Product (SKU)** Month**	Promotion Depth** Month**	Product (SKU)** Promotion Price* Regular Price** Quantity* Promotion Depth**
R squared	0.82	0.60	0.69	0.45
Root Mean Square Error (RMSE)	20.06	70.96	27.00	11.06
10% Observed Range	88	88	28	33
Conclusion: *Goodness-of-fit*	*accepted*	*accepted*	*accepted*	*accepted*

Note:
1. *p<0.5, **p<0.01
2. *Goodness-of-fit accepted* if *RMSE<10% observed range*

The RMSE (Root Mean Square Error) coefficient is used to test the goodness-of-fit, which is to see whether the resulting model is in accordance with the data in the field, so it can be accepted. A rule of thumb to estimate fit models using RMSE is to compare it with 10% of the target property value (in this case the number of products sold), i.e. RMSE <10% observed range (Alexander et al., 2015). From the goodness-of-fit (RMSE) and coefficient determinant (R^2) test results, as shown in Table 4.2.3, it can be seen that the whole results of the goodness-of-fit test are acceptable because the RMSE of each category (Category ABC, Category A, Category B, and Category C) have coefficient values of less than 10% observed range.

Key drivers for sales in the ABC category, which consist of product, date, promotion price, regular price, quantity, promotion depth, and month variables, have a coefficient determinant R^2 of 0.82. This means that the increase in sales of products in the ABC category can be explained by 82% by the key driver group (strong predictive ability). Coefficient determinant R^2 of 0.60 for key drivers from category A means that an increase in sales of products from category A can be explained by 60% by product and month variables (moderate predictive ability). The key driver of category B products, i.e., the promotion depth and month variables, has a coefficient determinant R^2 of 0.69. This means that promotion depth and month can be used to explain the increase in sales of Category B products, by 69% (moderate predictive ability). Key drivers for the sale of products in category C, i.e. product variables, promotion price, regular price, quantity, and promotion depth, can be used to explain sales increases by 45% (moderate predictive ability).

Based on the value of the coefficient determinant R^2 generated for the key drivers for each category (Category ABC, Category A, Category B and Category C), it can be said, that product, date, promotion price, regular price, quantity, promotion depth, and month, are key drivers proven to have a moderate to strong predictive ability, to respond to increased sales. All resulting RMSE values are able to provide evidence that the data used in this study to measure the predictive power of key drivers from each category also matches the data in the field.

4.3 Ergonomic Dashboard
Based on ergonomic principles for visual displays related to human-machine interaction, which includes visibility, distinguishability, interpretability, completeness, and standards, thus a dashboard that can be recommended to

support store's demand forecasting and planning strategies is as shown in Figure 4.3.1 for alternative 1 and Figure 4.3.2 for alternative 2.

In accordance with the objectives of this research related to ergonomic dashboard display recommendation, in order to support store's demand forecasting and planning strategies, thus important information contained therein is made in line with the stated objectives. Store's demand forecasting is an operational activity, while planning strategies are a managerial activity. Information such as revenue, product and material quality, delivery, delay are important strategic components for managing supply and demand (Simchi-Levi et al., 2009). Information such as inventory, product, brand, quantity and forecasting are important components in operations related to demand and supply management (Coyle et al., 2013).

Figure 4.3.1 and Figure 4.3.2 illustrate a dashboard that contains important information related to total sales, inventory values, overall ratings, service levels, trends, key drivers, and the contribution of categories A, B, and C to sales. The information is intended to assist the management team in conducting analysis related to demand and supply in order to develop planning strategies in line with the organization's vision, mission, and milestones. Information related to product, brand, size, ratio of the amount of promotion (%) marketed, inventory level, availability of goods, as well as information related to forecasting, are intended to assist operations in meeting customer needs as optimally as possible in an efficient and effective way. Figure 4.3.1 and Figure 4.3.2 display the form of a dashboard that meets the ergonomic criteria related to display design, i.e. visibility, distinguishability, interpretability, completeness, and standards (Guastello, 2014).

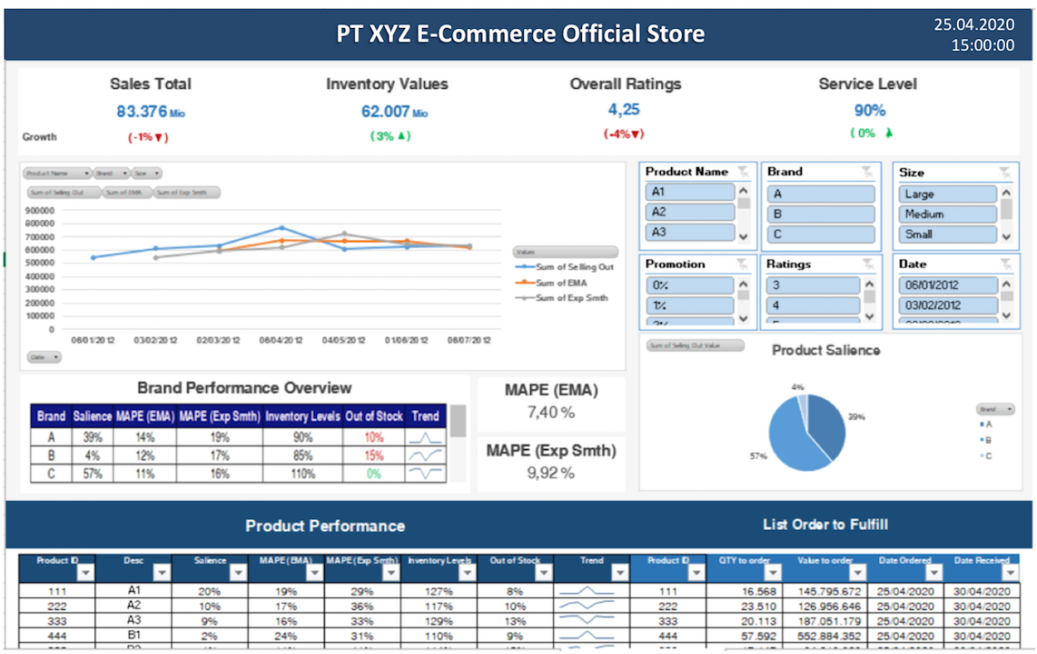

Figure 4.3.1
Ergonomic Dashboard Display Recommendation 1
Note: based on dummy data

Visibility criteria are met through clear diagram shapes and graphs, and key information is placed at the center of the display (Figure 4.3.2). Information in alternative display 1 (Figure 4.3.1) is grouped centrally based on interests, which are the interest for planning strategies (the upper part) and the interest for demand forecasting (the middle and bottom parts).

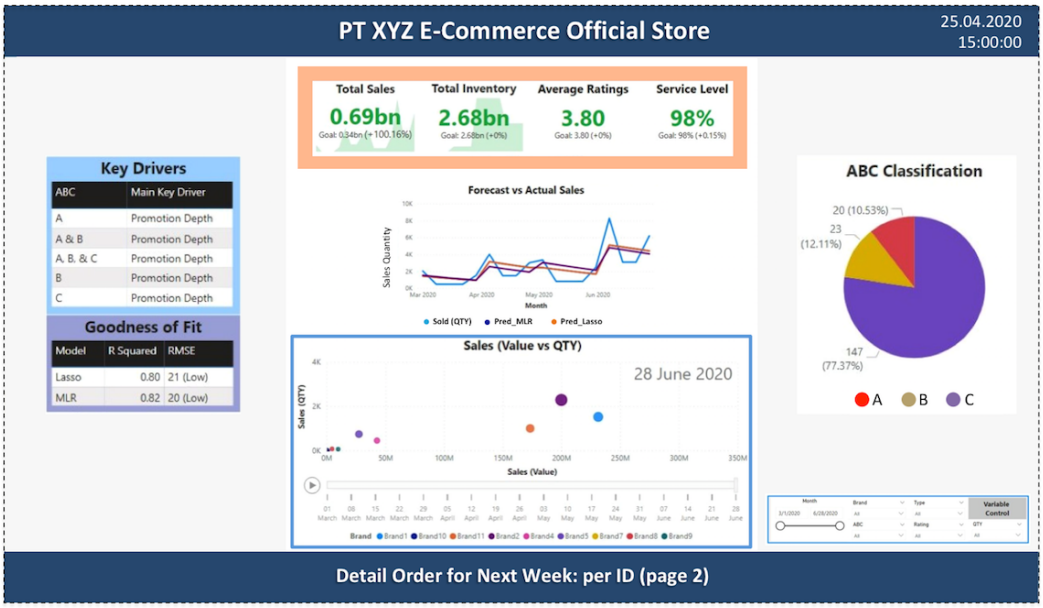

Figure 4.3.2
Ergonomic Dashboard Display Recommendation 2
Note: based on actual data

The distinguishability criteria are met through clear differences in size, title font thickness, subtitles and contents, and the distance between words. Both display alternatives are also equipped with a user control system, which makes it easy for users to see performance conditions clearly. For example, numbers in red give a clear distinction from green numbers. Likewise, colors on graphics and charts reflect the fulfillment of distinguishability criteria. Color can help users to differentiate information more easily (Kroemer & Grandjean, 2009).

The interpretability criteria are met through colors, images (such as graphics, charts, click buttons on control systems, numbers that relay meaning (such as percentages, proportions), historical data and forecasting. In alternative display 1 (Figure 4.3.1), it can be seen that triangles leading to the top in green relay a meaning of positive performance, while the triangles in red give the meaning of negative performance. The form of display in this criterion is expected to give meaning to the user to translate the existing conditions, and to be able to help the user to make decisions related to follow-up. Colors may help users to get orientation and identification of circumstances more quickly (Gamito & Moreira da Silva, 2015).

The completeness criteria are fulfilled through complete information needed by users who are tasked to perform store's demand forecasting and planning strategies (team operations and management). The two display alternatives (Figure 4.3.1 and Figure 4.3.2) display information related to revenue, inventory value, rating, service level, sales, historical data and forecasting, as well as product performance, which are expected to help carry out tasks related to store's demand forecasting and planning strategies to be more efficient, objective and increasingly optimal.

Standard criteria are met through corporate identity colors (dark blue), terminology used in work groups or companies, colors that are common for performance improvement or to inform about alerting conditions (yellow) and danger (red), including formulas used for the displayed calculation results, and sequence of information (information starts from the top to the bottom or from the left to the right, in accordance with the culture applicable in the local workplace).

Based on the description above about the ergonomic form of the dashboard along with the important information contained therein that is aimed to help store's demand forecasting and planning strategies, it can be said that all the criteria of an ergonomic display design have been fulfilled.

5. Conclusions

Based on the research results described in the previous section, it can be concluded as follows. Product, date, promotion price, regular price, quantity, promotion depth, and month variables are key drivers that can be used to improve product sales in general (Category ABC). Sales improvement for products in category A (Category A) can be done through product and month variables as both of them are the sales key drivers for category A products. Sales improvement for products in category B (Category B) can use promotion depth and month variables as both of them are the key drivers for category B products. Product, promotion price, regular price, quantity, and promotion depth variables can be used to increase the sales of category C products as they are the key drivers of category C products.

Based on ABC classification calculations, out of 190 SKUs (products) sold by PT XYZ via e-commerce in an online mall, 20 SKUs are in category A, 23 SKUs are in category B, and 147 SKUs are in category C. Inventory control and establishment of safety stock can be done based on the characteristics of each category. Product category A (20 SKUs) needs the most attention and time in terms of analysis and inventory control as well as providing the greatest opportunity to reduce costs or increase profits. Less time and attention can be given to category B products, including further monitoring of possible shifts, whether it approaches category A or category B. Very little time and attention is given to category C products, for further decisions, so as not to continue to be company expense.

Important information to support demand forecasting consists of the level of inventory and the level of accuracy of the prediction calculation results. Meanwhile, to support planning strategies, the important information are total sales, inventory values, overall ratings, service levels, trends, and product salience.

Based on the approach of ergonomic principles related to the visibility, distinguishability, interpretability, completeness, and standard factors, this study can provide two recommendations on the ergonomic appearance for the official dashboard of PT XYZ in the field of e-commerce. The corporate identity color of PT XYZ, which is dark blue, becomes the color used to give nuance in the dashboard display.

5.1 Theoretical Implication, Limitations, and Further Research

Based on the results of ABC classification calculations, suggestions to be given are as follows. Analysis and inventory control need to be done intensively on products in category A. Dynamic transactions from category A products open up enormous opportunities for cost reduction efforts. Management related to inventory control should distinguish between methods used for products in categories A, B, and C. For example, the greatest amount of time and attention needs to be given to category A products, medium amount for category B products, and the least amount given to category C. This study also advises PT XYZ to set different policies in the management of its products based on categories A, B, C. Category B products need to be monitored further to see the shift in its transactions, whether it gets closer to category A or closer to category C. This is important to do so that the next strategic decision taken can be more precise and effective towards reducing costs or increasing profits. Category C products, theoretically, do not need attention in controlling inventory. However, practically, a large inventory is a cost that burdens companies. Therefore, the results of this study also want to advise PT XYZ to provide a little time and attention for further management of Category C products. For example, whether it will be withdrawn from the e-commerce market, or to make different sales promotions that are expected to increase demand in Category C SKUs and to move into categories more appropriate for more attention.

Related to the results of this study regarding ergonomic dashboard, some suggestions that can be given are as follows. An evaluation of the effectiveness of the ergonomic dashboard in supporting store's demand forecasting and planning strategies needs to be done, including improvements that need to be conducted in line with the evaluation results. Integrated and ergonomic information systems also need to be built with interconnected data from other departments and real-time from the market to further complement the benefits of an ergonomic dashboard, which minimizes human error and increases productivity.

As a final word, this study would like to provide general advice, both to relevant agencies and to other researchers for further research. Some following suggestions are expected to be able to complement the suggestions that have been delivered in the previous section. The categorization of products based on ABC classification can provide objective recommendations to the company in the context of making further effective strategic decisions. Opportunities to increase profits and reduce costs from category A products are available. Each product has its own uniqueness, so that the company's treatment in marketing can also vary within certain limits. ABC classification is

one of the techniques that can help categorization. Of course there are many more methods that can be used to assist companies to conduct classification objectively, directed and appropriately. Further research can be done by involving a much more complete data collection to improve sales prediction or other predictions. The impact of key drivers on sales in this study is still general. This research has not measured the strength of each variable in predicting sales from each category. Further detailed calculations of the predictive power of each variable can provide recommendations for better planning strategies. Further research can also consider other variables that can increase the predictive power of sales from each category. The goal is that strategic efforts related to increasing sales can be more directed and effective. Global competition demands quick and precise decision-making based on objective information. Therefore, the ergonomic dashboard is not only used for operational departments, but it is also recommended to be used by various other relevant departments in the company. The aim is that strategic decision making at a higher level can be carried out in a faster time. Process monitoring, target control from related departments are designed and integrated into the ergonomic dashboard at a higher level. In line with the Industrial Revolution 4.0, in the future, e-commerce trading will be increasingly widespread and competitive. Related research about how to increase competitive advantage for platforms or malls and of e-commerce sellers, can be further improved, so that the quality of life of many people, both as customers and employees in the organization, can be better, for example through a controlled and directed level of satisfaction.

References

Afolabi, O. J., Onifade, M. K., and Olumide, O. F. (2017). Evaluation of the role of inventory management in logistics chain of an organization. *LOGI-Scientific Journal on Transport and Logistics*, *8*(2), DOI: 10.1515/logi-2017-0011.

Alkhaffaf, M. (2012). The role of information systems in decsion making: The case of Jordan bank. *Computer Engineering and Intelligent System*, *3*(10), pp. 19-22.

Alexander, D. L. J., Tropsha, A., & Winkler, D. A. (2015). Beware of R^2: Simple, unambiguous assessment of the prediction accuracy of QSR and QSPR models, *Journal of Chemical Information and Modeling*, *55*(7), pp. 1316-1322.

Al-Mamary, Y. H., Shamsuddin, A., and Aziati, N. (2013). The impact of management information systems adoption in managerial decision making: A review, *Management Information Systems, 8*(4), pp. 010-017.

Bandara, K., Shi, P., Bergmeir, C., Hewamalage, H., Tran, Q., and Seaman, B. (2019). Sales demand forecast in e-commerce using a long short-term memory neural network methodology. In: Gedeon T., Wong K., Lee M. (eds), *Neural Information Processing. ICONIP 2019.* Lecture Notes in Computer Science, vol 11955, pp. 462-474. Springer, Cham. DOI: 10.1007/978-3-030-36718-3_39.

Carvalho, R., and Soares, M. (2012). Ergonomic and usability analysis on a sample of automobile dashboards. *Work, 41,* pp. 1507-1514.

Chase, C. W. Jr. (2013). Using demand sensing and shaping to improve demand forecasting. *The Journal of Business Forecasting*, *32*(4), pp. 24-31.

Chaves, R., Yu, W., Feng, M., and Wiengarten, F. (2014). The effect of customer-centric green supply chain management on operational performance and customer satisfaction. *Business Strategy and the Environment, 25*(3), pp. 205-220.

Chopra, S. (2019). *Supply Chain Management: Strategy, Planning, and Operation*. 7th ed. England: Pearson Education Limited.

Chopra, S., and Meindl, P. (2013). *Supply chain management: Strategy, planning, and operation*. 5th ed. England: Pearson Education Limited.

CNN Indonesia. (2020). *Tren dan peluang industri e-commerce di Indonesia*. Available: https://www.cnnindonesia.com/teknologi/20200205204206-206-472064/tren-dan-peluang-industri-e-commerce-di-indonesia-2020 [2020, April 9]

Coyle, J. J., Langley Jr., C. J., Novack, R. A., and Gibson, B. J. (2013). *Managing supply chains: A logistics approach*, 9th ed. Canada: South-Western, Cengage Learning.

Dominguez, R., Cannella, S., and Framinan, J. M. (2015). The impact of the supply chain structure on bullwhip effect. *Applied Mathematical Modeling*, *39*, pp. 7309-7325.

Elsayed, K., and Wahba, H. (2016). Reexamining the relationship between inventory management and firm performance: An organizational life cycle perspective. *Future Business Journal*, *2*, pp 65-80.

Epstein, M. J. (2004). *Implementing E-Commerce Strategies*. Connecticut: Praeger Publisher.

Fisher, M., and Vaidyanathan, R. (2012). Which product should you stock?. *Harvard Business Review: Operations management*, November 2012 issue. Available: https://hbr.org/2012/11/which-products-should-you-stock [2020, April 11].

Freivalds, A., and Niebel, B. W. (2014). *Niebel's methods, standards, and work design*, 13th ed. New York: McGraw-Hill.

Gallmann, F., and Belvedere, V. (2010). Linking service level, inventory management dan warehousing practices: A case-based managerial analysis. *Operations management Research*, *4*(1), pp 28-38.

Gamble, K. R., Cassenti, D. N., and Buchler, N. (2018). Effect of information accuracy and volume on decision making. *Military Psychology*, *30*(4), pp. 311-320.

Gamito, M., and Moreira da Silva, F. (2015). Color ergonomic function in urban chromatic plans, *Procedia manufacturing, 3*(2015), pp. 5905-5911.

Guastello, S. J. (2014). *Humand factors engineering and ergonomics: A systems approach*, 2nd ed. Boca Raton: CRC Press.

Hair, Jr. J. F., Black, W. C., Babin, B. J., and Anderson, R. E. (2014). *Multivariate data analysis*, 7th ed. Harlow: Pearson Education Limited.

Hartati, E. R. (2019). *Platform e-commerce akan semakin diminati*. Available: https://investor.id/business/platform-ecommerce-akan-semakin-diminati [2020, April 7].

Hugo, J. V., and Germain, S. St. (2017). *Human factors principles in information dashboard design*. Available: https://www.osti.gov/servlets/purl/1358407 [2020, April 2].

Hull, B. Z. (2005). Are supply (driven) chains forgotten?. *International Journal of Logistics Management*, *The, 16*(2), pp. 218-236. DOI: 10.1108/09574090 510634520.

Hsieh, P. H. (2019). A study of models for forecasting e-commerce sales during a price war in the medical product industry. In: Nah FH., Siau K. (eds), *HCI in Business, Government and Organizations. eCommerce and Consumer Behavior. HCII 2019*. Lecture Notes in Computer Science, vol 11588, pp. 3-21. Springer, Cham. DOI: 10.1007/978-3-030-22335-9_1.

Hymanson, J. (2013). *Unlocking the promise of demand sensing and shaping through big data analytics: How to apply high-performance analytics in your supply chain*. SAS Institute Inc., USA. DOI: 106218_S102350_0313.

Kementerian Perindustrian Republik Indonesia. (2018). *Making Indonesia 4.0*. Available: www.kemenperin.go.id/download/18384 [2020, April 9].

Khan, R., Surti, A., Rehman, R., and Ali, U. (2012). Knowledge and practices of ergonomics in computer users. *J Pak Med Assoc., 62*(3), pp. 213-217. Available: https://pubmed.ncbi.nlm.nih.gov/22764450/ [2020, July 17].

Kroemer, K. H. E., and Grandjean, E. (2009). *Fitting the task to the human: A textbook of occupational ergonomics*, 5th ed. London: Taylor & Francis Ltd.

Li, C., and Liu, S. (2013). A robust optimization approach to reduce the bullwhip effect of supply chains with vendor order placement lead time delays in an uncertain environment. *Applied Mathematical Modeling, 37*, pp. 707-718.

Liu, J., Liu, C., Zhang, L., and Xu, Y. (2019). Research on sales information prediction system of e-commerce enterprises based on time series model. *Information Systems and e-Business Management*, 22 January, DOI: 10.1007/s10257-019-00399-7.

Logility. (2017). Successful sales and operations planning in 5 steps. Logility Inc. Available:www.supplychain247.com/paper/successful_sales_and_operations_planning_in_5_steps/Logility#register [2020, April 9].

Logility. (2019). Eight methods to improve forecast accuracy in 2019. Logility Inc. Available: http://www.supplychain247.com/search/results/search&category=&keywords=Eight+methods+to+improve+forecast+accuracy+in+2019/ [2020, April 9].

Lurie, N. H., and Swaminathan, J. M. (2009). Is timely information always better? The effect of feedback frequency on decision making. *Organizational Behavior and Human Decision Processes, 108*(2), pp. 315-329.

MacKenzie, S. I. (2013). *Human-computer interaction: An empirical research perspective*. USA: Elsevier Inc.

McKinsey&Company. (2018). *The digital archipelago: How online commerce is driving Indonesia's economic development*. Available: www. mckinsey.com [2020, April1].

Melnyk, S. A., and Stanton, D. J. (2017). The customer centric supply chain. *Supply Chain Management Review*, pp. 8-17.

Mendes, P. Jr. (2011). *Demand driven supply chain: A structured and practical roadmap to increase profitability*. Springer Heidelberg Dordrecht, New York.

Moore, D. S., Notz, W. I., and Flinger, M. A. (2017). The basic practice of statistics, 8th ed. Macmillan Learning.

Nagy, J., Oláh, J., Erdei, E., Máté, D, and Popp, J. (2018). The role and impact of industry 4.0 and the internet of things on the business strategy of the value chain—the case of hungary. *Sustainability*, *10*(10): 3491, DOI: 10.3390 /su10103491.

Ren, S., Chan, H. L., and Siqin, T. (2019). Demand forecasting in retail operations for fashionable products: methods, practices, and real case study. *Annals of Operations Research*. DOI: 10.1007/s10479-019-03148-8.

Richard, Vic. (2014). *Demand shaping: Achieving and maintaining optimal supply-and-demand alignment*. SAS Institute Inc., USA, DOI: 107018_S11 9142.0314.

SAS (2014). *Demand Sharping: Achieving and Maintaining Optimal Supply-and-Demand Alignment.* 107018_S119142.0314. USA, SAS Institute Inc.

Simchi-Levi, D., Kaminsky, P., and Simchi-Levi, E. (2009). *Designing and managing the supply chain: Concepts, strategies, and case studies,* 3rd ed. Boston: McGraw-Hill.

Snapp, S. (2013). *How to best use aggregate planning in demand and supply planning*. Brightwork: Demand Planning, August 31. Available: https://www.brightworkresearch.com/demandplanning/2013/08/the-basics-of-aggregated-planning-across-supply-chain-planning-domains/. [2020, April 11].

Sohail, N., and Sheikh, T. H. (2018). A study of inventory management system case study. *Journal of Dynamical & Control Systems*, *10*(10-special issue), pp. 1176-1190.

Tabachnick, B. G., and Fidell, L. S. (2019). *Using multivariate statistics*, 7th ed. New York, NY: Pearson.

The European Business Review. (September 20, 2018). *Enhancing value through customer supply chain*. Available: www.europeanbusinessreview.com [2020, April 1].

Tolkach, D., King, B., and Pearlman, M. (2013). An attribute-based approach to classifying community-based trourism networks. *Journal Tourism Planning and Development*, *10*(3), pp. 319-337.

Wang, X., and Disney, S. M. (2016). The bullwhip effect: Progress, trends and directions. *European Journal of Operational Research*, *250*, pp. 691-701.

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