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Research Article

Sales Forecasting in Fashion Retailing-A review

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Abstract

In fashion retailing, forecasting is determining the inventory needs of the product. An accurate forecast is very important in fashion retailing. Therefore, the forecasted demand is tested for error. An accurate demand forecast will satisfy the retailer and also the customer and an inaccurate demand forecast lead to situations like Over Stocking (OS) and Out of Stock (OOS). The data for forecasting are from various sources like past sales data, intentions data, preview data, expert opinion data. Existing techniques for analyzing data are generally divided into two groups, classical techniques based on statistical models and Artificial Intelligence (AI) techniques. In this article, around 70 articles from reputed journals were collected. The review gives a detailed analysis of the sources of data for demand forecasting and data analysis. It concludes by throwing an opportunity and the use of various sources of data for forecasting in fashion.

Keywords

Past sales data; stated preference data

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Introduction

In fashion retailing, apparel is characterized by uncertain demand, huge variety, and changing consumer needs. A fashion retailer estimates the demand and makes sure that they bring the right product, at the right time, at the right place, and with the right price for the consumer. If there is a mismatch between the retailer's estimate and the consumers' needs, the retailer incurs a loss in terms of discount sales of unsold merchandise and lost sales of the product that is not available in the store. Therefore, accurate estimation is required. Hence, literature related to demand estimation is reviewed elaborately in this article.

Retailing

Retailing encompasses the business activities involved in selling goods and services to consumers for their personal, family, or household use(Berman, Evans, & Chatterjee, 2018). In general, retailing has evolutionized from single product stores in the late 1800s, and currently facing tremendous growth(Pattanaik & Mishra, 2016). In the retailing sector, the term product is defined as "any offering that can satisfy a need or want" (Fransi & Viadiu, 2007)and offering takes different forms namely goods, services, experiences, events, persons, places, properties, organizations, information, and ideas(Kotler, 2000). Retailing encompasses the activities involved in selling products such as apparel, food, pharmaceutical, furniture, etc. to the consumer.

Fashion Retailing

In the textile domain, the term apparel specifically represents the clothes worn by men, women, and children. Apparel retailing in simple terms is expressed as selling apparel goods to consumers. In India, among other retailing sectors, apparel retailing is one of the most important sectors, which has a share of around 8% in the whole retailing sector(Das, 2015). Globally, India's apparel market is gaining importance due to economic expansions and due to an increase in the number of middle-class families. According to a report by (Fransi & Viadiu, 2007) around 300 international fashion brands are expected to open stores in the next two years in India and as mentioned in the report that India's apparel market will be the sixth-largest in the world in 2022.

Fashion Retailing Process

The fashion retailing process involves various operations like merchandising, marketing, store operations, finance, human resource, and logistics (Fransi & Viadiu, 2007) Among these operations, merchandising is considered one of the most important operations due to its major role in retailers' profit (McGill, 1953)

Merchandising

In fashion retailing, merchandise indicates goods offered for sale to the consumer. Merchandising is a process consisting of the activities involved in a retailer buying goods and making them available for sale(Berman et al., 2018). Merchandising is defined as the "process by which a retailer attempts to offer the right quantity of the right product at the right place, at the right price and right time while meeting the retailers' financial goals" (Beheshti-Kashi, Karimi, Thoben, Lütjen, & Teucke, 2015; Fransi & Viadiu, 2007) Merchandising decides the profitability and image of the retailer. Merchandising is the analysis, planning for the raw material, acquisition of them, handling, and control of the merchandise(Siganul, Yoag, Tanakinjal, Jiony, & Gom, 2015). Merchandise can be divided into two types staple merchandise and fashion merchandise(Mentzer, Stank, & Esper, 2008). In general, the majority of the apparel product falls under the fashion merchandise category. Merchandising consists of various activities like forecasting, formulating an assortment plan, determining the appropriate inventory level, developing a merchandise management plan, allocating merchandise to stores, and monitoring the performance of the merchandise.

Forecasting

In fashion retailing, among the various steps involved in merchandising, forecasting the demand for the merchandise is the first step. Demand forecasting is defined as the "activity of estimating the quantity of merchandise that will be in requirement in future"(Ni & Fan, 2011). It serves as the basis for all the activities in the apparel industries like production planning, allocation, etc(Fumi, Pepe, Scarabotti, & Schiraldi, 2013). The demand forecast is very important for the retailer in maximizing customer service and capital investment(Nenni, Giustiniano, & Pirolo, 2013). Forecasting demand for fashion apparel is complex (Mostard, Teunter, & De Koster, 2011) as the merchandise is characterized by volatile demand and huge variety i.e., demand is highly fluctuating and there are too many styles. Because of the above-stated nature of the fashion product, they are termed as a single-period product(Murray, Talukdar, & Gosavi, 2010). Demand forecasting involves predicting the consumers' needs in the future period. Demand forecasting is determining the inventory needs of the product. In apparel retailing, demand forecasting is mostly done by the merchandiser. Merchandiser, a role in the merchandising department, is involved in the quantitative aspect of buying. They perform forecasting, sales analysis, budgeting, profit margin analysis, etc (Liu, Ren, Choi, Hui, & Ng, 2013) Demand forecasting answers questions like what products to be purchased, how much to purchase in each product, etc. A forecast is done for a specific period. The forecast may be a short-term forecast, medium-term, or long-term forecast (Noh & Ulrich, 2013) The forecast performed a month prior is known as short-term forecasts and which are performed one year before the selling period are known as long-term forecasts. Effective forecasting helps in planning the production and deciding on a price, etc. Once demand forecasting is developed it is tested for error. In fashion merchandising, an accurate forecast is very important. An accurate demand forecast will satisfy the retailer in terms of profit and also satisfy the customer by making expected products available(Aksoy, Ozturk, & Sucky, 2012), and inaccurate demand forecasts lead to situations like Over Stocking (OS) and Out Of Stock (OOS)(Pashigian, 1988). OS and OOS have an influence on the cost due to inventory and lost sales. OS is a situation where the retailers carry certain items more than the customer demand, later these items are sold at a discounted price whereas OOS is a situation where retailers carry items lesser than the customer demand leading to understocking. If a retailer fails to predict demand accurately, it leads to many short-term and long-term issues. Short-term problems of inaccurate forecasting include overstocking and understocking. The problem of overstocking and under-stocking exists for more than three decades. (Ben-Akiva et al., 1994)observed the markdown pricing in many apparel categories like women's fashion apparel. The results showed that overstocking leads to discounted pricing in the range of 7.0% to 16.8% of the sales during the observed years. In another work conducted , he studied the impact of overstocking and under-stocking on retailers' costs. The study was carried out in a fashion catalogue retailer for three years from 1993 to 1995. Their results show that overstocking costs and understocking costs for each year were 16% of sales. A research was conducted by(Campo, Gijsbrechts, & Nisol, 2004), to understand the sales loss due to OOS in a fashion company for women's apparel and accessories. Further, the researcher analysed the sales loss in 137 stores for three months. They found that by avoiding OOS the retailer can increase revenue by 28.7%. Apart from the above fashion apparel, the OOS and OS costs are also recorded in other non-fashion product categories like food and grocery by (Campo et al., 2004; Corsten & Gruen, 2003) Apart from the above-stated short-term problems, inaccurate forecasts lead to long-term problems like customer store switching. Customer switching store is caused due to inaccurate forecasting which results in non-availability of the product. Customer store switching leads to customers not turning to the retailer forever and also passes the negative word of mouth to their friends. Further, in OOS situations, when a customer was not able to find the desired product while shopping, customers reacted in five ways such as switch store, switch item, switch brand, delay purchase or do not purchase at all (M. Fisher & Raman, 1996)A study by investigated the consumer's response to stock out with two different products such as cereals and margarine. One important finding is that 2% of the margarine customers and 3.3 % of the cereal's customers switch stores. The author states that as cereals are a high involvement product, customers were ready to switch stores. Similarly, in the case of fashion apparel, a high involvement product, retailers will lose their customers to competitors due to inaccurate forecasting.

Demand estimation

In demand forecasting, demand estimation is performed to estimate the future requirements of quantity. Demand estimation is defined as the link between the level of demand and the influencing variables like price, colour, etc. Many research works were carried in the past on-demand estimation, to optimize assortment plans, to plan the production, and to improve retailers' profit (M. Fisher & Raman, 1996; Ma, Deng, & Lan, 2016)

Sources of data

Demand estimation is performed in two steps: data collection, and data analysis. For data collection, data sources have to be identified. From the published literature, it can be observed that the demand estimation is performed by using data collected from various data sources such as past sales data, expert opinion data (Chambers & Eglese, 1986)early sales data(Frank, Garg, Sztandera, & Raheja, 2003), revealed preference data, stated preference data, etc. Once the data is collected, the data analysis is carried out. Based on the number of variables, analysis can be classified as Univariate method and Multivariate methods. The univariate method uses only one variable as an input variable. Generally, the data is analyzed using the moving average method, exponential smoothing, and Auto-Regressive Integrated Moving Average (ARIMA)., etc. Multivariate methods use many variables such as price, advertising, competition, etc. Commonly used analysis methods are multiple regression, conjoint analysis, cluster analysis, etc (Armstrong, 2001; Thomassey & Fiordaliso, 2006)

Past sales data

Among the data sources mentioned above, past sales data is mostly used to predict the demand. In apparel retailing, retailers store sales data for future reference. This data is otherwise known as time-series data. Past sales data are pure extrapolation, in which estimations are based on the assumption that past trends will continue in the future. Past sales data is easy to use and is inexpensive to collect.

Analyzing techniques

Techniques for analysing data are generally divided into two groups, classical techniques based on statistical models and artificial intelligence techniques To estimate the demand for fashion apparel, statistical methods face difficulty in capturing the non-linear pattern in data. As there are too many variables like size, price, color, the statistical methods are unable to respond, and they suffer when there are more uncontrollable and unidentifiable factors, thus resulting in poor accuracy. To overcome the limitations, soft computing techniques were carried research to forecast women's apparel sales, using time series data and analysed the data using Artificial Neural Network (ANN). They compared the following three methods Seasonal Single Exponential Smoothing (SSES), Winters' three-parameter model, and soft computing model ANN. While comparing the three methods, ANN showed a good coefficient of R squared and a poor coefficient of correlation between actual and forecasted sales i.e R is low. This low correlation can be attributed to noisy data. To avoid the noise in the data, more data can be used in training the network and forecasting can be made more accurate. ANN and fuzzy-based approaches were introduced in the first. From review, it can be understood that fuzzy-based fashion forecasting was introduced as early as 2005. They presented a review of various models for fashion forecasting. Fuzzy-based models have served as an efficient multivariate model when compared with traditional statistical models and ANN. The review also suggests that fuzzy-based models, when combined with speedy statistical models, can work best for short fashion forecasting. The earlier work using Neural Network (NN) posed problems in forecasting due to limited past sales data. (Thomassey & Fiordaliso, 2006)developed a fashion forecasting model using fuzzy logic in combination with NN for the mid-term and short term in forecasting. Past sales data was collected from a French textile distributor for 322 families of products. The proposed model, when compared to Holt-Winter with Seasonality (HWS) model, provides a lesser error in both midterm and short-term forecasting. Later, (Thomassey & Fiordaliso, 2006)performed mid-term and short-term fashion forecasting at family, item, size, and color levels. To overcome the issues of limited past sales data and lack of reliability in expert data, they proposed a neuro-fuzzy model. They collected three years of data for 42000 items from a French textile distributor. The error in terms of Median Absolute Percentage Error (MdAPE) in comparison with HWS and Auto-regressive Moving Average eXogenous (ARMAX) model against the proposed hybrid model are 52.3, 67.2, and 47.5 respectively, from which it is clear that the forecasting error is lesser in the hybrid model. This method resulted in inaccurate forecasts when compared to traditional models. This technique overcame the deficiencies with time-series data and hence this model is better in accuracy even for colour-wise forecasting. It was suggested by (Thomassey & Happiette, 2007)that fuzzy and neuro-fuzzy models are not interpretable and require prior aggregation of data. Therefore, they introduce a combination of machine learning methods like decision tree classification and clustering algorithm. A decision tree is a popular data-mining tool, which outperforms the neural network in terms of interpretability. They had used the K-means clustering tool for clustering the data based on product similarity. The other methods require large past sales data. They propose mid-term forecasting using past sales data. The data is first aggregated at the category level using clustering and the decision tree assigns each future item to one cluster. Past sales data for two years was collected from a French textile distributor. The results suggest that the model based on clustering and decision tree was able to accurately estimate the demand of the future item. In general, it is easy to estimate an aggregate forecast using past sales data. According to (Au, Choi, & Yu, 2008) proposal a hybrid method for new apparel items combining neural clustering and classification. This method was proposed to overcome the difficulty in clustering using hierarchical clustering. The hybrid method was applied in midterm forecasting for a French ready-to-wear distributor where data was collected for 482 items. The performance of the model was compared in terms of Mean Absolute Percentage Error (MAPE) and MdAPE and the performance was found to be accurate. According to (Au et al., 2008) who performed a forecast for a fashion retailer using past sales data. Data were collected for two years for T-shirts and jeans. They have used Evolutionary Neural Network (ENN). They have compared the Mean Squared Error (MSE) with ENN and showed that ENN model accuracy is better than Seasonal Auto-Regressive Integrated Moving Average (SARIMA) model. But ENN outperforms the SARIMA model only in cases where there is a low degree of demand uncertainty like an ordinary T-Shirt. There is another drawback that ENN is time-consuming than the SARIMA model and computational costs are also high. But it can outperform SARIMA because in SARIMA the parameter selection is manual whereas in ENN it is automatic and hence more suitable for fashion apparel which is characterized by season trends. ENN model performs well when there are lower product demand fluctuations and it consumes a lot of time. To overcome this issue (Xia, Zhang, Weng, & Ye, 2012) proposed the Extreme Learning Machine (ELM) which performed sales forecasting for a fashion retailer in Hong Kong in the jeans product category. In this study, factors like size, color, and price were considered. They claim that when the coefficient of variation (CV) that is the fluctuations in product demand is higher with the use of ELM the predictive error is lower. According to (Pashigian, 1988) used a hybrid method to forecast demand for a clothing manufacturer. They use an adaptive-network-based fuzzy inference system (ANFIS) this is a combination of fuzzy methods and a neural network for a forecast horizon of one month. The results suggest that the forecasts are much closer to the actual and the error in terms of Mean Absolute Error (MAE), MAPE, and MSE is much lower when compared to ANN. (Choi, Hui, Liu, Ng, & Yu, 2014)performed a demand forecast for fashion. To overcome the issues with ELM that it suffers from underfitting or overfitting, and to improve forecasting accuracy the authors combined ELM with adaptive matrices. They showed that ELM outperformed auto regression ANN & ELM. Three cases of data were taken, one for high-priced products, one for medium-priced products, and one for basic apparel. The MAPE was very low when compared to ANN, AR, ELM. The MAPE is 15.33% for ANN and 6.02% for AD-ELM. Thus, showing a higher accuracy. This method uses the Point of Sale (POS) data for forecasting. According to(Luce, 2019), though ELM is faster than ANN methods, it requires a lot of time. In real cases where the retailers have to perform forecast for around 10000 SKUs every hour, then these methods are slow and also requires a lot of data to achieve efficient forecast. Therefore, they proposed the use of the Grey Method (GM) which has proved to work well even when there is less data, but in isolation, they are unreliable due to high volatile data. So, they proposed a new method combining GM and Extended ELM (EELM). EELM is performed by running ELM multiple times for getting an average. Data was collected from a knitwear fashion company adopting fast fashion. In this study when the forecast time is 10sec, the forecasting error was 43.5% Error increased to 45.1% when the forecast time was reduced to 0.5sec. Further, when the forecasting time was reduced to 0.36 seconds for one data and the forecasting error was 50.7%. This study proved to be faster, but accuracy has to be foregone in situations where it requires a much quicker forecast. The author has shown that this hybrid method is well suited for fast fashion. From the above literature, it is clear that though ELM performs faster it compromises accuracy for time. Therefore, hybrid models came into use. Hybrid, as the name suggests, is the combination of different models to form a new forecasting model. Currently, demand estimation in fashion exploits methods like new hybrid and deep neural networks (Beheshti-Kashi et al., 2015) The above literature shows the application of past sales data in soft computing, though it is better than statistical methods and was able to bring accurate results. However, soft computing techniques require a large number of data and time to forecast (Kök & Fisher, 2007)

Problems in using past sales data in fashion industry

While forecasting, it is important to include substitution. (Kök, Fisher, & Vaidyanathan, 2008)used past sales data adjusted with buyer intuition. The estimated demand insisting substitution. They developed an assortment plan with the data for a grocery chain. They also checked for forecast error using Mean Absolute deviation (MAD), the results suggest that the profit was 13.8% higher than the current assortment. In general, while using the past sales data there is a drawback that it gives information only about the product already stocked in a store; with no history for new styles. There are various issues in using past sales data in fashion forecasting. In a study carried out by [22] to quantify OOS in fashion apparel, they clearly stated the issues in using past sales data. While using past sales data, it represents only past sales and not past demand. This data reflects only what was sold, but not what was demanded. Therefore, forecasts based on past sales data will be either overestimated due to substitution or underestimated when the item went on OOS. Many of the above-discussed methods are employed on the group level or at the categorical level and not at the SKU level. Moreover, these methods do not consider substitution. However, the use of past sales data in apparel forecasting has certain drawbacks. It is not applicable for estimating the demand for a new product, it does not reflect the consumer substitution(Mantrala et al., 2009), consumers taste changes(M. L. Fisher, Raman, & McClelland, 2000), and also due to inaccurate data storage by the retailer(Fader & Hardie, 1996). Similarly, the other data sources such as expert opinion data, early sales data, revealed preference data have limitations like subjective error, improper store selection and do not reflect the preference for new products respectively. So, the attribute-based method which incorporates consumer preferences would be suitable for demand estimation in apparel. The researchers (Mantrala et al., 2009) also pointed out the need for an attribute-based method to estimate demand. According to (Mantrala & Rao, 2001) proposal a demand estimation model based on attributes for a new line of products in fabric softener. Their main goal was to model consumer choice among SKUs based on the attributes that characterize the product. But they have used scanner panel data, which is similar to past sales data, where only sales are registered, which we found not suitable for fashion apparel. (Anupindi, Gupta, & Venkataramanan, 2008)discussed various advantages of the attribute-based approach being presented to consumers rather than SKU based approach. The attribute-based approach does not provide dissatisfaction to respondents; no fatigue is involved and can predict sales for new styles. It was explained how few fashion companies use attribute-based methods for demand estimation. They explain that while using the attribute-based method, consumers' preference for each attribute and its combination with other attributes can be derived. This method can be adopted even if the product were never being offered for sale. The attribute-based method is developed using consumer stated preference data, which is data collected from the consumers. This led to the use of consumer intention data otherwise known as the consumer preference data in demand estimation. Which is not used in fashion forecasting, but has a long history.

Intention data

According to (Ajzen, 1985; Patch, Tapsell, & Williams, 2005)behaviour intentions is an indication of a person's readiness to perform a behaviour, often used as a predictive measure of subsequent purchase behaviour routinely in research for the forecast. In introducing a new product or a new style, in such cases when there is no demand data, retailers ask customers whether they will use such a product and consolidate the customer's future purchase intentions. The advantage of this method is that the purchase intention measure is a good indicator of behaviour because it allows each respondent to relate all the factors involved and decide on the purchase intention. Initial literature discusses whether customers' intentions can predict their future actions. Intuition-based data are based on theory. (Infosino, 1986)proposed the Theory of Planned Behaviour. According to this theory, a person's behaviour is guided by three kinds of variables attitude, sub norms, & perceived behaviour. This demonstrates the direct information that they have on behavioural intention where, intention influences behaviour. (Morwitz & Schmittlein, 1992)proposed the use of intention data. The author had proposed a model to predict future sales for a new product using purchase intention i.e. the likelihood of purchase by the customer. His model is based on the success of earlier studies that demonstrate a strong correlation between intention rating and purchases. In this study, the infrequently purchased non-durable product was considered. But the model can also be used for durable products. The data were collected through a mailed questionnaire. The intention data was compared against the purchase behaviour by the respondents within three months of the product availability in the market. The result suggests reasonably accurate predictions. This study shows that the forecast of sales can be estimated using purchase intention data. According to(Armstrong, 2001), purchase intentions are well suitable for short-term predictions. The author shows how intentions can be used to reflect behaviour. Results showed a week but positive relationship between stated intention and behaviour. The results suggest that the accuracy of the sales forecast based on purchase intent can be improved by first using certain kinds of segmentation methods to segment the panel members. (Ben-Akiva et al., 1994)examined the accuracy of intentions-based forecasting methods and found it to be more accurate than an extrapolation of past sales data. This was tested in four different products like the automobile and wireless services. Under the broad category of intentions data, there are various types of market research data like stated preference data, revealed preference data, stated judgments, attitudinal rating, these are either preference data or based on observations (Wu, Liao, & Chatwuthikrai, 2014)

Types of intention data

Stated preference (SP) data are expected future choice behaviour of a customer, usually collected through a survey context over hypothetical scenarios in response to a description of a future choice situation. A stated preference technique is a discrete choice technique that derives data from respondents' preferences. Stated preference data that is data based on behavioural intention are collected from consumers who have the intention to buy a product. The main advantages of these methods are that they are easier to control, more flexible, cheaper to apply. Revealed preference (RP) is observations on past or present actual market choice behaviour made by the respondents. These are the most widely used methods. These methods understand customers' intentions and convert them to utility scores, a value that customers derive when using the product. In general, revealed preference data are used in understanding demand. These data will include preferences only for a product that is in stock; preferences for new products which are yet to be released cannot be estimated. Stated preference data and Revealed Preference are used in isolation and are also combined in many cases. Stated Preference data and revealed preference data has advantages and disadvantages when used separately. Stated preferences can be used to predict future purchase behaviour. When tested on various products, consumer purchase intentions have shown a positive correlation with purchase behaviour. According to (Louviere, 1988), the external validity of stated preference methods is proved in many studies Therefore, there is considerable evidence that stated preference data can predict the real behaviour of real individuals in the real market. (Kikulwe, Birol, Wesseler, & Falck-Zepeda, 2011)used a combination of stated preference and revealed preference data and tests it in transport preferences. Though the combination of data has advantages, the author suggests that combination is not a statistically sound option and many issues need to be considered in data combination. suggested other issues in developing a survey instrument, decision on sample size, tests of validity, treatment of new alternative, etc. Using revealed preference data in isolation has certain disadvantages like it does not provide information on preferences for non-existing products.

Usefulness of stated preference data in fashion industry

Therefore, among the intention data, stated preference data is most commonly used. The stated preference method is a combination of techniques using individual respondent's statements about their preferences to estimate utility. Stated preferred methods are very useful in forecasting as it accomplishes forecasting at an SKU level, considers the product as a combination of attribute and customers substitution pattern can also be accommodated while estimating demand. For forecasting demand for a new SKU, several authors discuss the complications of limited demand information and forecasting inaccuracy for new SKUs on production and inventory planning for those SKUs. Forecasting consumer demand for a new product is becoming difficult as consumer preferences change rapidly. All the products under the category of fashion apparel cannot be termed as new products. Among particular categories, for eg. in women's casual wear, the T-shirt is a standard product but its demand is difficult to predict because there is always newness in the style, colour, fabric, etc. Therefore, apparel products are seen as a combination of various attributes. Consumers choose apparel based on the preferences for various attributes and not a preference for a product as a whole. (C.-Y. Lee, Lee, & Kim, 2008)discussed the best method to elicit preferences from customers was to present them the attributes, which the customers did not find tedious to decide. Social psychologists studied how attitude influenced behaviour and developed multi-attribute models. Stated preference has seen the application in other industries and apparel. Consumer stated preference data is also used for demand estimations, for diesel passenger cars, for newly introduced home networking technology, to estimate demand for large-screen television sets, used an assortment selection for products that lack sales history(Guyon & Petiot, 2011; J. Lee & Cho, 2009). However, in other industries when there is a new product introduction and when there is no past sales data available they have adopted methods using stated preference data (Kikulwe et al., 2011; Kroes & Sheldon, 1988) Stated preference data is analysed by using various methods like conjoint analysis, functional measurement, trade-off analysis, and the transfer price method(Lancaster, 1966). Among these, conjoint analysis is a popular method because it is a decomposition method, i.e. the overall preference for a product can be decomposed into preferences for each attribute. And conjoint analysis is used to estimate the preference for new products that are yet to be released to the market. To estimate accurate demand, many research works used conjoint analysis in various other retail sectors like electronics, food products, automobiles, transport, etc. Demand prediction can be done by modelling individual choice behaviour. For this purpose, choice models are used. Choice models can be categorized as discrete choice and probabilistic choice. A discrete choice model specifies the customer who will look at the choice set and decide what level of utility each alternative will give and choose the alternative that gives him the greatest utility. The choice set contains a finite number of alternatives. Discrete choice experiments- responses are choice-based. Discrete choice models understand and model the behaviour process of subjects that leads to choose. Discrete choice models can be derived from utility theory. The discrete choice experiment is founded in Random Utility Theory (RUT) and is consistent with Lancaster's theory. In general, attribute-based demand estimation models have their base on the new economic theory of consumer choice which states that the total utility of a product is based on the characteristics/attributes of that product. Consumers choose an alternative that gives them the maximum utility. A Random Utility model maps the observed characteristics into preferences.

Conclusion

The literature review, explains the forecasting process in fashion industry. The problems faced during fashion sales forecasting in fashion industry is also evident. Among the types of data sources past sales data and intention data are discussed thoroughly. The issues with forecasting using past sales data was also clearly explained. It is it is evident that RU models are useful for new product development, forecasting and can also be useful in determining the number of units required to buy. Thus, to incorporate consumer preferences in demand estimation, consumers stated preference data is highly effective and useful.

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