International Review of Management and Marketing

ISSN: 2146-4405

available at http: www.econjournals.com

International Review of Management and Marketing, 2022, 12(6), 55-63.

Analysis of Factors Affecting Product Sales with an Outlook toward Sale Forecasting in Cosmetic Industry using Statistical Methods

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Received: 27 June 2022 **Accepted:** 15 October 2022 **DOI:** https://doi.org/10.32479/irmm.13337

ABSTRACT

There are several factors associated with the sale of cosmetic products which contribute to gaining market share for related companies in this industry. Furthermore, sales forecasting is indispensable in all levels of a company's supply chain including production, distribution and logistics, marketing, and sale. This article mainly focuses on the analysis of characteristics affecting sales and sales forecasting in the cosmetics industry in which it will be helpful in determining sales strategies of cosmetics companies. Therefore, as a case study in this study, the main factors affecting the sale of cosmetic products were determined and categorized; accordingly. Three products including moisturizing cream, perfume, and sunscreen were examined using a statistical method. The effect of factors on product sales was predicted using the spline smooth prediction method and based on the predicted values, using the non-parametric Friedman test and Mean Rank, the effective factors were ranked in each of the three products. Moreover, the company's sales volume in each of the three products was forecasted by using ARIMA models. The results demonstrated that factors such as "price" and "product" elements are the main drivers influencing the sales of moisturizing creams and "promotion" and "Inflation rate" factors play the most effective role in the sales of the perfume. Also, the compound aggregated growth rate (CAGR) for moisturizers, perfumes, and sunscreens over a 5-year period in the study company are 30%, 29%, and 45%, respectively. It is very clear that to achieve ideal sales, paying attention to these influential factors and forecasting product sales lead to predicting material procurement of manufactures, distribution channels, and sales which finally provides business with customer satisfaction.

Keywords: Cosmetic Industry, Marketing, Sale Forecasting, Purchasing Power, Time Series, ARIMA Model
JEL Classifications: C32, C39, D49, D53

1. INTRODUCTION

The cosmetic industry grows in developed and developing countries throughout the world. Such constant growth and development in the cosmetic industry may provide a good opportunity for fans of this trade to introduce their cosmetic products. The Asian cosmetic market has been turned into one of the attractive and ever-growing markets in the world. The size of Asian and Oceania markets has been increased to more than 70 billion USD that is the second premium market after the western European market in the world (Hassali, 2015). At present, attitudes may vary toward the use of cosmetics among people. Personally, the females have attached great importance to cleaning and also the employed women and those with higher income are often interested in purchasing the premium personal caring products (Swidi, 2010).

Some of the cosmetic artifacts, which have been probably used for ornamentation of the eye and as perfumes, may indicate the first archeological pieces of evidence of cosmetics in Egypt for over 4000BC. At that period, cosmetics were assumed as an important part of dressing for the Egyptians. In addition, cosmetics were created for personal care and health because of hot and dry sunlight and weather and sandy land in Egypt. Cosmetics were consumed almost widely in all items throughout the world in the middle of the twentieth century. Following to rising number of employed women and increase in urbanism sales of beautification products was continued (Eze, 2012).

Conducting a study on the cosmetic industry is not only vital to the world's Gross National Product (GDP) but also essential because of its noticeable impact on the social life of humans in the world. As people talk about the cosmetic industry, they mainly refer to cosmetic tools that comprise a bit higher than 18% of the total market for the personal care industry (Kumar, 2005).

The US is the largest cosmetic market and France acts as the greatest exporter of cosmetic products in the world. The growth of this market has been transferred from the western hemisphere to the developing regions in South America, Eastern Europe, and Asia, especially China. Despite the world economic crisis, with an average growth rate of over 5% in this industry, the cosmetic industry has experienced good performance (Kumar, 2005). This industry has recorded a recession in growth for sales and peerless revenue in other economic resources. The great and private enterprises are still active in this field as well. Most of the given reports from sales and revenue may show that the previous growth is going to progress, while one could surely look at growth objectives in the long run (North, 1963).

Some of the well-known foreign manufacturers have devoted the relatively great market share in this industry at world level, but new rivals have affected the share market of these enterprises by manufacturing products proportional to the needs and requests of consumers, affordable prices, modern techniques to supply products, and extensive promotions, etc. The present paper is focused on the study and analysis of key effective factors on three selected products from one of the middle east's enterprises. As a result of this study, effective factors on sales of products have been ranked throughout the country and the rate of sales is estimated for a 5-year period conceptual model of the study is evaluated. This study has been prepared in 5 sections. Section 2 discusses the theoretical bases of research and related concepts. In Section 3, the selected products and methodology are explained in detail. Then, the analytical results are interpreted in Section 4 and our concluding remarks are presented in the final section.

2. LITERATURE REVIEW

Sales forecasting is indispensable in all levels of a company's supply chain including production, distribution, logistics, marketing, and sale (Sohrabpour and et al., 2021). Forecasting and predictions have constructive effects on shorter lead times, improving customer expectations, and better dealing with limited resources (Boone et al., 2019). In some industries, forecasting acts as an input to many operations and business decisions that affect the profitability of the firm; in production planning, long-term forecasting is employed to determine an adequate level of manpower and acts as an input for business planning, such as planning for expansion or contraction of production units (Sa-ngasoongsong et al., 2012).

As mentioned above, forecasting future sales is too important for many companies as it contributes to operational decisions for future strategies. This is especially relevant for Fast-moving consumer goods (FMCG) due to the potential replacements' items in competitive situations. One solution for sales forecasting is time series prediction methods. With accurate estimations, company managers can rapidly respond to changing market signals and consequently adjust their strategies with the volatile markets (Haselbeck et al., 2021).

A comprehensive view of sales forecasting and customer demand is provided in the recent study by Lasek et al. (2016). Ryu and Sanchez (2003) compared several methods (moving average, multiple regressions, and exponential smoothing) in order to estimate the consumer demands where the multiple regressions resulted in the most precise predictions. Reynolds et al. (2013) apply multiple regressions to forecast the annual sales volume of the restaurant industry (and of certain sub-segments). Forst (1992) applied autoregressive integrated moving average (ARIMA) and exponential smoothing models to predict the weekly customer demand at a restaurant. Hu et al. (2004) used ARIMA methods to forecast the sales at casino buffets. Also, the exponential smoothing method was applied by Cranage and Andrew (1992) for forecasting the monthly sales of a restaurant.

Bujisic et al. (2017) in their paper examined forecasting approaches for restaurant sales based on different factors; however, they pointed out that most studies are associated with aggregated forecasts. Furthermore, machine learning methods were used by Tanizaki et al. (2019) to forecast the number of consumers in which the forecasting was raised from POS data with external data, e.g., weather information and event data. Likewise, Kaneko and Yada (2016) developed a deep learning approach to present a forecasting model for sales at retail stores.

Taylor and Letham (2018) proposed a decomposable time series model consisting of three main elements trend, seasonality, and holidays where the model benefits an analyst to adjust the model while allowing human interpretation for each parameter. The time series applied in the paper had various features including multiple strong seasonality, trend changes, outliers, and holiday effects.

Berry and West (2019) used multiple items at variable levels and demonstrated diverse patterns over time for developing prediction uncertainties. Some previous forecasting models propose challenges in daily sales forecasting begin with intermittent demand problems (Berry et al., 2020). In this regard, a bias-adjusted extension (Syntetos and Boylan, 2005), bootstrapping methods (Willemain et al., 2004), and the aggregation-decomposition approach of Li and Lim (2018) are the previous models which have addressed intermittent data problems. Moreover, various modified models were used to address high variability and extreme values challenges in daily sales of items that sell more frequently in which Chen.

Li and Sriboonchitta (2016) presented the autoregressive conditional negative binomial technique and Chen and Lee (2017) applied the Possion log-linear and negative binomial GARCH. Snyder and et al., (2012) applied the hurdle-shifted Poisson model, the McCabe and Martin (2005) practiced the Bayesian integer-valued autoregressive model with negative binomial arrivals. The Bayesian Gamma-Poisson local level and a multivariate time series model for over dispersed discrete data were used by Yelland (2009) and Terui and Ban, (2014) respectively.

Berry and West (2019) incorporated dynamic random effects to demonstrate unpredictable variation in sales. Aktekin and et al. (2018) applied cross-series relationships which need the modeling of multivariate series of counts; accordingly, this study linked forecasting models to provide improved probabilistic predictions. Another search area that is conducted in sales forecasting includes empirical cases on export sales forecasting (ESF).

Recent studies in this area were employed by Çabuk (2019); Nie and Oksol (2018); Okorie and Ohakwe (2018) and Wanto et al. (2019). Moreover, Hoyle et al. (2020) considered the importance of sales professionals including sales managers and salesperson in providing sound data analysis for sales forecasting projections. The paper studied the perceptions concerning several forecasting sales force automation components including enterprise resource planning (ERP), and customer relationship management (CRM) software. According to former studies, most of which were examined in the past sentences, there is no inclusive study presenting determinant factors related to the sales and enhancing selling of products. Studies usually talked about marketing strategies and sales approaches for enhancing a company's sales, though no comprehensive study was observed that has determined and analyzed major effective factors on sales, especially in the cosmetic industry. There is no doubt that there are contributing criteria that indirectly impact a company's sales like factors that make purchasing behavior for consumers.

However, such effects have not been examined by previous researchers. Thus, we intended in the present study first to identify all determinant criteria that either directly or indirectly contribute to selling products and second to predict sales of three selected products in a Manufacturing Company.

2.1. Related Concepts

The foremost effective factors on consumer's sales have been assumed as effective factors of sales and they are classified into three categories of Marketing, Purchasing Power, and Time-effect as follows:

2.1.1. Marketing category

Regarding to Marketing standpoint, one of the critical factors of decision making and business evaluations for companies is the marketing mix from which essential elements for planning and operation process have come; besides, marketing mix elements have interdependent factors affected mutually. As a result, making a decision about one of them might profoundly affect others which means if these marketing mix elements combine effectively, it can end up with a decent marketing system (Aghaei and et al., 2014). Conventionally, the pillars of marketing were known as 4Ps demonstrating Product, Price, Place, and Promotion. However, as the customers are becoming more sophisticated, three further "Ps" were added which are included People, Process, and Physical Environment. These considerations are called 7P's marketing mix, which is related to the company's sales based on marketing strategies raised from them to increase sales (Hashim and et al., 2014).

- Product elements-Service products consist of core and supplementary (value-added) elements
- Place and time-service distribution through physical and non-physical channels
- Price and other user outlays-generation of incomes and profits with consideration of other customer costs
- Promotion and education-Provide information, persuade customers and teach customers to become effective through the service process
- Process-The operation of inputs and outputs from marketers/sellers to customers.
- Physical environment-design services cape (physical appearance) and provide tangible evidence of service performance
- People-Interactions between customers and contact personnel can affect their satisfaction.

Considering the purchasing power, it should be noted that this criterion determines the value of a currency expressed in terms of the number of services or products that a specific amount of a currency can buy. Purchasing power is considered a relative factor that is significantly influenced by both macroeconomic and microeconomic factors over time. The consumer buying and purchasing decision significantly depends on their purchasing power which is caused by the economic situations of a market. In this regard, whenever a nation's purchasing power is strong it is associated with the country's economic factors including employment, wages, prices/inflation, and so forth. Whereas, a sluggish economy determines a situation in which the purchasing power has been become weak due to poor economic factors. Under these circumstances, companies' sales would experience a drastic decline raised from an incoherent existence between sales and customers' purchasing power; accordingly, the economic factors that most affect the demand for consumer goods directly related to sales are taxation and interest rates, inflation rate and currency exchange (Ramsay, 1994). In this study, the most effective economic factors associated with purchasing power consider as a category that correlates highly with a company's sales. The following list is provided for further information about the related factors in purchasing power category.

2.1.2. Purchasing power category

2.1.2.1. Currency exchange

Economists proposed that floating rates have an adverse impact on the economy since every country uses the currency as an intermediate for purchasing goods and services in international trade. Hence, once the exchange rate becomes volatile, the market is faced with uncertainty regarding the unpredictable changes over time that can be defined as volatility. Generally, the causes of currency exchange rate volatility can be categorized into domestic and external real shocks affecting supply and demand and nominal shocks reflecting changes in the money supply. Therefore, shocks are the main source of unpredictable fluctuations that can affect the price of consumer goods directly influence a company's sales (Morina and et al., 2020).

2.1.2.2. Interest rates

Changes in interest rates contribute to different impacts on consumer purchasing behaviors depending upon a number of factors including current rate levels, short term, and long term, consumer expectations about the future rate, and the healthy economy. The Kapoor and Shamika, (2009) study demonstrates that an increase of basis points in the interest rate on deposits leads to an immediate decline in consumption of household expenditures in which once the interest rates rise, consumers may be more prone to saving costs so as to gain from higher interest rates rather than spend.

2.1.2.3. Inflation rate

Inflation demonstrates a decline of purchasing power of people for a given currency over a period of time. Remesh, (2021) maintains price inflation causes each unit of currency to purchase fewer goods and services; subsequently, inflation reflects that consumers lose purchasing power per unit of money which means a loss of real currency exchange value within the economy.

2.1.2.4. Tax (goods and services tax)

Purchasing power has a profound effect on the purchase decisions of consumers; besides, the purchasing power of consumers is affected by taxes imposed on the prices of goods and services. Consequently, taxes have a direct positive correlation with the disposable income of consumers in which it is so crucial that companies develop their marketing strategies and price planning aligned with the changes in the tax policies. This is because often taxes contribute to reducing a consumer's purchasing intention insofar as the company's sales would be influenced by losing customers (Ramkumar and Chitra, 2020).

And finally, concerning the Time outlook, it is a paramount element which customers give up so as to purchase goods and services. According to Jacoby et al. (1977), time plays an inextricable dimension of consumer behavior and consumer purchasing. Furthermore, Hawkins (2004), maintained that consumers benefit from time as an available resource for making decisions in their purchases. Time has effects on consumption in two main forms as following which means these forms would indirectly impact on company's sales originating from consumer purchasing behaviors.

2.6. Time Effect

2.6.1. Seasonal factor

One paramount context which has been recognized as a vital factor for modeling consumers purchasing patterns is seasonality effects which refer to the existence of variations that occur at certain regular intervals including weekly, monthly, or quarterly. Moreover, seasonality is associated with stable patterns and well-established forms in which occasional irregularities have not existed. Various factors might cause seasonality like natural calamities, weather, holidays, vacation, and so forth. Consumers purchasing behavior tremendously has been affected by such a prominent factor-like seasonality that impacts the company's sales (Ardeshiri and et al., 2019).

2.6.2. Time pressure

Most merchants employ sales with limited purchase time to increase sales and boost profits in which they provide customers with deep discounts strategies and promotion plans for a limited time duration. This time limitation makes a sense of urgency for purchasing which drives customers to buy either products or services.

Conversely, exposed to make a purchase decision in a short time, customers are more prone to become anxious and stressed insofar as this perceived time pressure would have a negative impact on their decision making in terms of purchasing; therefore, the time pressure would also have compromising effect on the relationship between sales promotion and purchase intention. Thus, the product category is a relevant factor in determining the time pressure effect on consumer purchasing which indirectly influences a company's sales (Peng and et al., 2019). The effective factors on sales are summarized and classified as research variables in Table 1.

3. MATERIALS AND METHODS

Three selected cosmetic products from the selected company consist of Moisturizer (P1), Perfume (P2), and Sun Cream (P3). Thirteen effective variables on sales were classified into three groups: Marketing, Purchasing Power, and Time-Effect.

Based on a survey during a 5-year period (2012-2016) at this study that was conducted as cross-sectional, 20 experts in the fields of marketing and corporate sales were asked in polling about the impact of each of 13 effective factors on sales of Company's products within the Likert 5-scale spectrum. The rounded value of mean responses from interviewees was considered as a criterion score about pricing for sales of products per year.

Table 1: Classification of effective factors on sales

Characteristics	Category
Marketing	Product elements
	Place
	Promotion
	People
	Price
	Process
	Physical environment
Purchasing power	Tax (GST)
	Inflation rate
	Currency exchange
	Interest rate
Time effect	Seasonal factor
	Time pressure

To determine validity through the Delphi technique, the aforesaid tools were given to 20 experts in marketing and sales and their comments were implemented at the first turn, and then the results were returned to them for their reconfirmation. To analyze Delphi's results at the first round, content analysis was done to identify the main themes in the initial questionnaire and the results of the given questionnaire were converted into the final questionnaire. Cronbach alpha coefficient was utilized to measure the reliability of research variables. The reliability value was $\alpha = 0.88$; therefore, research variables are highly reliable and one could ensure from internal consistency of these variables. Similarly, the rate of sales of three products was measured within a 9-year period and during years (2012-2020).

Spline Smooth Prediction was used in the first round of analysis for the prediction of values of 13 variables within years (2017-2020). In the second round, Friedman's nonparametric test was employed for ranking 13 variables in terms of impact on sales of each of selected products using mean rank and based on the predicted value at the first round of analysis.

As a result, when the hypothesis of the Mean Rank equality for variables is rejected, this criterion will be used to rank the variables. By fitting of appropriate ARIMA model at the third round, sale values are forecasted for either of the selected products in a 5-year period (2021-2025). Statistical analyses were done in R-software.

4. RESULTS

To predict the values of variables, the year and product's type (P1, P2, P3, and P4) as the regressors has been included and input the 13 qualificative characteristics as the response variable to the model. By the means of the values of the qualitative features through 2012 and 2016, a prediction is accomplished for corresponding items in years between 2017 and 2021. Whereby a comprehensive package of simulated data between 2012 and 2021 is obtained. At this phase, the TTR and the graphics packages of R-software have been utilized for data analysis. Table 2 shows the output of the prediction Table 2.

Variable relating to i^{th} variable in Table 2 is shown as x_i. This table represents that from 2012 up to 2014, the most effective variables are ×1 (Product elements) and ×10 (Currency Exchange), related to the P1. However, during 2015 and 2020, ×5 (Price) play a significant role as an effective variable on the P1. Finally, it is clear that in 2021, ×3 (Promotion) for P2 is the most effective variable.

It can be seen from Table 2 that the greatest impact on sales occurred in 2021 for the variable ×3 (promotion) and then the variable ×5 (price). Also, the lowest value is obtained for the variable ×11 (interest rate) in 2020. The variable ×2 (place) also has very small values, so that the maximum value is 4.501 and the lowest value is 1.398 in 2021.

In Figure 1, based on Table 2, scatter plot is depicted to make it possible to compare the effect of variables on sales.

Figure 1: Scatter plot based on spline smooth prediction for (a) marketing variables (b) purchasing power variables (c) time effect variables

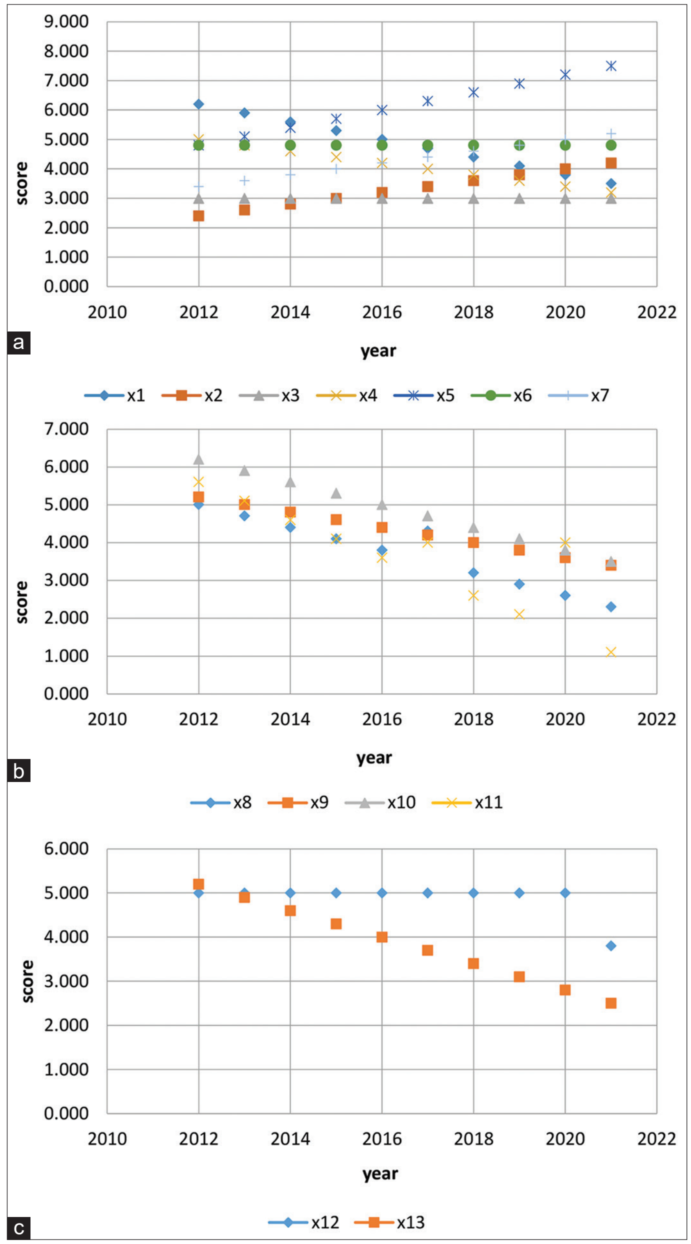


Figure 1a shows that the scores of the variables ×2 (Place), ×5 (Price) and ×7 (Physical environment) have an increasing trend and the scores of the variables ×1 (Product elements) and ×4 (People) have a downward trend. Also, the score of variable ×3 (Promotion) has a fixed value of 3 and variable ×6 (Process) has a slight downward trend. The largest impact on sales in the Marketing category belongs to the variable ×5 (Price) in 2021.

Figure 1b shows that the score of all variables is decreasing in total and the highest impact on sales is related to the variable ×10 (Currency Exchange) in 2012 and the lowest impact on sales is related to the variable ×11 (Interest rate) in 2021.

It can be seen from Figure 1c) that the variable ×12 (Seasonal Factor) has a fixed score of 5 by 2020 and its score decreases

Table 2: Predicted values of variables using spline smooth prediction

Year	Product	×1	×2	×3	×4	×5	×6	×7	×8	×9	×10	×11	×12	×13
2012	1	6.200	2.400	3.000	5.000	4.800	4.800	3.400	5.000	5.200	6.200	5.600	5.000	5.200
	2	3.000	3.200	3.200	1.800	5.000	2.000	3.000	2.800	5.200	5.000	4.000	3.800	4.000
	3	3.000	1.800	1.800	5.200	2.400	3.801	4.200	5.201	4.600	4.000	4.000	4.600	5.000
2013	1	5.900	2.600	3.000	4.800	5.100	4.800	3.600	4.700	5.000	5.900	5.100	5.000	4.900
	2	2.900	3.000	3.700	2.100	4.700	2.000	3.300	3.100	4.900	4.700	4.000	3.800	4.000
	3	3.300	2.100	2.100	4.900	2.600	3.700	3.900	4.700	4.700	4.000	3.900	4.700	5.000
2014	1	5.600	2.800	3.000	4.600	5.400	4.800	3.800	4.400	4.800	5.600	4.600	5.000	4.600
	2	2.800	2.800	4.200	2.400	4.400	2.000	3.600	3.400	4.600	4.400	4.000	3.800	4.000
	3	3.600	2.400	2.400	4.600	2.800	3.600	3.600	4.199	4.800	4.000	3.800	4.799	5.000
2015	1	5.300	3.000	3.000	4.400	5.700	4.800	4.000	4.100	4.600	5.300	4.100	5.000	4.300
	2	2.700	2.600	4.700	2.700	4.100	2.000	3.900	3.700	4.300	4.100	4.000	3.800	4.000
	3	3.900	2.700	2.700	4.300	3.000	3.500	3.300	3.700	4.900	4.000	3.700	4.900	5.000
2016	1	5.000	3.200	3.000	4.200	6.000	4.800	4.200	3.800	4.400	5.000	3.600	5.000	4.000
	2	2.600	2.400	5.200	3.000	3.800	2.000	4.200	4.000	4.000	3.800	4.000	3.800	4.000
	3	4.200	3.000	3.000	4.000	3.200	3.400	3.000	3.201	5.000	4.000	3.600	5.001	5.000
2017	1	4.700	3.400	3.000	4.000	6.300	4.801	4.400	4.300	4.199	4.700	4.000	5.000	3.700
	2	2.500	2.199	5.700	3.300	3.500	2.000	4.500	2.701	3.700	3.500	3.500	3.801	4.000
	3	4.500	3.300	3.300	3.700	3.400	3.301	2.701	3.201	5.100	4.000	2.601	5.101	5.000
2018	1	4.400	3.599	3.000	3.800	6.600	4.800	4.599	3.201	3.999	4.400	2.601	5.000	3.400
	2	2.401	1.999	6.200	3.600	3.201	2.000	4.799	4.600	3.400	3.201	4.000	3.801	4.000
	3	4.799	3.600	3.600	3.400	3.599	3.400	2.401	2.202	5.200	4.000	3.401	5.202	5.000
2019	1	4.100	3.799	3.000	3.600	6.900	4.801	4.799	2.901	3.799	4.100	2.102	5.000	3.100
	2	2.301	1.799	6.699	3.900	2.901	2.000	5.099	4.900	3.100	2.901	4.000	3.801	4.000
	3	5.099	3.900	3.900	3.100	3.799	3.103	2.101	1.703	5.300	4.000	3.301	5.303	5.000
2020	1	3.799	3.999	3.000	3.400	7.201	4.802	4.999	2.601	3.598	3.799	4.000	5.000	2.799
	2	2.201	1.598	7.199	4.201	2.601	2.000	5.399	5.201	2.799	2.601	3.201	3.802	4.000
	3	5.399	4.201	4.201	2.799	3.999	3.003	1.802	1.204	5.400	4.000	1.103	5.404	5.000
2021	1	3.499	4.198	3.000	3.200	7.501	4.802	5.198	2.301	3.398	3.499	1.103	3.802	2.499
	2	2.101	1.398	7.699	4.501	2.301	2.000	5.699	5.501	2.499	2.301	4.000	5.505	4.000
	3	5.699	4.501	4.501	2.499	4.198	2.904	1.502	0.705	5.501	4.000	3.101	5.200	5.000

in 2021. Also, the amount of points of the variable ×13 (Time Pressure) has a decreasing trend. The highest and lowest impacts on sales are related to the ×13 variable in 2012 and 2021, respectively.

To examine more closely, the Mean Rank is used to compare the impact of factors on the sales of selected products. Research variables were ranked in terms of rate of effect on sales of products using pmr package in R-software. The hypothesis of equality of 13 variables is rejected concerning the Moisturizer Cream (P1) from Friedman test result with P = 0.04 at a significance level of 0.05 (0.04 < 0.05). Therefore, variables could be ranked according to mean rank. The mean rank of factors is shown in Table 3.

Table 3: Mean rank of factors for moisturizer cream (P1)

Variable	Mean rank
×1	5.299
×2	2.999
×3	3.000
×4	4.399
×5	5.700
×6	4.800
×7	3.999
×8	4.172
×9	4.599
×10	5.299
×11	4.2693
×12	4.978
×13	4.299

Thus, variables ×1, ×5, ×10, and ×12 have the greatest impact on sales of moisturizer products respectively. Regarding Perfume (P2), the hypothesis of equality of mean rank is rejected for 13 variables from the Friedman test result with a value of P = 0.004 at the significance level of 0.05 (0.004 < 0.05). Thus, variables could be ranked according to mean rank. The mean rank of factors is shown in Table 4.

Table 4: Mean rank of factors for perfume (P2)

Variable	Mean rank
×1	2.700
×2	2.599
×3	4.699
×4	2.700
×5	4.100
×6	2.000
×7	3.899
×8	3.554
×9	4.299
×10	4.100
×11	3.925
×12	3.831
×13	4.000

Therefore, variables of ×3, ×5, ×7, and ×9 have the highest effect on sales of perfumes. There is no reason to disprove the hypothesis of equality of mean rank for research variables to the product of Sun Cream (P3) with a value of P = 0.2 at a significance level of 0.05 (0.2 > 0.05). Thus, all variables are identically significant in sales of the third product.

Concerning the forecast of sales, the rate of sales is predicted in 5-year period (2021-2025) based on sales at an interval of years (2012-2016). To this end, the ARIMA model is fitted automatically by suitable parameters on data using the forecast package in R-software. Whereas the diagram of sales includes increasing trend, therefore, the logarithmic transform was used for obtaining stationary time series. Time series diagram is shown for data relating to three products along with confidence interval concerning the forecast values in Figure 2.

In Figure 2, for forecast points over a 5-year period between 2021 and 2025, two confidence intervals are shown, one 80% in bright blue and the other 95% in light blue. It can be seen that the forecasted values also have an increasing trend and the width of the confidence interval in Figure 1a and 1b is less than Figure 1c. This may indicate a slight increase in forecast accuracy.

In order to determine the goodness of the fitting model, autocorrelation function (acf) and partial autocorrelation function (pacf) diagrams were used for the rest of the models. Diagrams related to time series model are shown in Figure 3. It is seen in *acf* diagram the values are placed within the confidence interval after the first lag and *pacf* diagram is also included in the confidence interval.

Usually, acf and pacf graphs are plotted for different lags for the data, and by comparing the graphs, the auto regressive order (AR), moving average (MA) and a combination of auto regressive and moving average are identified and the model order will be determined. It is clear from Figure 2 that ARIMA (0, 1, 0) is the best choice for the goodness of fit of time series belong P1 and P2, and ARIMA (0, 2, 0) is the best choice for the goodness of fit of time series belong P3.

In order to analyze the hypothesis of independence of residuals, the Ljung-Box test is used. Results are shown in Table 5.

It is observed from the results of all three tests that there is no reason to reject the hypothesis of independence of residuals with $P > 0.05$ at the significance level of 0.05. Table 6 shows the forecast values for sales of the product in a 5-year period.

Table 6 represents an ascending trend for the selected products' sales through 5 years from 2021 up to 2025, whereby it is predicted that the sale values for P1, P2 and P3 in 2025 will touch 3677.576, 22271.52 and 113709.2, respectively. Moreover, Compound Aggregated Growth Rate (CAGR) to moisturizer, perfumes, and sun cream are 30%, 29%, and 45%, in order, for a 5-year period.

Table 5: Testing results for box-ljung test

P1	P2	P3
X-squared=0.19706 P=0.9062	X-squared=0.68964 P=0.7083	X-squared=0.66092 P=0.7186

Table 6: Sale forecasting values for selected products

Year	2021	2022	2023	2024	2025
Sale					
P1	1282.962	1669.364	2172.14	2826.343	3677.576
P2	8002.746	10336.34	13350.4	17243.37	22271.52
P3	25719.64	37294.46	54078.93	78417.31	113709.2

Figure 2: Diagram of time series for sales of (a) moisturizer; (b) perfumes and (c) sun cream

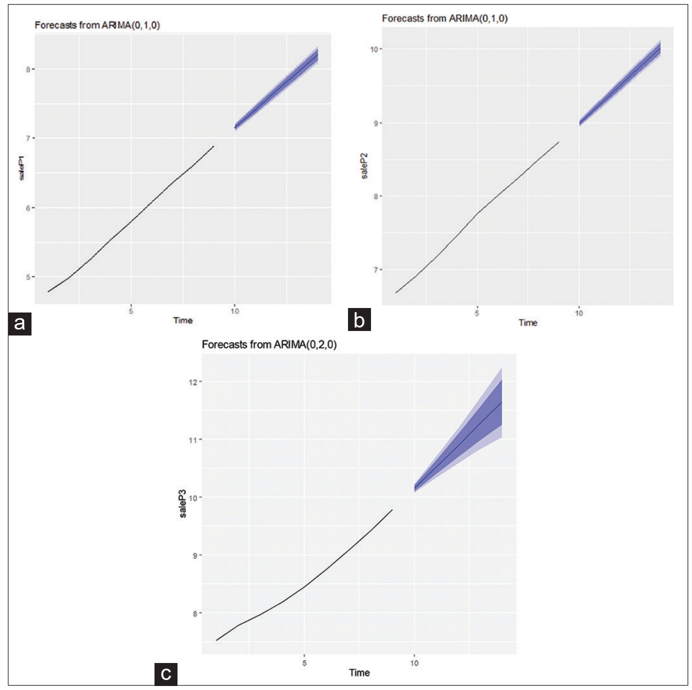
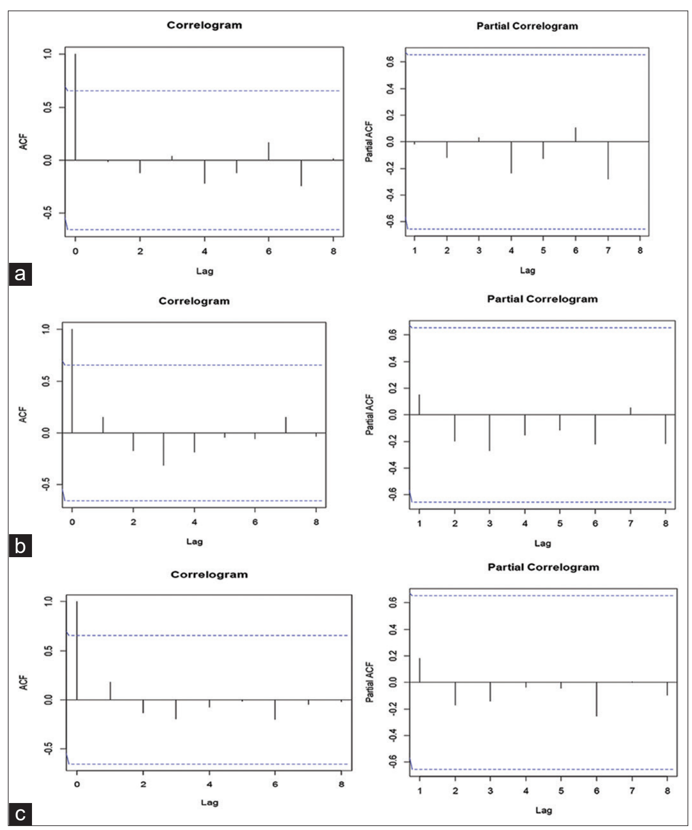


Figure 3: acf and pacf diagrams of Time Series for the (a) first product; (b) second product; (c) third product



5. CONCLUSIONS

The present study aims to identify and analysis of effective factors on sales of cosmetic products and to forecast the rate of sales of selected products in a typical manufacturing company of cosmetic products using statistical methods. This study concludes that factors of price, product elements, currency exchange, and seasonal factor have the highest impact on sales of moisturizer, and variables of promotion, inflation rate, price, and physical environment have the greatest effect on sales of perfumes. Out of all the elements, it is obvious that one of the most important leverages is, of course, the price. Price refers to the value that is put for a product. It depends on costs of production, segment targeted, abilities of the market to pay plus a host of other direct and indirect factors. This conclusion is also aligned with the study's results of Jamaluddin and Esa (2020). Moreover, the marketing mix contributes to the set of tools, all of which are qualified for increasing the company's sales performances and promoting the goods and services in the mind of customers. This result is also compliant with Gituma study in terms of effects of marketing mix on sales performance (2017).

As the previous studies such as Kapoor and Shamika (2009) showed, the interest rate has impact on purchasing behaviors concerning the household expenditures, though fast moving consumer goods like cosmetic products are not included high-end consumer goods, such as jewelry, automobiles and so forth, which are often purchased by credits via consumers. Higher interest rate means a rise in borrowing costs for consumers purchasing on credits while often high-end consumer goods are purchased under this circumstances. As a result, the customers might not be affected profoundly by "Interest rate" in terms of purchasing goods like cosmetic products; accordingly, as the study's results showed the interest rate factor has a little impact on purchasing of cosmetic products.

Forecasting of sales is deemed as an important subject in the management of product and supply chains. Lack of forecasting may influence the trend of materials, sales, and customer satisfaction. The ARIMA models were used for forecasting of sales of three selected products in this study. As a result, the forecast values for Compound Aggregated Growth Rate (CAGR) to moisturizer, perfumes, and sun cream are 30%, 29%, and 45% respectively for a 5-year period. Three variables, including wage, customer confidence, and employment, are those factors that may affect sales of cosmetic products. Thus, analysis of the effect of these factors on sales will be an appropriate subject for future studies.

REFERENCES

Aghaei, M., Vahedi, E., Safari, M., Pirooz, M. (2014), An examination of the relationship between services marketing mix and brand equity dimensions. Procedia Social and Behavioral Sciences, 109, 865-869.

Aktekin, T., Polson, N.G., Soyer, R. (2018), Sequential bayesian analysis of multivariate count data. Bayesian Analysis, 13, 385-409.

Ardeshiri, A., Sampson, S., Swait, J. (2019), Seasonality effects on consumers' preferences over quality attributes of different beef products. Meat Science, 157, 107868.

Berry, L.R., Helman, P., West, M. (2020), Probabilistic forecasting of heterogeneous consumer transaction-sales time series. International Journal of Forecasting, 36(2), 552-569.

Berry, L.R., West, M. (2019), Bayesian forecasting of many count valued time series. Journal of Business and Economic Statistics, 38(4), 872-887.

Boone, T., Ganeshan, R., Jain, A., Sanders, N.R. (2019), Forecasting sales in the supply chain: Consumer analytics in the big data era. International Journal of Forecasting, 35, 170-180.

Bujisic, M., Bogicevic, V., Parsa, H.G. (2017), The effect of weather factors on restaurant sales. Journal of Foodservice Business Research, 20(3), 350-370.

Çabuk, Y. (2019), Forecasting the export of wood panel industry in Turkey and determining the best method of forecast. Bartın Orman Fakültesi Dergisi, 21, 426-431.

Chen, C.W.S., So, M.K.P., Li, J., Sriboonchitta, S. (2016), Autoregressive conditional negative binomial model applied to over-dispersed time series of counts. Statistical Methodology, 31, 73-90.

Cranage, D.A., Andrew, W.P. (1992), A comparison of time series and econometric models for forecasting restaurant sales. International Journal of Hospitality Management, 11(2), 129-142.

Eze, U.C., Tan, C.B., Yeo, A.L.Y. (2012), Purchasing cosmetic products: A preliminary perspective of Gen-Y. Contemporary Management Research, 8(1), 10149.

Forst, F.G. (1992), Forecasting restaurant sales using multiple regression and box-Jenkins analysis. Journal of Applied Business Research, 8(2), 15-19.

Gituma, M.M. (2017), Effects of Marketing Mix on Sales Performance: A Case of Unga Feeds Limited. Kenya: United States International University Africa.

Haselbeck, F., Killinger, J., Menrad, K., Hannus, T. and Grimm, D.G. (2021), Machine learning outperforms classical forecasting on horticultural sales predictions. Machine Learning with Applications, 7, 100239.

Hashim, N., Hamzah, M.I. (2014), 7P's: A literature review of islamic marketing and contemporary marketing mix. Procedia Social and Behavioral Sciences, 130, 155-159.

Hassali, M.A., Al-Tamimi, S.K., Dawood, O.T., Verma, A.K., Saleem, F. (2015), Malaysian cosmetic market: Current and future prospects. Pharmaceutical Regulatory Affairs, 4(4), 155-157.

Hawkins, D.I., Best, R.J., Coney, K.A. (2004), Consumer Behavior: Building MARKETING Strategy. 9th ed. New York: McGraw-Hill.

Hoyle, J.A., Dingus, R., Wilson, J.H. (2020), An exploration of sales forecasting: Sales manager and salesperson perspectives. Journal of Marketing Analytics, 8, 127-136.

Hu, C., Chen, M., McCain, S.L.C. (2004), Forecasting in short-term planning and management for a casino buffet restaurant. Journal of Travel and Tourism Marketing, 16(2-3), 79-98.

Jamaluddin, B., Esa, S.A. (2020), Effect of price on sales volume. Journal of Undergraduate Social Science and Technology, 2(2), 3748943.

Kaneko, Y., Yada, K. (2016), A Deep Learning Approach for the Prediction of Retail Store Sales. In: 2016 IEEE 16th International Conference on Data Mining Workshops. p.531-537.

Kapoor, M., Ravi, S. (2009), The Effect of Interest Rate on Household Consumption: Evidence from a Natural Experiment in India, Available from: https://www.ssrn

Kumar, S. (2012), Exploratory analysis of global cosmetic industry: Major players, technology and market trends. Technovation, 25(11), 1263-1272.

Lasek, A., Cercone, N., Saunders, J. (2016), Restaurant Sales and Customer Demand Forecasting: Literature Survey and Categorization of Methods. Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering. Vol. 166. Champaign: Springer.

Li, C., Lim, A. (2018), A greedy aggregation-decomposition method for intermittent demand forecasting in fashion retailing. European Journal of Operational Research, 269, 860-869.

McCabe, B.P.M., Martin, G.M. (2005), Bayesian predictions of low count time series. International Journal of Forecasting, 21, 315-330.

Morina, F., Hysa, E., Ergün, U., Panait, M., Voica, M.C. (2020), The Effect of exchange rate volatility on economic growth: Case of the CEE countries. Journal of Risk and Financial Management, 13(8), 177.

Nie, J., Oksol, A. (2018), Forecasting current-quarter US exports using satellite data. Economic Review Federal Reserve Bank of Kansas City, 103, 1-20.

North, J.E. (1963), The cosmetics and toiletries industry. Financial Analysts Journal, 19(1), 39-50.

Okorie, I.E., Ohakwe, J. (2018), Forecasting Nigeria's inflation and the world prices of her major agricultural export commodities with probability distributions via VaR and ES and estimating their dependence via copula. Communications in Statistics Case Studies Data Analysis and Applications, 4, 28-45.

Peng, L., Weiguo, Z., Wang, X., Shuyi, L. (2019), Moderating effects of time pressure on the relationship between perceived value and purchase intention in social E-commerce sales promotion: Considering the impact of product involvement. Information and Management, 56(2), 317-328.

Ramkumar, G., Chitra, S. (2020), Goods and services tax and consumer buying behavior-A Study. Palarchs Journal of Archaeology of Egypt Egyptology, 17(6), 2777-2787.

Ramsay, J. (1994), Purchasing power. European Journal of Purchasing and Supply Management, 6(3), 125-138.

Remesh, V.P. (2021), A Study on Inflation. Available from: https://www.ssrn

Reynolds, D., Rahman, I., Balinbin, W. (2013), Econometric modeling of the U.S. restaurant industry. International Journal of Hospitality Management, 34, 317-323.

Ryu, K., Sanchez, A. (2003), The evaluation of forecasting methods at an institutional foodservice dining facility. The Journal of Hospitality Financial Management, 11(1), 27-45.

Sa-Ngasoongsong, A., Bukkapatnam, S.T.S., Kim, J., Iyer, P.S., Suresh, R.P. (2012), Multistep sales forecasting in automotive industry based on structural relationship identification. International Journal of Production Economics, 140, 875-887.

Snyder, R.D., Ord, J.K., Beaumont, A. (2012), Forecasting the intermittent demand for slow-moving inventories: A modelling approach. International Journal of Forecasting, 28, 485-496.

Sohrabpour, V, Oghazi, P, Toorajipour, R., Nazarpour, A. (2021), Export sales forecasting using artificial intelligence. Technological Forecasting and Social Change, 163, 120480.

Swidi, A., Cheng, W., Hassan, M.G., Al-Hosam, A., Mohd Kassim, A.W. (2010), The Mainstream Cosmetics Industry in Malaysia and the Emergence, Growth, and Prospects of Halal Cosmetics. Malaysia: College of Law, Government and International Studies, Universiti Utara Malaysia. p1-20.

Syntetos, A.A., Boylan, J.E. (2005), The accuracy of intermittent demand estimates. International Journal of Forecasting, 21(2), 303-314.

Tanizaki, T., Hoshino, T., Shimmura, T., Takenaka, T. (2019), Demand forecasting in restaurants using machine learning and statistical analysis. Procedia CIRP, 79, 679-683.

Taylor, S.J., Letham, B. (2018), Forecasting at scale. The American Statistician, 72, 37-45.

Terui, N., Ban, M. (2014), Multivariate time series model with hierarchical structure for over-dispersed discrete outcomes. Journal of Forecasting, 33, 379-390.

Wanto, A., Hayadi, B.H., Subekti, P., Sudrajat, D., Wikansari, R., Bhawika, G.W., Sumartono, E., Surya, S. (2019), Forecasting the export and import volume of crude oil, oil products and gas using ANN. Journal of Physics Conference Series, 1255, 012016.

Willemain, T.R., Smart, C.N., Schwarz, H.F. (2004), A new approach to forecasting intermittent demand for service parts inventories. International Journal of Forecasting, 20, 375-387.