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**PREDICTION OF SHARE OF VISUAL INVENTORY
USING STORE DISPLAY, CHANNEL,
AND PRODUCT VARIABLES**

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ABSTRACT

The purpose of this study is to predict the share of visual inventory (SOVI), which is defined as the number of stock-keeping units (SKUs) of a company's products, calculated as a percentage of the total SKUs on the display of all products. Research studies in the past have focused mainly on the impact of inventory, which includes back end and visual inventory, on sales but less attention has been given to the impact of SOVI on sales. To address this research gap, this study attempted to create an analytics model to predict SOVI at the category of soft drinks level using four predictor variables namely point of purchase display, channel/sub-channel, package group, product category, and derived

variable gross national income (GNI). The results were encouraging confirming the effectiveness of such a model. The researchers utilized a data set collected over a period of 18 months (February 2016 to July 2017) by a soft drink firm headquartered in the United States. Based on the findings, it is suggested that this prediction model can be utilized by other researchers and practitioners to predict SOVI of other soft drinks, fast-moving consumer goods (FMCG), and food and beverage companies.

Keywords: Share of visual inventory, inventory, sales, store display.

INTRODUCTION

It is a known fact among marketing researchers and practitioners that the amount of inventory displayed has an impact on the demand for many retail items. Keeping more shelf stock of an item increases the demand for it due to higher visibility, permits decreased replenishment frequencies, and increases inventory holding costs (Hübner & Schaal, 2017). There is an increasing interest among retail practitioners in understanding sales data/inventory management systems which enable stores to make the best use of scarce shelf space by stocking optimal merchandise assortments (Orenstein, 1999). Ensuring optimum retail product availability creates the elementary criterion for its sales, i.e., for achieving the desired transaction with the customer which in turn affects sales (Dubelaar et al., 2001).

Large retailers and manufacturers are focusing increasing attention on product availability. Retailers need to have more control over their ordering size and policies so that they can manage inventories (Sabir & Farooquie, 2018). Reduction of inventory by 3 percent may lead to a 1 percent revenue reduction (Rus, 2009). It is no longer sufficient that a marketer's products are present in retail outlets and other distribution channels; it is important how these products are displayed and what percentage of the retailers' shelf space is occupied by the given marketer's products in the respective product categories. A marketer must ensure that its products are physically on the shelf and must work to enhance the share of shelf facings. This in turn will drive demand and will result in increased sales performance. This research paper addresses the importance of predicting SOVI as a metric to predict potential sales.

Most of the research studies in the past have focused mainly on the impact of inventory on-demand generation and sales but less attention has been given to the impact of SOVI on sales. Some past studies have tried to quantify the relationship between inventory and sales (Metzger et al., 2007; Rus, 2009). However, the current study focuses on the impact of SOVI on sales. From the literature review, it is evident that not all inventory is displayed in retail outlets (part of the inventory may be stored by retailers in storerooms or back end and may not be visible to consumers). Nevertheless, many past studies have formulated models to predict the impact of total inventory on retail sales resulting in a research gap. Another research gap is that the majority of past studies are not category-specific as they deal with overall retail inventory. However, the current study is restricted to the category of soft drinks.

Several past studies have investigated the out-of-stock (OOS) problem and its impact on retail sales. However, these studies have not investigated in detail the impact of retail stores maintaining a diminished amount of inventory or sub-optimal levels of inventory. The current study concentrates on predicting the potential level of visual inventory that a retail store should maintain of a particular brand in order to achieve higher sales. This research aims to identify underperforming stores in terms of visual inventory of any particular brand in a specific category of products. There is a clear gap in the literature concerning this aspect. Some of the earlier studies focused on predicting optimal inventory levels at retail store level and a few other studies concentrated on analyzing the impact of optimal inventory on sales. However, the present study does not concentrate on overall optimal inventory levels across categories; instead, the study only focuses on the category of soft drinks.

From the review of literature, it is evident that there is a research gap pertaining to the use of predictor variables such as point of purchase display, channel/sub-channel, package group, and product category used to predict SOVI in the present study. Past researchers have tried to find the impact of these individual variables on sales. On the other hand, the present study attempts to find the cumulative impact of these predictors on sales through the determination of SOVI using an analytics model on data. Therefore, the main objective of this study is to predict SOVI at the category of drinks level with the help of four predictors, namely point of purchase display, channel/sub-channel, package group, and product category and derived variable gross national income (GNI).

LITERATURE REVIEW

Share of Visual Inventory

Share of visual inventory (SOVI) is an important concept for brands in a retail set up. SOVI is a key performance indicator (KPI) tracked by marketers of impulse goods such as soft drink firms (Ho, 2017). SOVI is the extent of the presence of a brand or product on the retailer's racks. The underlying logic behind SOVI is that higher visual inventory will translate into greater sales. As part of their regular job, salespeople routinely collect details such as the number of SKUs ('fronts') on display at each store. SOVI is the number of SKUs of the company's brands/products, calculated as a percentage of the total SKUs on display of all brands/ products including competitors' brands/products.

A significant proportion of manufacturing firms duly understand the importance of encouraging channel partners to hold higher inventory levels as this will have a positive impact on retail sales. When retailers are well stocked with the firm's brands there is a significant increase in sales whilst a decrease in inventory levels of a particular brand will not only reduce the sales of the brand but also increase the sales of competing brands. Visual inventory serves as a reminder and an effective advertisement at the point of sale. This is especially true for impulse purchases or unplanned purchases.

Soft Drink Industry

Soft drinks mainly consist of carbonated water, sugar/saccharine, and added flavors. Approximately 200 countries consume soft drinks; however, the per capita consumption varies drastically among these countries. The world's beverage sector is dominated by the soft drink industry in terms of volume. The soft drink industry is a very competitive sector characterized by numerous small companies and dominated by a few multinationals. The consumption of soft drinks has increased considerably over the last 50 years. The change in consumer behavior is the prime reason for this increased demand for soft drinks. A total of 14.03 percent of consumer-packaged goods (CPG) marketplace is represented by soft drinks. The soft drink sector is continuously evolving and it is not just consumption growth. As a

result, soft drink companies have no other choice than to invest in innovation, research, and development to match the competition and to be able to cater to the needs of the market (Arcese et al., 2015). New marketing strategies are much needed and are frequently ranked higher in the order of importance than the product when it comes to satisfying new consumers' needs (Falcone et al., 2016). The soft drink industry is currently influenced by different trends, namely: (a) the reduced inclination to pay for the purchase of well-known F&B products (Blackman, 2005); (b) the rise of healthy foods and beverages due to the increase in health-conscious consumers (Massoud et al., 2010); (c) escalation in prices of raw materials in the recent past (Wieselhuber & Partner, 2011); (d) a large variety of packaging leading to high complexities (Mahalik & Nambiar, 2010) and (e) increased usage of premium quality products (Rubini et al., 2013). A handful of brands dominate the soft drink industry. These brands have a large amount of market share in most countries. The economic indicators that can be used to evaluate the soft drink industry are market size, growth rate, and overall profitability (Deichert et al., 2006).

Most often consumers make decisions while viewing the display of soft drinks in the cooler at the point of sale. Consumers who otherwise prefer water may be tempted to buy soft drinks due to the attractive visual display of soft drinks especially on a hot day. Soft drinks cooler is an important asset in a small convenience store. The marketer's first challenge is to ensure that his product is available on store shelves/cooler shelves. The next step is to gain a significant SOVI on the store shelf or in the cooler. This requires careful coordination with the retailers, the distributors, and the merchandisers.

Since soft drinks are impulsive purchases, SOVI can be used to predict demand. Soft drink companies have realized that the key to increasing market share and sales is to increase shelf presence in retail outlets. The majority of local soft drink companies offer higher margins to retailers and depend on push sales, whereas well-known multinational corporations (MNCs) depend on the pull strategy. Soft drink MNCs employ a large amount of the mass media including digital and social media in their advertisements. If their products get excellent visibility in the supermarkets, hypermarkets, mom and pop stores, etc. then there is a good chance of increased sales, as brand awareness is not a problem in most of the markets for these leading soft drink MNCs.

Besides that, soft drink companies find that some retailers perform below their potential. Nevertheless, predicting underperforming retailers in a huge market is like looking for a needle in a haystack and is rather expensive and time-consuming. Hence, there is a need to develop reliable models to predict the SOVI for soft drinks at the retailer level.

Impulse Purchase

An unplanned decision to buy a product or service is known as an impulse purchase. Impulse purchase decisions are made spontaneously just before the purchase. Abratt and Goodey (1990) stated impulse buying as a decision made in-store with no clear identification of a need for such a purchase before entering the store. Soft drinks fall under the category of impulse purchases. A person who makes impulse purchases is known as an impulse buyer. Both organized and unorganized retailers attempt to attract impulse buyers especially with respect to convenience goods such as soft drinks. The consumer may not follow the regular process of prudently searching, evaluating, and then deciding in the case of impulse buying. On the contrary, the consumer often ends up buying a product or brand based on impulse. The majority of consumers tend to purchase soft drinks on impulse, while some consumers may purchase them to quench their thirst or for some other occasions like a party or get-together, etc. Retailers constantly try to enhance impulse purchases with the application of visual merchandising techniques such as store ambiance, product display, colors and lighting, merchandise arrangements, package design, and design of the store. The rising income level of consumers is one of the primary reasons for the increase in impulse purchases. Intelligent store design and layout, product displays, and signage can help consumers to find the right products.

Inventory/Sales Relationship

The relationship between inventory levels and sales had been examined in numerous studies. Based on their investigations, Schary and Becker (1972) concluded that the availability of product/brand had a positive impact on stimulating demand. According to Levin et al. (1972), adequate availability of inventory motivated the customer

to purchase. A study of 132 non-clothing chain store units located in shopping malls by Hise et al. (1983) using linear regression found that retail sales could be predicted using inventory levels and the number of employees as positive predictors. Larson and DeMarais (1999) stated that display inventory was an independent variable category of inventory and could be used as a determinant of sales. Silver and Peterson (1985) in their study related to inventory and sales in the retail environment noted that sales at the retail level were likely to be proportional to inventory displayed. Benmaor and Mouchoux (1991) found a strong positive correlation between the increase in shelf space and brand sales.

Baker and Urban (1988) developed a set of inventory models showcasing demand rate as a function of the inventory level of an item on display on retail shelves. Subsequently, researchers have tweaked these models to account for the effect of deteriorating items (Padmanabhan & Vrat, 1995; Mandal & Phaujdar, 1989). Nevertheless, these models assume that the entire inventory is displayed. This may be suitable for some applications (where the entire inventory can be seen by the customer). However, many organizations (e.g., retail outlets) have a backroom inventory or warehouse in which inventory is stored, before being placed in the showroom. Thus, there is a limited amount of displayed inventory that has an effect on sales; much of the inventory is not within the customers' view and thus has no impact on sales. Demand may be stimulated by stocking large quantities of inventory in retail outlets along with improvement in service levels. Urban (1998) developed a model which showed demand rate as a function of displayed inventory. He also investigated product assortment and shelf-space allocation problems.

Cachon and Terwiesch (2008) found a correlation between retail inventory levels and service levels. They stated that service levels increased due to the increase of retail inventory levels, thereby resulting in increased sales levels. According to Balakrishnan et al., (2008), higher retail inventory had a combined effect of better customer service along with stimulation of customer demand leading to increased sales. According to Ton and Raman (2010) the probability that the customer will find and purchase a desired product increased with a higher number of available products in a retail store.

Retail Product Availability

It has been recognized that one of the basic prerequisites for sales in a retail outlet is optimum retail product availability. Retail product availability has a direct effect on sales (Dubelaar et al., 2001). Koschat (2008) refers to the positive effect of inventories on sales through product availability as availability effect. Large retailers' and manufacturers' attention are increasingly being drawn towards the challenge of maintaining optimum retail product availability.

Ettouzani et al. (2012) stated that product availability in retail outlets was frequently analyzed and described in the context of the OOS problem. They further indicated that the OOS rate was often used as a basic indicator. Metzger et al. (2007) studied the effect of stockouts on sales losses for large retail outlets. They found that stock out rates of between 5 and 10 percent resulted in sales losses of up to 4 percent. This translated to hundreds of millions of dollars for large retail chains. This research paper found that lack of inventory visibility due to inefficiencies in in-store logistics was the most significant cause for stockout situations. The literature has many studies investigating the OOS problem. Some of the researchers focused on identifying OOS situations (Papakiriakopoulos & Doukidis, 2011; Papakiriakopoulos et al., 2009), measuring OOS (Corsten & Gruen, 2005), understanding the effects of OOS (Gruen & Corsten, 2007; Musalem et al., 2010), analyzing the main root causes (Ehrenthal & Stolzle, 2013; Fernie & Grant, 2008) and investigating customer responses in OOS situations (Zinn & Liu, 2008; Van Woensel et al., 2007).

Predicting Variables

Displays and shelf presence could increase purchases (POPAI Europe, 1998). Displays could increase sales of the featured brand (Grover & Srinivasan, 1992). Dagnoli (1987) stated that display was a significant aspect in supermarkets since maximum grocery purchase decisions were done at the point of purchase. Inman et al. (1990) found that some consumers responded to promotional signals such as point-of-purchase displays without considering the price. Woodside and Waddle (1975) also discovered that point-of-purchase signing at reduced prices could increase sales further compared to periods

without advertised price reductions. DiClemente and Hantula (2003) revealed that point-of-purchase stimuli were generally related to an increase in sales. Halim and Good (2005) claimed that retailers should employ various advertising techniques at the point of purchase. According to them, these techniques were effective in attracting impulsive consumers confused by too much choice.

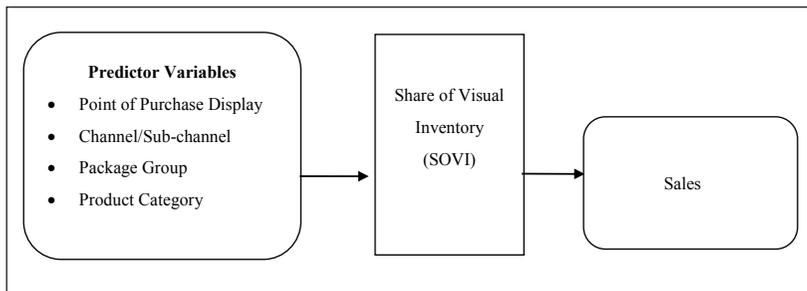
Coelho et al. (2003) in their study of UK organizations found that 62 organizations measured several metrics of channel performance. According to them, these could be condensed to two broad dimensions: sales and profitability. The results from their research indicated that higher sales performance and lower channel profitability were associated with multiple channels. Hsieh et al. (2014) developed a model that helps buyers to make a choice between two different categories of channels.

At the point of sale, packaging was an important factor that determined the decision-making process (Silayoi & Speece, 2004; Kuvykaite et al., 2009). Wansink (1996) concluded through a series of experiments that package size was positively correlated with the usage of the product. Bettman (1979) stated that package appearance played a central role in reshaping the choice process due to its ability to alter or interrupt search. Shruthi et al. (2016) stated that honest and effective packaging would attract consumers and positively impact their intentions to buy products. Deliya and Parmar (2012) indicated that packaging had an influence on consumers and hence would help the company to generate more sales by positively changing consumer behavior towards the brand. According to Dubé (2004), consumers regularly purchased assortments of products for several product categories, such as ready-to-eat cereals, carbonated soft drinks, canned soups, and cookies. He further indicated that consumers often purchased multiple products within the category and for each alternative selected, consumers bought multiple units.

Based on the literature review, the researchers have developed a conceptual model for this study as depicted in Figure 1. The model proposes that the predicting variables, which are routinely measured by MNCs and FMCG companies can be used, to predict SOVI. Further SOVI can be used to predict sales.

Figure 1

Conceptual Model Showing the Impact of the Independent Variables on the Dependent Variable



METHODOLOGY

The data for this study was gathered from a well-known soft drink MNC that operates all over the world. This MNC is interested in understanding the demand for soft drinks in various retail outlets. The MNC provides refrigerators with display windows and other types of display racks to retailers. The MNC has observed that good display leads to an increase in sales of its soft drinks. It considers the SOVI as an important parameter. SOVI is measured as the percentage of the company's products to the total soft drinks displayed in retail outlets.

Even though the MNC gives incentives to retailers in terms of coolers and promotional support, many retailers stock local soft drinks, and the competitors' products in the company provided coolers. The stock ordered by the retailers depends on demand, the season, competitor products, and per capita consumption of soft drinks in the state/country. It is difficult for the company to predict demand in new markets i.e., countries where the MNC has yet to capture market share. The MNC also faces a dilemma regarding which retailers to support with sales promotion allowance.

Since soft drinks are impulsive purchases, SOVI can be used to predict demand. The company has realized that the key to increasing market share and sales is to increase shelf presence in retail outlets. The majority of the local competitors offer higher margins to the

retailers and depend on push sales whereas this MNC depends on a pull strategy. It uses a great deal of the mass media as well as digital and social media to drive its advertising. If their products get good visibility in the supermarkets, hypermarkets, mom and pop stores, etc. then there is a good chance of increased sales, as brand awareness is not a problem in most of the markets. However, some retailers are performing below potential.

The researchers attempted to create an analytics model to predict SOVI at the category of soft drinks level, utilizing past data of the store, city, and country-level data collected over 18 months (2016, 2017) by a soft Ho (2017, August 8) drink firm headquartered in the United States (US). All the data was from stores in countries near the US. Most of the variables in the data set were categorical and consisted of store profile (city, country, channel, and subchannel), brand, packaging size, category, display cooler ownership, and type. The researchers attempted to use the above variables and some derived variables to detect a pattern in the brand, store and display data to predict SOVI at the category of drinks level. This data was too fragmented with very low individual SOVI numbers to be of much use at brand level. Besides, business use of the prediction would be more relevant at category level.

Research data of about two hundred thousand data records were collected by salespersons from stores in the region over an 18-month period from January 2016 to May 2017. More data from earlier years were available, however, the researchers restricted modeling to the most recent data as they felt that the number of records was adequate and to avoid the problem of models fitting noise. The researchers felt that recent data could help create better predictive models by removing environmental effects. The researchers utilized as predictors the categorical variables: point of purchase display type, channel/sub-channel, package group, product category, and the derived variables GNI (country) and season. GNI country was categorized into four equal intervals and the SOVI into three categories of below 5%, 5 to 10%, and above 10%.

The distribution of records in the SOVI buckets was: 60 percent below 5 percent; 20 percent between 5 to 10 percent; and 20 percent above 10 percent. With the relatively low incidence of records between 5 to 10 percent and above 10 percent in the SOVI and the subsequent poor performance of models in detecting these categories, the researchers

utilized oversampling for both of these categories for the training data. The records selected were in the ratio of: 47.82:26.09:26.09 for the three categories. There was no particular reason to choose this ratio except for the limited availability of data in the two categories – the 5–10 percent category and above 10 percent category. Utilizing 30,000 records for each of these categories resulted in the 47.82:26.09:26.09 ratio. Validation classification matrices were suitably corrected for this oversampling.

RESULTS

Training and Testing the Models

The total data records were split 60:40 using random sampling. 60 percent of the data was used for training and 40 percent for testing the models. Naïve Bayes and Logistic Regression models were created using R Studio version 3.3.2 and RapidMiner Studio Version 7.6.001. Naïve Bayes was used as it is a robust tool (works well even with some missing data and missing variables) for classification and works well in real-time prediction. Naïve Bayes is well-suited when the predictor and validating variables are categorical, which was the case in this research. Logistic regression as a predictive tool was used as it is suited for categorical and numerical variables. RapidMiner was chosen as it could handle large data as compared to Excel Miner and also for its relative ease of use.

Table 1

Naïve Bayes Model – Classification-Confusion Matrix

		Training data			
		TRUE			Precision
		Below 5	5 to 10	Above 10	
Predicted	Below 5	35701	8916	6845	69.37%
	5 to 10	2776	1878	1312	31.48%
	Above 10	5180	5813	11255	50.59%
Total		43657	16607	19412	
Accuracy					61.29%

As illustrated in Table 1, the Naïve Bayes model delivered an accuracy of 61.29 percent in the detection of SOVI with a Kappa value of 0.31(acceptable) for the training data. The precision for prediction of SOVI in Category 1 (below 5%) was 69.37 percent, Category 2 (5% to 10%) was 31.48 percent and Category 3 (above 10%) was 50.59 percent. Categories 2 and 3 error rates were higher; therefore, an attempt was made to oversample in these two categories.

Table 2

Naïve Bayes Model Validation Classification Matrices

(Corrected for oversampling)

		Corrected Validation Data			
		TRUE			Precision
		Below 5	5 to 10	Above 10	
Predicted	Below 5	43632	6534	4963	79.15%
	5 to 10	4233	1626	1112	60.72%
	Above 10	6905	4572	8808	34.04%
Total		54770	12732	14883	
		Accuracy	65.63%		

The oversampling produced an improvement in accuracy to 65.63 percent in the detection of SOVI for the validation data in the Naïve Bayes Model. The precision for prediction of SOVI in Category 1 was 79.15 percent, Category 2 was 60.72 percent and Category 3 was 34.04 percent.

For Logistic Regression, as there were three categories, the researchers utilized a polynomial by binomial operator to arrive at the three classifications. As illustrated in Table 3, the Logistic Regression Model delivered an accuracy of 63.66 percent in the detection of SOVI with a Kappa value of 0.32 (acceptable) for the training data. The precision for prediction of SOVI in Category 1 was 67.81 percent, Category 2 was 34.03 percent and Category 3 was 53.72 percent. Categories 2 and 3 error rates were higher therefore an attempt was made to oversample in these two categories.

Table 3

Logistic Regression Model – Classification-Confusion Matrix

		Training data			
		TRUE			
		Below 5	5 to 10	Above 10	Precision
Predicted	Below 5	39020	10814	7706	67.81%
	5 to 10	300	330	332	34.03%
	Above 10	4337	5463	11374	53.72%
Total		43657	16607	19412	
		Accuracy	63.66%		

Table 4

Logistic Regression Model Validation Classification Matrices

(Corrected for oversampling)
Corrected validation data

		TRUE			
		Below 5	5 to 10	Above 10	Precision
Predicted	Below 5	47637	7653	5216	78.73%
	5 to 10	991	594	532	46.81%
	Above 10	6143	4485	9134	31.08%
Total		54771	12732	14882	
		Accuracy	69.63%		

The oversampling produced an improvement in accuracy to 69.63 percent in the detection of SOVI for the validation data in the Logistic Regression Model. The precision for prediction of SOVI in Category 1 was 78.73 percent, Category 2 was 46.81 percent and Category 3 was 31.08 percent. The Logistic Regression model delivered the lowest error rates.

DISCUSSIONS AND IMPLICATIONS

This study has attempted to predict demand based on the inventory displayed. The majority of the stores that were part of this study had a SOVI of less than 5 percent (a significant number of retailers had a SOVI of less than 2%) which was quite low. One reason for this low figure is that these are multi-product retailers and soft drinks is just one of the categories.

The present study used an analytics model to predict SOVI using variables and data that are routinely collected by soft drink majors to extract KPIs, one of which is SOVI. The study results indicated that the store display, channel, and product variables appeared to facilitate the prediction of SOVI (detectable up to 70% accuracy). Further attempts at modeling using ensemble models were not very effective and produced no further improvement in accuracy. Data on environmental variables and other market-related variables like per capita consumption of soft drinks, special offers by brands, or competitions were not available and seemed to have had a significant impact (30.27%) on determining SOVI. As demand estimation for new territories is usually an aggregate estimation, the model prediction should be useful at an aggregate level. Further, with several thousands of stores being serviced by the firm, anomaly detection can deliver substantial cost benefits in avoiding detailed visits/investigations of too many stores where SOVI values are way below predictions by the model.

Past studies have established that inventory levels and visual inventory can be used as indicators to predict sales (Silver & Peterson, 1985; Benmaor & Mouchoux, 1991; Larson & DeMarais, 1999). Some other researchers have emphasized the positive effect of inventories on sales through product availability (Dubelaar et al., 2001; Koschat, 2008). In addition, several past studies have established demand rate as a function of displayed inventory (Baker & Urban, 1988; Urban, 1998). The present study takes this relationship between displayed inventory and sales at the retail level as a base. The underlying logic of this study is that it is easier for FMCG companies to measure the share of visual inventory at the retail level in a given sales territory as compared to predicting potential sales or estimating potential

demand. Marketers can use SOVI prediction models to predict the ideal SOVI levels for retail outlets based on predictor variables like point of purchase display, channel/sub-channel, package group, and product category, derived variable gross national income (GNI) etc., and compare them with actual SOVI levels.

In terms of practical implications, the potential use of the model developed in this study is in the planning and estimation of stocking for new territories based on channel/store, product/brand, and display parameters. A firm can estimate demand at an aggregate level and utilize the model for planning stock based on replenishment policies. The model would also be useful in detecting anomalies in current SOVI patterns before pursuing a more detailed investigation. Stores exhibiting drastically lower SOVI than that predicted by the model can be explored to understand underlying reasons. Corrective action can be taken in terms of better distribution strategies and trade incentives to improve the SOVI of underperforming stores.

CONCLUSION, LIMITATIONS, AND DIRECTIONS FOR FUTURE RESEARCH

This research proposes models for the prediction of SOVI using store-based and product variables that are measurable. FMCG companies, food and beverage companies, as well as other national and international companies distributing their products through brick-and-mortar stores are able to utilize this research. Many companies routinely collect this data as part of their internal reporting system. These companies can improvise on the models proposed in this research and fine-tune them according to their requirements and predictor variables to predict SOVI. The prediction of SOVI using the proposed models and comparing it to the actual SOVI at the store level for different types of stores and geographies give marketers an idea as to whether the stores are performing up to their potential with regard to sales of the company's products.

The data for this study was collected from stores in countries near the US. The data is predominantly an opportunity for researchers to do similar studies on data collected from retailers in other continents

or countries. In addition, the data for this study is limited to the soft drinks sector and one global MNC's data. Similar studies to predict SOVI for other soft drinks brands could be conducted in the North American continent. Hence, there is a challenge in terms of generalizing the data to other contexts. Another limitation could be the varying impact of SOVI on the demand/sales for different product categories. Researchers could also conduct replication studies by investigating data for different categories of FMCG products.

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