Demand Forecasting in the Fashion Industry:
The Shift to AI-Based Methods

by

Samia Hubeishi

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AI	Artificial Intelligence
SKU	Stock Keeping Unit

1. Introduction

1.1 Demand Forecasting

In Operations Management, demand forecasting is crucial to ensure efficiency in the planning process. Demand forecasting is the process of estimating and predicting a product's future demand.[1] The series of these steps involves the demand anticipation under factors that are both capable of being controlled or uncontrolled.

Forecasting demands successfully can be difficult especially in a business world that includes risks and uncertainties. Firstly, forecasting sales can be challenging when SKU's and stock levels can not be monitored accurately. When stock levels lack visibility and are incapable of being accessed easily, it might result in excess unnecessary stocks or shortages of stock during high peak of demand seasons for specific products. Moreover, historical based data are the basis for inventory planning, and the lack of these data can also be another challenge for the accuracy of future forecasts. It is also important and challenging for suppliers to calculate order fulfillment lead times correctly when ordering new inventory. Another main challenge for demand forecasting is during introducing new products. Due to the lack of any historical data, producing forecasts and predicting the correct levels of stock is quite challenging.

Despite its challenges and difficulties, demand forecasting is essential and aids the organization with making decisions. These decisions include constructing pricing strategies, finances provisions, planning and scheduling the process of the production, and planning and implementing the advertisement of a specific product.[2] Thus, to ensure a successful demand forecasting method, it should be a systematic process.

[1] Cf. (Business Dictionary, 2018).

[2] Cf. (Tradegecko, 2018)

1.2 Problem Description

Demand Forecasting plays a crucial role in the management of operations, especially in the Fast-Fashion Industry, in which demand can be very volatile and lumpy due to frequently changing customers tastes and the development of technology. However, demand forecasting is essential for optimizing the inventory levels efficiently, assisting with predictions of upcoming cash flow, and allowing business managers to know when they need to increase staff and/or other resources. Demand forecasting is a very popular research topic in the fashion industry which has recently undergone some major developments. As the world moves forward into the digital age, a trend in forecasting research in the fashion industry is noticed.

1.3 Aims of Thesis

Since many previous studies has been done in this area, this thesis will be an extended study to the previous research done. In my thesis, I aim to analyze and cluster demand forecasting methods and approaches in previous research which have been recently going through an obvious trend and direction towards a more digital supply chain and automated forecasting methods. Next, I aim to first address the developments in the fashion industry and link the previous forecasting methods to the current market features. Current existing challenges and barriers will be identified in order to be able to propose future research areas and framework in demand forecasting in the Fast Fashion Industry. Therefore, the questions that I plan to address in my thesis are:

- What are the current challenges in the fast-fashion industry due the recent developments?
- What are the previous demand forecasting methods and approaches most frequently researched in the past years in the fashion Industry?

- Which approaches seem to best suit the current market features, and what results have been reported on popular applications implemented by leading companies?
- What are the industry's future opportunities, and what can still be done in this research area?

1.4 Course of Research

To analyze and cluster the previous demand forecasting methods, a literature about previous fast-fashion demand forecasting studies will be completed. Additionally, to analyze the performance of a demand forecasting method in real-life application, I will conduct a case study on a german fashion retailer. Finally, I will interview with a big data analytics software and consulting solution to discuss the current trend and which approaches best suit the industry with the current market features.

After completing these methods, I will be able to link the methods with the current market features, analyze their performance and identify existing challenges that remain. Therefore, that will enable me to suggest future research opportunities in demand forecasting in the fast-fashion industry, and which approaches are best suitable today.

2. Fast-Fashion Industry

Companies in the fast-fashion industry provide clothes and accessories that are on trend as seen on catwalks at cheap prices. Fast-Fashion stores "quickly" copy styles that are inspired by high-fashion runways and brands, but with the opportunity of spending much less money which is what the masses prefer. In other words, they provide high fashion styles with mid to low prices which is one of the main reasons behind its large annual growth. Moreover, these stores can put together a clothing line within seven to thirty days, while delivering bestsellers to stores within as fast as five days.

The speed of the fast-fashion brands means that the lead times for the production are only weeks, and not many months as it used to be in old times. They are forced to dispose of the materials in advance and to produce in selected product groups either closer to the sales market or accept more expensive transport routes. Thus resulting in high production pressure that forces suppliers to comply with extremely tight delivery schedules. Therefore, success of companies such as Zara and H&M can be explained by the fact that they have the shortest market lead times. Moreover, fast fashion provide a large variety of products that have short life cycles. Moreover a lot of factors influence the industry such as seasonal sales, marketing campaigns, and weather conditions.

2.1 Developments in the Fashion Industry

The fashion industry has been undergoing a state of transition in the past two decades. This transition is a result of various factors including globalization, changing consumers' expectations and psychology, the evolvement of technology and the rise of E-commerce.

To gain a substantial cost advantage, the fashion industry has been undergoing the growing trend of globalization for not only production, but also retailing. This however has shown disadvantages in cases where it led to noticeable longer lead-times, which is a very important risk to consider for the fast-fashion industry as mentioned. Therefore, reducing overall cost is a factor that is impacting the developments in the industry. To gain competitive advantages, the fast-fashion industry has been shifting towards buying materials and moving the production processes to developing countries. Hence, production is significantly cheaper as a result of less labour cost in these countries.

Another important factor is technology. Technology has a huge influence on the fashion industry as it offers various of opportunities. Technology has enabled brands to forecast trends in a much faster manner. It has reduced the overall time consumption since in the past trend forecasting required traveling and a much more complicated process. [3] As a result, trend forecasting is now done and analyzed on a daily basis. Additionally, it resulted in the improvements of the retailers, manufacturers and wholesalers capabilities with sharing data and taking better and more efficient business decisions. Moreover, customers knowledge of brand information and new trends have risen dramatically. As a result of social media, almost all brands have a social media presence which enables the brands to manage customers through better interaction and receiving feedback.

Technology has lead to easy accessibility to fashion for people all around the world due to the help of the internet. This has led to a rise in E-commerce that allows consumers to access and purchase all sort of fashion products through the internet. This has lead to a shift in the fashion industry from being just brick-and-mortar to a more mobile and social media-friendly space. This shift has opened up many applications in fashion that helps in molding the future of the customer experience.[4] Cumulative data paints a bright portrait, with worldwide revenue expected to rise from $481.2 billion in 2018 to $712.9 billion by 2022. [5]

As a result of consumers' adoption of digitalization, a raise of customer experience expectations and a higher scrutiny on convenience, price, quality, newness and a personal touch has been noticed. [6] Therefore, customer requirements have been increasing and are becoming more demanding. Additionally, their tastes are varying continuously and dynamically. As a result, companies must meet their expectations in a product level as well as in the service level.

The above mentioned factors have resulted in the fast-fashions industry change rapidly with its flexibility and responsiveness. Previous trends that appeared across the fast-fashion

[3] Cf. (Signature Weaves, 2017).

[4] Cf. (Techemergence, 2017).

[5] Cf. (Shopify Plus, 2018).

[6] Cf. (Business of Fashion, 2018).

industry are vertical integration and outsourcing, quick supply chain and quick responses. To increase efficiency and better comprehend the needs of the consumers, fast-fashion companies have been experiencing vertical integration. Moreover, manufacturers tend to seek a complete outsource for the production in effort to gain competitive advantage.[7] Additionally, it has been proven that a rapid organization that is within a supply chain performs better than the forecast-driven and conventional supply chains. Finally, fashion retailers adopted measures such as the quick response policy which is beneficial in reducing the inventory level. This quick response policy refers to the quick incorporation of what the consumer prefers into the overall processes of supply chain. This system would allow the manufacturer to customize the production into various colors, sizes and styles as a response to the sales in retail.

2.2 Demand Forecasting in the Fast-Fashion Industry

Demand forecasting in fast-fashion is especially a challenge due to the product type that the industry provides, the complexity of the fashion markets and the developments that the industry has gone through. Products in this industry are usually characterized by short selling seasons, short life-cycles and long replenishment lead times with unpredictable demand. These factors are risks that might lead to inaccurate forecasts.[8]

Additionally, the features of the demand in the fast-fashion industry is distinguished from other industries due to various reasons. Firstly, the demand for the fashion products are almost never stable, thus resulting in high volatility. This demand is influenced by many factors such as television, celebrities, or even the weather. As a result of this volatility, it is very difficult to accurately forecast the demand on a weekly basis and per item and thus, there is low predictability.

[7] Cf. (Marchegiani L., Giustiniano L., Peruffo E., Pirolo L., 2012), pp. 157-177.

[8] Cf. (Lee H.L, 2002), pp. 103-117.

Secondly, the buying decisions made by the consumers in this industry are mostly made at the purchasing point. That means that the buyer will make the decision after seeing the product. Therefore, it is critical that these companies provide availability and a large variety of products. As a result of this variety and the high variance of demand, there is a high number of stock keeping units and the number of sales per SKU is low.[9] Therefore, even with the possibility of predicting demand with a certain amount of certainty, the way that this demand will be distributed among the products offered will be very difficult.

3. State of the Art

Demand forecasting is a big challenge in any industry for all retailers, manufacturers, and wholesalers. This topic has received a lot of attention from not only researchers, but also practitioners. Moreover, to accurately create a sales forecast, three types of information are needed. These information include: Internal Data, External Data and Future Information. Therefore, the forecasting method used will depend on the information's type that is available. In this section, I will discuss the forecasting methods and approaches in the most influential existing literature.

Exponential smoothing, Double Exponential Smoothing, Moving Average, Weighted Average, Bayesian Analysis, AutoRegressive Integrated Moving Average and Linear Regression are traditional forecasting methods that have been proposed in many papers in the past.[10] Among these methods, two of the most discussed and used approaches are exponential smoothing and moving average. For moving average, the sales of the most recent periods are required. Moreover, exponential smoothing depends on the weighted moving average of previous forecast levels and demand to estimate the sales of the future. However, these

[9] Cf. (Gutgeld Y., Beyer D., 1995), pp. 55–60.

[10] Cf. (Brown R.G, 1959).

methods are mainly designed for demand of a nature that is of high-volume and smooth, as opposed to a lumpy and intermittent demand that exists in the fashion industry.

Additionally, another group of papers discuss the usage of these statistical methods[11], of which some suggest extending these standard methods and deriving variants of previous standard models.[12] One of the methods discussed is a method derived from the Poisson Model. According to Boylan and Johnston, "the poisson process is adopted for demand forecasting. Especially, the linkage between demand forecasting and inventory management can be applied in a model with condensed and compounded Poisson mixed"(1996). Other methods discussed are methods derived by the binomial distribution[13], the bootstrap methods[14], and the Croston's model.[15]

Another proposed approach are models that are mainly based on the consumer behavior.[16] One of the important models is the multinomial logit model, or MNL.[17] The MNL model is based on the assumption that each purchasing decision, including the decision of not purchasing, is in association with a utility. Another model is the exogenous demand model, which assumes that the customer will make the purchasing decision if his or her favourite product is in the assortment. Otherwise, a customer will choose a substitute of his or her favourite item. The substitute that the customer will choose will have a probability δ, and will not choose a product with probability 1 - δ. This type of model is in use widely especially for the management of inventories and consider the behavior of customers' substitution.

[11] Cf. (Fumi A., Pepe A., Scarabotti L., Schiraldi M.M, 2013).

[12] Cf. (Wang H.J, Chien C., Liu C., 2005), pp. 20–31.

[13] Cf. (Cachon G., Fisher M., 2000), pp. 1030-1042.

[14] Cf. (Varghese V., Rossetti M.D., 2008).

[15] Cf. (Johnston F.R., Boylan J.E, 1996, pp. 111-123.

[16] Cf. (A. G. Kök, M. L. Fisher, and R. Vaidyanathan, 2015), pp.172-237.

[17] Cf. (P. M. Guadagni and J. D. Little, 1983), pp. 202–240.

Another approach towards demand forecasting was with supervising the levels of uncertainty that exists within the fashion industry. These studies' target was developing a single algorithm through a simulative approach to try measuring a framework's performance in comparison to existing ones.

According to Bartezzaghi, the main causes of the lumpiness that exists in demand are: "High numerousness of potential customers, high heterogeneity of customers, low frequency customer requests, high variety of customers requests, and high correlation between customer requests".[18]

The causes the author mentioned in his paper can be also used describe the demand in the fashion industry. Additionally, he proposes approaches for managing and supervising uncertainty levels that are present in an irregular demand. The first approach includes using the information from the actual orders that have been received already for future delivery. Making Bayesian rules of these information can provide correlation between the two portions of demand, unknown and known. The second approach targets anticipating future lumpy or irregular requirements includes the exploitation of the process that the customer undergoes before he places the actual order or purchase. This approach is called order over-planning, and it can be used as a forecasting unit not for the overall demand, but for each single customer.

However, a comparison amongst the models has been conducted that analysed their performance.[19] The general agreement amongst these methods has been that the performance is interdependent with the level of attributes; hence in the case of a lumpy demand[20]. Additionally, it was demonstrated that time-series methods may not be sufficient with identifying nonlinear patterns in given data due to the lack of historical data that exists in the

[18] Cf. (Bartezzaghi E., Verganti R., 1995), pp. 110-121.

[19] Cf. (Willemain T.R., Smart C.N., Shocker J.H., DeSautels P.A., 1994), pp. 530-540.

[20] Cf. (Gutierrez R.S., Solis A.O., Bendore N.R., 2004).

fashion industry. According to Brannon[21], time series techniques are quantitative-: “that is they use values recorded at regular time intervals (sales history) to predict future values”. (2000) Without the availability of clear and regular relationships or trends, time series forecasting techniques are not of much use. [22]

As previously mentioned, the nature of the demand in the fast-fashion industry includes lumpiness and irregular patterns. Therefore, with statistical and time series methods, that can result in a reduced fulfillment of the overall main target.

As a solution for the previously mentioned limitations, authors have suggested the use of expert systems based on Artificial Intelligence. One popular example of these systems is the Artificial Neural Network, known as ANN. The Artificial Neural Network is a computational structure that is composed of interconnected and simple elements called neurons that are able to process and exchange information in a similar way to the neurons within the brain[23].

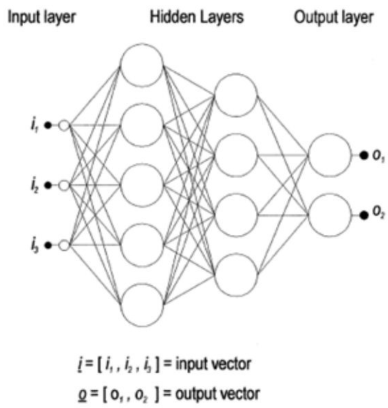

Figure 1: Artificial Neural Networks

Source: Gutierrez R. S., Solis A., Mukhopadhyay S. (2008)

[21] Cf. (Brannon E., 2000), pp. 261-262.

[22] Cf. (Gutierrez R. S., Solis A., Mukhopadhyay S., 2008), pp. 411-422.

[23] Cf. (Coruña A., Outubro De., 2014).

As shown in Figure 1, the ANN is organized in layers that are made of interconnected neurons. The input layer receives patterns and then transmitted into the hidden layer which processes the data. Finally, the hidden layer is then connected to the outer layer where the results are presented.

As a result of ANN, useful and positive outcomes have been observed[24] [25], that can even have effective applications to the fast fashion industry.[26] [27] However, one downside to the usage of ANN is the required forecasting time, despite having the possibility of yielding accurate forecasting. This is due to the time required for training that is directly related to the complexity and variety of data.[28] This limitation in time is a barrier that renders the practicality of ANN in the fast fashion industry due to its requirements of responding fast and the short selling seasons that deeply influences the industry.

One other popular method that uses artificial intelligence in previous literature is fuzzy logic models.[29] Zahed proposed this theory that has been applied to various areas.[30] This method requires a sufficient amount of data and it is suitable for short term forecasting. [31]
Other popular existing methods in this area include extreme machine learning[32], support vector machines[33], and regression tree. [34]

[24] Cf. (Chang P.C., Wang Y.W., Liu C.H., 2007), pp. 87-90.

[25] Cf. (Ling S.H., 2010).

[26] Cf. (Yu Y., Choi T., Hui C., 2015), pp.7372-7380.

[27] Cf. (Au K.F., Choi T.M., Yu Y., 2011), pp. 614-631.

[28] Cf. (Sun Z.L., Choi T. M., Au K. F., Yu Y., 2014), pp. 400-420.

[29] Cf. (G. E. P. Box, G. M. Jenkins, G. C. Reinsel, 2008).

[30] Cf. (P. A. Mastorocostas, J. B. Theocharis, and V. S. Petridis, 2001).

[31] Cf. (L. M. Sztandera, C. Frank, B. Vemulapali, 2004), pp. 1190-1199.

[32] Cf. (F. Chen, T. Ou, 2016).

[33] Cf. (K.-R. Müller, A. J. Smola, G. Rätsch, B. Schölkopf, J. Kohlmorgen, V. Vapnik, 1997), pp. 999-1004.

[34] Cf. (K. Johnson, B. H. A. Lee, D. Simchi-Levi, 2014).

One recent method that is based on Artificial Intelligence and uses machine learning algorithms is by Lokad, a big data analytics software and consulting solution for both retail and eCommerce businesses. Lokad released an engine in 2016 that they describe as “a game changer for fashion”. [35] Their forecasting engine is specifically designed for the challenges the fashion industry faces with regards to the demand patterns. The engine leverages the attributes of the product such as color, brand, style, price point, fabric, category, etc. These information are then used to build a demand forecast that is based on the performance of products that are similar in previous collections. In 2017, Lokad has been driving the supply chain of fashion companies and have experienced positive outcomes as a result of their forecasting engine.

The forecasting engine computes the similarities in a fully automated way via machine learning algorithms. Lokad’s forecasting engine however provides probabilistic forecasts, which means that it provides the probabilities for almost all the demand scenarios, as opposed to only one demand forecast. Defined by Lokad, “probabilistic forecasting presents an estimation of the respective probabilities for all the possible future outcomes of a random variable”. It represents a density probability function in contrast to single-valued forecasts as shown below in Figure 2.

[35] Cf. (Lokad, 2016).

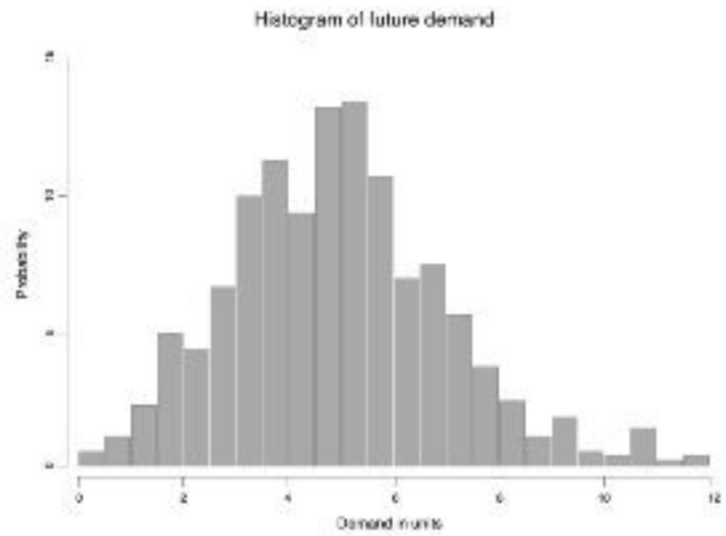

Figure 2: Probabilistic Forecasting

Source: Lokad, 2016.

As opposed to single-valued forecasts, probabilistic forecasts reflect on extreme situations and asses the probabilities of the negative situations to balance the resource allocations while still maintaining the quality of the service level of the supply chain.

Another recent method using Artificial Intelligence is Deep Learning. Deep Learning is an advanced unique way to forecast new launching products which is essential in fast fashion. This method relies on image processing capabilities to identify product similarities based on products' attributes. It results in increased accuracy as a result of better acknowledgement of the lifecycle of a product. [36] Moreover, this leads to a reduction of the overall time of execution as a result of the automation of the process. [37]

A group of papers also discuss methods that combine both Artificial Intelligence Models and

[36] Cf. (Xiao, H., Rasul, K., Vollgraf, R., 2017).

[37] Cf. (Merkel, G., Povinelli, R.J.,Brown, R.H., 2017).

Statistical Methods. These methods are called Hybrid Methods. This approach aims to utilize the positives and eliminate the negatives from the other approaches[38], thus forming a new forecasting method. Therefore, this approach have been researched to prove a better performance than pure artificial intelligence and pure statistical approaches[39] [40]. In literature this approach is mainly divided into subcategories including: Fuzzy Logic Based [41] [42], Neural Network Based [43], Extreme Learning Machine Based. [44]

Fuzzy Logic Based models have been proven to have a better performance than pure statistical methods[45], however arguments have been risen about the ability of these models to process uncertain data and the accuracy of the results. [46]
Neural Network Based models have been researched and applied with noticed positive outcomes. [47] GM and ANN are upon the best two hybrid methods and are able to predict demand by using colors despite having very few historical data available.

Extreme Learning Machine based models is much more developed and fasert in predicting demand. ELM based models have been very used to develop a successful color-based fashion forecasting hybrid method. However, one disadvantage noticed in ELM based models is unstability.[48]

[38] Cf. (Q. Wu, 2010).
[39] Cf. (W. I. Lee, B. Y. Shih, C. Y. Chen, 2012).
[40] Cf. (F. Pan, H. Zhang, and M. Xia, 2009).
[41] Cf. (S. Thomassey, M. Happiette, J.-M. Castelain, 2005).
[42] Cf. (E. Yesil, M. Kaya, and S. Siradag, 2012), pp. 1-5.
[43] Cf. (Y. Ni, F. Fan, 2011).
[44] Cf. (Y. Yu, C.-L. Hui, T.-M. Choi, 2016).
[45] Cf. (S. Y. Ren, T. M. Choi, N. Liu, 2014).
[46] Cf. (M. Xia, Y. C. Zhang, L. G. Weng, and X. L. Ye, 2015).
[47] Cf. (Pathak, J., Wikner, A., Fussell, R., Chandra, S., Hunt, B. R., Girvan, M., Ott E., 2018).
[48] Cf. (Egrioglu, E., Yolcu, U., Baş, E. and Dalar, A.Z., 2017).

3.1 Clustering

Considering the most popular forecasting methods found in the current literature for the fashion industry, forecasting methods are grouped and summarized according to their type of approaches in Table 1.

Approaches	Methods
Statistical Forecasting Methods	Exponential Smoothing, Moving Average, Bayesian Analysis, Linear Regression, AutoRegressive Integrated Moving Average
Artificial Intelligence Methods	Artificial Neural Networks, Extreme Learning Machine , Fuzzy Logic Models, Support Vector Machines, Regression Tree, Deep Learning
Hybrid Forecasting Methods	Fuzzy Logic Based, Extreme Learning Machine Based, Neural Network Based

Table 1: Clustering and summary of most popular forecasting approaches in the Fashion Industry.

After gathering an insight on the forecasting methods that exist in the current literature, I analyze my findings and discuss the advantages and disadvantages of the approaches. Hence, the outcome of this analysis will be the challenges that exist in the fashion industry.

The popularity of the methods using the statistical methods such as exponential smoothing can be explained by the fact that they are simple and easy to comprehend. Moreover, they have good ability to capture seasonality and trends. However, as previously mentioned, several limitations were noted with regards to traditional forecasting methods such as exponential smoothing. Firstly, using this method can increase the effect of the bullwhip effect for the supply chain of the company.[49] Additionally, such methods can not forecast demand for any new products, it is only limited to old already existing products. Therefore, it requires historical data which is often lacking in the fast-fashion industry due to the shortness of the life-cycle.

With regards to demand models that are based on the behavior of the consumers, some limitations in its practicality are noted. In practice, often there are many years of attributes that can be taken into account that are needed for selecting subset attributes. Therefore, these models tend to also be time consuming and that renders its applicability into the fast fashion industry. [50]

Artificial Intelligence Methods and Hybrid Methods might have a lot of challenges; However, in comparison with the statistical methods, they usually lead to better performance and results. [51] These methods address the previous challenge of forecasting new products in the fashion industry by incorporating the products' different attributes. [52] However, this might also be a challenge due to the absence of selecting variables that are useful as a result of the existence of large numbers of features in a huge data set despite the fact that the factorization of machine has proven a positive performance in the utilization of categorical data. Moreover, these methods usually require a large amount of information and data which can be a challenge for its application in the fashion industry. Additionally, these methods are time consuming, and that can be a barrier in an industry that requires fast responses and is influenced by short selling seasons.

[49] Cf. (F. Chen, J. K. Ryan, D. Simchi-Levi, 2000), pp. 270-288.

[50] Cf. (L. Lapide, 2002).

[51] Cf. (K. Johnson, B. H. A. Lee, D. Simchi-Levi, 2014).

[52] Cf. (M. Fisher, R. Vaidyanathan, 2014), pp. 2400-2415.

Probabilistic Forecasting has various advantages and good performance have been noticed. Demand is uncertain, especially in the fashion industry, therefore it is not meant to be was not precise, since we are in fact determining the probability of the demand. Therefore, this approach seems to be logical and it redefines the meaning of demand forecasting. This acknowledgement and acceptance of the demand uncertainty in the industry has been more popular recently.[53] This fully automated approach towards forecasting demand results in zero required statistical knowledge, zero expectation of fine-tuning and zero required maintenance in order for the business to be aligned with the forecasts. [54]

3.2 Analysis

From the reviewed previous literature above, we summarize our findings according to the evolution of the fast fashion forecasting methods that have been studied over time in Figure 3.

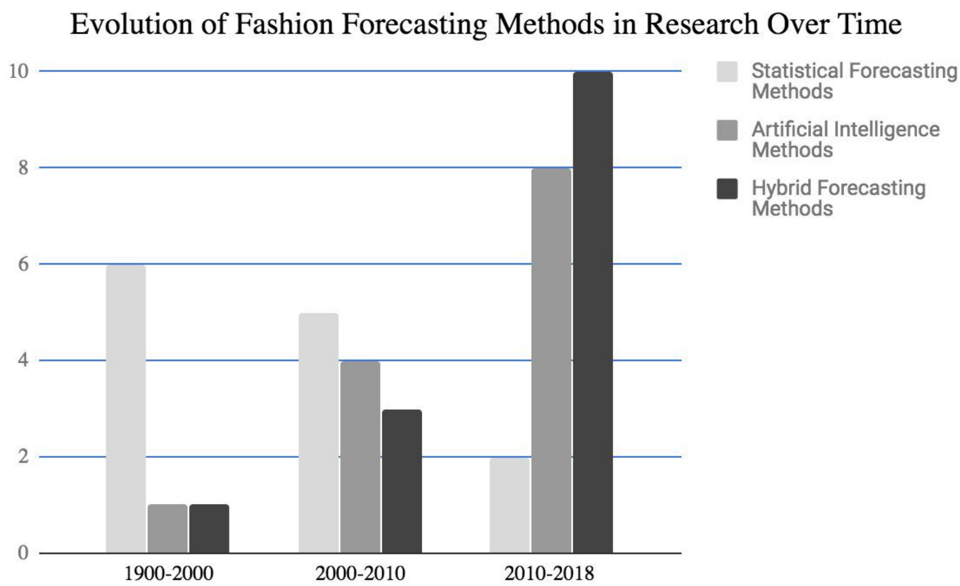

Figure 3: Evolution of Fashion Forecasting Methods in Research Over Time

53 Cf. (Business of Fashion, 2017).

54 Cf. (Lokad, 2016).

According to Figure 3, it is important to notice that Statistical Forecasting Methods have not been popularly researched in the past 20 years. However, statistical forecasting methods are still used to this day in the fast fashion industry. This decrease in popularity over time could be for two main reasons:

1. Statistical Forecasting Methods have already been well-explored in the industry in the past.
2. According to the current market features and developments of the industry, methods that are based entirely on statistical models are not sufficient enough to lead to accurate forecasting results.

On the other hand, methods that are based on Artificial Intelligence and Hybrid approaches have been appearing more frequently in comparison with statistical methods. This can be explained by the beneficial additions these approaches bring to the industry as the market develops. Artificial Intelligence and Hybrid Methods allow planners more advanced capabilities such as accessing knowledge through huge and complex datasets.

The application of these methods into real-life situations in the industry revolutionize demand forecasting by identifying trends that may be missing by pure statistical methods that are configured by humans. A summary of the evolution of topics of Artificial Intelligence Based methods in the last eight years of literature in different countries can be found below in Table 2.

2010	2011	2012	2013	2014	2015	2016	2017	2018
Expert Systems, China Genetic Algorithm and Variable Neural Networks, Germany	Dynamic Sales Forecasting Model, China Fourier Analysis for Demand Forecasting, Italy	Fuzzy Forecast Combiner Design, Indonesia A Hybrid Artificial Intelligence Sales Forecasting System, UK	Artificial Intelligence Model, Spain	Hybrid Forecasting Model of Panel Data, China Analytics for an Online Retailer, Canada	Extreme Learning Machine, USA An Intelligent Fast Sales Forecasting Model, China	Forecasting of Fashion Color Trend, Poland Gray Extreme Learning Machine, Taiwan	Neuron Model Artificial Neural Network, USA Computer Vision and Pattern Recognition, USA Deep Neural Network Regression, USA	Hybrid Forecasting of Chaotic Processes, UK State of Fashion, USA Artificial Intelligence Discussion, USA

Table 2: Summary of papers from different countries between 2010-2018 about Artificial Intelligence Based methods.

According to findings by McKinsey & Company in 2017 [55], an AI-based approach towards fashion could:

1. Reduce forecasting errors by up to 50 percent.
2. Reduce inventory levels of 20 to 50 percent.

Machine learning processing has been advancing at a rapid pace and according to Boston Consulting Group in 2017, “It is, by far, the most important technology that is already here, growing and will change the fashion industry.” Additionally, according to the International Data Corporation the expected growth of the market for machine learning applications is an estimation of £30 billion by the year 2020.

Additionally, most brands, such as H&M and Zara, now have online presence that allows customers to shop online and get items delivered at the comfort of their home. Moreover, as seen in Figure 3 below, many customers are preferring and adopting the digital shopping channels. This trend is expected to grow majorly by the year 2020.[56] Therefore, applications

[55] Cf. (McKinsey & Company, 2017).

[56] Cf. (State of Fashion, 2018).

of methods based on machine learning such as Deep Learning will contribute positively to the industry considering this obvious shift towards omnichannels and e-commerce. These advanced methods will allow the companies to have access to information such as customer shopping patterns or most important attributes that will lead to accurate and successful forecasting in a more efficient and faster manner.

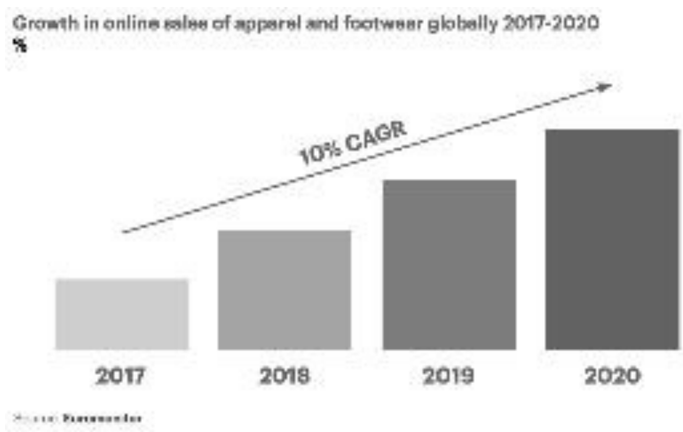

Figure 4: Mainstream fashion customers are adopting digital channels
Source: BoF McKinsey Global Fashion Survey 2017

4. Case Study: Otto Group

Artificial Intelligence Approach - Deep Learning

A company in Germany called Otto Group recently incorporated AI into its business activities. As Otto dives into the future of retailing, this approach has improved its overall business activities and resulted in a more accurate forecasting. In this section, a case study about Otto Group is completed to discuss the opportunities that Artificial Intelligence has opened for the company.

About Otto Group

Otto Group, founded in 1949, is an e-commerce retailer based in Hamburg, Germany. It is one of the largest online retailers with sales of around 7 billion Euros. Additionally, it operates in more than 30 countries in Europe, Asia, South America and North America with around 50,000 employees. Amongst many other products, Otto is also a fashion retailer that promises its customers a large variety of catwalk inspired fashion products. [57]

The Challenge

Data analysis has proved that customers are less likely to return an item that they bought online if they receive it in two days. Additionally, customers prefer to receive all their orders in one package rather than in multiple packages on different days. Considering that Otto is a retailer that sells items from other brands, it is not possible that it stocks the items that customers order. Therefore, the main two challenges that the company faced are: (1) avoiding shipping delays and (2) avoiding delivery of multiple packages. [58]

Therefore, the solution of these problems is a better demand forecasting method. With an enhanced forecasting method, Otto will be able to forecast what customers are going to purchase in the future and therefore order these items ahead of time. Customer reviews are essential factors that affect the decision making process a consumer.

The Approach

In 2017, the retailer started using Artificial Intelligence to improve its activities. Despite machine learning being used in retailing before for customer management purposes, Otto's approach towards Artificial Intelligence is unique due to its applications of Artificial Intelligence in business decisions and forecasting accuracy through automation that surpasses its employees capabilities.

[57] Cf. (Otto.de, 2018).

[58] Cf. (The Economist, 2017).

Customer reviews are essential factors that affect the decision making process a consumer. Therefore, Otto created a system using a technology based on a deep-learning algorithm, a machine learning method based on artificial neural networks. The artificial neural networks are able to process data and draw conclusions for the input. The system that Otto created is able to analyze three billion past transactions, 200 variables and one million product reviews every night. The algorithm develops output patterns by filtering the most frequently mentioned aspects of customer reviews and indicates the amount of positive, negative, and neutral reviews. This system enabled Otto to predict the orders of the customers a week prior of their purchase by identifying the most important and popular aspects of clothing items for the customers.

Results

Using Deep Learning has addressed the main challenges and resulted in many positive outcomes for Otto by enabling the retailer to predict trends and optimize its overall business processes. Hence, the impact of using artificial intelligence has been demonstrated by helping company make smarter decisions with more accurate and real-time forecasting.

As a result of this innovative approach, Otto has cut its surplus stock by 20 percent and reduced its returned items by more than two million products per year. The system has demonstrated 90 percent accuracy with forecasting what the retailer will sell in the next thirty days. Therefore, Otto is able to order 200,000 items a month from third-party brands without human intervention. [59]

5. Interview

Lokad, a big data analytics software and consulting solution for both retail and eCommerce businesses, released a forecasting engine in 2017 using probabilistic forecasting as mentioned earlier in the State of the Art. The approach was interesting and can be differentiated from the

[59] Cf. (McKinsey & Company, 2017).

other approaches by looking at demand forecasting through a different perspective. Therefore, in this segment, an interview with Lokad has been conducted to understand how probabilistic forecasting can be useful in fast fashion and which challenges does it address.

The interview was conducted over a scheduled phone call that was requested through the website of the company with one of Lokad's employees. The interview took around 12 minutes. The written version of this interview can be found in the Appendix.

The interview started with a question about the main concept of the probabilistic forecasting approach and how it works. The main aim of this question was to better understand the concept behind this approach and what differentiates it from other concepts.

The interviewee answered the question by explaining the importance of not looking at demand forecasting as a method that should have just one certain outcome, especially since the future is uncertain. Therefore, Lokad had a different vision of demand forecasting. Probabilistic forecasting takes the uncertainty of the future into account and uses modern math as opposed to just standard moving average and exponential smoothing.

The second question was about the process and the applicability of the approach. The main of this question was to better understand this approach in practice and what are the steps involved to successfully forecast the demand of a product.

The interviewee explained the two stages involved in probabilistic forecasting, which are forecasting lead times and then forecasting the probabilistic demand that consists of uncertain horizons. It is a fully automated process that is quite technical, however the main idea that it consists of is quite simple and logical. He also mentions the fact that they are currently working with over one hundred companies.

The third question in the interview was about the models that this approach is based on. The main aim of this question was to compare the basis of this approach with the the other approaches discussed earlier in the State of the Art. The interviewee explained that they are mainly based on machine learning models and algorithms that have been developed more by the company. Moreover, it was also mentioned that in the past, the company has used standard models such as exponential smoothing, however, a better performance has been noticed by the machine learning models.

Next, the main challenges that the fashion industry generally faces were discussed with the interviewee, which are:

1. The lack of historical data, therefore the inability to forecast demand for new products.
2. The time constraints of the fashion industry.

The main aim of these two questions was to analyze whether or not this approach addresses the forecasting challenges in the fast fashion industry.

The interviewee explained that this method takes into consideration the constraints of the fast fashion industry by explaining how Lokad are able to forecast the demand of the new products by using the attributes of similar and comparable older products. Moreover, to address the second challenge the interviewee explained it is a programmatic process that uses a domain-specific programming language, therefore it is not time consuming and it is much more efficient than using pure statistical methods.

5.1 Reflections

Lokad’s approach using probabilistic forecasting stands out for three main reasons. The first reason is the fact that this approach acknowledges the uncertainty of the future and of the lead times. That is quite interesting as it reflects a redefinition of demand planning, which is not meant to be precise as most of the previous statistical approaches try to achieve. The numbers that demand planning results represent are in fact just probabilities of the demand, therefore, taking a different approach and viewing demand planning from a different perspective seems to be more logical. This new perspective seems to be the new direction that the industry is heading to. In 2018, “industry players are coming to accept unpredictability as the new normal, and fashion executives will respond by focusing their energy on improving what is within their control.” [60]

The second differentiation between Lokad’s approach and other approaches is the fact that they use modern math. The fact that Lokad stated that they have used standard models in the past but they experienced better outcomes with the current modern models’ explains how a more advanced approached better fits the current market features of the industry.

This seemed logical since most of the models that were found in the previous literature were mostly based on 1990’s approaches. This reflects the shortage of advanced approaches in demand forecasting for fashion in literature. The industry has undergone major developments and therefore, also requires advanced approaches. Therefore, Lokad’s innovative approach seems to result in positive outcomes.

The process of forecasting the demand is fully automated. This is also a very important and different aspect of the approach since it can benefit E-commerce fashion retailers. The use of machine learning improves the planning of the master data as well as the sensing in the supply chain. Lead times, capabilities, locations and routes are not constant, and the usage of machine learning will be beneficial in diving improvements. As previously mentioned, technology is one of the main drivers behind the change of the fashion industry, and therefore, using the developments in technology to find innovative approaches towards demand forecasting might be beneficial.

[60] Cf. (McKinsey & Company, 2018).

To conclude, as the industry move towards a more digital world, using a probabilistic approach, machine learning models, and innovative new ideas have seemed to solve main problems that exist in the fashion industry such as the inability to predict the demand for new products, and the time constraints that exist in the industry.

6. Conclusion and Future Directions

With all the developments that occured in the fashion industry, “uncertain” and “challenging” remain the most common words that executives have used to describe the state of the industry currently. Additionally, the main dominant factors are its supply chain and product features.

The main barriers in forecasting the industry’s demand are:

- Short selling seasons
- Lumpiness of the demand
- Lack of historical data

Advancements in technology increase the complexity of the fashion industry’s supply chain, however it also opens a wide variety of opportunities that enables companies to achieve a level of productivity that can’t be reached by humans. Additionally, this can also be noticed in recent literature, where there has been a noticeable shift in research papers towards Artificial Intelligence and Hybrid approaches.

As seen through Otto’s case study and the interview with Lokad, Artificial Intelligence enables retailers closer and better interaction with their customers. This leads to providing customers products that they actually want and being able to forecast demand with increased accuracy. Therefore, the inaccurate forecasting models that are mostly used currently would be replaced by a more innovative solution.

Artificial Intelligence enables e-commerce retailers to know which products are selling by analyzing the data of the consumers. Through product attributes and acknowledging the most popular geographics and demographics, companies are able to forecast what consumers are willing to buy, hence, leading to successful sales forecasting. Additionally, with Artificial Intelligence, companies can analyze the trends that are spreading through social media.

Most approaches that are being applied in the industry towards demand forecasting are based on standard models from a long time ago. Therefore, as a first step to move forwards, updating these models and integrating modern math and artificial intelligence into supply chain concepts that are traditional, may result in a better performance as a result of a better fit to the current market features of the industry. Currently, there are not many applications of artificial intelligence for demand forecasting in fashion companies in comparison to applications that enhance customer experience. Therefore, integrating machine learning into more complex business decisions in fashion companies can lead to positive outcomes similar to Otto's and Lokad's. However, one limitation is noticed in this research, as there is only one case study that analyzes AI applications into an Ecommerce retailer. Therefore, the applicability of AI into brick-and-mortars retailer stores is not studied.

For further reading of the Logistics Engineering and Technologies Group please refer to Auerbach & Uygun, 2007; Besenfelder et al, 2013a; Besenfelder et al 2013b; Droste et al., 2008; Güller et al., 2017; Güller et al., 2015; Güller et al., 2013; Jungmann & Uygun, 2010; Karakaya et al., 2016; Keßler & Uygun, 2007; Keßler & Uygun, 2010; Keßler et al., 2007; Kortmann & Uygun, 2007; Kuhn et al., 2009; Mevenkamp et al., 2015; Reynolds, & Uygun, 2018; Scholz et al., 2013; Uygun & Ilie, 2018; Uygun & Straub, 2013; Uygun, 2008; Uygun, 2012a; Uygun, 2012b; Uygun, 2012c; Uygun, 2013; Uygun & Kuhn, 2010; Uygun & Luft 2010; Uygun & Reynolds, 2016; Uygun & Schmidt, 2011; Uygun & Straub, 2012, Uygun & Wagner, 2011; Uygun & Wötzel, 2009, Uygun et al., 2012; Uygun et al., 2015.

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