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DATA ANALYTICS AND APPLICATIONS IN THE FASHION INDUSTRY: SIX INNOVATIVE CASES

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Introduction

More and more business activities are becoming digitized, and fashion companies are no exception. With the development of mobile devices, the Internet, social networking services (SNS), and numerous other new technologies that can create data (Kauffman, Srivastava, & Vayghan, 2012), fashion companies have easy access to a myriad of new information sources, such as website click-through rates, browsing histories, and website feedback and social media comments. Much of this information is useful to the fashion industry (McAfee & Brynjolfsson, 2012). For example, customers' potential interests and demands and customers' sentiments towards brands and products can be utilized for future product design, sales forecasting, trend-spotting, product recommendations, personalized service design, and decision-making. To increase competitiveness and succeed in a data-filled environment, companies must be highly capable of extracting valuable insights from existing data and applying these insights to actionable practices (Kauffman et al., 2012). The fashion industry is changing rapidly, particularly due to the short life cycle of fashion items and fickle customer demands (Ren, Hui, & Choi, 2018). This quick pace of change requires fashion companies to update their strategies according to market demands and technology innovations in near real time to beat the competition (Lake, 2018; Thomassey & Zeng, 2018).

Data analysis is important both in the past and the present in the fashion industry. Different types of statistical approaches, such as time series analysis, regression analysis, and multiple factor analysis, have been utilized for fashion sales forecasting (Liu, Ren, Choi, Hui, & Ng, 2013; Ren et al., 2018), apparel manufacturing decision-making (Jelil, 2018), and textile sensory evaluation (Xue, Zeng, & Koehl, 2018). These approaches are well-explored, fast, and useful ways to handle linear relationships among variables and are efficient for analyzing structured data (Jelil, 2018; Ren et al., 2018; Xue et al., 2018). But nowadays, various types of fashion data are available, and they can be structured, semi-structured, or unstructured (e.g., text and image data in customers' reviews and SNS and numeric data from sales reports). It is challenging to use classical tools to interpret semi-structured and unstructured data (Tan, Zhan, Ji, Ye, & Chang, 2015) because complex nonlinearity among diverse variables cannot be handled by traditional tools that cause the loss of valuable information from the data (Jelil, 2018; Xia, Zhang, Weng, & Ye, 2012; Xue et al., 2018). Also, these classical methods usually have strict requirements for the size and distribution of the data set (Xue et al., 2018). When the data set is relatively small, such as one for forecasting new product sales, which is a lack of historical sales data, or when the data set is extremely large, it is challenging to use traditional approaches for comprehensive analysis (Liu et al., 2013; Tan et al., 2015). Furthermore, data integration and analysis have traditionally been done at a regular interval (e.g., daily, weekly, monthly), but those intervals can no longer satisfy the demand for real-time data insights. Due to the large volume of data generated every second, if a company cannot utilize these data in a real-time manner, the data will lose some value (Liu, Iftikhar, & Xie, 2014).

With the evolution of data, big data analysis has emerged as a popular new data analysis field over the past decades, and it represents complicated and intelligent data analysis (Chen, Chiang, & Storey, 2012). Big data is commonly defined as the four Vs (Acharya, Singh, Pereira, & Singh, 2018): *volume*, referring to the enormous amounts of data; *velocity*, which stresses the high speed of data generation and/or the high frequency of data delivery; *variety*, which relates to the various formats and sources of data; and *value*, which highlights the beneficial insights that can be extracted from these data (Acharya et al., 2018). These four characteristics of big data correspond to the characteristics of data generated under the trend of digitalization and constitute the complexity of big data. As of 2018, 2.5 exabytes of data are created each day at our current pace (Marr, 2018). That amount of data is expected to grow to 35 zettabytes by 2020 (Tan et al., 2015). According to Marr (2018), there are over 40,000 searches completed on Google every second, on average, which serves to show the high velocity of big data. Data from Google Analytics, Google Trends, social media, GPS signals, sales data, customer text feedback, and the images and physiological data collected by sensors in smart clothing can all be counted as constituting fashion big data. Because of the highly valuable insights that can be extracted from big data, it enables fashion firms to become resourceful in handling various challenges and gaining competitiveness (Acharya et al., 2018; Tan et al., 2015). However, implementing big data analytics requires both highly capable technologies and organizational flexibility (Acharya et al., 2018).

With the development of computing technologies, many artificial intelligence (AI) based methods are proving to be more versatile, efficient, and accurate than some pure statistical approaches at getting valuable insights from data (Guo, Wong, Leung, & Li, 2011; Jelil, 2018; Liu et al., 2013; Ren et al., 2018; Xue et al., 2018). These AI-based methods are competent at handling structured, semi-structured, and unstructured data; can effectively solve nonlinear problems and noisy data; precisely interpret data; and have requirements for size and distribution of a database that are not strict (Liu et al., 2013; Xue et al., 2018). They include genetic algorithms, fuzzy logic, machine learning, and so on (Guo, et al., 2011; Jelil, 2018; Liu et al., 2013; Ren et al., 2018; Thomassey & Zeng, 2018). Machine learning is a field that enables computers to learn to perform a task from a training data set and then apply what they learned to a new data set to perform the same task, with minimal human intervention (Louridas & Ebert, 2016). It is a large subset of AI technology, which includes neural networks (Sze, Chen, Yang, & Emer, 2017). Artificial neural networks are inspired by the workings of the biological brain (Goodfellow, Bengio, & Courville, 2016) and mathematical theories of learning, which enables the machines to learn from input data (Guo et al., 2011). Neural networks consist of a set of processing units, and the organization of these units determines the topology of the neural networks. Deep learning refers to deep neural networks (Sze et al., 2017), which breaks required complex mappings into multiple simple connected mappings (layers) for computers to more easily understand input data (Goodfellow et al., 2016). These advanced data analysis tools have a promising performance in garment design (Guo et al., 2011; Liu, 2018; Liu, Zeng, Bruniaux, Tao, Kamalha, & Wang, 2018), fashion-item image detection (Colson, Coffey, Rached, & Cruz, n.d.; Krishnan, 2019), apparel manufacturing related decision-making (Guo et al., 2011; Jelil, 2018; Sirovich, Craparotta, & Marocco, 2018), and fashion retailing (e.g., sales prediction, fashion recommendation, supply chain management) (Au, Choi, & Yu, 2008; Guo et al., 2011; Liu et al., 2013;Ren et al., 2018; Xia et al., 2012) on an experimental basis.

With the widespread availability of big data and the rapid development of data analysis techniques, companies are experiencing a data-driven revolution in management (Acharya et al., 2018). Despite the necessity of these new approaches for business success, not all fashion firms apply them. Further, while many tools have become open source (and thus more accessible), applying these advanced data analysis techniques is still challenging because of the need for advanced technological capabilities (Akter, Wamba, Gunasekaran, Dubey, & Childe, 2016). This requires companies to acquire related human and technical resources, shift their cultures from well-placed people decisions to data priority, and prepare other necessary resources before seeing positive results (Porter & Gogan, 2013). Furthermore, data analytics and applications raise common concerns about data privacy and security, and there is a lack of information about fashion industry practices using these advanced data analyses.

Motivated by the power of the data analytics trend and the lack of articles systematically exploring the intelligent data analytics utilized by fashion retailers, this paper seeks to give examples of data analytics applications in the fashion industry and discuss the benefits and challenges of these applications through reviewing the literature regarding these six companies' practices. This paper will provide both industry experts and academics with an overview of data analytics in the fashion industry, as well as an inspiration to implement suitable data analysis techniques in their own businesses and research. A potential future research direction is discussed in the Conclusion.

Amazon's Echo Look, Amazon's StyleSnap, Burberry's Customer 360, Gap Inc.'s new design process, Ralph Lauren's PoloTech Shirt, Rent the Runway's (RTR) operations model, and Stitch Fix's operations model were selected to be the fashion industry cases for this study. These six companies have different business models and uniqueness in applying data analytics in their businesses, which could represent different areas of the fashion industry. Amazon is the American e-commerce company that is the world's biggest, which shows the great capability of technological innovation for the fashion industry. Burberry is a well-known luxury brand that has been investigating the capabilities of data analytics to offer customer's personalized services. Gap Inc. is a traditional mass retail brand that failed to respond to the market and is trying to utilize big data analytics to restore its business. Ralph Lauren is the first main luxury brand to invest in smart clothing, and it has relied on data analytics to aid in designing the functions of its PoloTech Shirt. RTR's new fashion rental business model requires the support of data analytics.

Stitch Fix’s innovative business model is driven by data: sending customers fashion items based on analysis of customer data by both algorithms and stylists.

Review of Industrial Literature

Amazon

Company description.

Amazon is an American technology company founded in 1994 by Jeff Bezos that is focused on e-commerce, artificial intelligence, media streaming, and cloud computing. It began with selling books online then expanded to selling electronics, furniture, video games, apparel, food, Amazon devices such as the Amazon Echo and Kindle E-reader, and more. Amazon became the largest e-commerce company in the United States in 2008, and the company’s revenue reached around $233 billion in 2018 (Mims, 2019). Amazon has also become the leader of the world’s cloud computing services (Mims, 2019).

The market value of global apparel and accessories is more than $1,000 billion and the profits of apparel and accessories are greater than those of other categories of products, such as electronics or food (Nicolaou & Hook, 2018). Thus, investing in apparel and accessories will earn Amazon the funds to achieve other ambitious investment plans (Nicolaou & Hook, 2018). Amazon has always been considered as only an online basic fashion product retailer (Nicolaou & Hook, 2018). However, in recent years, Amazon has made significant efforts to participate in the fashion industry (Stevens, 2018) to garner more market share, such as by launching private label fashion brands and introducing Prime Wardrobe, Echo Look, and StyleSnap. There are currently more than 180 private label and exclusive clothing, shoes, and accessories brands on Amazon, and they account for 40% of Amazon-owned private labels and exclusive brands across all categories (Smith, 2019). In 2018, Amazon launched its “try before you buy” program, Prime Wardrobe, exclusively for US Prime customers (Keyes, 2018). This initiative provides customers with a seven-day trial period to try on fashion items and find their favorite styles and fit before they buy. This program is intended to partially solve the problem of customers being unable to try on apparel when shopping online (Keyes, 2018).

Amazon has made substantial progress in the company’s fashion industry goals. According to predictions by Wells Fargo (Franck, 2018) and Morgan Stanley (Thomas, 2018), Amazon will have overtaken Walmart to become the leading apparel retailer in the United States with their 2018 retail sales (Frank, 2018; Thomas, 2018). Furthermore, their market share has increased by 1.5% since 2017 (Thomas, 2019). Amazon has also dominated the online apparel and footwear market, which accounts for 35% of the company’s market share, and the gross merchandise value (GMV) of Amazon’s apparel and footwear sales approached $25 billion in 2017 (Franck, 2018).

Initiatives on data analytics.

Amazon is also known for its capability in implementing AI technology to help improve customer shopping experiences. Intended for fashion customers, Amazon’s Echo Look is a device based on data analytics that offers near real-time fashion insights. The available features include Style Check, to help users select between two outfits; Collections, which organizes a user’s wardrobe; and suggestions for new pieces to complement the user’s existing wardrobe (Amazon.com, 2018). With Style Check, when a customer uploads images of two outfits, Echo Look will give the customer near real-time suggestions about which one looks better. In addition, Amazon has a newly launched feature called StyleSnap, which has been available through the Amazon app since June 2019 (Krishnan, 2019). It utilizes deep learning to analyze customers’ uploaded image data and recommend similar clothing available on the Amazon site (Krishnan, 2019).

Data analytics and applications.

Echo Look.

According to a 2018 Amazon press release (Amazon.com), its new Echo Look features a depth-sensing camera, built-in LED lighting, and computer vision based background blur. The device also comes with Style Check software. Echo Look can give customers personalized recommendations, helps customers organize their closet and build personal lookbooks by categories like season, weather, occasion, and more, and provides fashion inspirations (Amazon.com, 2018; Amazon.com, n.d.-b). The Internet connected camera (Fowler, 2017) is designed to take high-quality photos and videos when the user says, “Alexa, take a picture” or “Alexa, take a video.” The Echo Look app can also store photos and videos for future reference (Fowler, 2017; Hartmans, 2017). Amazon’s 2018 press release about the Echo Look (Amazon.com) states that its Style Check software can give customers near real-time advice on which of two outfits looks better, using machine learning algorithms and stylists’ suggestions based on fit, color, styling, and current trends. To start the Style Check, customers only have to submit two photos of themselves wearing the outfits to the Echo Look; no other information needs to be provided. Although there is no information clearly outlining how Amazon developed the machine learning algorithms to judge which outfit looks better when the app is first used, after the customer gives feedback to Style Check results, the feedback will be input to optimize the algorithms in order to offer the customer a more satisfying Style Check service (Fowler, 2017). Thus, the analysis accuracy of Echo Look is improved over time with more customer feedback data. In order to get more relevant and accurate suggestions, customers have to keep providing feedback. The results are presented in the format of a percentage likelihood of each outfit looks better on the customer plus succinct notes from a stylist explaining the reason (Fowler, 2017). However, after reviewing all the literature, it appears there is also no detailed information disclosed about exactly how the fashion specialists assist with Style Check. Figure 1 (Pagano, 2018) shows an example of how, based on these two looks, Style Check gives a higher score to the look on the right side. The color of that outfit looks better on the wearer, while the left side look has a better shape and fit. Thus, it seems that color makes a greater contribution to building a good look in this case (Pagano, 2018). However, there are no details explaining how Style Check weighs each fashion attribute of outfits.

Additionally, customers' photos and videos are "automatically grouped into Collections on the Collections page in the Echo Look app" (Amazon.com, n.d.-b, para. 1). In the "Created for you" section, algorithms help curate the photos into categories based on seasons, occasions, local weather, and more, and customers can also design their own collections with personalized titles and descriptions (Amazon.com., n.d.-b). As with Style Check, automatic Collections become smarter as the customer updates the app with more photos, descriptions, and feedback.

Echo Look can also recommend items that are available on Amazon that might pair well with items customers already own (Amazon.com, 2018). Customers can choose to share photos of their existing outfits through Echo Look, and Amazon's fashion specialists will provide personalized suggestions (Amazon.com, n.d.-a). But again, there are no details on how this function works. This feature not only helps customers make better use of their existing wardrobe but also helps Amazon promote its fashion items. In addition, Lomas (2017) indicates that Amazon also uses the data collected from Echo Look owners to build its own data set to better manufacture its private fashion label by understanding customer preferences.

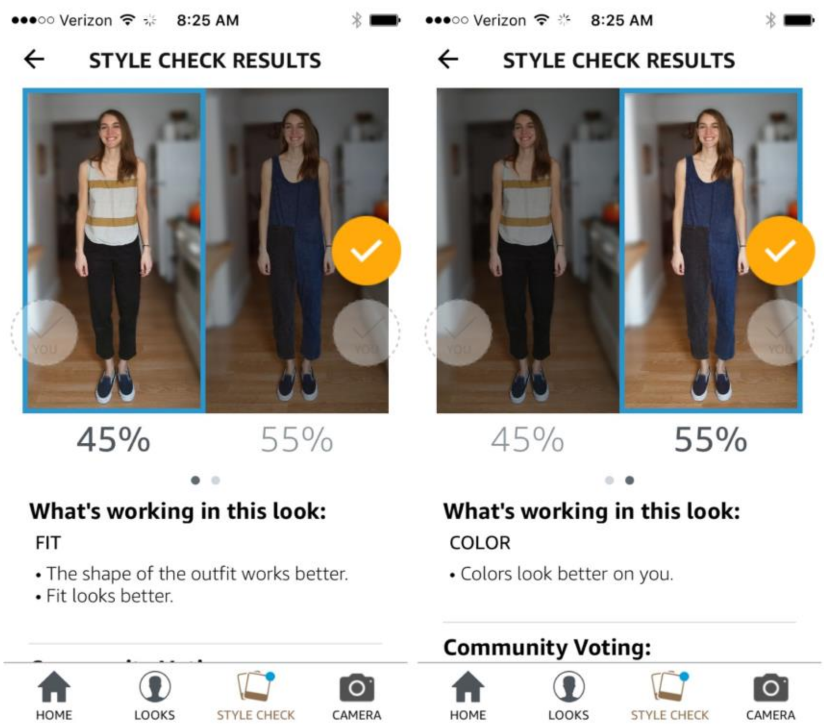

Figure 1. Example of Style Check results (Pagano, 2018).

StyleSnap.

In order to solve the problem of customers seeing a look they like but not knowing the brand and being unable to describe the style well, which makes it quite difficult to quickly find a related outfit, Amazon launched StyleSnap in June of 2019 (Krishnan, 2019). Amazon is hoping StyleSnap can improve customer engagement by helping them get fashion inspiration in real time (Krishnan, 2019). StyleSnap, which is available on the Amazon app, allows customers to upload a picture or screenshot of a fashion look they like and get immediate recommendations of similar items available from Amazon (Krishnan, 2019). The process is shown in Figure 2. Back-end optimized computer vision and deep learning models enable StyleSnap to offer customers recommendations based on brand, price range, and customer reviews. The app localizes the picture and weakens the influence of any interfering factors in the image, such as something in the background of the photo (Krishnan, 2019). The neural networks are trained to detect different fashion apparel through inputting of large volumes of images of every kind of fashion apparel, which are used to learn the features of the category of clothing based on color, pattern, fit, style, and more (Krishnan, 2019). In order to accurately detect a higher number of attributes, deep-layered neural networks are required (Krishnan, 2019). However, when a certain number of layers are stacked, vanishing or exploding gradients can happen in forward-propagation neural networks (He, Zhang, Ren, & Sun, 2016; Krishnan, 2019), which will lead to more extensive training errors (He et al., 2016). Thus, Amazon utilizes residual networks to solve this problem (Krishnan, 2019), and the accuracy of residual networks will increase with increases in network depth (He et al., 2016). In this sense, residual networks are the deep neural networks that implement shortcut connections to allow some signal propagation to skip some layers and the network to detect images through basic concepts like edges, colors, and patterns first and then through more complex concepts like style and fit (Krishnan, 2019). The uniqueness of Amazon's work is that its neural networks can remember features it has already learned and also learn new features at the same time, which enables StyleSnap to effectively process and analyze a large volume of data (Krishnan, 2019).

A similar application called Pailitao was launched in 2014 by Alibaba. Pailitao has received excellent feedback, and the average daily active users increased to more than 17 million in 2017, and the number of daily active users nearly doubled during the 2017 China Double 11 Shopping Festival (Zhang et al., 2018). Pailitao's recommendation, initially based on similarity, are then re-ranked taking into consideration sales volumes, conversion rates, applause from other uses, and user pictures to improve the quality of results (Zhang et al., 2018). Pailitao provides this service for a variety of different product types other than clothing, including kitchen items and electronics, which is broader than what is offered by StyleSnap. But the down side to the wider range of products is that there can be items in the results other than fashion items. Pinterest, Google, and eBay ShopBot have similar visual search services to improve customer engagement, but Amazon was the first to use visual search specifically for fashion apparel retailing.

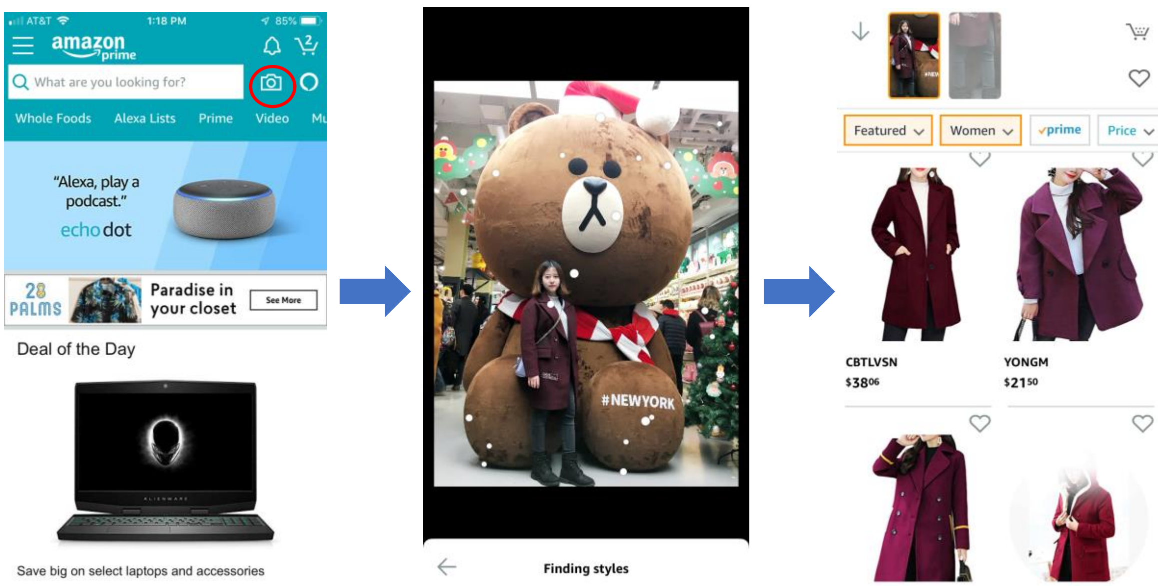

Figure 2. The working process of StyleSnap (Zhang, Pan, Zheng, Zhao, Zhang, Ren, & Jin, 2018).

Summary.

Echo Look is a good novelty item because it can help customers check their fashion style and conveniently buy matching items from Amazon. However, Style Check cannot always work ideally because the algorithms are lacking potentially important style inputs like location, age, culture, occasion, and weather. Moreover, the notes explaining why one look is better can be vague and confusing for customers (Pagano, 2018). For example, Pagano (2018, para. 11) mentioned that it can be hard to tell the difference between “outfit shape works better for you” and “fit looks better”. There is also a concern that Echo Look will cause some privacy problems not only from the photos that customers upload but because Amazon can garner extra data about the customer aside from fashion-related elements, and all of the photos and results are recorded (Applin, 2017). If the customer wants to avoid leaking privacy to Echo Look, they should remember to turn the device off (Hartmans, 2017).

Overall, providing Amazon with data does bring customers some convenience. However, the attributes input in the style-checking algorithms should be updated over time to ensure the accuracy of fashion suggestions made to customers. Also, the notes explaining the reasons why one look outperforms the other should contain more detailed information to give customers a guide for future fashion choices. It was a good idea to synthesize data analytics and fashion specialists to offer fashion insights. In future studies, to gain more comprehensive knowledge about how the Echo Look works, interviews should be conducted with Amazon staff.

StyleSnap enables fashion customers to find what they want and love in a convenient manner. And as Krishnan (2019) stressed, the success of StyleSnap can be attributed to the powerful technical support available from Amazon, and as a result, StyleSnap could be a good tool for Amazon to use in attracting more customers and gaining more influence in the fashion industry.

I tried StyleSnap several times and found that it worked well for basic, solid-colored clothing with simple patterns. But when I tried clothing with more complex patterns, the recommended items were not truly close, although they did have a similar style, such as with the patterned T-shirt example shown in Figure 3. There is no clear declaration from Amazon about how similar the recommendations will be, and different customers can have varying expectations about the recommendations. If the customer thinks similarity of style is enough without matching the pattern and color, the results will be fine. However, if the customer expects StyleSnap to recommend very similar products, such as a patterned T-shirt with the same or nearly the same pattern and the same color, then the accuracy of image retrieval will need to be improved or Amazon's inventory will need to be frequently replenished since StyleSnap only recommends products that are available on Amazon. Frequently updated inventory would partially solve this problem; however, it also requires Amazon to have high-capability neural networks to deal with the frequent new input products and offer high-quality recommendations.

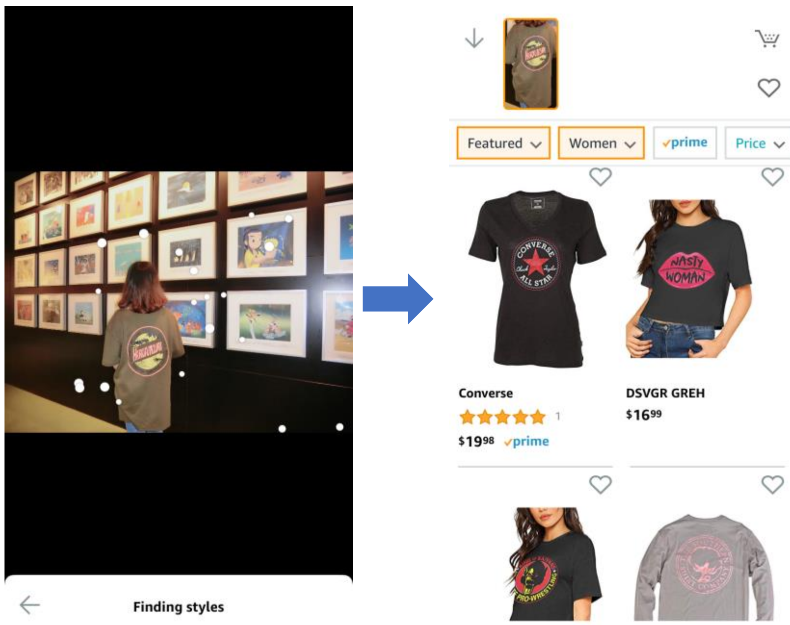

Figure 3. An example of StyleSnap failing to give similar recommendations.

Burberry

Company description.

British fashion brand Burberry is one of the most famous luxury labels in the world, offering premium quality products, recognizable designs, heritage, exclusivity, and a global reputation (Amatulli, Mileti, Speciale, & Guido, 2016). Burberry first opened in 1856 in a small garment store (Cotte & Jarosinski, 2017). In 1880, the company invented gabardine, which is a breathable, waterproof, and tear-proof fabric, and the invention made Burberry famous (Cotte &

Jarosinski, 2017). The company continued to gain popularity by designing outfits for British officers, famous actors, and some sporting or outdoor events (Cotte & Jarosinski, 2017). Burberry experienced a boom in sales and branched out into fragrances, accessories, and children's wear in 1997 (Cotte & Jarosinski, 2017). After Ahrendts became the new CEO of Burberry in 2006 and consolidated the power of headquarters over the brand, the company again achieved sales boosts (Cotte & Jarosinski, 2017). At the same time, the company began to invest in gaining digital influence by placing iPads in the stores, launching its official website, and engaging in social media (Cotte & Jarosinski, 2017). According to the company's 2018 annual report, sales were growing from 2004 to 2017, but there was a temporary 1% decline in revenue in 2018 due to wholesale decreasing 16% after Burberry licensed its beauty division out to Coty.

Initiatives on data analytics.

During the 2010s, experience-based luxury has become a new part of the luxury retail industry (Cotte & Jarosinski, 2017). In order to sustain a company's success, the ability to adjust strategies in a timely manner to deal with the changing trends is the key. Experiential shopping focuses on providing customers with personalized and memorable shopping experiences (Pine & Gilmore, 1998). In line with the experiential luxury trend, the customer experience during shopping has received more and more attention from luxury companies (Cotte & Jarosinski, 2017). As shown in its 2018 annual report, Burberry implemented data analytics with customer feedback to better understand customers and offer personalized services through the omnichannel (app, website, email, and in stores), which helps enrich customers' experiences and builds a better connection between the company and their customers. Burberry also keeps conducting quantitative and qualitative research into luxury fashion customers to make sure their products can still excite customers and their spirit can also inspire customers.

Data analytics and applications.

Customer 360.

To follow the new trend in the luxury fashion market, Burberry focused on a new customer-centric service, “clienteling” (Cotte & Jarosinski, 2017). Clienteling can be defined as a business practice that analyzes customer information and offers personalized and memorable service in order to establish a more interactive relationship with customers, which gives customers intangible benefits that can even surpass the product’s functional quality (Cotte & Jarosinski, 2017). In 2013, Burberry launched a data-driven program called Customer 360 to help them achieve clienteling, to offer exceptional customer service and increase sales (Marr, 2017; Soudagar, 2013). This program is designed to identify ideal products and services that meet customer demands by synthesizing interactions with customers from all the channels (Mullich, 2013). This program invites customers to voluntarily digitally share their buying history, shopping preferences, and experiences through a number of loyalty and rewards programs (Mullich, 2013). For instance, the items a customer tries on in a store can be recorded by using radio frequency identification (RFID) tags (Soudagar, 2013) and used to build the customer’s profile. These profile data can be analyzed to better understand the customer’s interests and actual purchases. These data can also be combined with other data to offer customers more relevant shopping experiences. It is unique that nowadays consumers are showing the willingness to trade some private information to get more relevant and personalized services from retailers (Mullich, 2013).

The Customer 360 program relies on the support of the SAP HANA platform to analyze a large volume and variety of data quickly and give real-time recommendations based on the results of this analysis of customers’ preferences, previous purchases, and social media activity, along with current fashion trends. This information is delivered to a store employee's tablet in real time (Soudagar, 2013), which lets the brand provide accurate, detailed, and timely personalized service to its customers ("Clienteling & CRM," 2016). For example, if a customer buys a particular coat, the salesperson can recommend a handbag that was bought by others who also purchased the same coat (Marr, 2017). The customer can view more details about the handbag on the salesperson's tablet, and the salesperson can instantly know where the handbag is available and even order it using the most convenient method for the customer (Soudagar, 2013).

Facebook chatbot.

Social media is becoming a significant marketing channel for luxury fashion because it increases the opportunities for retailers to communicate with potential customers (Achille, Marchessou, & Remy, 2018; Cotte & Jarosinski, 2017). Burberry's 2018 annual report shows that social media is the biggest contributor to customers getting connected with the company. Burberry has more than 51 million social media followers around the world on 13 different platforms with 24 accounts in 11 languages, and it utilizes data analytics to offer customers personalized content. Although social media tools intensify the competition among brands, they also help customers become more well informed about luxury brands (Cotte & Jarosinski, 2017) as customers are more digitally influenced today (Achille et al., 2018).

During the 2016 London Fashion Week, Burberry created a Facebook chatbot to show off their latest collection and offer customer service at the same time (Arthur, 2016). The Facebook chatbot Burberry used is an automatic communications tool that can understand human language and answer customer questions by providing options, then customers click the best option to find their answer, step by step. Chatbot offers personalized interaction, and although it is not as intelligent as a human customer service agent, it is good for finding answers to some frequently asked questions (Jani, 2018). Customers could also view the collections and shop on Burberry's official website through the chatbot. During conversations, chatbot can monitor the interaction and record data about the customer's preferences and choices and offer the customer relevant responses based on what it learns (Jani, 2018). And the data collected by chatbot can be processed and analyzed for different purposes (Jani, 2018). For example, chatbot analytics lets Burberry know what makes customers happy and what has disappointed them, based on customers' responses. That, in turn, lets Burberry reach its customers more effectively (Jani, 2018). When connected with a relevant back-end system, the data collected by chatbot can be combined with data collected from other channels (Jani, 2018) to help the company gain integral and more accurate insights into customer behavior. Chatbot utilization represents a step further in Burberry's data analytics applications. In the future, as the technology behind chatbot keeps updating, it could become a more effective tool for the company to understand its customers and have better predictive abilities when making buying decisions (Jani, 2018).

Summary.

The data analytics used by Burberry is focused on gaining an understanding of its customers and offering them high-quality personalized service to enable experiential shopping, which is consistent with the core culture of the luxury market. With the investment made in experiential shopping through its Customer 360 program, in 2015, Burberry had 50% more repeat purchases (Marr, 2017). The capabilities of data analytics applications have made it more economical and simpler for customers to purchase personalized products and increase brand loyalty (Liu, Li, Mizerski, & Soh, 2012) because customers can enjoy real-time personalized service without paying extra money. However, according to Burberry's 2018 annual report about operating risks, there has been some external and internal damage to Burberry's data security from hackers and employees abusing privileged access to the data. The company is taking actions to reduce these risks, like improving cyber security and creating a data protection office to monitor internal processes and protect the collection, security, storage, retention, and privacy of data. Its General Data Protection Regulation (GDPR) and Social Media Privacy Steering Group have a monthly meeting to work toward creating a safe environment for data usage. Data security is a big issue, and if a company cannot convince its customers that their personal data are being safely and reasonably used, those brands can lose customer trust, which in turn, leads to less brand loyalty. Thus, as Burberry works to improve the capability of their data analytics, they must also strengthen data protection.

Gap Inc.

Company description.

Gap Inc. is a leading US-based global apparel retailer that was founded in 1969 by Donald and Doris Fisher. Gap Inc. currently owns seven brands: Gap, Banana Republic, Old Navy, Athleta, Intermix, Hill City, and Janie and Jack, offering apparel, accessories, and personal care products for men, women, children, and babies. According to Gap Inc.'s 2018 annual report, the company has its own brand websites and 3,666 physical stores around the world. It generated global sales of $16.58 billion in 2018. Millard "Mickey" Drexler became the CEO of Gap Inc. in 1983 (Israeli & Avery, 2018) and sparked the trend toward khakis and casual Friday within a decade (Groth & Aquino, 2011). Gap Inc.'s annual sales increased dramatically from $480 million to $14 billion during the 1990s (Israeli & Avery, 2018), and its market share reached its peak of approximately $40 billion in 2000 (Safdar, 2016). At that time, the entire company and all the brands depended on Drexler, who also worked as Gap's creative director, for his vision and tastes (Israeli & Avery, 2018). Once he was off trend, it damaged the company's sales (Israeli & Avery, 2018). At the same time, consumers' ever-changing tastes and the rise of fast fashion also gave Gap Inc. a serious challenge because of fast fashion's quick response to the market and low prices (Israeli & Avery, 2018; Safdar, 2016). For example, Inditex SA, the Spanish multinational clothing company that owns Zara, has become one of the biggest competitors to Gap Inc, as we can see in Figure 4. Drexler left Gap Inc. in 2002 after two years of revenue decline, which is attributed to a failure to respond to customers and the market quickly and accurately (Israeli & Avery, 2018; Safdar, 2016). For the same reason, and with slow growth in the US and Canadian apparel markets, the core markets of Gap's sales, along with the rise of online shopping turned Gap's large number of physical stores into a liability (Israeli & Avery, 2018; Safdar, 2016). There has been no great improvement in the company's performance even after changing CEOs and creative directors several times (Safdar, 2016). Figure 5 shows how the years from 1995 to 2000 were glory days for Gap Inc., and they are really difficult to surpass. Gap Inc. today is still a $16 billion company, so it is clear that perform not that great is relative, but sales are still dropping and something has to be done to help the company rebuild its former glory (Israeli & Avery, 2018; Kenny, 2018).

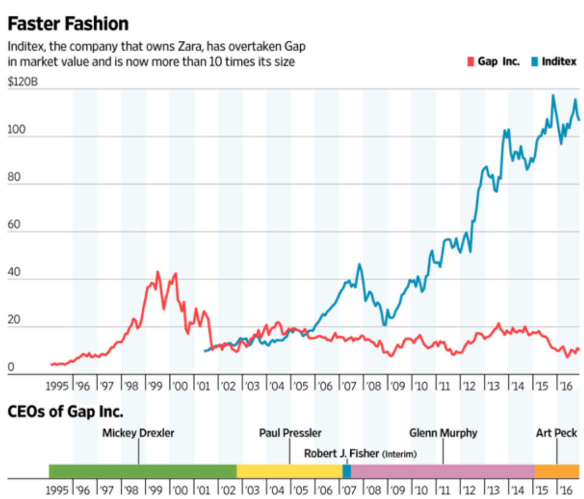

Figure 4. Comparison of the market values of Gap Inc. and Inditex (Safdar, 2016).

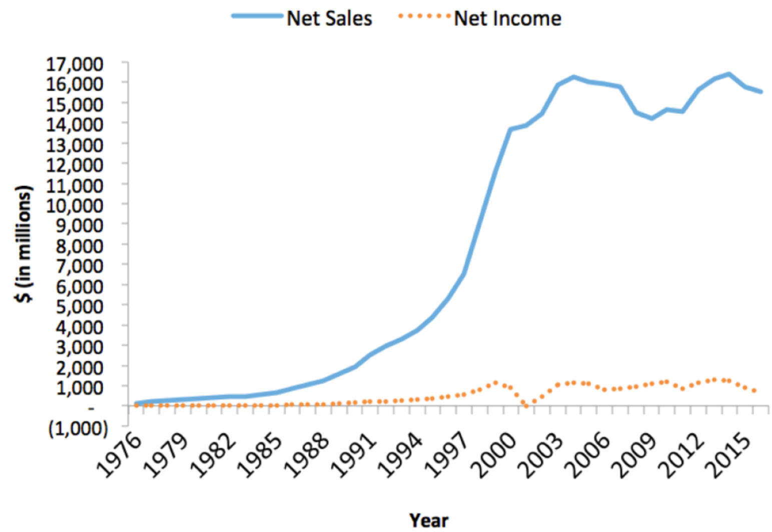

Figure 5. Gap Inc.'s sales and net income (in millions), 1976–2015 (Israeli & Avery, 2018).

Initiatives on data analytics.

Before becoming the CEO of Gap Inc. in 2015, Art Peck was Gap Inc.'s President of Growth, Innovation, and Digital. He put forth tremendous effort toward enabling customers to seamlessly shop omnichannels (Israeli & Avery, 2018). Omnichannel shopping helps Gap Inc. attract customers and gives the company more access to customers' data (Israeli & Avery, 2018). At the same time, data analytics can make contributions to building a quick response system because of its great capability to extract useful information from related data, which can provide a reliable basis for decision-making when creative directors are being criticized for slow response to customer demands by Gap Inc. While these are creative directors who have been with the company for almost 50 years and were the company's visionaries who controlled the design process and expressed the brand's vision to the public (Israeli & Avery, 2018), their decisions can sometimes be very subjective and governed by instinct in a way that there exists conflict between the creative directors' seasonal vision and customers' aesthetic sense (Israeli & Avery, 2018). Waiting for the approval of creative directors can also be time-consuming, which can lead to a long pipeline for certain collections. Peck thinks the right products are the key, but Gap Inc.'s traditional model failed to select the right assortment (Israeli & Avery, 2018).

On the positive side, learning from its fast fashion competitors, Gap Inc. did many things to achieve a quick and accurate response system in order to gain competence, and data analysis was one of them (Israeli & Avery, 2018). In order to shorten the cycle from design to sale and find the right trends, Peck started to push the company to utilize a data mining approach to extract the market trend for the next season's collections instead of relying solely on one person's vision (Israeli & Avery, 2018; Kenny, 2018). Under Gap Inc.'s traditional creative-led model (see Figure 6), Creative directors create some inspirational pieces for lower-level designers and merchants to follow up and have the power to make decisions on the design of other products (Israeli & Avery, 2018; Kenny, 2018). It usually takes 10 months to almost a year to see the new products appear in stores and Gap had done this for almost 50 years (Kenny, 2018).

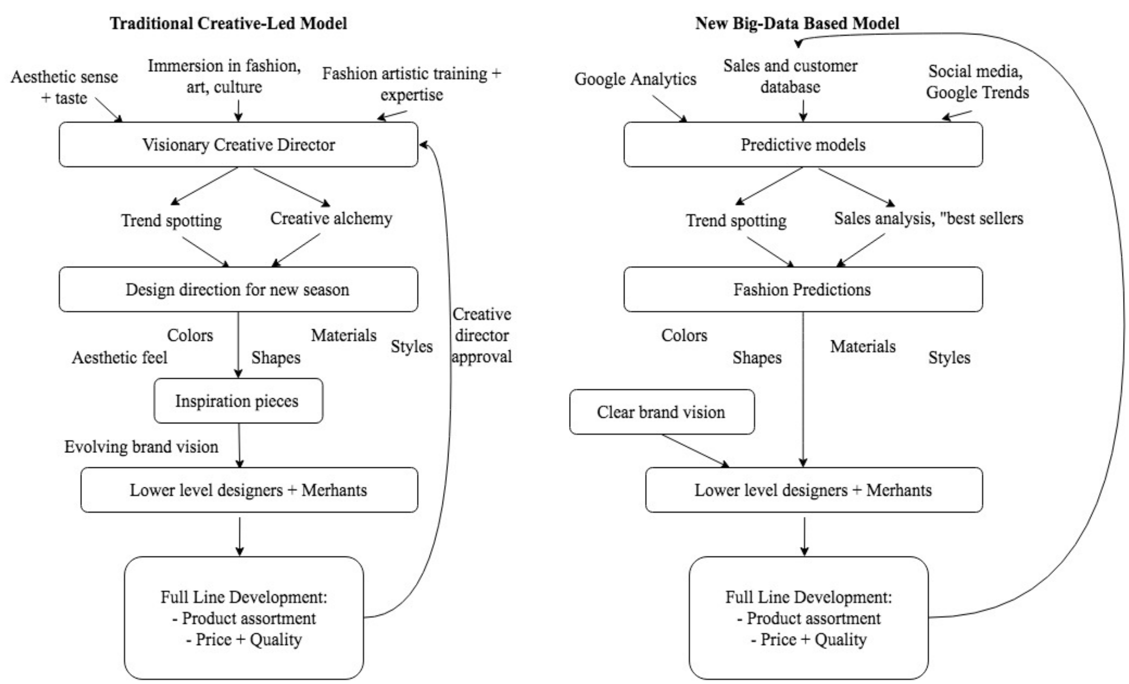

Figure 6. Gap Inc. Brands design process (Israeli & Avery, 2018).

Data analytics and applications.

Now, the company collects data from Google Analytics, Google trend, social media, the company's own sales, brand websites (customer browsing and purchasing history, click-through rate, and time on the website), customer databases (feedback, demographic data, etc.), and even Gap's external vendors to understand customers' interests and exploit those insights for fashion trends (Israeli & Avery, 2018) through its predictive models (see Figure 6). Google Analytics help track and report a company's website and app real-time data such as number of users, total number of pages viewed, total number of sessions (the period of time a user is actively engaged with the website or app), customer demographic data, the keywords and sites that referred them, and more ("Get to Know Your Customers", n.d.). These data can be used by Gap Inc. to better evaluate the performance of its website and app and gain more valuable data about its customers. For example, Gap identified the trend of men's jogging pants because data from Google Analytics told Gap's managers that the number of customers using the search term "men's jogging pants" in North America was increasing (Israeli & Avery, 2018). Then men's jogging pants started to be progressively brought to the market in different areas of North America based on the locations of these searches (Israeli & Avery, 2018). Google Trends can report the regional popularity of a search term or topic spanning a certain period of time. The site is also useful for spotting customers' preferences through its trend comparison function. Also, the company's in-store and e-commerce sales operate on the same platform, which enables the data team to have a globally transparent vision of its inventory data (Arthur, 2014).

In addition, every brand under Gap Inc. has different styles and differently oriented customers. For example, Gap is more casual, while Banana Republic is more classic, and Athleta is workout style. Thus, it is important to sort the data for every brand through filter algorithms trained from the brand's vision statement (Israeli & Avery, 2018), which can identify the special characteristics of each brand in order to match that image (Kenny, 2018). Jeff Kirwan, Gap Inc.'s Global Brand President elaborated that "who we are as a brand, what our lifestyle is, and the authenticity of who we are as a brand" is the standard for filtering (Israeli & Avery, 2018, p. 9). Only after this process can the trend be appropriate and specific to every brand (Kenny, 2018). After that process, the appropriate commercial trend for each brand can be immediately applied to the design process (Israeli & Avery, 2018).

Previously, the company always chose to buy a large inventory for each season, which would lead to inventory backlogs and deep discounting (Israeli & Avery, 2018). According to Israeli and Avery (2018), in the company's "in-season open program", the company decides the final quantity for production after quickly analyzing the real-time sales data of a small amount of trial products. Data analytics tools improved the company's ability to react to the market. Combined with shifting some manufacturing from Asia to the Caribbean to receive products faster and be able to store huge quantities of fabrics means that, now, most of the cycles from design to stores have shortened to eight to ten weeks (Kenny, 2018). This strategy will help Gap Inc. become competitive again through its speed in bringing popular products to the market and achieve a more predictive, demand-driven business model with a more flexible inventory (Israeli & Avery, 2018).

Summary.

However, relying on data too much may weaken the creativity and uniqueness of the brands and the ability for a brand to set a trend (Kenny, 2018). If the company reacts to existing trends before designing and producing garments, there will be times when the products appear in stores behind the trends (Kenny, 2018). But it also depends on the brand positioning (Kenny, 2018). It could be a good thing for Gap because it is no longer a design-led brand (Israeli & Avery, 2018).

While an effective and efficient data analytics approach helps Gap Inc. understand its customers, respond to the market in a timely fashion, improve the flexibility of its inventory, and optimize decision-making, it is still too early to determine whether big data analytics can replace creative directors in predicting the appealing trends for boosting sales and restoring Gap Inc. (Israeli & Avery, 2018). Using data to spot trends makes the company follow mass market trends and could lead to one brand looking more similar to other brands, which might mean they lose the competitive advantages in the long run (Israeli & Avery, 2018). While the first two years' results from Peck's strategies are disappointing, with two consecutive years of dropping sales, if we look at the following two years' sales as shown in Figure 7, there does exist an increasing trend.

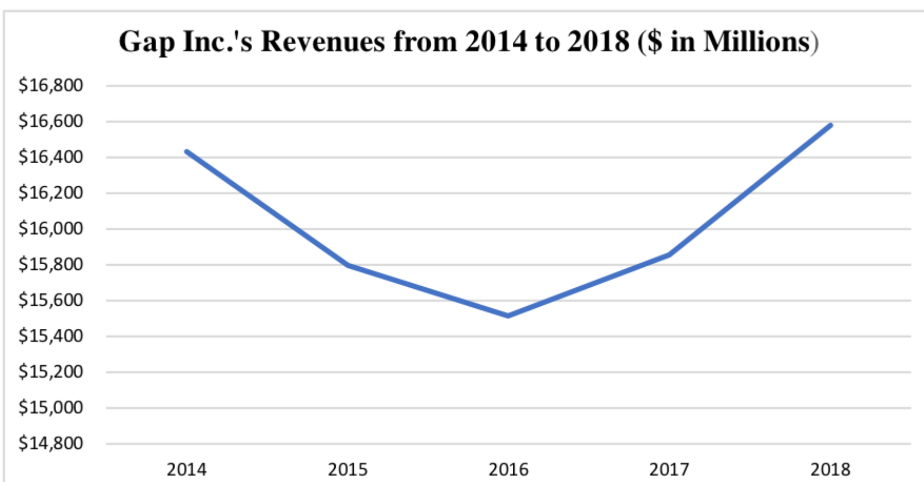

Figure 7. Gap Inc.'s revenues from 2014 to 2018 (in millions) (Gap Inc., n.d.).

This is a good opportunity for the company to rethink if it is still in a position of setting trends and how fashion forward every brand appears and hopes to be (Kenny, 2018). Peck was also considering selling products on Amazon in order to increase revenue because of Amazon's tremendous influence (Rupp, 2016). Cooperating with Amazon could help Gap have better insight into its customer behavior due to the additional data the company could get from Amazon (Israeli & Avery, 2018). However, the company would have to give up part of their control over distribution and share some customers with Amazon (Israeli & Avery, 2018).

As Peck said, the fashion industry is changing dramatically (Israeli & Avery, 2018), and opportunities and challenges come out one after another. Some methods that work now won't necessarily still work in the future. While the methods are changing, however, the essence does not change. In order to boost sales, fashion companies should respond to the market and understand customers in a timely manner. For now, data gives human beings more insights, while human beings help adjust the results of data analysis to a more socially acceptable form. Both of them are indispensable.

Ralph Lauren Corporation

Company description.

With customers' increasing awareness of fitness and wellness (Hanuska, Chandramohan, Bellamy, Burke, Ramanathan, & Balakrishnan, 2016), wearable technology is becoming more and more popular in the sports and fashion industries (Smithers Apex, 2014). Wearable technology, which can be defined as the integration of various micro sensors into wearable items for the purpose of collecting biometric data for monitoring and improving fitness and wellness. These devices give wearers real-time insights into their wellness activities through wireless communications (Chen, Ma, Song, Lai & Hu, 2016; Hanuska et al., 2016). Smart clothing is a subset of this category that consists of wearable technology embedded into clothing (Fernández-Caramés & Fraga-Lamas, 2018; Hanuska et al., 2016). There are four main categories of wearable technology applications: for entertainment purposes, for fitness and wellness purposes, for military and industrial purposes, and for health care and medical purposes (Hanuska et al., 2016). Of the currently available wearable technology applications market, fitness and lifestyle related products account for the largest proportion, and smart watches are the most popular wearable devices (Hanuska et al., 2016).

Ralph Lauren Corporation is the first major premium fashion brand to attempt to market smart clothing, which could mark the milestone of a fashion company entering the smart clothing market that has to date been dominated by big sports brands (Smith, 2015). Ralph Lauren Corporation is an American fashion corporation known for its apparel, household products, accessories, fragrances, and hospitality. The company has had partnerships with the United States Golf Association (USGA) since 2011 and the United States Open Championship tennis tournament (US Open) since 2005 (Long, 2011), and these partnerships have encouraged the company to create better, more efficient sportswear and think about wearable technology (Ulanoff, 2014).

Initiatives on data analytics.

Ralph Lauren stepped into the wearable technologies market with a trial of the PoloTech Shirt in conjunction with the 2014 US Open. The shirt was professionally developed in cooperation with the Canadian company Omsignal, which is considered the expert in wearable technology (Smith, 2015). The PoloTech shirt was available to the public only from August 31, 2015 to September 13, 2015 (Smith, 2015), and while the PoloTech shirt was designed to help customers live a healthier and more informed life, with built-in sensors worn close to the rib cage in order to collect real-time physical signal data and a connected app to offer real-time customized workout plans (Atkins, 2015), the price of the PoloTech shirt, $295, is very steep.

Furthermore, according to the instructions on the official website for the shirt, the PoloTech app was only available for the iOS platform for Apple's Watch, iPhone, and iPod Touch.

Data analytics and applications.

The PoloTech shirt has a compression design that ensures the sensors are close enough to the body to get the most accurate readings (Wollman, 2014). A black module that snaps into the shirt on the left side of the chest contains a Bluetooth transmitter, accelerometer, and gyroscope, which stream data to wireless devices to record the users' acceleration and direction (Atkins, 2015; Ulanoff, 2014). Biosensing silver-yarn-based sensors woven directly into the shirt across the chest collect biological and physiological data (Smith, 2015; Ulanoff, 2014) as well as physiological and kinetic data (Ulanoff, 2014), including heart rate and variability, breathing depth and recovery, intensity and speed of movement, strength and stress levels, steps taken, energy used, and calories burned (Atkins, 2015).

The data collected by wearable technology are then used in machine learning algorithms for related applications, or the data may be directly displayed to the user and/or stored on wireless devices or in the cloud (Chen et al., 2016). In this case, the data collected by the shirt are uploaded to the PoloTech app (Marr, 2016). Equipped with an optimized data processing framework and data analysis platform (Chen et al., 2016), the data are stored, processed, analyzed, and visualized to provide customers with real-time biometric readings and help users adjust their workout plans immediately (Smith, 2015). The workouts supported by the app are focused on three categories: strength, cardio, and agility ("PoloTech Cardio," n.d.). For each of these categories of workouts, the app offers a 21-day plan, giving tips for the workout and suggesting what and when to eat ("PoloTech Cardio," n.d.). The app can display real-time data and automatically remind users where and when to make adjustments through voice prompts

(Atkins, 2015). Thus, users have to take the electronic devices where the app is installed with them during their workouts. The app might tell the user to add more power, push harder, or breathe more deeply by synthetically analyzing the data using machine learning algorithms based on previously accumulated data (Chen et al., 2016) with the aim of helping users grow and stretch their limits while at the same time preventing injuries (Atkins, 2015). This process of data processing, analysis, and visualization is detailed in Figure 8 (Chen et al., 2016).

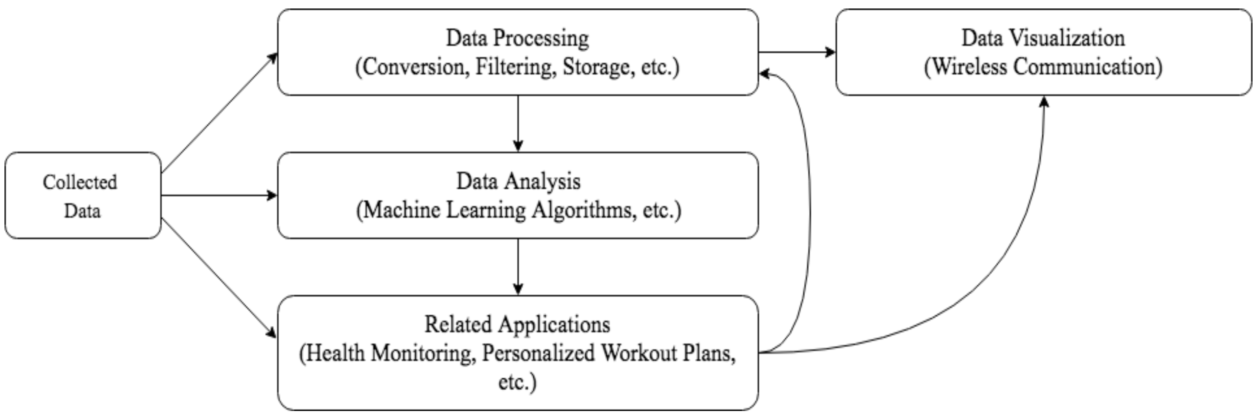

Figure 8. Process of PoloTech shirt data collection, processing, analysis, and prediction (Chen et al., 2016).

Summary.

This data-enabled technology not only helps improve the quality of users' workouts and decrease their risk of injury during workouts but also offers customers more interactive experiences. Apart from the benefits for individual users, companies can use these data and predictive analytics to identify trends and develop products to improve the health and safety of large populations (Hanuska et al., 2016). Unfortunately, Ralph Lauren's PoloTech shirt has some drawbacks. It only supports the iOS system, is only available as menswear, and is expensive.

In addition, there are the challenges holding back the expansion of wearable technology that include physiological and environmental interferences that influence the effectiveness of data collection as well as the data privacy and security that customers are worried about (Chen et al., 2016; Fernández-Caramés & Fraga-Lamas, 2018). The data collected by sensors built into smart clothing can be heterogeneous because of the use of different types and modalities of sensors, which means these data have different structures, making interpretation of the data more complex (Hanuska et al., 2016). Highly capable computation is necessary, while data cleaning, revising, and integrating have to be done before these data can be used in a practical way (Chen et al., 2016). Thus, there is still a long way to go to improve the accuracy of data collection, processing, and analysis for wearable technology. Further, especially for smart clothing, other factors have to be carefully considered, including washability, comfort, heat dissipation, miniaturization, and flexibility of the sensors. The design and selection of fit and material should be optimized to ensure the sensors can work well (Wollman, 2014). In addition, the high sales price necessitated by the embedding of highly capable sensors into these garments can negatively affect customers' desire to purchase these items (Chen et al., 2016).

Rent the Runway

Company description.

Rent the Runway (RTR) is a fashion company, cofounded in 2009 by Jennifer Hyman and Jennifer Fleiss, that rents out designer clothing and accessories for women and girls and has a direct partnership with designers (Eisenmann & Winig, 2012). A dress's rental price is usually 10% to 15% of the retail purchase price (Eisenmann & Winig, 2012). If a customer finds designer clothes that she likes but cannot afford or will not wear very often, RTR can be a good choice (Ferguson, 2014). The company has stores both online and offline. Through May 2018, the company has had nine million members and more than $100 million in yearly revenue (Kavallines, 2018). Jennifer Hyman believes that RTR can become a $100-billion company over the next five years. She indicates that the company's business model is globally applicable, and she is eager to filter out bad fashion from her business (Amed, Balchandani, Beltrami, Berg, Hedrich, & Rölkens, 2018). RTR encourages its customers to discover and try out new favorite trends, styles, and designers and to become more environmentally responsible at the same time ("Our Story", n.d.). The company believes that renting is more environmentally sustainable than a throw-away culture, and it seems more viable for customers to rent clothes rather than spend hundreds of dollars on dresses they would only wear a few times (Hyman, 2017).

According to RTR's website, customers can place an order for a one-time rental of four to eight days or they can become an RTR member through the RTR Update or RTR Unlimited plans. The company's website offers 500 different designer brands for reserve rentals and Unlimited members and over 350 brands for Update members. To ensure the clothing fits, RTR ships the same style in a backup size for free. Customers are also given the option of shipping a second style. The company makes sure that every item is of perfect quality by doing quality inspections and handling dry cleaning and garment restoration ("Our Process", n.d.). Repairs can also be done when necessary ("Our Process", n.d.).

Initiatives on data analytics.

With regards to rental economics, how to build a business, attract customers, and gain a profit are all new to the fashion industry ("Never do laundry again", 2018). Thus, it is important for the company to build its brand and expand its customer base. RTR's Chief Analytics Officer stressed that "we had to be really good at making the economics and the back-end infrastructure work and that's where tech and data really come into play" ("Never do laundry again", 2018). RTR has its own reverse logistics (Amed et al., 2018; Goodman, 2018), which means "rental items are always going out and coming back in [;] the company benefits from being in a ‘feedback loop’ providing RTR a huge opportunity with data and experiences” (Goodman, 2018, para. 3). RTR’s website says, “At Rent the Runway, the Analytics team not only provides insights into the business through reporting on marketing, operations, and inventory but also informs new products through algorithms for best shipping practices, future demand, and predicting a customer’s perfect dress” (“Who We Are,” n.d.).

Data analytics and applications.

Logistics data analysis.

The first part of RTR’s data analysis is logistics data analysis (Gutierrez, 2014). With the fast expansion of RTR’s business, there are more and more physical sources that need to be organized, scaling not only servers but also physical spaces and processes (Dunn, 2018). Because of its unique operating mode, it is important for the company to know where items are and how much time every process will take to make sure that rental turnover time is satisfactory. Thus, data analytics are utilized to coordinate rental items at various stages—on the racks in the warehouse, out with customers, returning from customers, and waiting for dry cleaning or repairs (Dunn, 2018; Ferguson, 2014; Gutierrez, 2014)—to make the whole rental process more efficient (Melendez, 2014). The shorter time of rental turnover, the more profit RTR will make (King, 2015), so it is critical to make every shipment on time. There are many attributes that must be considered for every shipment, such as return, dry cleaning, and repair times (King, 2015). Some items are popular, so they have to move faster, and some may require more dry cleaning or repair time (“Never do laundry again”, 2018). The data team uses an algorithm to sequence their inventory based on these attributes to make sure a unit can be shipped to the customer, returned, and shipped to the next customer on time (“Never do laundry again”, 2018).

UPS data gives RTR information on where a package is and whether it is being shipped to customers or returned, which enables the company to know its current transit status and approximately how long it will take for the package to arrive back at the warehouse (Goel, 2014). Anna Smith, who worked as a data scientist at RTR from 2013 to 2016, indicates that the company uses this transportation data to optimize the flow of apparel (Gutierrez, 2014), because, based on this data, the company's custom shipping software can help decide when the customer should return an item via ground delivery or next-day air (Melendez, 2014) in order to reduce costs (Goel, 2014). There is also the possibility of losing a package during the shipping process, and the next customer may have reserved an item that was lost, so missing items are another problem to consider (Gutierrez, 2014). RTR has been developing a predictive model to determine whether a unit will come back in time for its next rental, taking into account the possibility of lost packages (Gutierrez, 2014).

Unlike other retail companies, RTR has to take care of the entire life cycle of their merchandise, from buying to dry cleaning to the end of an item's life ("Never do laundry again", 2018). Therefore, the company uses data to figure out how to best take care of the items and prolong their life according to different materials and uses ("Never do laundry again", 2018). Different cleaning methods, machines, and chemicals as well as different repair methods and so on are tested on all types of fabrics, requiring different amounts of time for each item ("Never do laundry again", 2018). In an interview conducted by Deciding by Data Website, Subramanian explained that the company has several odd fabrication codes for every unit of inventory and track the performance of the fabric during each process. Bases on these data, the data team can get the insights of how to best take care of every product ("Never do laundry again", 2018).

Customer data analysis.

The second part of RTR's data analysis is customer data analysis. Fit is an important attribute to consider with apparel, and different designers' have different size charts or elasticity of fabrics, causing variations in fit (Gutierrez, 2014). Thus, RTR's data team digs into customers' reviews about their body data and clothing fits in order to provide customers who have similar bodies with more useful and trustworthy information (Gutierrez, 2014). Customers can provide body data through customer profiles, which include height, weight, bust size, body type, primary dress size, backup dress size, typical jean size, and more. When a customer writes a review of a rented item, the customer has to provide an overall rating for the product, the size of the rented clothes, the overall fit, and the occasion the clothes were rented for. This part of data is easy to process and analyze. However, customer reviews also include customers' summaries of the clothing fit, pros and cons, and other helpful highlights. Smith indicates that this part of the data is hard to use, explaining that the data team has to "parse all that information out with natural language processing to expose the relevant details" (Gutierrez, 2014, p. 208). Collobert and Weston (2008, p. 160) explained that "the field of Natural Language Processing (NLP) aims to convert human language into a formal representation that is easy for computers to manipulate". The RTR data team collects data from customers' profiles and reviews, and they will evaluate it and provide customers with the right fit insights for every style to read, giving customers more opportunities to find the right clothes (Gutierrez, 2014).

Based on analyzing the customer's feedback, profile data, and rental history, a webpage with personalized products will be shown to the customer (Melendez, 2014; Schwartz, 2018). It aims to bring customers more relevant shopping experiences and help them find items they like more quickly, rather than becoming fatigued from looking through too many styles (Melendez, 2014). Data analytics can provide customers with opportunities to try more brands and discover new favorites (Amed et al., 2018).

Besides customer data analysis, stylists work with customers to give them more personalized experiences, professional suggestions, and detailed information about the clothes (Eisenmann & Winig, 2012). Customers can get suggestions from stylists on the phone, through email, or face to face at the company's brick-and-mortar stores.

It is not only customers who benefit from data analytics but also the top 100 brands who cooperate with RTR (Amed et al., 2018). From the wholesale side, brands can gain insights from RTR's data analytics to know customers' preferences and use them as a basis to produce new collections (Amed et al., 2018).

It is important for RTR to collect and analyze data from various reliable sources in order to understand customers (Gutierrez, 2014). Sometimes, the reason why a customer rents an item is because it is the only item available ("Never do laundry again", 2018). Thus, the data team tracks customer data, such as what customers are searching for and what they are filtering, in order to better understand customers' true demands and how miscued the company is ("Never do laundry again", 2018). This will heavily affect RTR's buying decisions by comparing customers' real demands with the company's current inventory ("Never do laundry again", 2018).

Website- and app-data analysis.

The third part of RTR's data analysis is website- and app-data analysis. This part is focused on tracking how customers find the items they want, what kind of web or app features they like, and finding ways to improve those features (Gutierrez, 2014). The data team started to do data combination after RTR launched its mobile app in September 2013 (Brooke, 2013; Gutierrez, 2014). The company has its own procedure of combining different types of data—

combining pixel logs with Google Analytics for example—to create a clearer and more feasible way to look at and analyze the data (Gutierrez, 2014). Smith explained that pixel logs can show customers' activities on the company's website, such as what items they are clicking on, their navigation paths, and more (Gutierrez, 2014). The data team analyzes data collected from both app and website users, such as who they are, how they use the app, how customers are distributed between the website and app, their activities on the app, and what and why they rent (or do not rent) on the app versus the website. Analyzing this data helps the company have a better understanding of the differences between their customer groups (Gutierrez, 2014). For example, some customers visit the website frequently without renting anything, while others rent weekly, and still others are in between (Gutierrez, 2014). After understanding customer behavior on different platforms, the company can tailor its service for different customers on those platforms (Gutierrez, 2014).

The RTR data team also does AB testing to determine "whether new or improvements of existing user-facing features add business value" (Trog, 2014, para. 1). Here, AB testing means randomly splitting users into two independent, equally sized sample groups, and showing one of two versions of the company's website (version A and version B) to each group, respectively (Dubarry, 2015). The performance of each version is decided after relevant metrics been computed (Dubarry, 2015). For example, this testing method can be utilized to compare the performance of RTR's original checkout page with its new checkout page. The data team can allocate 50 customers to a new checkout page and 50 customers to the original checkout page. Then, the data team can assess how customers perform with each version, collecting and analyzing the relevant data to decide on which page performs better (Trog, 2014). The data team can compare the performance of the checkout pages by, for example, calculating the ratio of successful transactions on each page or the average time customers spend on each checkout page. This can give RTR more insights into improving its website operation.

Summary.

The apparel rental business is still new, and it takes time and effort to cope with the technological and logistical challenges (Amed et al., 2018). Data analytics has contributed to the company's successful operation, and data is in the company's DNA ("Never do laundry again", 2018). In the future, better data, better models, and better processes are still needed to help the company achieve its business goals (Gutierrez, 2014). It is also important to have a collaborative culture between different teams, enabling them to know each other better, learn from each other, and solve actual problems for different teams (Gutierrez, 2014; "Never do laundry again", 2018). RTR is building its own Dress Code Blog to show people what different teams in the company are doing and to attract more people to join those teams (Gutierrez, 2014). In addition, according to Smith, there are written and unwritten rules about the limits of talking about data, and protecting the privacy of data is an important way to gain trust from other people in the company (Gutierrez, 2014). It is also practical for companies to have a data team that is interested in doing research and finding more insights and new opportunities rather than just providing business metric reports (Gutierrez, 2014).

Data is not enough, developing software that can extract insights from data and use those insights in a practical way is even more valuable ("Never do laundry again", 2018). To ensure the authenticity and effectiveness of these insights, running experiments with this data is indispensable. It is more meaningful to use data to figure out a long-term development plan rather than focusing only on the present. With the flourishing of rental cultural, Subramanian

("Never do laundry again", 2018) expressed the hope that RTR's business can finally serve worldwide customers.

Stitch Fix

Company description.

Stitch Fix is an American online commercial fashion company that utilizes the insights extracted from customer data and the aesthetic sense of stylists to deliver personalized shopping experiences for women, men, and children (Smiley, 2019). Stitch Fix launched in the UK in May 2019 (Bond, 2018). As of 2018, Stitch Fix had 2.9 million clients (Thomas, 2018) and net revenue of $1,226.5 million. According to the official Stitch Fix website, after users sign up for the service, they fill out a Style Profile, which gathers detailed information about the customer's body data, fashion preferences, fashion lifestyle, and fashion demands. Then, the customer receives a five-item package that includes clothing, shoes, and accessories carefully selected by both data analytics and stylists. They only pay for the items they keep, and they return the rest of the items at no cost. It is not a subscription service, where customers can either schedule a shipment on demand or set up an automatic delivery interval. Before shipping the package, Stitch Fix will use customer data and warehouse data to find the optimal shipping route considering the distance between the customer and the warehouse, along with matching the level of the customer's demand, such as how quickly the items are needed, with warehouse inventories to determine the optimum warehouse and shipping method to reduce costs (Colson et al., n.d.). Customer data are also used by Stitch Fix to design its private label, Hybrid Designs (Lake, 2018), in order to fill the gap between customers' expressed preferences and their demands and the apparel offered by other brands (Smiley, 2019). Brad Klingenberg (2019, para. 2), Chief

Algorithms Officer of Stitch Fix, illustrated that "data science is engaged with virtually every aspect of our business from the management of inventory, operations, marketing, the matching of stylists to clients and, of course, deciding what to send to clients." There are more than 100 data scientists at Stitch Fix, and they have generated hundreds of millions of dollars in profit (Colson, 2019).

Initiatives on data analytics

Stitch Fix applies data analytics to selecting ideal fashion items for customers throughout the entire universe of the fashion world (Smiley, 2019). Customers fill out the lengthy Style Profile to start the process of getting the personalized experience. The Style Profile collects detailed data about each customer's basic and body information, fashion preferences, fashion lifestyle, and fashion demands. Basic information includes customers' birthdays, occupations, and whether they have kids. Body information includes height, weight, size, proportions, and body shape. Fashion preference determines customers' preferred fits, colors, patterns, fabrics, styles, brands, jewelry styles, denim fit preferences, how adventurous they want to be with their Stitch Fix selections, the body part they would like to show off or downplay, and the products they would never want to receive. Fashion lifestyle relates to things like how often the customer wears pants or jeans as opposed to dresses, budgeting for fashion, and luxury preferences. Fashion demand is how often the customer wants to receive Stitch Fix shipments focused on certain occasions. Stitch Fix uses the interesting tactic of encouraging customers to link their Pinterest accounts to their Style Profile, and Stitch Fix collects more detailed information about customers' tastes from their Pinterest boards (Stitch Fix, n.d.).

Data analytics and applications.

Recommendation systems.

For each customer's shipping request, based on shipping time and cost, the degree of matching to the customer's demand, and inventory, an optimized method of handling warehouse allocation and selection can be found through calculating the cost function for each warehouse using an algorithm (Colson et al., n.d.). The shipment will be assigned to the selected warehouse, and then various algorithms will be run to sequence the warehouse inventory (Colson et al., n.d.). After that, a filtering step removes items the customer has received before or that the customer has responded to negatively to form an inventory list. Finally, the system predicts the probability that the customer will love particular items more than the others, based on customer demand and feedback (Colson et al., n.d.). This prediction is done several times with different algorithms to improve the accuracy of predictions, and the scores given to the different predictions are ranked (Colson et al., n.d.). In addition, if the company is lacking some elements of the customer's preferences, other methods will be applied, such as collaborative filtering algorithms that operate on the assumption that customers who have had a preference for some items will have the same preferences to other particular items (Colson et al., n.d.). Thanks to the wide variety and tremendous quantity of data that Stitch Fix can collect, the company can gain many latent insights to improve the accuracy of its collaborative filtering algorithms (Colson et al., n.d.). For example, at Stitch Fix, fit is treated as a multidimensional attribute that can be affected by the customer's body shape and the cut used by different manufacturers and for different styles (Colson et al., n.d.). Thus, in designing its own brand, Stitch Fix will adjust the size of clothing as appropriate to offer customers more relevant experiences (Lake, 2018).

Apart from the data collected from the Style Profile, Stitch Fix has access to many images and text, such as from inventory style photos, Pinterest boards, feedback, and requests from customers (Colson et al., n.d.). Sometimes, it can be hard to describe fashion preferences in words, but images can provide inspiration (Levy, 2018). Style Shuffle is a program offered by Stitch Fix for use on their website and in their app that allows customers to rate clothing images by giving the items a thumbs up or down to show their attitudes toward the items. In a *Fast Company* article, Lauren Smiley (2019, para. 3) notes that "more than 75% of Stitch Fix's 2.9 million customers have used it, providing the company with more than a billion ratings." For these data, Stitch Fix uses trained neural networks to "derive vector descriptions of these images" and then "compute a cosine similarity between these vectors and pre-computed vectors for each item in the inventory" to find similar items (Colson et al., n.d., para. 21). This process is shown in Figure 9. Stitch Fix uses natural language processing to analyze text, such as customers' requests and feedback, and uses what it learns to help give each item in the inventory a matching score (Colson et al., n.d.). Ultimately, the results of analyses will be presented to a stylist to consider. Matching the stylist with the customer is also done by matching models and considering both the customer's and the stylist's expressed and latent style preferences (Colson et al., n.d.). While machines are good at performing certain predesigned calculations, stylists have strengths in creativity, knowledge of constantly changing social norms, and the ability to relate to customers (Colson et al., n.d.). The stylist comprehensively evaluates the results of the data analyses and customer demand and makes the final decision on the items that will be shipped (Colson et al., n.d.) This entire process is laid out in Figure 10 (Colson et al., n.d.).

Figure 9. Analyzing image data using trained neural networks (Colson et al., n.d.).

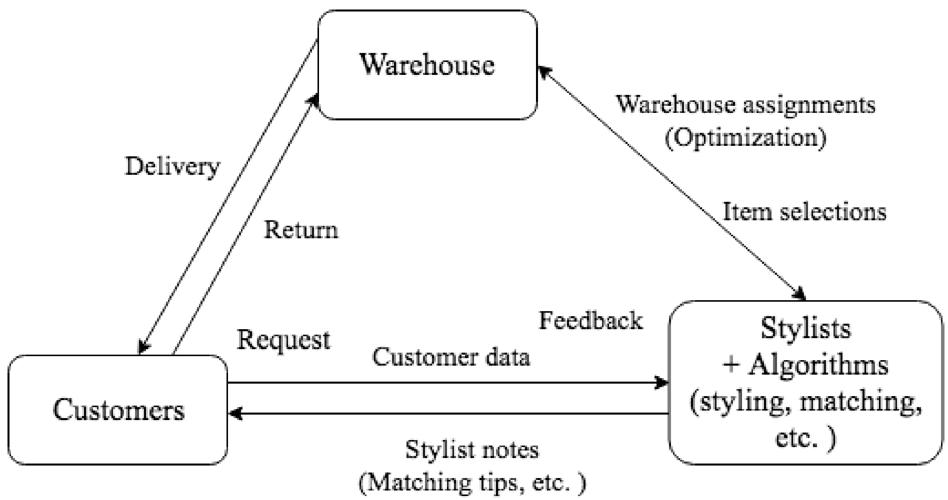

Figure 10. The Stitch Fix style selection and shipment process (Colson et al., n.d.).

New style development.

Stitch Fix also uses data analytics to improve its operations. The company not only works with more than 1,000 brands but also designs its own private labels to improve the flexibility of the inventory available to customers in a timely manner (Smiley, 2019). Sometimes, clothing from other brands cannot meet the needs of a customer in one or more various ways, or the product may not be available when the customer wants a delivery. Stitch Fix now has its private label to fill those gaps (Smiley, 2019). The method they use to develop new collections is inspired by genetic processes (see Figure 11). All the apparel in inventory makes up the initial population, and each piece of clothing has various attributes such as type of collar, color, and pattern (see Figure 12). Customer feedback and sales data are used for selecting popular attributes (Colson et al., n.d.). Then these attributes are recombined and some mutations happen (alterations are made). In order to improve the quality of the next collection, a model is developed that predicts the probability a given set of attributes will satisfy customers (Colson et al., n.d.). The attribute sets with the higher probability of being loved by customers will be selected, and finally, the stylists and designers modify the sets of selected attributes to create the new collections (Colson et al., n.d.).

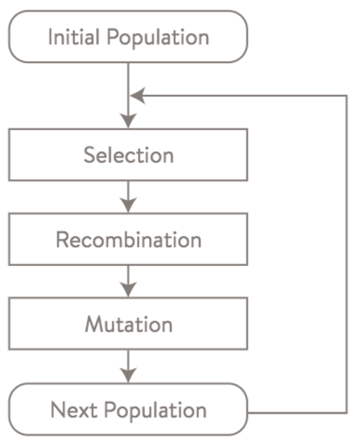

Figure 11. Process of Stitch Fix "natural selection" (Colson et al., n.d.).

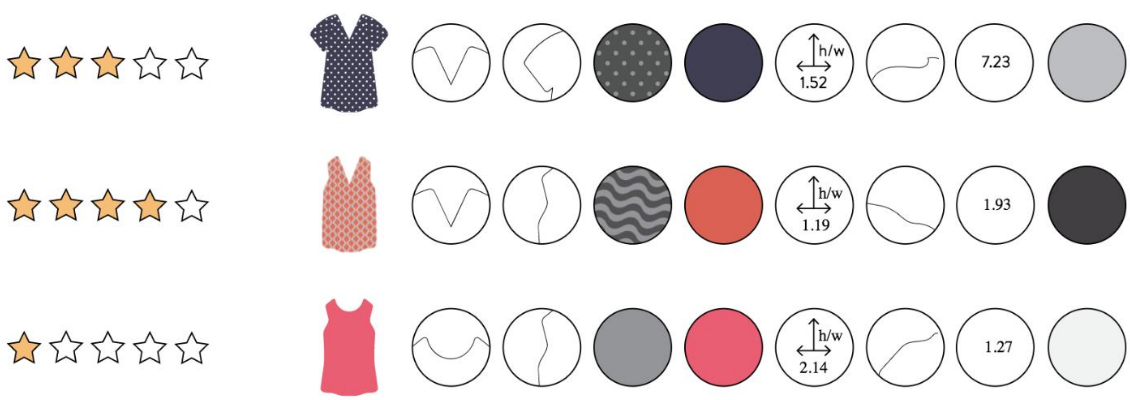

Figure 12. Attribute sets of clothing in inventory (Colson et al., n.d.).

Summary.

Thanks to the partnership of merchant, marketers, stylists, and data analytics, Stitch Fix is creating more convenient, relevant, and personalized shopping experiences for their customers (Klingenberg, 2019). Stitch Fix transforms how people can get fashion where customers do not have to browse clothing or try to keep up with fashion trends by themselves. Instead, they can just fill out a Style Profile and wait at home. The goal of the company, according to Klingenberg (2019, para. 3), "is not to replace the role of human judgement, but to enable humans to do things they'd never be able to do alone—like simultaneously considering the inventory preferences of our millions of clients."

However, adding a challenge for Stitch Fix, Amazon is now testing a shopping site that is similar to Style Shuffle in that it lets customers give a thumbs up or down on an item, and during the rating process, customers could be inspired by something they want to buy (Levy, 2018; Pan, 2018). Amazon's site is currently available for home furniture, kitchen and dining products, lighting and bedding, home decor, patio furniture, women's shoes, and men's athletic apparel. As Amazon moves forward with their ratings system, Stitch Fix may lose its advantage of owning data insights from image ratings. Stitch Fix also has to address the fact that some customers complain that they do not receive anything close to their expectations (Cheng, 2018). It is crucial to keep learning from failed initiatives (Lake, 2018).

Conclusion

Data analytics enables companies to generate valuable insights to make better fact-based decisions with the goal of taking actions to improve business performance (Tan et al., 2015). However, few articles illustrate the specific real-world application of data analytics in the fashion industry. Thus, this paper aims to introduce the innovative endeavors of fashion firms by discussing six cases with a focus on their data analysis and applications. The six companies in the case studies utilize pertinent data-related methods to seize opportunities and manage challenges while following new market trends. Each case includes specific data analysis methods, processes, and results. Collectively, the cases reveal several beneficial outcomes from the application of data analytics in the fashion industry, including highly relevant service, optimized logistics, timely trend-spotting, and accurate customer-related predictions and recommendations.

Benefits

First, these new data analysis approaches operate in real time, which is critical in allowing fashion companies to rapidly adjust to market trends and customer demands. Ralph Lauren’s PoloTech Shirt with built-in sensors can collect a wearer’s real-time physiological data such as heart rate, breathing depth, steps taken, and calories burned. These collected data can be immediately read on the PoloTech app and analyzed through machine learning algorithms to help the wearer make timely adjustments to his or her workout plan and improve the quality of the workout. Similarly, a customer only needs to simply upload photos of two outfits to Amazon’s Echo Look to have the device give the customer near real-time feedback about which outfit looks better, taking into consideration color, fit, style, and current trends, all done with the help of machine learning algorithms and Amazon’s trained fashion specialists. Likewise, customers can find similar styles of fashion apparel they like on Amazon at once by uploading the image of the item to Amazon StyleSnap. With the support of powerful neural networks, StyleSnap can detect images and promptly recommend similar products available on Amazon to the customer.

Second, data analysis technology optimizes the fashion companies' recommendation systems. When customers go shopping on the Stitch Fix website, they do not have to select products. The only thing they do is provide their body data and express their demands. Stitch Fix's data-based recommendation system can effectively analyze numeric, text, and image data provided by customers to predict their demands and match those demands with inventory products. In parallel, Burberry encourages its customers to voluntarily share their shopping preferences, purchase history, and social media accounts through its digital loyalty program, Customer 360. Based on those data and current market trends, Burberry's Customer 360 program can extract valuable insights about its customer and help offer personalized recommendations and services. The purpose for the recommendation system is to improve customer shopping experiences and promote the company's products.

Third, data analytics improves the performance of inventory and logistics management. To avoid deeply discounting items due to overstocking, Gap Inc. first produces a small number of products and tests them at stores to gather consumer reactions to the products. The company has collected and analyzed real-time data of consumers' evaluations and sales and then determined how many products to produce. This application contributed to opportunely adjusting inventory according to market demand and reducing costs due to overstock. At RTR, data analytics is applied to everything from inventory selection (e.g., which fabric is easy to take care of and has a long life) and tracking to inventory sequencing to shipping method selection. The algorithms consider shipping time, request interval, dry cleaning and repair time, and the possibility of package loss to make predictions that guide decisions on the order process and shipping method in order to ensure the products will be delivered on time and at the lowest cost.

Fourth, data analytics changes the decision-making process of the fashion industry, which has historically been dominated by intuition and experience (McAfee & Brynjolfsson, 2012). For example, Gap Inc.'s current CEO has replaced existing design decision-makers with a data-based model to increase accuracy and efficiency in spotting market trends and, therefore, produce optimal products. However, data analysis applications do not eliminate the need for human beings. Amazon, Stitch Fix, and RTR all have stylists who cooperate with analytical applications to offer customers more understandable and accurate suggestions. The fashion industry still needs human insights, not only for product development and management but also for building harmonious relationships among "customers, employees, stockholders, and other stakeholders" (McAfee & Brynjolfsson, 2012, para. 31).

Challenges

The case studies also revealed several challenges with data analysis applications. First, it takes time to develop and run high-performance algorithms to process and analyze various categories of data, such as the recommendation algorithms at Stitch Fix. Inventory products are selected through multiple instructions, including filtering, warehouse assignment, and match to customer demand. To analyze customers' needs, the company depends on constantly updated customer profile data, feedback, request notes, and Pinterest data. It includes numeric, text, and image data, which requires several complicated processes for analysis. Second, data privacy and security vulnerability have become common issues due to external hackers and internal abuses of access to sensitive information. Many companies have taken actions to mitigate these risks, including establishing related teams to monitor computers and networks, developing data security training for employees, and investing in better cyber security. Maintaining data privacy and security plays an important role in gaining trust from both customers and other competitive companies. Last, complex data preparation and calibration are required to handle heterogeneous data and interferences in the data collection process, as shown in the Ralph Lauren case. Due to the different types and modalities of sensors, the data collected have various structures, which leads to increasing difficulties in interpreting data. Thus, data cleaning, revision, and integration all must be done before these data can create value.

Overall, the examined companies have benefited from data analytics. It will take time to determine whether data analytics will have a positive influence on companies' development in the long run. Since the fashion market is ever-changing, techniques and strategies should be continuously updated to achieve better business performance; however, as we know, not every fashion firm implements these new data analysis approaches. Based on this study, it can be seen that data analytics first requires rich data sources and professional data teams, which small- and medium-sized fashion firms generally lack. Thus, before investing in data analysis-related strategies, a company must determine whether its assets and capabilities can afford the investment (Porter & Gogan, 2013) Second, the decision-making culture also affects the implementation of data analysis. Many fashion firms, such as Gap Inc., have historically employed their own creative directors to design new collections based on their own fashion intuition. Applying data analytics will create cooperation between humans and data and between data teams and other teams in the company, which means decision-making shifts from an individual responsibility to a collaborative one. However, it is not easy because different people can have cognitive differences that are highly likely to cause disruption and changes in power structures and individual roles in a company (Frisk & Bannister, 2017). In summary, although data analytics is currently popular, it is important that companies implement strategies based on their own unique situation.

Future work

As illustrated in the Introduction, many researchers have developed and implemented advanced data analysis techniques for the examination of real data in the fashion industry, and many have proven the superior or potentially superior capabilities of these methods for making contributions to more accurate analyses. However, there are still very limited numbers of fashion firms applying these approaches in a practical manner in their business. Although some factors that may prevent fashion firms from implementing advanced data analytics have been suggested, there is to date no study describing an experimental investigation of the barriers in the fashion industry. Thus, future research should be conducted that aims at understanding the actual barriers and reasons for the limited use of advanced data analytics in the fashion industry.

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