Application of Predictive Analytics

to Sales Forecasting in Fashion Business

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ABSTRACT

Like many others, fashion companies have to deal with a global and very competitive environment. Thus companies rely on accurate sales forecasts - as key success factor of an efficient supply chain management. However, forecasters have to take into account some specificities of the fashion industry. To respond to these constraints, a variety of different forecasting methods exists, including new, computer-based predictive analytics. After the evaluation of different methods, their application to the fashion industry is investigated through semi-structured expert interviews. Despite several benefits predictive analytics is not yet frequently used in practice. This research does not only reflect an industry profile, but also gives important insights about the future potential and obstacles of predictive analytics.

1. Introduction

1.1 The apparel supply chain

The fashion industry includes many companies from spinning to distribution which are required to fulfill all the manufacturing steps to transform the fibre into the final garment hanging in the store. This leads to quite a long and complex supply chain shown in figure 1. Additionally the apparel market is regarded as a highly competitive one due to a relatively constant oversupply produced by the many brands of clothing, so that consumers are very disloyal and base their choices quite often on the price. Consequently the fashion companies have to reduce their production costs in order to stay efficient, so that most of the manufacturing processes elaborated in figure 1 are realized in far away and low cost countries in Asia. This globalization increases the lead time again (Thomassey, 2010).
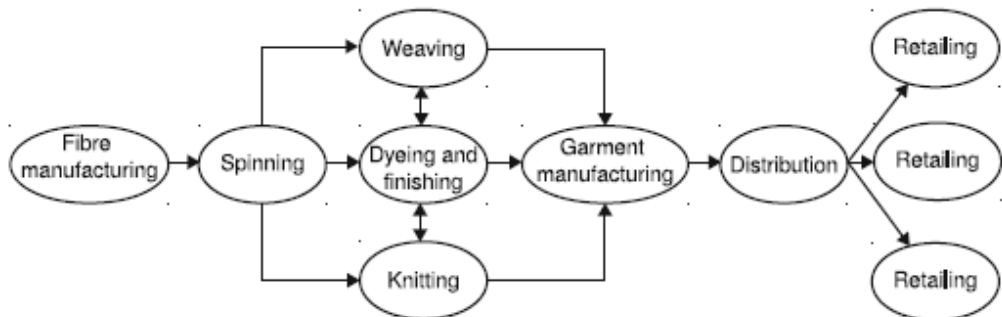

Figure 1: The apparel supply chain (Thomassey, 2014, p. 10)

By contrasting the long time-to-market with the short life cycle of fashion products it becomes obvious that the apparel supply chain must be absolutely optimized. In this context, sales forecasting as "the projection of expected demand given a set of environmental conditions" (Brannon, 2010, p. 308) becomes the key success factor of the supply chain management (Thomassey, 2010).

Accurate sales forecasting does not only result in lower costs but also in increased sales and higher levels of customer satisfaction:

- It reduces the Bullwhip effect caused by demand volatility by optimizing the inventory levels and consequently the inventory costs of the companies along the apparel supply chain (Zhang, 2004).
- It prevents the distributor from markdowns, when unwanted, remaining items must be sold at a loss of the profit margin at the end of the season. At the same time it avoids stockouts, so that customers can buy their desired items in the locations and in the quantities demanded, and therefore improves the customer service level (Brannon, 2010).
- Moreover it enables all the upstream suppliers to optimize their resources and generally improve their sourcing strategy, which leads to higher efficiency and lower costs (Zhao, Xie, & Lau, 2001).

As the distributor however is the main actor within the apparel supply chain, placing the orders for the upstream suppliers and providing the garments for the customers, it is the driver of the whole flows within the supply chain (Thomassey, 2010). Consequently distributors have to apply sales forecasting methods to ensure an efficient supply chain and make the best of the benefits described above.

But in order to perform suitable sales forecasts, it is essential to know the specificities of the fashion business, which should be taken into account by building a sales forecasting model for this industry.

1.2 Specificities of apparel sales and related forecasts

For most of the products, the life cycle can generally be summarized in six stages: the product development, the introduction, the market development, the maturity, the saturation and finally the decline (Brannon, 2010). Still it is commonly known that the life cycle of fashion products is quite short, especially compared to their long time-to-market, and looks different among the products according to their fashion level: Basic items are offered throughout the year or at least every year,

whereas fashion items are only sold punctually in a short period. Best selling items usually appear every year with slight modifications according to the fashion trends and can be replenished during the season. Of course every category has a distinct sales behavior, which should be taken into consideration in the forecasting process (Thomassey, 2014).

Considering the different life cycles and the long lead-time for design, production, transportation, quality control and distribution, two horizons of sales forecasting have to be distinguished: On the one hand the system has to be able to carry out a long-term forecasting (horizon of one season or year) to plan the sourcing and production. But on the other hand short-term forecasting (horizon from one week) is essential in order to replenish best-selling items or readjust the forecasts (Thomassey, Happiette, & Castelain, 2005).

Another constraint of the fashion industry is the product variety. The fashion trends contain many styles and colors, so that in combination with variations in size the number of stock keeping units to be managed becomes very large (Vaagen & Wallace, 2008). This is the reason why an aggregation of the data up to the level of the product family is often made. Thus the number of sales forecasts gets reduced and at the same time the amount of historical data for every SKU increases. Still each collection includes a lot of new items with no historical data available. Consequently data mining techniques for clustering and classification have to be applied to make sales forecasting possible in this special case (Thomassey, 2014).

The nature of clothing itself leads to an additional specificity of the fashion industry: high seasonality. Corresponding to the climatic changes the sales volume of some product categories like swimwear or pullovers varies a lot, whereas other items are logically not that impacted by seasonal variation. Nevertheless seasonality gives an overall trend for the sales, which should definitely be integrated into the forecasting system (Thomassey, 2010).

Like other industries the apparel market finally gets influenced by so called explanatory factors, which can be more or less controlled, sometimes even unknown, but with an impact on the sales. The variables under-control involve the marketing strategy, realizing promotional and advertising actions to boost sales, retailing strategy, controlling the number of stores, and the feature of the products itself with respect to their match with the fashion trends. On the contrary changes within the competitive environment, macro-economic developments and the calendar or rather weather data are regarded as uncontrollable factors (Little, 1998). Although the impact of these explanatory variables is difficult to quantify, they have to be considered in the sales forecasts (Thomassey, 2010).

1.3 Big Data and new forecasting opportunities arising from it

Besides the specificities of the fashion industry, which make sales forecast-ing quite complex, the amount of data collected by the retail point-of-sale technolo-gies as well as by web site traffic and e-commerce has been exploding (Kim, Fiore, & Kim, 2011). As a result, Big Data, referring not only to the quantity but also to the quality, velocity and variety of different data types collected, is the buzzword and challenge of the moment. However, in connection with analytical techniques from statistics to data mining and machine learning it can be regarded as a huge oppor-tunity to better predict future sales, summarized under the term predictive analyt-ics. In this context, the use of predictive analytics will soon become a major differen-tiator among fashion companies (Liu, 2015).

From the discussion mentioned above, it is very clear that fashion sales forecasting is a truly important topic in practice. Nevertheless fashion companies are confronted with such a great variety of forecasting methods, from the traditional forecasting systems to advanced predictive analytics, each one responding different-ly to the constraints of the fashion industry. Thus it is the objective of this paper to compare the existing sales forecasting methods and to investigate their application to the fashion business. In this context interviews with experts of the apparel indus-try are conducted in order to get an overview on which forecasting methods are applied in practice and why.

The organization of this paper is given as follows. In section 2 commonly used as well as advanced sales forecasting methods are detailed and evaluated. Sec-tion 3 describes the methodical approach of this paper – the consultation of experts. The results of the interviews are presented in section 3, followed by their discussion, summary and implications in section 4.

2. Literature Review

2.1 Traditional sales forecasting methods

Generally two major categories of forecasting techniques have to be distin-guished here: quantitative and qualitative methods. Traditionally, fashion sales fore-casting is accomplished by quantitative, statistical methods like time series and re-gression models, which are the most commonly used techniques for prediction of sales data according to literature (Makridakis, Wheelwright, & Hyndman, 1998).

Time series forecasting looks only at patterns in sales history reflected by the level, overall trend, seasonality and noise of the sales data and projects those patterns into the future. The statistical methods have developed from simply using the average of all past sales as a forecast, to moving average, where only the most recent periods of sales data are included up to exponential smoothing, weighting the most recent sales period more heavily in the forecast than older ones (Mentzer & Moon, 2005). As time series methods are simple to understand and inexpensive to use, they are very popular in fashion sales forecasting. Nevertheless the approach of using the average neutralizes any fluctuations like noise, trend as well as seasonality and additionally ignores all the exogenous factors that might have influenced demand like promotions, competitive actions, economic activity and so on. This is the reason why time series should in any case be applied for some short term forecasting within the fashion industry (Brannon, 2010).

Another common forecasting method is the regression technique, which focuses on the correlations between sales and all the explanatory, outside factors discussed above. Regression models investigate how sales will develop if the exogenous factors change, for example if a marketing action such as a sales promotion program is carried out. Consequently they provide a broad environmental perspective for forecasting sales (Mentzer & Moon, 2005). However regression models need huge data sets including past history on each factor and sales volume and therefore are most useful when the time horizon is more than six months (Brannon, 2010).

In addition to that some further, more complex developments of time series and regression models do exist as well as their combination like in the Box & Jenkins ARIMA model. Nevertheless more sophisticated forecasting models need not necessarily perform better than the simple ones. In general all the statistical methods are not efficiently implemented in the fashion industry, because they require a big amount of historical data, a complex optimization of their parameters and they are limited to linear structure and the assumption that past pattern will continue in the future (Thomassey, 2010).

As it is commonly known that pure statistical methods are insufficient to produce satisfactory forecasting results for fashion sales (Choi, Hui, & Yu, 2011), there are many examples in literature, where additionally qualitative methods are applied in order to adjust the forecasting results. Qualitative techniques make use of the expertise of people in the organization. This is especially useful for predicting changes that cannot be seen in the sales pattern or for sales forecasting of new products where no historical data is available. Here the intuition, experience and judgement of experienced executives represent an extremely rich data source that

should be incorporated into the forecasting process (Mentzer & Moon, 2005).

There are several qualitative methods: Sometimes adjusting quantitative forecasts depends on a key employee – an in-house expert – with the skill and experience to see beyond the numbers into the dynamics of the apparel market. An alternative to the single in-house expert is to involve groups of executives from various corporate functions, like sales, marketing, finance, buying and design. Especially the salespeople closest to the customers can provide important sales information. The executive committee should then jointly work on a sales forecasting adjustment. Another technique called the Delphi method makes use of a polling process. Internal as well as external experts provide written forecasting recommendations, which then are summarized and shared again, so that the participants can refine and clarify their responses until a best guess scenario is achieved. As this procedure needs some time, the Delphi method is mainly used for the prediction of long-term sales forecasting (Brannon, 2010).

2.2 Advanced methods – predictive analytics

With the advance of computer technology and the increased availability of data the field of business intelligence, as taking raw data and turning it into knowledge used to support business decisions, yields a new analytical, three-stage approach: the evolution from descriptive to predictive to finally prescriptive analytics (Koch, 2015).

Descriptive analytics refers to the question what is happening or rather what happened in the organization and provides a basic understanding of the data. Thus as a first analytical step key statistical characteristics about the collected data are examined and visualized, in order to gain essential insights and to resolve imperfections or problems in the data (Sharda, Asamoah, & Ponna, 2013).

Then predictive analytics aims to determine what will happen in the future. This prediction is based on advanced mathematical models and algorithms as well as on more recently developed techniques that fall under the general category of artificial intelligence and data mining, which will be detailed later (Sharda, Asamoah, & Ponna, 2013). Using these advanced, computational methods predictive analytics tries to discover meaningful patterns in the data and project them into the future.

Lastly prescriptive analytics attempts to positively influence the forecasting (how can we make it finally happen?) applying various optimization tools. Thus it identifies the actions needed to be taken to drive predicted outcomes and gives recommendations on different alternatives. Prescriptive analytics utilizes advanced

automated data-driven decision making techniques. It finally converts the companies into more proactive market players (Koch & Hamilton, 2015).

In the context of sales forecasting predictive analytics with its various types of models is in the center of attention. A predictive model can be defined as a mechanism that predicts an outcome or a behavior of an individual taking descriptive attributes as input and factoring them together for prediction. The predictive model in turn is built by an automated computer machine learning process utilizing historical data (Siegel, 2013). In the following the most common types of predictive models will be described:

- Fuzzy inference systems model non-linear and incomplete data. As fuzzy logic is based on linguistic rules, human knowledge and consequently the complex influences of explanatory variables on sales can be included. Using expert knowledge and machine learning the model is able to automatically reproduce the expert approach when performing intuitive forecasts (Thomassey, 2010).
- Neural networks also describe complex, non-linear relationships without any prior assumption about the underlying data-generating process. Generally the neural network consists of three layers: In the first layer weighted variables get introduced as input to the system. The hidden, middle layer then builds the model, so that the forecast will be presented in the output layer. To create the model the neural network has to be trained with some historical data (Alon, Qi, & Sadowski, 2001).
- As the training phase of a neural network based on a learning algorithm requires quite a long time, the extreme learning machine models have emerged as a very fast alternative (Sun, Choi, Au, & Yu, 2008).
- When it comes to classification, decision trees are among the most popular predicting modeling techniques. All the trees can be read as a series of "if-then-else" rules that ultimately generate a predictive value in terms of the assignment to a certain category using a segmentation algorithm (Abbott, 2014).
- Last but not least clustering is a prominent data mining technique whereby items with similar attributes are grouped together in order to reveal structure in the data. Moreover data clustering helps to identify, learn or predict the nature of new data items. As clustering algorithm K-means or K-nearest neighbor are used (Bari, Chaouchi, & Jung, 2014).

In the literature fuzzy logic based techniques as well as neural networks using historical sales, color, size, price and many other variables, including explanatory factors, as inputs exhibit a superior fashion sales forecasting performance in comparison to traditional forecasting methods and are especially useful for short-term forecasts. Due to their speed extreme learning machine models are regarded as very good candidates for sales forecasting in fast fashion companies (Liu, Ren, Choi, Hui, & Ng, 2013). Regarding the forecasting of new apparel items with no historical data, the clustering technique can be applied: First the historical items with similar sales profiles are grouped together, then links between the sales behavior and descriptive criteria are established, so that in the third step each new item can be classified to one sales profile according to its descriptive attributes. This procedure is detailed in figure 2 (Thomassey & Happiette, 2007):
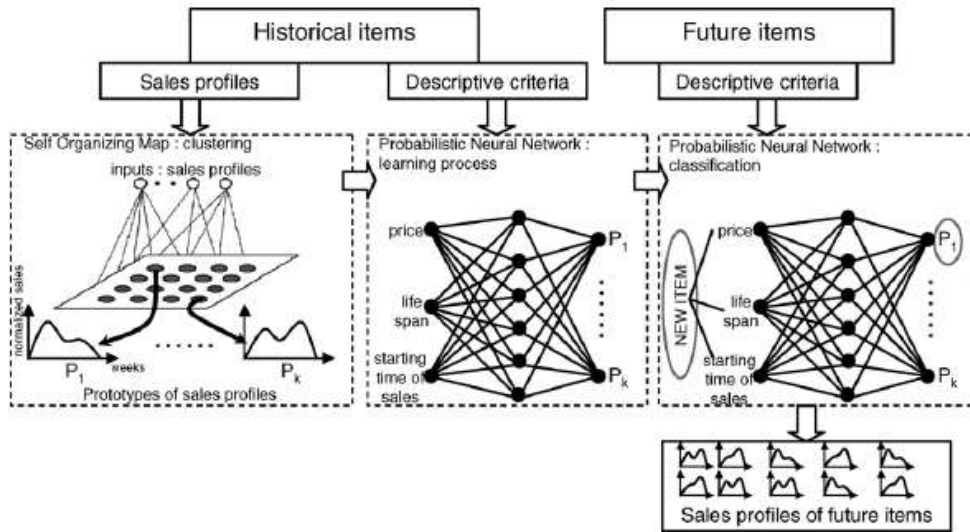

Figure 2: The Clustering and Classification Forecasting Model (Thomassey & Happiette, 2007, p. 1178)

In contrast to the application of predictive analytics to fashion sales forecasting, a lot more literature and applications can be found in the area of advertising, including target marketing and recommender systems, finance and risk analytics (Miller, 2014), fashion trend forecasting and design as well as manufacturing issues (Guo, Wong, Leung, & Li, 2011).

Although predictive models make about 20 – 30 % more accurate forecasts and overcome the limitations of traditional methods including speed, misspecification, biased outliers, assumption of linearity and the need of a huge amount of historical data (Finlay, 2014), Thomassey estimates that the sales forecasting in the majority of the fashion companies still consists of a baseline forecast, which is basically the sales of last year and which then get reworked and adjusted by the practitioner according to explanatory factors. Even though the result can be very accurate, this procedure has some important drawbacks: The number of explanatory variables taken into account as well as the number of items to be forecasted are limited; otherwise the analysis becomes too complex and imprecise. Generally qualitative adjustments are quite expensive, because they require a lot of time. Finally the results depend very much on the experience of the practitioner (Thomassey, 2014).

Having all the benefits of predictive analytics in mind the following questions arise: In which extent do fashion companies already make use of these advanced techniques for their sales forecasting and why have others not applied them so far?

3. Methodology

To obtain a richer, deeper understanding of the procedures of sales forecasting in practice and the reasons behind the different approaches telephone semi-structured interviews with experts from the fashion industry have been conducted. This is regarded as a very economical research technique, which allows to get direct and quick access to the insider-knowledge, experience and opinion of the practitioners and to reveal even deeper insights and practical problems directly from the field. In this context, an expert is defined as someone who has specific expertise in a particular area due to practical experience and at the same time carries certain responsibility. Consequently he or she is of less interest as a person than in his or her capacity of being an expert for sales forecasting (Bogner, Littig, & Menz, 2005).

3.1 Data collection

The study participants were purposively sampled based on the latest ranking of the biggest textile and clothing manufacturers and retailers in Germany – a list that contains all fashion companies with more than 50 million Euro turnover in Germany provided by the professional journal TextilWirtschaft in 2014. After eliminating discounters, furniture stores, small distributors without private label or without any contact to the end customer and generally companies with no headquarter in a Ger-

man speaking country, to make sure that all the interviews can be uniformly and unproblematically conducted in German, a list with the most important 108 companies remained to represent the German fashion industry.

All the 108 fashion companies have been contacted by telephone. After convincing the so-called gate-keepers the interview request and some pre-information including the introduction of the researcher, a short description of the research topic and objective, the general organizational framework and the intended use of the findings were sent via email to the potential interview partners (Kaiser, 2014). In total 24 experts participated in the interviews during October and November 2015, which leads to a response rate of 22 % confirming the relevance of the topic. The 24 companies participating represent all type of apparel firms: Most of them, 54 % offer clothes for women, men and children, sometimes additionally home textiles, whereas 25 % are specialized on womenswear, 17 % are specialized on menswear and one kidswear company. Among the participants were also two traditional department stores. Regarding the business model 50 % concentrate on their own stores in connection with an online shop, 42 % base their distribution mainly on wholesale partners and 8 % focus on mail order business and online shops. 43 % of the interview partners – 19 men and 5 women – were from purchasing and merchandise management and at 57 % from the sales and sales controlling department, especially at wholesale driven companies. Moreover the interviewees had a minimum of five years, in the average eleven years of experience within the area of sales forecasting; 71 % of them have an executive position.

Each telephone interview took between 25 and 50 minutes. A guideline was developed and pretested, in order to achieve certain comparability, a thematic structure and a co-expert status of the interviewer. Nevertheless the guideline was used in a very flexible way according to the conversational situation (Kaiser, 2014).

In the very beginning the interviewer once again introduced the research and the objective of the interview and expressed her thanks for the participation. As the opening question the participants should then introduce their positions and experience in the area of sales forecasting. During the interview each expert was asked several open questions on two main topics: First he or she should describe the current sales forecasting procedure, including if necessary responding to detailed questions of the interviewer regarding the explicit characteristics of the method, the handling of the specificities of the fashion industry and the satisfaction with the actual process. In the second block the expert was confronted with predictive analytics as a new forecasting method and asked to state his or her opinion on their potential in the future and the current obstacles to their application. On closing each inter-

view, the possibility of additional questions as well as the further proceedings were clarified, including the promise of the results (Bogner, Littig, & Menz, 2014).

3.2 Data analysis

All the interviews were audiotaped with the expert´s agreement and literally transcribed for analysis purposes. As the interviews were mainly aimed at gathering information and estimations of the experts, the transcription as well as the analysis focused principally on the content of what is being said (Dresing & Pehl, 2013).

Thus qualitative content analysis according to Mayring was used in order to systematically structure, summarize and finally analyze the data, comprising of the following steps (Mayring, 2007):

- *Analysis unit:* The textual material was divided into units for further analysis. In this study the respective answers to each question, consisting of ether several, coherent sentences or just one word, represented the analysis unit.
- *Category system:* Categories were deductively developed based on the question categories of the interview guideline and were therefore organized in a certain, thematic system. Then step by step every analysis unit was assigned to the corresponding category – every answer to the corresponding question. Although the categories were defined a priori, they were inductively checked and adjusted on the textual material.
- *Analysis technique:* The primary focus and objective of the analysis was the summarization of the material. Consequently, after categorizing the statements, the material was summarized and reduced to the essential points, paraphrasing the content supporting passages of each statement. Paraphrases with similar meaning again were bundled together.
- *Interpretation technique:* Finally the paraphrases of the statements of the different interview partners regarding each question category were compared. In order to get an industry profile, the paraphrases were summarized using quantitative evaluation measures like frequency distributions. The reasons behind distinct approaches and opinions were of course also analyzed.

The described, systematic content analysis approach should ensure the traceability of this research and at the same time achieve the quality criteria of reliability and validity (Mayring, 2007).

4. Results

4.1 Applied sales forecasting methods and used data

As the key objective of this research was to get an overview of the sales forecasting methods applied to the fashion business, the description of the current sales forecasting procedures by the experts was a fundamental first step. In general the sales forecasting process begins with the overall planning of the annual turnover for the next year, which in 54 % of cases is set top-down in advance, whereas 46 % take more of a bottom-up approach. At a surface level, all experts claimed to have a unique approach. Yet at a deeper level 23 out of the 24 interviewed companies base their sales forecasting on the same method: a combination of time series analysis based on historic data and qualitative adjustments.

> *Informant 7:* "Yes, precisely - in our company, it is a very retrospective considera-tion. This means that we operate strongly based on historical data."

> *Informant 21:* "The very first and easiest thing we do is a comparison with the previ-ous year, which means that sales figures from the past year get married in a certain way with sales trends from this year."

> *Informant 11:* "What we do is a mixture between historic data, if available, this has always been the issue too, and then there is also a meeting with buyers and mer-chandise planners. This meeting is about finding out the most important future trends in fashion business and consequently adjusting the forecast with a rather op-timistic or pessimistic trend. So we are mostly interested in data from the past (…) and then we add a coefficient – the trend."

Having a closer look at the time series analysis 82 % use only the data of the previous year or season on an either monthly or weekly base, because of the short life cycles and therefore the low comparability of the articles over several seasons.

> *Informant 11:* "No, this refers only back to the last year. The problem is, we always have a lot of modifications for our customer, we do not have many basic articles, which we are offering regularly every year. Of course we create some similar arti-cles, but most of them have a very short lifespan. (…) Only if there is a super similar product, we go three, four years back, but otherwise it is quite risky for a live cycle."

Nevertheless 9 % make use of the data of the last two years, in order to smooth out extreme deviations within one year. Another 9 % even refer back to the last three years to gain a clear tendency.

The historic data represent the input of the time series analysis. 63 % of the interviewed fashion companies work with real sales figures, whereas 37 % - only or mainly wholesale driven companies - utilize the order figures of their wholesale partners. Half of these companies complained that they do not have access to EDI (electronic data interchange) sales information of their wholesale partners, while the other half receive the real sales figures at least partly from some wholesale partners via EDI connection. Still this transmitted sales information is incomplete, which is the reason why it primarily serves as input for the development of new collections or the analysis of bad-best-seller lists rather than for the sales forecasting. Only one of the wholesale driven companies has the entire sales figures from their partners via EDI connection, so that they can base their sales forecasting on the real sales figures to the final customers.

> *Informant 9:* "Unfortunately not all of our customers, even though we are in the year 2015, are well connected. And in addition to that there are 20 – 30 % who do not want an EDI connection and 10 – 20 % who have their own system, which is not compatible with our system. The interconnectedness is definitely expandable."

> *Informant 22: "*This is exactly the point; we do not have the real sales figures of our wholesale partners. This is not yet included in our sales forecasting."

21 out of the 24 interviewed companies additionally run an online shop, which can be regarded as a huge data source. Still 86 % do not include the (customer) data generated therefrom in the sales forecasting. Three companies use the online shop as an indicator of potential bestsellers, but only one company analyses the online purchase history of their customers and the customer journey between the segments for the sales forecasting. Moreover none of the companies who offer a customer card integrate the sales and customer data therefrom into their sales forecasting. The result of the time series analysis depending on the aggregation level of the input data is in 25 % of the cases a forecast per label or segment, in 42 % a forecast on product group level and in 33 % a forecast of the quantities on item level.

As time series analysis - a purely statistical method - is not satisfactory for sales forecasting in fashion business, all experts emphasized that it only provides basic data. The forecast additionally gets qualitatively adjusted. This way on the

companies add strategic corporate objectives as well as explanatory factors to their forecasting. The qualitative adjustments happen in consideration of bad-best-seller lists, fashion trends, the current collection, the latest turnover trend, assortment and area management, price ranges and stocks. Several interviewees indicated that buyers and sales personnel adjust the forecast in accordance to their experience, fair visits, trips abroad, exchange with other companies, information from market research institutes and feedback from retailers. Consequently the expertise of these employees plays an essential role within the forecasting process.

> *Informant 21:* "Basically [the forecast] is also strongly based on the experience of the people (…) There is definitely more information than just the sales history. There are mega trends influencing the whole fashion market. Therefore we have colleagues who are away on business fairs or are working in the stores. From here the information is bundled and rewinded to the product development."

> *Informant 15:* "Additionally there are three factors which I take into account. First public holidays, secondly I have to clean up the data from marketing actions in the past causing abnormalities in the data, and the third factor are mega trends."

In addition most of the mainly or partly wholesale driven companies wait for the first orders of their wholesale partners as an indicator, in order to project them into the future and again adjust the forecast. A grossing-up factor is built to bring the actual order trend down to the individual items. The same projection logic is applied within the catalogue business, after the first order week.

30 % of the experts also mentioned that the sales forecasting process for the NOS (never out of stock) articles differs in that an automatic replenishment system exists, which can rely on historic data from several years. Therefore the NOS articles can be easier systemized and in the end better forecasted. This is also the reason why one company with a significant percentage of NOS items renounces time series analysis and qualitative adjustments. Instead a standard order rhythm is employed, projecting the incoming orders through algorithms into the future.

As a first and direct finding it should be noted that apart from this NOS driven company none of the remaining interviewed companies already applies predictive analytics as a sales forecasting method. Though several experts expressed their interest in the implementation of predictive analytics in the near future, only one company will actually soon go live with a new software including predictive analytics as sales forecasting module.

4.2 Characteristics of the applied sales forecasting methods

The majority, 46 % of the interviewed companies carry out two forecasts per year, which cover respectively the time horizon of half a year. 30 % just realize one forecast for the whole year; however this usually gets updated half-yearly. It became quite clear that most of the fashion companies still think in the traditional two seasons: spring/summer and fall/winter. Consequently 70 % offer two (main) collections per year, sometimes with two smaller pre or post season programs in between. In order to include short-term developments and trends, some updates are necessary. Thus half-yearly, monthly or most frequently weekly updates are made, depending on the reporting cycles of the company. Some, mainly wholesale driven companies update their forecasts even daily, especially during the order phase. In general, the more collections and the more new, innovative fashion items, the more forecasts and updates are conducted. This ranges up to six, ten or even twelve collections per year with respectively as many forecasts and shorter time horizons according to the sales period of the collections.

The fashion industry is known for its long lead times. Likewise, the sales forecasting is done in 22 % of the interviewed companies from three-quarters up to one year in advance, in 57 % half a year in advance; 21 % have a lead time of only three to five months between the sales forecasting and the delivery of the products. This is the reason why the experts several times compared the sales forecasting to "taking a look into the crystal ball".

The distinction of the sales forecasting regarding different distribution channels or regions plays a subordinate role. One third of the companies do not treat the online shop differently, so that despite the particular processes and data it is forecasted like a store or a customer. On the contrary two third have a separate forecasting for each channel, whereby above all the data base and the projection method between the own retail and wholesale business differs. Another prominent topic among the interviewed experts was that the forecast for their own stores has to be finished earlier in comparison to the wholesale business and that the assortment in the online shop is broader, deeper and more fashionable, consistent with a younger target group. The regional adjustment of the forecasting happens in 78 % automatically, as the quantities and assortments are planned on store or wholesale customer level. Especially the national forecast differs from the export countries. In contrast 22 % do not have any regional distinction regarding their sales forecasting.

4.3 Sales forecasting management

To investigate the functional integration the experts were asked which departments are usually involved in the sales forecasting process. Every participant first named the buying followed by the sales division, together representing the key responsible departments. About half of the experts mentioned a collaboration with the design and controlling, far less with marketing, production and merchandise management. Although sales forecasting became very analytic, only one company reported the involvement of an IT data analyst. Generally 79 % described a close collaboration, having the input of all important functional areas in the forecast. Still in 21 % each functional department independently develops its own forecast.

> *Informant 1: "*In the end everybody works separately and the machine then brings it together to an overall plan. We have once tried coordination meetings, but until they are ready, we are running out of time."

The role of the top management mainly consists in approving the developed forecasts or setting the annual overall turnover in case of a top-down management approach. In terms of the significance, the majority (75 %) emphasized the great importance of sales forecasting, as it affects the whole supply chain. Nevertheless 25 % stated that sales forecasting may be necessary, but because precise forecasts have never come true, a huge effort is not worth it.

As for the performance measurement, 75 % of the interviewed companies evaluate the accuracy of their sales forecasting as a plan-actual-comparison on item level, which is principally realized monthly, but with an increasing tendency to weekly or even daily, in order to react as quickly as possible on market trends. On the contrary 25 % do not measure the forecasting performance. These companies try to gather a learning effect through bad-best-seller lists.

4.4 Difficulties and satisfaction of the current sales forecasting process

When it comes to the specificities of the fashion industry the interviewed experts agreed that one of the biggest challenges regarding the forecasting consists of the extreme variations in sales primary caused by external factors, with the result that a few best-sellers become very strong and on the other hand bad-sellers remain very poor. Another frequently mentioned problem was the conflict between the fast pace of trends and the long lead times, which makes short-term reactions on the

market extremely difficult. In addition to that the fashion companies complained about constant discount battles and a high competitive pressure. Many interviewees also see a major problem of the fashion industry in the management of the goods, which is not orientated to the needs of the customer. At the same time customer behavior gets more unpredictable and spontaneous.

To handle extreme fluctuations and fast-moving trends most of the interviewed companies keep an open-to-buy budget for the reorder of best-sellers or for trendy flash programs and carry out in-season management. Therefore some experts also stressed their close cooperation with suppliers or wholesale partners. A rarely mentioned action was the strategic choice of the production countries, not too far away, so that the reaction and transportation time get reduced.

*Informant 11: "*We always try to produce as lately as possible. Therefore we produce in countries like Morocco, where we can react quickly. (…) But on the other side we have to achieve a greater flexibility with our far-east suppliers, by only fabric or capacity blocking or by producing white items and making the color in the very last step of the process (…) sometimes not before it comes to Europe."

More popular among the interviewed experts were price reductions as well as spontaneous marketing actions in response to market variations. Moreover the expertise of buyers and sales persons adjusting the forecasts to external factors and trends plays an essential role. Still some companies - wholesale-driven specialists - did not see themselves much affected by the specificities of the fashion industry, having a stable product range and consequently steady sales and stock volumes. When it comes to new items without historical sales data – another specificity of the fashion industry – 88 % of the interviewed companies refer to the sales data of comparable articles. 42 % additionally indicated the importance of experience and feedback from wholesale partners and finally 29 % used to initially plan small quantities and simply accept a certain degree of risk.

When asked for their satisfaction with the current sales forecasting, 29 % of the participative experts stated their discontent, whereas 71 % were satisfied, even though mainly with the process, not yet with the system-based support. This was consequently the most frequent answer (83 %) regarding potential for improvement. The fashion companies want a better system-based support, in order to bring together sales data, product data, customer data and marketing data and to conduct more detailed analysis on item and store level. This leads to a better overview and data base for the decision makers, superior customer orientation and less depend-

ence on subjective assessments. Besides several experts complained about availability and validity of sales and customer data, expandable EDI connection with wholesale partners, acceptance of the sales forecasts and the lead times. Interestingly, a few respondents wish to simplify the sales forecasting process instead of the introduction of computer-based systems.

4.5 Application and potential of predictive analytics to sales forecasting

First of all the familiarity with predictive analytics was queried. 42 % of the experts were not at all familiar, 58 % knew the basic idea, but emphasized that they are just at the beginning of the change process towards Big Data. Regarding the application only one company already worked with predictive analytics within the NOS area and another one was about to implement it as a forecasting tool. The mathematical model behind it probably is a neural network with self-learning algorithms.

Nevertheless, when asked about the future potential of predictive analytics as sales forecasting method in fashion business, only two out of 24 interviewed companies – a wholesale driven specialist and one department store – denied its huge potential. All the others saw a great opportunity in predictive analytics, as it could represent the desired system-based support. Many of these experts identified the most potential in the forecasting of NOS items, as they have large historic data sets. Additionally they would like to use predictive analytics within the marketing area, analyzing customer data for target marketing and shopping basket analysis. 58 % of the interviewed companies already applied predictive analytics for this purpose to the marketing, but not yet to the forecasting process. The wholesale driven companies mainly restricted the potential on the business with end customers, since predictive analytics is based on the recognition of patterns in a huge data set.

As another objective of this research was to find out the reasons why predictive analytics is not yet widespread in the fashion industry, the companies were asked to describe obstacles to the implementation. The most frequently mentioned problem relates to the data and its availability, quality as well as variety. But as a condition for the application of predictive analytics sales, customer and article data must first be maintained and united, which requires great effort and certain IT-infrastructure. Another relevant topic was the complexity of predictive analytics, leading to a lack of comprehensibility and therefore to a lack of confidence and acceptance by the users. At the same time many experts indicated that they currently do not have the resources regarding time, costs and qualified personnel to introduce predictive analytics. In the end it is always a cost-benefit issue. Some experts also com-

plained that there are too many external, soft factors causing extreme variations, which cannot be modeled by any system. Finally, when it came to the clustering technique in order to forecast new items, the company already using predictive analytics for NOS articles mentioned the difficulty to find comparable attributes among the items and the problem that customer behavior is still not corresponding to these attributes and therefore unpredictable. Examples of dominant obstacles are listed with participant comments in table 1.

Obstacle	Participant Comment
Data availability, variety and quality	*"In my opinion the problem is the quality of the data, as we need to correlate a lot of data in various constellations with each other. (…) Then we have to make huge efforts to enter as a first step all the basic product data, attributes and cluster assignments into the system."*
	"(…) we have not yet structured data from all involved departments."
	"At the moment the biggest obstacle is the IT-infrastructure. As a first step we have to bring together the different data sources - sales data, customer data and marketing information."
	"At first we have to introduce a customer card and collect data. (…) With this the desire to analyze all the information will grow. This will facilitate the investments for predictive analytics."
	"In our case it is the EDI connection with our wholesale partners and therefore the availability of the sales data."
	"If you want to do it properly, you need the sales data from everybody, worldwide. I consider this utopia."
Lack of comprehensibility and trust because of the complexity	*"I am opposed to things passing automatically through machines (…) In the end there are successful buyers behind it and without them you can forget any system."*
	"The challenge is to connect predictive analytics with the employees, so that the system pre-defines a forecast, which is understood and adjusted by the operatives. (…) The operational level will not accept it, if it is not understood by them."

"The biggest problem is the acceptance of this method by the decision-makers, who sometimes make the decisions driven by vanity. A long-serving buyer should now count on an automatic data analysis? It is not that simple."

"I experienced that, as soon as a system or algorithms calculate the forecast, the user cannot interpret it anymore and tends to either copy it to 100 percent or totally mistrust the system, which leads to an acceptance rate of zero percent."

"It always involves change. This needs time and people have to be willing. (…) First you have to explain them the cost-benefit effect."

Lack of resources	*"We have enough data from the POS, but sometimes simply not the resources to analyze them respectively."*
	"Predictive analytics has no longer been pursued because of the costs, capacities and resources."
External factors	*"I have to say quite clearly that the systems can only be as good as the user, who feeds it. A lot of information has to be provided for a good result. The system has to know all the factors, influencing the sales."*
	"Empirically the more variables, the more complex and imprecise the forecast. With all the factors of the fashion industry, it is not calculable, forget it. Some logic, common sense and a good data base are much more worth."
Unpredictable customer behavior	*"Of course we can get some more insights, but this should not be over-estimated. For this our industry is too fast and difficult to predict. (…) It is incredibly hard to grab the end consumer, as he has so many opportunities nowadays due to omni-channel strategies."*
	"The problem is that the attributes of the items are not generalizable. First it is very difficult to find comparable attributes. Secondly the customer does not behave according to these attributes. For the customer the first impression counts, which sometimes has nothing to do with the attributes."

Table 1: Obstacles for the application of predictive analytics with participant comments

5. Discussion and implications

Initially it has to be stated that regarding the application of different sales forecasting methods to the fashion industry the research results clearly confirm what Thomassey assumed in former studies: The majority of the fashion companies still make use of simple time series analysis, basically sales of last year, combined with qualitative adjustments in order to incorporate the specificities of the fashion industry. Thus the interviewed companies give enormous weight on the employee´s personal estimation and expertise. As already evaluated above this approach is quite simple, comprehensible and long-established, but unfortunately not suitable for big data sets and less analytic. Likewise also many experts, mainly in controlling positions, showed themselves unsatisfied and therefore willing for a change in the sales forecasting method. The top answer to the question "What would you do, if you could change one thing within your current sales forecasting process?" was to introduce a better system-based support, in order to become more analytical and achieve certain security in times of extreme fluctuations, fast pace and unpredictable customer behavior. Predictive analytics could serve not only as a computer-based support system, but also as an automatic forecasting tool.

The fact that almost half of the interviewees, above all wholesale-driven companies, have never heard about predictive analytics so far and only one company already applies it (even though only to the NOS items) shows, that the fashion industry is just at the beginning of its transformation towards computer-based forecasts. Interestingly predictive analytics enjoys a broader application in the marketing area, when it comes to the analysis of customer data and the targeted selection of customers for a certain marketing action. The interest in the topic definitely exists. Regardless of the size, segment and distribution strategy of the companies as well as regardless of the department or experience of the interviewed experts 92 % see theoretically great potential and the future in predictive analytics, especially in the area of the more stable NOS items. But because of missing empirical knowledge about the practical success of predictive analytics within the fashion industry the interviewed experts are still very skeptical. As shown in table 1 there are a lot of obstacles that have to be overcome first, so that the companies did not seem to be ready yet for such a big change. Besides the described problems concerning the data, complexity, acceptance, resources, explanatory factors and customer behavior, the mere description of the current sales forecasting process by the experts revealed that generally their mentality has to be changed.

In the following some practical implications are presented, in order to finally provide the right analytics culture in terms of an organization´s attitude to data, analytics and automated decision making, driven by predictive analytics, as base for this transformation (Finlay, 2014).

Concerning the number, horizons, update intervals and lead times of the sales forecasts the fashion companies still think too rigidly in the long wholesale rhythms of spring/summer and fall/winter season. However, given the nature of the (fast) fashion industry, very short-term forecasting and quick lead times are ever more important. Therefore the interviewed fashion companies have to become faster and realize more, short-term orientated forecasts taking advantage of the speed of predictive analytics. This would also lead to an improvement of their flexibility and reaction time.

Data as the input of every forecasting and its availability has always been a big issue in the interviews. Of course, the first step consists of obtaining the real sales figures from the wholesale partners, of collecting some customer data and of merging all the data from the different departments, but at the same time the fashion companies must recognize the value of that data. Too many companies indicated, that they have an online shop as well as a customer card, but they do not use or integrate this information in the sales forecasting. But how can they benefit from it, if not analyzed and integrated? To value the data is also an initial step to become a data driven company - another condition for the successful implementation of predictive analytics. Decisions will become more evidence-based, drawn from what predictive analytics gathers from the data. This does not mean that experience and human judgement are unimportant, but they will lose weight compared with the basic sales forecast delivered automatically by the predictive analytics system.

Regarding the sales forecasting management it is essential to have the commitment of senior managers who highlight the importance and the big impact of sales forecasting on the whole supply chain, which is currently not rated highly enough. In addition to that the top management must support the use of predictive analytics. This will also facilitate the allocation of sufficient financial and human resources. Up to now only one of the interviewed companies mentioned the involvement of data analysts in the sales forecasting development. In the future a skilled analytical team is needed to support, explain, train and convince the users of predictive analytics. Thus the understanding and consequently a better acceptance rate among the users should be realized, too. In general the functional integration not only of the business intelligence team, but of the whole sales forecasting process could be improved, so that the input from all the different areas is recognized and

forecasting is seen as a cross-functional process that serves the entire company. As the sales forecasting will become more analytical, the accuracy of the forecast on item level must be measured, in order to constantly check and improve the system. At the moment the performance measurement of the forecasts only plays a subordinate role and should not be confused with the sales performance of the items.

Finally the widespread top-down approach setting overall sales targets instead of basing the business plan upon the sales forecasts, leads to frustration among the forecasting personnel. On the other side a bottom-up approach emphasizes the importance of an accurate sales forecasting and should consequently be integrated in the top-down target setting procedure.

During the transformation process the three-stage model described before can serve as an orientation. In the very first step the companies should concentrate on the generation of a clean as well as complete data base and the application of descriptive analytics. In doing so essential basic analyses of the data are performed and first insights can be discovered. Only then and after establishing the necessary analytics culture predictive analytics can be introduced. In the last step prescriptive analytics should convert the fashion companies finally into proactive rather than reactive market players. Potential for improvement can be found within the handling of market fluctuations, which often consists of very reactive price reductions and marketing actions.

As the sample size of this research was considerably large including a great variety of different fashion companies in terms of the size, segments, distribution channels and strategies the findings can be regarded as significant, reflecting a broad industry profile. Nevertheless, future research should be conducted including the pure online-players or fast fashion companies, who are probably more advanced in the topic of predictive analytics and could report about their experience in practice. Though this study makes a substantial contribution to the literature, since the status of predictive analytics within the fashion industry has never been investigated through expert interviews before. In this way difficulties could be identified, which for the moment prevent the fashion companies from the application of predictive analytics on their sales forecasting.

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