PREDICTIVE ANALYSIS OF RETAIL SALES: FURNITURE AND HOME FURNISHINGS

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Abstract — Over the years, the retail sales of furniture products and home furnishings has had a gradual growth except for the decline seen during the recession from 2007 to 2009, and now the "coronavirus recession" caused by the outbreak of a pandemic this year (2020). This report evaluates the applied technique (Holt-Winters Model) to carry out predictive analysis by forecasting furniture retail sales for the next 2 years (24 months). The result of the prediction shows that the impact of coronavirus (COVID-19) affecting several businesses across the world, will impact retail sales of furniture for the next two years and more strategies will be required to gain a faster recovery. Business insights based on predictive analysis for IKEA Furniture are also presented in this report to provide management or decision makers of the business with valuable insights for strategic planning to increase sales.

Keywords: Retail Sales, Furniture, Business Insight, Predictive Analysis, Holt-Winters Model

I. INTRODUCTION

Many businesses benefit greatly from implementing a strategic plan based on data insights or results inferred from predictive analysis. Application of predictive analysis therefore provides such businesses with a competitive advantage. The retail industry also leverages on analytical insights provided from such predictions to guide their sales or marketing strategy.

Retail sales of furniture products and home furnishings has experienced a steady growth over the years. However, the *great recession* [1] that occurred between December 2007 and June 2009 in USA, had a ripple effect across the world causing a global financial crisis. Due to this crisis, the retail industry suffered great loss and it took about 4-5 years for the retail sales in furniture to gain full recovery from this crisis [2]. Many business activities shutdown this year, while some slowed down with gross impact on their respective revenue. This was caused by the outbreak of global pandemic (Coronavirus, known as COVID-19) in January 2020, from Wuhan, China [3]. This pandemic resulted in a recession now termed globally as the *coronavirus recession*. Projections by the International Monetary Funds (IMF) revealed that this recession will have more impact than the great recession [4][5].

This project evaluates business values obtained from insights gained from predictive analysis carried out with the selected model for prediction of retail sales of furniture products.

1. OBJECTIVES

- To predict retail sales of furniture for the next 2 years (24 months)
- To critically analyse the historical data to extract past, current, and futuristic insights of significant business value for the business domain (furniture retail sales).
- Evaluate different models applicable to predicting retail sales of furniture.
- Develop a model with significant accuracy for predicting furniture retail sales

2. RESEARCH QUESTION

- Will there be an increase or decrease in retail sales of furniture products for the next 2 years (24 months), Post-Covid19?

3. HYPOTHESIS

- The impact of coronavirus recession will result in poor sales performance for only the next six months.

II. RELATED WORKS

As suggested by Yucesan et al. [6], the cost and benefits of a forecasting model should be evaluated by the decision makers of the business domain before selecting the model for use. In the research they carried out, they applied artificial neural network (ANN) model to monthly sales data for a corporate furniture manufacturing company. Their results showed that Bayesian rules training (a component of ANN model) can be applicable for forecasting a periodic data (such as the monthly sales data used). The research by Fildes et al. [7] on forecasting retail demand revealed the retailers need for forecasts. They highlighted the retailers forecasting needs on a tactical level, operational level, and strategic level. They further examined forecasting demand for new product in retail, drivers of demand, aggregate sales forecasting on a market-level and characteristics of retail sales data on a product-level for managerial decisions.

A sales forecast on furniture retail sales data provided by a global furniture retailer located in Turkey was carried out by Aras et al. [8]. They implemented five models (ARIMA model, AFRIMA model, ANFIS model, ANN model and state space model) and compared results of the models against each other. The result of their forecasts showed that the performance of the individual models was relatively the same. They concluded that combining the time series models could yield a better sales forecast result. Ansuj et al. [9] carried out analysis on sales behaviour of a medium sized enterprise in brazil, which involved the use of two time series models; neural network back-propagation model and ARIMA model. Their forecast result showed that the accuracy for the back-propagation model was better than that of ARIMA model.

Zhang [10] recommended that a combination of autoregressive integrated moving average (ARIMA) model and artificial neural network (ANN) model will yield a better performance than using the individual models alone. The methodology of model combination is effective in improving the accuracy of the forecasts. Ramos et al. [11] compared the performance of ARIMA model and State Space model for predicting retail sales. They however concluded that both models will have similar performance in prediction for both multi-step forecasts and one step forecasts. Zhang and Qi [12] investigated the effectiveness of data processing (detrending and deseasonalization) on neural network model's forecasting performance. They researched the issue of modelling time series with seasonal and trend patterns effectively. They evaluated with ANN (a feedforward neural network model), as the seasonal autoregressive integrated moving average (SARIMA) also requires seasonal adjustment. The performance of ANN was compared with SARIMA and was found to outperform the SARIMA model. Their result clearly revealed that neural networks cannot model seasonality directly, as it requires data pre-processing. Also, the trend times series does not satisfy the universal approximation theory of the feedforward neural network model. They research justified the most effective data pre-processing approach to be the combined use of detrending and deseasonalization to achieve better forecast accuracy.

Aye et al. [13] used 26 models (3 combined models and 23 independent forecasting models) to predict South Africa's aggregate seasonal retail sales. Their result revealed that that the combined forecast models produced better forecasts for retail sales and was not affected by time horizons or business cycles in its forecasts. The discounted combination forecast model (DISC) which is based on discounted mean-square forecasting error, uses more weights of current information than that of the past. It outperformed other used individual models. Khashei et al. [14] overcame the limitation of linear relationship and large amount of data required for the SARIMA model by combining the seasonal autoregressive integrated moving average (SARIMA) model with computational intelligence techniques such as artificial neural networks (ANN) and evolutionary fuzzy modelling (FUZZY) for seasonal time series forecasting. This hybrid model effectively improved the forecasts accuracy seasonal time series data.

Sun et al. [15] applied extreme learning machine (ELM), which is a single hidden-layer feedforward neural network (SLFN) for prediction of fashion retail sales. Unlike other gradient-based learning algorithm (such as the ANN model), ELM learns faster with a higher generalization performance. The proposed ELM model for forecasting fashion retail sales overcomes the long computational time and over tuning in ANN model. Xia et al. [16] proposed the use of extreme learning machine with adaptive metrics of inputs (AD-ELM) for practical fashion retail sales. Results of this model was evaluated using MAPE and NMSE. The result performed better than extreme learning machine for predicting fashion retail sales, this is because the AD-ELM overcomes the problem of overfitting or underfitting seen in ELM.

Aburto and Weber [17] developed a hybrid intelligent system using ARIMA and Neural Networks (MLP) for forecasting demand to help improve supply chain management in the retail industry. Their result showed that the proposed additive hybrid model performed best, while the multilayer perceptron (MLP) model (a type of ANN model) performed better than the ARIMA model. They also carried out a comparison between ARIMA and MLP models. Yucesan et al. [18] carried out a study on autoregressive integrated moving average with external variables (ARIMAX) and ANN model to forecast monthly sales of furniture products for a turkey based manufacturer. They however developed a hybrid model using the ARIMAX and ANN model, which proved to perform better in accuracy than the independent models and reduce the risk of failures in a single model.

Oblak et al. [19] carried out a forecast for parquet sales by analysing two quantitative methods which are linear regression of the first (1^{st}) order and Holt-Winters method of exponent smoothing of higher orders to get the model with the best forecast result. Parquet sales data used is a monthly data from 2000 to 2009. The Holt-Winters multiplicative method however produced the best results. Wicaksono et al. [20] compared Moving Average, Naïve, Holt-Winters, Exponential Smoothing and ARIMA methods in forecasting of daily demand for home furniture delivery in Indonesia and Thailand. They also compared the use of dynamic forecasting and static forecasting for the daily demand dataset. Dynamic forecasting which requires for updating of the parameters regularly produces better results in accuracy than static forecasting. Once again, the Holt-Winters model proved to be a better model for short-term and long-term sales forecast when compared with other models.

Fang et al. [21] acknowledged that the Holt-Winters model of forecasts is widely applied because of its, low expenses, simplicity and constant result. Holt-Winters Model is based on the decomposition method, in which level, trend and seasonality are smoothed exponentially period. The Holt-Winters multiplicative model is suitable for the seasonal variations which varies.

Based on the reviewed related works, it can be seen the Holt-Winters Model is ideal for a time series data with components of *trend* and *seasonality*. The dataset used for forecasting in this project contains both trend and seasonality. Hence, selecting Holt-Winters Model (HWM) for the time series forecast will aid achieving the objective of this research, which is a short-term forecast. Also, using a combination of models can be expensive and slightly computationally intensive. The assumptions of some of the models from the related works, to ignore seasonality can affect its prediction relatively. The selected time series model (Holt-Winters Model) is easy to use, costs less and can be interpreted easily.

III. METHODOLOGY

The predictive analysis carried out with the dataset was implemented with the strategy illustrated below.

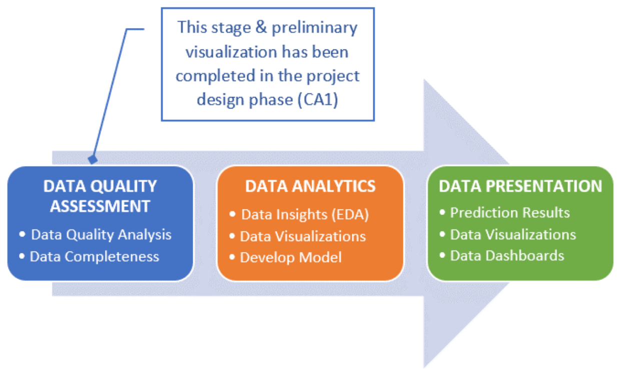

Fig. 1. Strategy implemented to analyse the dataset

The sourced dataset was examined at the data quality assessment stage shown in the project design phase. The data analytics and data presentation stages are well covered in this project implementation phase to successfully carry out predictive analysis.

IV. TECHNIQUE EMPLOYED

Based on the time series dataset obtained and research carried out on applicable techniques for predicting furniture retail sales, the Holt-Winters method has been selected to make forecasts of retails sales of furniture products. The model was selected solely because of the components (comprising of trend and seasonality) of the dataset and objective of the research (short-term forecast).

- **Holt-Winters Exponential Smoothing Model**: This is a time series model used to estimate the level, slope, and seasonal component at the current time point of the data.

1. Model Assumption

- *Pattern*: The time series data when plotted shows components of trend and seasonality. Fig. 2. below shows the plot of the time series data of retail sales of furniture from January 1992 to June 2020.

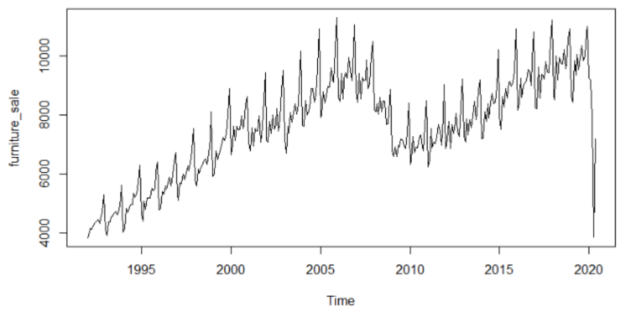

Fig. 2. Plot of the time series data

- *Decomposition*: Due to the presence of seasonality identified in the data, the components of the time series was broken down into its four-composition using the *decompose* function in R.

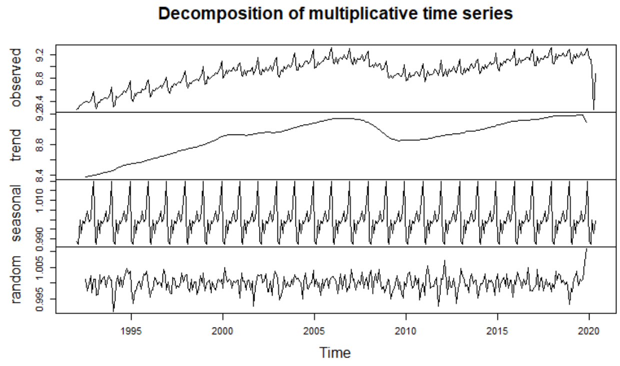

Fig. 3. Plot of decomposition of the time series data

Fig. 3. shows the decomposition of the time series data into its four (4) components (observed, trend, seasonal and random).

2. Model Validation

The model was tested against the actual times series data to validate its forecasts accuracy.

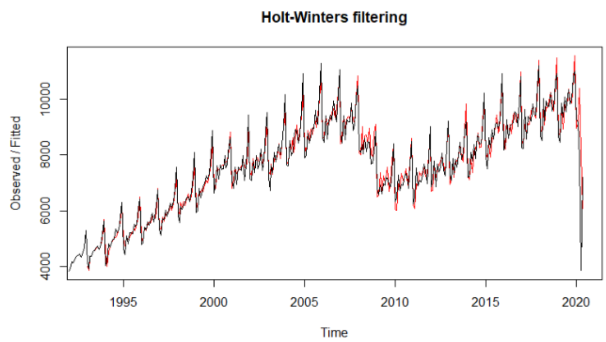

Fig. 4. Plot of forecast values against original time series data

Fig. 4. shows the plot of original time series (black line) and the forecasted values (red line) of the original values. The plot shows that the Holt-Winters exponential smoothing model closely predicts the seasonal peaks of the time series data for furniture retail sales (January 1992 – June 2020).

- **Ljung-Box test**

X-squared = 11.38, df = 20, p-value = 0.94

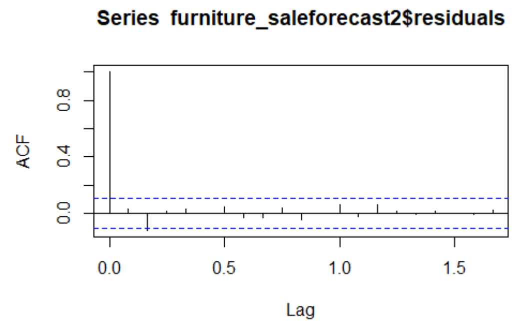

Fig. 5. Auto Correlation Function (ACF) plot of HW model

Fig. 5. shows the ACF plot of the Holt-Winters (HW) forecast model. The plotted correlogram shows that the

autocorrelations for the in-sample forecast errors did not exceed the significance bounds for lags 1 to 20. Also, the p-value for Ljung-Box test is 0.9, which indicates that there is little evidence of non-zero autocorrelations at lags 1 to 20. It also shows the residuals are independent. Therefore, we do not reject the null hypothesis which indicates that the model does not show a lack of fit and so does not need to be improved upon as both tests were satisfied.

- **Uncorrelated random error**: The error terms in the time series appeared to be randomly distributed. Also, the mean and variance were constant over a time.

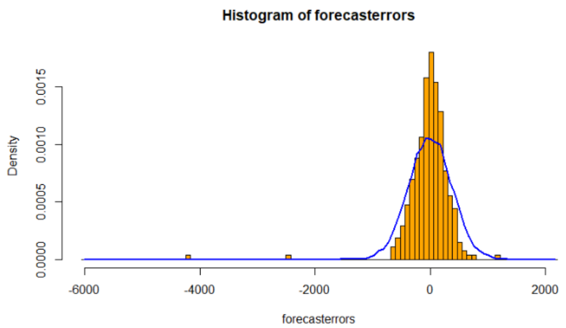

Fig. 6. Plot of histogram (with overlain normal curve) of forecast errors

Fig. 6. shows the histogram plot of the forecast errors (with overlaid normal curve) which shows that the forecast errors have a constant variance over time and are normally distributed with mean zero.

V. EVALUATION METHODS

Evaluation metrics are excellent ways to measure the performance of a model. The RMSE and MAPE were selected as metrics to evaluate the model. Table I below shows the values of the metrics used.

TABLE I
EVALUATION RESULTS

Metrics	Value
Root Mean Square Error (RMSE)	366.45
Mean Absolute Percentage Error (MAPE)	0.03

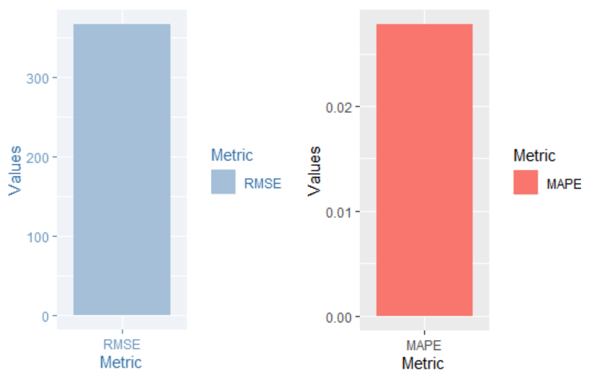

Fig. 7. Evaluation Metrics (RMSE and MAPE)

Fig. 7. shows the RMSE and MAPE evaluation metrics to examine the forecast result of retail sales of furniture.

- **Root Mean Square Error (RMSE)**: RMSE is the square root of the average of squared differences between the predicted and actual observation. RMSE increases with the variance seen from the frequency distribution of error magnitudes. RMSE has the same unit as the data. The lower the value for RMSE signifies a very good fit of the model. The value for RMSE is 366.45, which is low.

- **Mean Absolute Percentage Error (MAPE)**: MAPE is the average of absolute differences between predicted and actual observation, where equal weight is seen all individual differences. This metric is a measure of error and expresses accuracy as a percentage of the error. Therefore, the lesser the value the better the model's performance. The value for MAPE is 0.03, which is significantly low and excellent. Thiis means that on an average, the forecast is off by 3%.

VI. QUANTITATIVE RESULTS

The time series analysis carried out on the historic data of retail sales of furniture revealed the largest seasonal factor which was December (0.175) and November (0.089), while the lowest was for February (-0.112) and January (-0.099). This indicates that there seems to be a peak in sales in November and December, while there is a major drop in sales by January and February in each year.

- **Model Forecast**

  The forecasts of the furniture retail sales are shown as a blue line, the *ash-colour* shaded area shows 80% prediction intervals and the *grey-coloured* shaded area shows 95% prediction intervals.

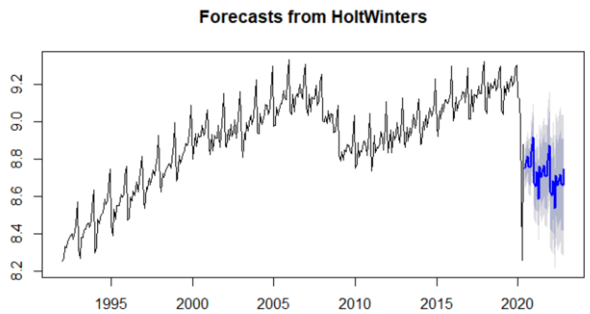

Fig. 8. Plot of 24-months of predicted furniture retail sales

Fig. 8. shows the forecast from July 2020 to May 2022 (24 more months) based on the historic time series data. This series exhibits strong, regular growth and pronounced, approximately multiplicative seasonality. The estimated values of alpha, beta and gamma for the forecasts are 0.52, 0.01, and 0.26, respectively.

- The value of alpha (0.52) is relatively low, indicating that the estimate of the level at the current time point is based upon both recent observations and some observations in the past.

- The value of beta is 0.01, which indicates that the estimate of slope b of the trend component is not updated over the time series, instead it is equal to its initial value.
- The value of gamma (0.26) is low, which indicates that estimate of the seasonal component at the current time point is based upon observations far more in the past.

VII. DATA DASHBOARDS

The data presentation stage covers presentation of data insights in a harmonized format. These insights have been complied into dashboards created with Power BI. Relevant information has been extracted from the past data and futuristic insights can be inferred from the visualization.

The dashboards are interactive and enhances depicting insights across multiple visualizations. The developed interactive dashboards are highlighted below.

Fig. 9. Performance Dashboard 1

Fig. 9. Shows the performance dashboard consisting of retail sales of furniture from 2015 to 2020, a drill down to the quarter level to examine the sales performance from 2015 to 2020 and a drill down to the month level to examine the sales performance from 2015 to 2019.

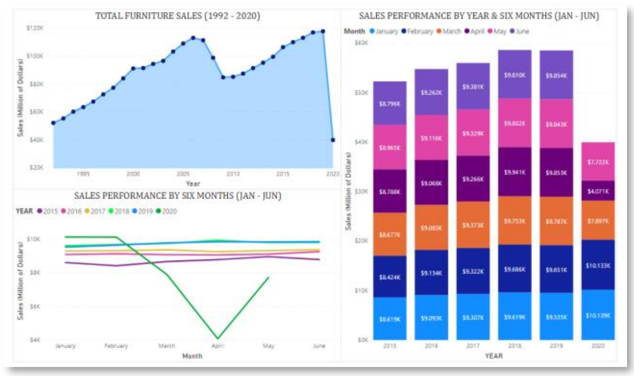

Fig. 10. Performance Dashboard 2

Fig. 10. Shows the performance dashboard consisting of the trend in retail sales of furniture captured from January 1992 to May 2020, a drill down to six months (Jan - Jun) and its corresponding monthly sales breakdown to examine critically the sales performance from 2015 to 2020.

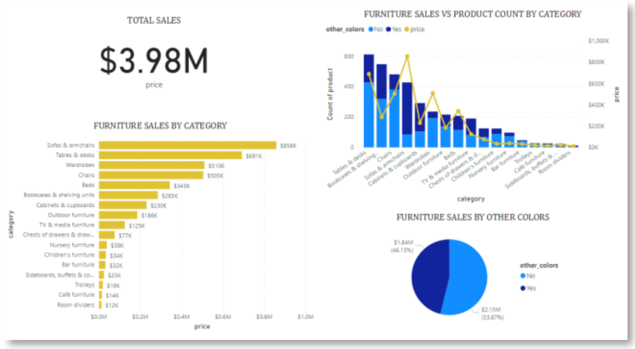

Fig. 11. Sales Dashboard 1

Fig. 11. Shows the sales dashboard consisting of the total sales of retail furniture for IKEA furniture products, sales performance of all 17 categories of the furniture products sold in 2020, the relationship between the count of the products sold and sales generated based on furniture category and a pie chart of furniture sales based on colour preference (brown or other colours) in 2020.

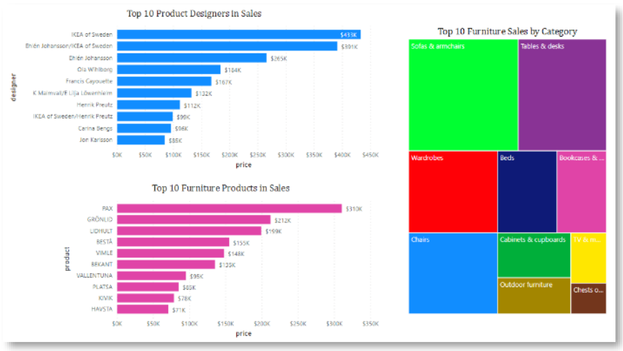

Fig. 12. Sales Dashboard 2

Fig. 12. Shows the sales dashboard consisting of the top 10 IKEA furniture product designers whose product generated more sales in 2020, the top 10 IKEA furniture products sold in 2020 and a quick glance at the proportion of top 10 furniture category generating the most in sales.

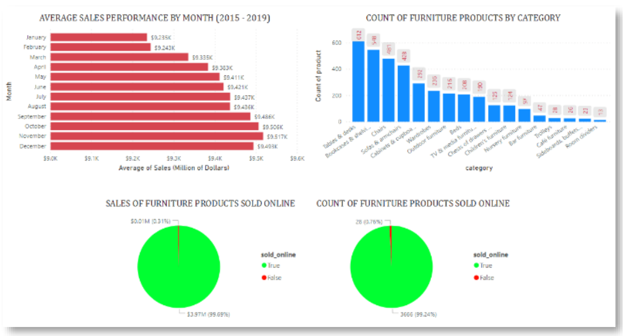

Fig. 13. Sales Dashboard 3

Fig. 13. Shows the sales dashboard consisting of the average sales performance by month from 2015 to 2019, count of sold IKEA furniture products by category, a pie chart showing the total sales/percentage of total furniture products sold online and another pie chart showing count/percentage of total furniture products sold online.

VIII. QUALITATIVE INTERPRETATION

Based on the quality assessment, exploratory analysis and forecasts carried out using the datasets for predictive analysis, some qualitative results and data insights are highlighted below.

- The sales performance for the captured years shows that in the history of the retail sales of furniture, 2018 and 2019 peaked in sales.
- The retail sales of furniture gradually recovered and by 2015, it began to maintain a steady increase. However, by 2020 the trend shows a great decline in sales. This decline is attributed to the current coronavirus regression. The trend also shows that the drop in sales is the worst seen since 1992 for retail sales in furniture.
- The comparison shows that in the first quarter (Q1) for Year 2020, the sales dropped, compared to steady increase seen since 2015. The second quarter (Q2) reveals the extent of the impact of the coronavirus recession on retail sales of furniture.
- Forecast of retail sales of furniture will not recover fully within the next two years. Hence, more strategies will be required to jump-start the recovery of retail sales.
- Furniture retail sales have been seen to be at its peak in November and December for each year. Therefore, more efforts will be required to strategically increase and maximise retail sales by November and December of year 2020.
- Sofas & armchairs category recorded the highest sales ($ 858,000), however it had the fourth (4^{th}) largest count of products sold.
- The furniture category (Tables & desks) recorded the second highest sales ($ 691,000) in year 2020. It however had the highest count of products sold. This shows there is a very high demand
- Five of the ten categories are associated with "Home-Office Furniture". This validates some of the emerged industry trends captured by MarketResearch.com [2], the rise of freelancing or working from home (teleworking) as well as remand for luxury furniture's.
- 53.87% ($1.84 million) of furniture's sold in Year 2020 was of the basic furniture colour (Brown). However, 46.13% ($2.15 million) of the total furniture sales for year 2020 was of products sold in other colours that were made available.

IX. KEY BUSINESS INSIGHTS

Based on obtained data insights from the analysis, some key data insights of business value and recommendations are highlighted below.

1. Products under the "***Table & desk***" category were purchased the most. Due to the pandemic (covid-19), many businesses/organisations have transitioned to working from home (Home-Office). Hence, a strategic marketing campaign for this category can increase sales of the corresponding and related products.
2. Products under the "***Sofas & armchairs***" category generated the most in sales. This can be attributed to the longer time spent at home. Hence, a strategic marketing campaign to appeal to customers need for comfort or luxury, can increase sales of products in this category.
3. Customers preference for furniture products available in other colours should be considered to increase sales. This is because ***46.13%*** of total furniture sales in year 2020 was for products sold in other colours.
4. More products designed by Ehlén Johansson, IKEA of Sweden, Ola Wihlborg, and Francis Cayouette should be made available, as top 3 furniture product designers had sales well-over $200,000. Also, furniture designs by a collaboration of either of the designers could attract more sales with the right marketing strategy.
5. As part of the plans to recover from the recession, more focus can be given to the top 10 furniture products in sales to sustain the business income generation.
6. 99% of the furniture products was sold online. This perfectly indicates the use of internet by consumers during this pandemic period for purchasing the products. Therefore, more strategy should be put in place to maximise online platforms, through use of digital ads, online promotions etc.

X. CONCLUSION

By initially carrying out a project design and then project implementation, predictive analytics was successfully applied to the domain of retail sales in furniture and home furnishings. The Holt-Winters model selected in this paper was evaluated and used to forecast furniture retail sales.

After the application of the forecast model and insights obtained, the answer to the *research question*: "Will there be an increase or decrease in retail sales of furniture products for the next 2 years (24 months), Post-Covid19?" is ***Yes, there will be a decrease in retail sales of furniture products for the next 2 years (24 months)***. Also, the *hypothesis*: "The impact of coronavirus recession will result in poor sales performance for only the next six months" is ***rejected***. The Holt-Winters model shows that the forecasts are as a result of learnt historical trends of decline in retail sales from the data. It would therefore take longer than six months to recover fully from the coronavirus recession. Also, recommendations presented in this paper can be strongly considered to aid quicker recovery in retail sales and company's revenue.

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