Traditional versus Big-data Based Fashion Trend Forecasting: An Examination Using WGSN and EDITED

Mikayla DuBreuil, Sheng Lu
University of Delaware

Effective trend forecasting is critical to a fashion firm's success—affecting its ability to build a product line that suits consumer preferences, generates sales growth, and make profits (Rousso & Ostroff, 2018). For decades, fashion trend forecasting, such as predicting the popular styles, colors, and patterns is typically conducted by professionals with a strong educational background in design or art (McKelvey & Munslow, 2011). However, with the emergence of data science, a growing number of fashion firms are exploring the possibility of using big-data tools to forecast fashion trends (Israeli & Avery, 2018; Chaudhuri, 2018).

The purpose of this empirical study is to compare the similarities and differences of the results of traditional human-based fashion trend forecasts with the ones generated by big data[1]. While existing studies have attempted to explore the application of big data in the business aspects of fashion, such as predicting retail sales and managing inventory, the academic literature on the usage of big data for fashion trend forecasting as a *creative activity* remains limited (Choi & Hui, 2011; Ren, Chan & Ram, 2017). Thus, the findings of this study will fulfill the research gap and significantly enhance our understanding of both the advantages and limitations of using big data for fashion trend forecasting. The findings of the study will also help fashion firms and educational programs gain more insights into the changing nature of the fashion apparel industry, which is becoming ever more technology-intensive and data-driven (Grammenos, 2015).

Reviewing the existing literature shows there is no consensus regarding the effectiveness of using big data analytics for fashion trend forecasting. On the one hand, some studies suggest that because consumers' fashion taste stays relatively stable over time, it is feasible to use historical data such as purchasing history to predict what fashion patterns, colors or styles consumers may like in the future (Gaimster, 2012; Israeli & Avery, 2018). Some also argue that compared with the traditional human-based approach, big data may improve the accuracy of fashion trend forecasting as it is more factual-based rather than relying on designers' "opinionated guesswork" (Tehrani & Ahrens, 2016). However, some other studies contend that the unpredictable nature of fashion and consumers' expectation for originality and uniqueness demonstrated in new season's design make it challenging to rely on historical information to forecast what fashion trends might be popular in the future (Ming, Zhang & Leung, 2004; Israeli & Avery, 2018).

[1] In this study, "big data" is defined as huge datasets whose size is beyond the scope of typical statistical or database software tools to store and analyze (Lee & Kang, 2015).

Given the competing theoretical views, in our study, we empirically investigated the similarities and differences of the results of fashion trend forecasts conducted in the traditional approach versus those based on using the big-data tool. For cases representing the traditional human-based approach, based on data availability, we collected all the 20 trend forecasts produced by WGSN for womenswear in the Spring/Summer 2018 season (S/S 2018) targeting the U.S. retail market (WGSN, 2019). WGSN's trend analysis is consistently cited throughout academic literature as one of the most trusted sources for traditional fashion forecasts (Jackson, 2007). Each of these 20 collected forecasts focuses on a particular product category (such as "Dresses & Skirts") during a specific time-segment of the S/S 2018 season (such as "Spring transition" running from January 30 to March 30). In correspondence with these 20 traditional trend forecasts, next we generated 20 comparative trend forecasts[2] by using EDITED, a big data analytics tool which covers the real-time pricing, inventory and assortment information of over 30 million apparel products at the Stock Keeping Unit level sold by more than 90,000 brands and retailers in the U.S. market since 2016 (EDITED, 2019). When using these millions of data points to generate trend forecasts, we particularly considered three factors deemed as the most critical for market-popular fashion items, including inventory level, retail price & markdown, and frequency of replenishment (Sterlacci & Arbuckle, 2009; Balar, Malviya, Prasad & Gangurde, 2013).

Then, following Jackson (2007)'s principles of fashion forecasting, the two researchers did a content analysis of each of these 40 paired trend forecasts (i.e., 20 by WGSN and 20 by EDITED) and coded their respective prediction for *color* (such as "red" and "green"), *patterns* (such as "Long Sleeve" and "V-neck") and *design details* (such as "Stripes—Parallel bands of color") (Holsti's reliability>0.9). Based on the results, the two researchers further rated the degree of similarities of the paired trend forecasts generated by WGSN and EDITED according to the following coding scheme[3]:

- Value=2 (Very similar): EDITED's forecast matched more than 50% of WGSN's forecast
- Value =1(Similar): EDITED's forecast matched some but less than 50% of WGSN's forecast
- Value =0 (Different): EDITED's forecast matched none of WGSN's forecast

Results of Independent Sample T-test (N=20)

Variables/Hypotheses	Mean=0	Mean=1	Mean =1.5	Mean =2
Design details	5.627**	0.000	-2.814**	-5.627**
	(0.00)	(1.00)	(0.01)	(0.00)
Patterns	22.584**	10.376**	4.273**	-1.831
	(0.00)	(0.00)	(0.00)	(0.83)
Color	13.581**	4.819**	0.438	-3.943**
	(0.00)	(0.00)	(0.666)	(0.01)

**: $p<0.01$ at the 95% confidence level; *: $p<0.05$ at the 95% confidence level

Additionally, to evaluate how statistically significant is the similarity of WGSN and EDITED's fashion trend forecasts, we conducted the independent sample test for the rating scores in the previous step (Ott

[2] Each big-data generated trend forecast focuses on the exact same product category of womenswear targeting the U.S. market during the exact same time segment of the S/S 2018 season as their paired WGSN forecast did.
[3] For example, for women's "Dresses & Skirts" during the S/S 2018 "Spring transition" season in the U.S. retail market, WGSN forecasts the trendy design details to be "plain; checks; and stripes", whereas EDITED's predictions are "plain; patterned; floral; and stripes." Because more than 50% of WGSN's trend forecast was captured by EDITED's forecast, we rated "2" for the variable *Design details* in this case.

& Longnecker, 2015). The results show that at the 95% confidence level: First, we couldn't reject the null hypothesis that the mean value for *Design detail* is 1 ($p=1.00>0.05$), i.e., WGSN and EDITED's forecasts are "Similar." Second, we couldn't reject the null hypothesis that the mean value for *Patterns* is 2 ($p=0.83>0.05$), i.e., WGSN and EDITED's forecasts are "Very similar." Third, we couldn't reject the null hypothesis that the mean value for *Color* is 1.5 ($p=1.00>0.05$), i.e., WGSN and EDITED's forecasts are between "Similar" and "Very similar."

The findings of the study have two important implications. First, the result confirms the overall feasibility and great potential of using big-data tools to forecast fashion trend as a creative activity. Second, the findings suggest that big-data tools have the strengths in forecasting color and apparel pattern, but may not be most effective in predicting design details which seem to be shaped by more unpredictable and complex factors. Future studies can expand the research scope to other product categories such as menswear and childrenswear or fashion seasons and continue exploring how big-data tools can contribute to fashion trend forecasting.

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