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The Impact of the Consumer Involvement in Big-Data driven New Product Development (NPD) in the Apparel Industry and Consumer Satisfaction of New Product

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1. Abstract

This study aims to evaluate the impact of Consumer Involvement in Data Collection (CIDC) and Consumer Involvement in Data Interpretation (CIDI), two key practice of integrating big data in the new product development (NPD) process with the objective of improving customer satisfaction within the apparel sector. Preliminary findings indicate that big data is growing and large quantities already exist as a resource that is waiting to be utilized. Success of early adopters such as Stitch Fix and Gap Inc. amongst others validate the proof of concept that the model is able to work, but a lack of studies in the way big data is applied in the apparel sector indicate the infancy of the research. For big data to be indicative of effective in the NPD process to improve customer satisfaction, it must be established that it is accurate in its forecasts and feedback on existing customer preferences, the inclusion of such data can provide statistically significant improvements in customer satisfaction and that it is a viable and feasible solution to be adopted within the apparel sector. The lack of research in this field in particular where customer's involvement in data analytic is concerned provides a wide scope of opportunity for further growth, and to understand the mechanisms behind how different ways of incorporating big data has benefitted early adopters. Due to the limited use and adoption of big data within the design process in apparel, findings from this study could then be used to guide future integration and provide practicable recommendations for existing businesses to transition towards an big-data-integrated NPD organization model.

2. Introduction

The advent of technology in society has effectuated an exponential increase in data generation. IBM (2013) stated that 90% of data worldwide was generated in the preceding two years (Zhan et al., 2016). With the likes of McKinsey (2011) and IBM (2013) proclaiming the era of 'big data', the ability to harness this resource and extract crucial insights could provide businesses with a competitive advantage (cited in Zhan et al., 2016). Big data is defined by the '4Vs' of volume (quantity of data), velocity (speed of data generation), variety (different types of data) and veracity (data trustworthiness). Currently, it is growing in significance within the apparel industry and is being increasingly introduced in 'trend forecasting, supply chain management and analyzing customer behavior, preferences and emotions' (Jain et al., 2017).

The apparel industry has traditionally followed a 'design-driven' business model (Bertola and Teunissen, 2018) following the trend and market predictions of the designer with collections designed at a minimum, a full season, ahead of retail. Attia Bashir, a designer at apparel retailer Bonmarché, states that they work on a 'basic principle of speculating demand early' (cited in Ahmad, 2012). Thus, it is predominantly a retailer-led model where consumer demand and desire are artificially generated after the designs are finalized. The incorporation of big data has the

potential to disrupt this product design process by being ‘consumer-driven’ based on consumer insights derived from big data. Therefore, the design develops from consumer preferences in lieu of designer whims.

The mechanisms and feasibility of how big data can be implemented in NPD is yet to be determined. The effect of two dimensions of data analytic, Consumer Involvement in Data Collection (CIDC), as defined by customer passive involvement as data provider only; and Consumer Involvement in Data Interpretation (CIDI), as defined by customer actively participating in data collection, analysis, feedback and interpretation of data in the product development process, will be examined against new product satisfaction.

3. Literature Review

An initial literature review was conducted to identify and evaluate existing data on the big data and NPD in the apparel industry. Keywords of this search include ‘NPD’, ‘Product Design’, ‘Big Data’, ‘Mass Customization’ and ‘Apparel industry’. Due to the limited studies currently conducted, the search was widened to include those not specified to apparel, and where possible, findings extrapolated to identify potential applications within the apparel sector for further research. The studies were analyzed and compared, and the critical discussion garnered from this allowed further insights to be developed and areas of ambiguity to be identified as areas of weakness to be developed. This provides a preliminary framework to illustrate interconnections across perspectives to produce a summarized reflection of the information applicable distilled down to answer the focused research question.

Current literature is supportive of customer involvement in the new product development (NPD) process (Tiedemann, Johansson and Gosling, 2018), and ‘novel approaches are required to ensure the active integration of customers into NPD’ accordingly (Zhan et al., 2016). NPD is defined by Ulrich and Eppinger (2004) as ‘the set of activities beginning with the perception of market opportunity and ending in the production, sale and delivery of a product’ (cited in Choi, Powell and Cassill, 2005). Big data is adeptly positioned to facilitate this as consumer feedback and lifestyle profile is provided on a population scale. Thus, large populations of consumers are able to provide feedback simultaneously with minimal effort. This is disruptive to the current NPD model in apparel design because the design initiates from consumer desire, rather than consumer desire being induced after the product is made. Further to this, as the development of application of big data in the NPD process gather pace, consumers increasingly play an active role in consolidating, analyzing and utilizing data, thereby becoming co-creators of new products with firms.

Consumer Involvement in Data Collection (CIDC)

Currently, it is an opportune time to utilize big data due to vast amounts of high dimensional or unstructured data available in addition to the amounts incessantly produced and stored at inexpensive costs, with predictions that this is to accelerate in coming years (Fan, Han and Liu, 2014). The large sample size enables analysis on a population level where trends can be identified more clearly overall in addition to subpopulations and various other market segregation demographics, which would not have been feasible with smaller market research sample sizes. Data analytics in this regard are often conducted by firms who have higher capability in analyzing big volume of data over individual customers. Customers involvement in this instance is passive, as a data supplier only.

Consumer Involvement in Data Interpretation (CIDI)

In the Consumer Involvement in Data Interpretation (CIDI) perspective, customers take on a more active role in big data analytic. As Zhang and Xiao state in their study, when customers are given opportunities to generate insights from big data analytics, the firm has an opportunity to obtain additional customer knowledge from those insights. Firstly, customers are more likely to focus on data more relevant to their own needs (Zhang and Xiao, 2020). If presented with multiple evaluative criteria in relations to product features, customer can also rank them into orders of significance according to their own needs, thereby making the ‘raw data’ more meaningful. As such, customers are more likely to translate their own needs and consumption experiences into useful insights for NPD. However, although higher customer involvement in this instance might result in higher customer engagement and therefore customer satisfaction, with this approach firms are unlikely to produce products that will satisfy broader customer base with more mass appeals as with the CIDC process.

Consumer Needs Disparity (CND)

Consumer Needs Disparity is defined as the measurements of functions and attributes of a product, on which consumers make their purchase decisions on. An example of a category of apparel product with low CND value would be a pair of socks, in which with the considerations in NPD, of material suitable for summer or alternatively, material suitable for winter, might be enough to meet the most basic functions of the apparel product addressing the consumer’s needs. An apparel product category with relatively higher CND value than socks would be the category of T-shirt, in which more different attributes of the T-shirt, such as long sleeves or short sleeves or sleeveless, in addition to the choice of materials, should be considered in the product development process to address different consumer’s needs.

In addition to literature reviews of previous studies in relations to the disparity of consumers’ needs in relation to a product, a preliminary investigations in the 10 most common apparel categories to determine their CND value will be conducted and justified prior to the tests of the hypothesis.

4. Hypothesis

Hypothesis 1: Consumer Involvement in Data Collection (CIDC) increases customer satisfaction to new apparel product

In their 2015 study, Tehrani and Ahrens successfully applied big data techniques including machine learning and clustering in the apparel sector to make statistically accurate sales predictions, concluding that they ‘advocate the usefulness of big data techniques’ in the apparel sector. Their study emphasizes that big data is more accurate because they are not under human bias, which is likely to influence traditional trends and market forecasters. Their aim of modelling ‘customer’s interest’ in the apparel sector proves promising in the potential for capturing consumer preference. In the Consumer Involvement in Data Collection (CIDC) model, customer is solely responsible for the source of data with data analytic being done by firms. This is supported by Chen and Luo (2016), in their use of machine learning techniques to analyze big data of an online shopping dataset to identify popular and preferable apparel features. They conclude that their experiment ‘is effective in discriminative mining of best-selling clothing features’ (ibid). Alton (2018) states that “Big Data analytics on purchasing behaviour from past seasons can help ascertain which fashion qualities or elements shoppers may respond favourably to in the future” (cited in Silva, Hassani and Madsen, 2019). DuBreuil and Lu’s 2019 study concluded that ‘big-data tools have the strengths in forecasting color and apparel pattern’, demonstrating strong promise in big-data in market forecast. The collection of existing, big data of consumers can be used to identify and forecast trends and apparel attributes that correlate directly to consumer preferences. Thus, the independent variable being tested is the adoption of big data in the NPD process under the CIDC procedures and the dependent variable to be measured is the change in customer satisfaction in new product.

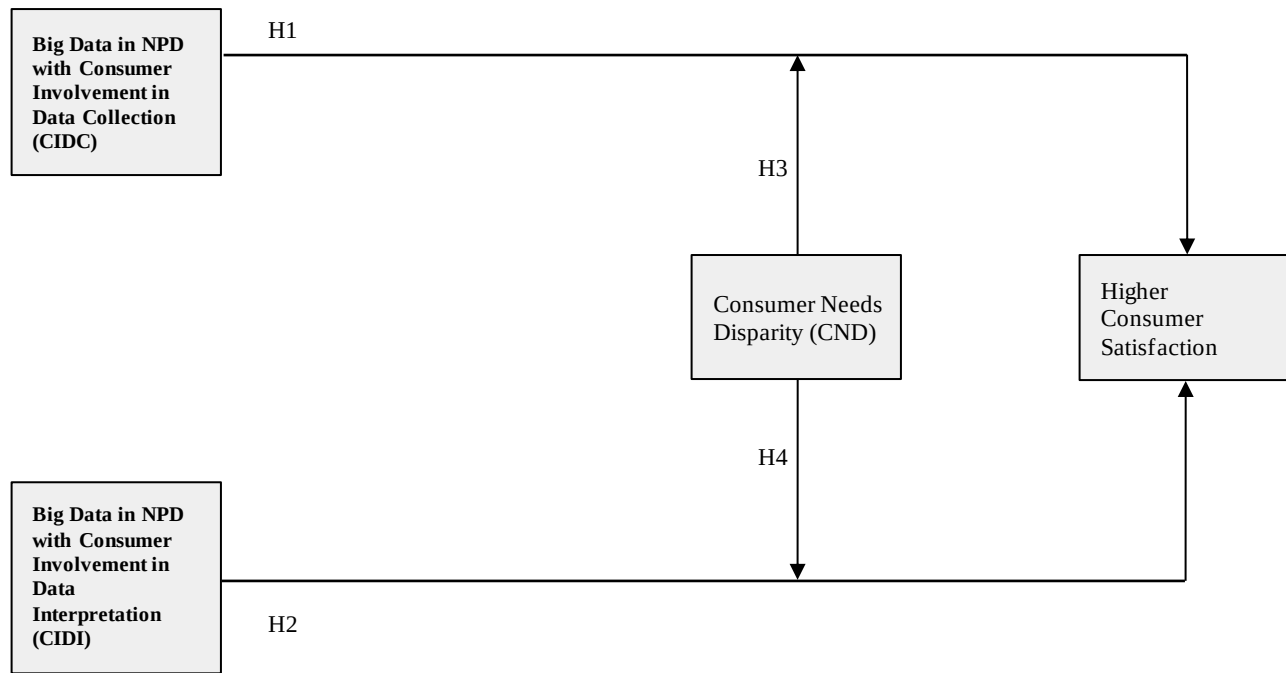


Figure: Graphical model of intended hypothesis to be tested

Hypothesis 2: Consumer Involvement in Data Interpretation (CIDI) increases customer satisfaction to new apparel product

The advancements in data science has established data as an indexical record of empirical fact, and this knowledge is more accurate than subjective conceptions of a sole creative designer in NPD (Athique, 2017). This information could then be disseminated to the NPD process as an effective tool in determining product specifications in NPD based on real-life feedback.

However, the volume of big data often comes from a wide market space and they are more likely reflect the average customers' need rather than specific group of customers' need (Zhang and Xiao, 2020). As Zhang and Xiao stated in their study, 'if a firm "outsources" big data analytics to its customers, the customers are likely to focus on data that are relevant only to their own needs (Zhang and Xiao, 2020). In this regard, they are unlikely to treat all data points objectively and equally, thereby limiting the quality and scope of big data analytics.' (Zhang and Xiao, 2020). With the potential of highly standardized offer, owing to the accommodation of wider demands, "the desire for differentiation with respect to other consumers and the wish to participate in the product design has risen sharply among consumers". (Grimal and Guerlain, 2014) With this second perspective of CIDI in NPD, customers provide data such as their preferences, conduct data analysis identifying specific focus of data that might be relevant to their own needs, and

engage in dialogue and interaction with the suppliers in product development processes, giving feedbacks and user experiences, sometimes beyond the production stage until the final product commercialization. Customers are thus being allowed to have some degree of ‘personalization’ in relations to their needs and become the co-creators of the product. Great examples of apparel firms that implement this form of big data NPD include Nike, Adidas, Levi’s.

Hypothesis 3: Consumer’s Needs Disparity (CND) moderates positively between CIDC and customer satisfaction to new apparel product

In the apparel market, multiple evaluative criteria such as design, colour, comfort, fabrication, fit, and workmanship are considered for customer satisfaction for a singular product. In product categories with more attributes addressing consumer’s need, in this respect, individual preference for each criterion and the overall needs of the consumer can be very diverse. Co-founder of London-based apparel retailer Editd which uses data-mining to guide decision-making, Julia Fowler, states that “People express opinions about fashion constantly — we have more than 100 million opinions sourced over the past 12 months specifically on individual garments, fabrics, prints and styles” (cited in Kansara, 2011). In the CIDC perspective, with the primarily objectives being predicting wider trends to accommodate broader demands, it can be expected this approach would have a high degree of accommodation of the diversity of needs. In this regards, a positive moderation effect is expected.

Hypothesis 4: Consumer’s Needs Disparity (CND) moderates negatively between CIDI and customer satisfaction to new apparel product

In the CIDI perspective, where customers are to analyze the data according to their own needs, engage in dialogues and interactions with the suppliers in the product design development process, in addition to providing data to the suppliers, it is expected customers’ needs disparity might have negative moderation effect to the relations between CIDI and customer satisfaction to a new apparel product.

5. Approach & Methodology

5.1 Design and Sampling

A survey questionnaire with multiple scale items, including the natures of customers’ needs, intrinsic criteria in relation to product satisfaction, and dissatisfaction will be conducted for hypothesis testing. Types of NPD data analytic will be monitored as constructs. Evaluative criteria adopted for intrinsic criteria would be design, colour, fabric, comfort, fit and workmanship, which are the common product satisfaction factors for apparel products. Items are rated on a 7-point Likert Scale with response anchors such as ‘strongly agree’ and ‘strongly disagree’ at the opposite spectrum of the scale. Constructs and scale items are shown in Table 1.

5.1.1 Table 1: Construct and scale items

Construct	Scale Item
Consumer Involvement in Data Collection 7-point scale 1 = Strongly Disagree 7 = Strongly Agree	In the new product development process Customers acted as data providers only Collection, analysis, adaptation of data by the firm to generate new products
Consumer Involvement in Data Interpretation 7-point scale 1 = Strongly Disagree 7 = Strongly Agree	In the new product development process Customers generated, analyzed and utilized data to generate new products Customers have opportunities to give feedback to drive product development
Product uniqueness 7-point scale 1 = Strongly Disagree 7 = Strongly Agree	New product share more common attributes with industry standard product New product have more unique attributes
Product Satisfaction 7-point scale 1 = Completely Dissatisfied 7 = Completely Satisfied	Design Colour Fabrication Comfort Fit Workmanship
Customer Retention 7-point scale 1 = No Retention 7 = Extremely High Retention	Customers are less likely to return for future purchases Customers are likely to return for future purchases
Consumer's Needs Disparity 7-point scale 1 = Extremely Low 7 = Extremely High	Customers have diverse needs Customers are not satisfied with standardized design Customers have diverse preference of individual modular product features
Number of Development Teams Involved Size of Firm	Number of product development teams involved in the NPD process Number of total employees in the company

5.2 Sampling procedures

A prescreening questionnaire will be sent out to the managers of apparel manufacturing companies in Greater China to ensure they are the target demographic and are qualify to answer the survey. Questions include:

- Respondent must be on a managerial position and that he / she has sufficient knowledge in the area of NPD to answer the survey question
- Respondent's firm(s) must conduct NPD activities within its business
- Respondent has access to customer feedbacks on the new product

Benefits of this sampling method is its feasibility and the ability to maximize the amount of data gathered as no further sampling needs to be done within the smaller pool of willing participants. A larger sample size not only yields more data, but also increases the validity of the study. Currently there are approximately 15,000 firms involved in either B2B or B2C manufacturing activities of apparel products in China. This research aims to recruit 375 company representative participants for the study.

Exploratory Factor Analysis (EFA) would be conducted before Confirmation Factor Analysis (CFA) to test the hypothesis.

5.3 Limitations

In this study overall customer involvement in NPD is considered. However, in a naturalistic scenario of NPD, the NPD processes are often very complex and contain multiple stages, in some cases these stages might take place across different departmental teams inside or outside of the firms. In this regard, CIDC or CIDI implementations at different stages very likely yield different results in terms of their influences in the NPD processes. In addition, sampling used in the study are managers and engineers in the manufacturing industry, which limits the generalization of findings.

Second, new product satisfaction is measured on intrinsic criteria feedback from customers, obtained by the firms. Although this might provide some insights into how customers' needs might drive innovation in product development, new product's financial performance and size of market share, which are more reflective of market adoption of the new product, are not captured or measured in this model.

Third, the resulting sample composition of CIDC and CIDI might be imbalanced due to the relatively new phenomenon of adoptions of big data analytic in the industry in particular with the case of consumer involvement in data interpretation.

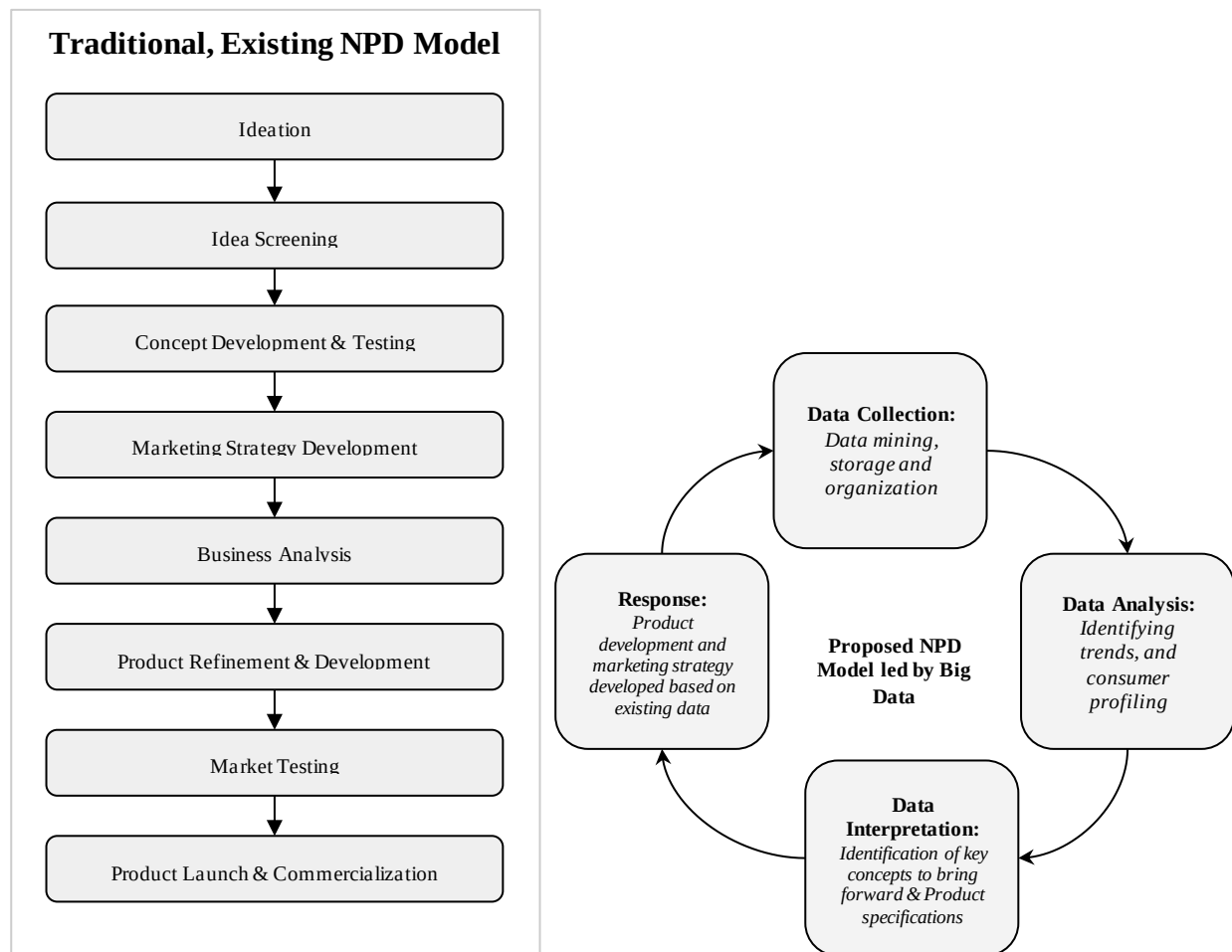
6. Preliminary Findings

6.1 Big Data in 'Design for Consumers' approach in new NPD model & Apparel

Using big data in NPD echoes the 'Design for Consumers' approach, whereby 'data on users and general theories and models of consumer behavior' serve as the basis for design (Fenko and Rompay, 2018). Whereas the traditional NPD focuses on '*the designer perspective*' with emphasis on the consumer's response to creation, harnessing big data democratises the design process by shifting the position of ideator towards the end user. This is beneficial because of variances in how designers and consumers interpret products, and 'express different aesthetic preferences' (Hsu, Chuang and Chang, 2000 cited in Fenko and Rompay, 2018). Thus, 'objective properties of a design are insufficient' in judgements on product appeal (Fenko and Rompay, 2018). This mismatch in perspectives opposes the objective of producing increasingly preferable products through the fallible assumption that designers and consumers inherently desire and prefer the same things.

Hekkert and Schifferstein (2008) found that customer's verbal responses were inadequate and overly superficial to provide substantial and meaningful insight in product development - as is common in the traditional NPD model. They elude the subtle meanings and values attached and the elicited feelings and emotions from interaction with a product (cited in Fenko and Rompay,

2018). Furthermore, the coordination and collection of this data is tedious and time-consuming and is limited by small sample sizes. Incorporating big data into the NPD process is able to bypass this by providing an all-encompassing overview of the customer's perspective and lifestyle in an objective, observational manner with minimal effort on the customer's part. Computer scientist and professor at Cornell University Kavita Bala believes that 'As machine learning gets more sophisticated, it will be able to detect micro trends before they become widely popular. This will be the holy grail of retail. With this, retailers can respond a lot faster to changing preferences. If we can forecast trends fast, it will fundamentally change how designs spread and might open the doors for 'smaller' designers to reach large audiences. A more democratic spread of design ideas can potentially be enabled' (cited in Cao, 2018).



Big data-driven apparel design brand, Hybrid Designs uses data mined by data scientists to drive ideation as opposed to designers. When their data revealed mid-40s female clients were seeking capped-sleeve blouses lacking in their inventory, they were able to produce such products to meet customer preference immediately. This allows them to see market gaps quickly and act responsively. In addition, they apply a quantitative approach to apparel measurement tracking of up to 100 measurements per garment. This provides information on optimal size ratios (eg. chest

width to shirt width ratios on shirts), to preferential button placements and inseam lengths on a large, population scale. This data drives their NPD process instead of being designer-led. Although different from industry norms, they have experienced success with this model thus it is likely to see others follow their model.

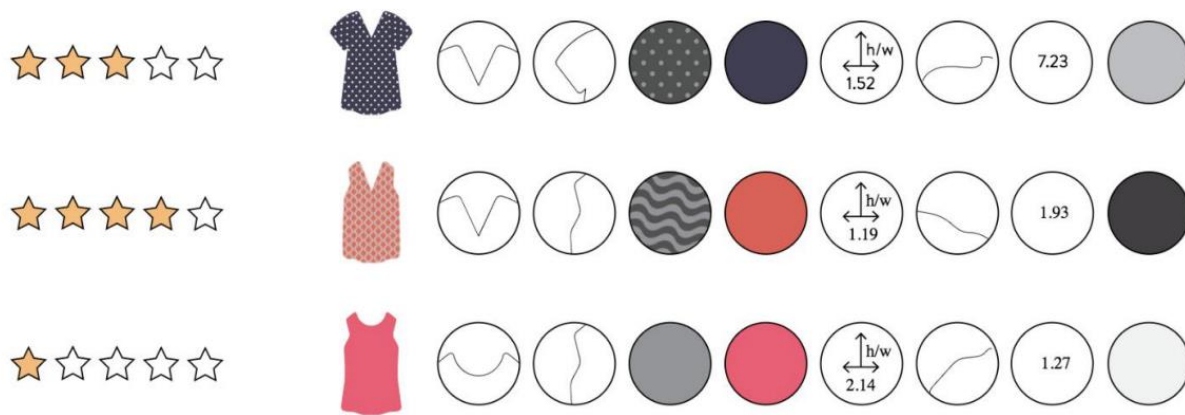


Figure: Hybrid Design collects information from consumer browsing behavior and surveys to understand consumer preferences to be used in their NPD (Colson et al., n.d. cited in Du, 2019)

6.2 Big Data in the Apparel Industry

Successful integration of big data in the NPD model to improve customer preference is seen in apparel retailer Zara. Using big data analytics of social media activity, Zara found substantial activity surrounding musician Beyoncé’s world tour. They used this data to guide their product ideation, development, marketing strategy and launch date of tour-themed apparel ahead of time, thus were primed and prepared to take full advantage of the opportunity (Brownlow et al., 2015). According to Silva, Hassani and Madsen (2019), apparel retailer Macy’s also found success through using big data analytics in their product pricing development. Analysis of consumer’s behavior on social media, their namesake website and other store transactions guide them towards increasing sales by creating targeted product discounts. Current techniques in big data analytics for fashion sales forecasting used in the industry include time series analysis, regression analysis and multiple factor analysis (Du, 2019).

Within the apparel industry, the shift towards using big data is also evidenced. Katrina Lake, CEO of American apparel retailer Stitch Fix (2018) states that at Stitch Fix, she ‘leverages data science to deliver personalization at scale’, demonstrating the viability of big data in NPD. In contrast to the norm in the apparel industry, Lake (2018) states that data science ‘is [our] culture’, whereby they employ over 80 data scientists with doctorates in fields of astrophysics, statistics, neuroscience and mathematics. She quotes (2018) that “the part of me that loves data knew it could be used to create a better experience with apparel. After all, fit and taste are just a

bunch of attributes: waist, inseam, material, color, weight, durability, and pattern. It's all just data. If you collect enough, you'll get a pretty good picture of what clothes people want". As an early adopter of big data in the apparel space, they have proven that big data is propitious in this industry, sales of \$977 million USD in 2017 and over 2 million active clients (Lake, 2018). In the NPD process, Stitch Fix uses data to determine which products to market ahead of commercialization, which Lake accredits this strategy of buying the right things for the right people for their high inventory turnover rate. This suggests implementation of NPD process improves customer preference as sales increase, but also because products are better matched with customer preference.

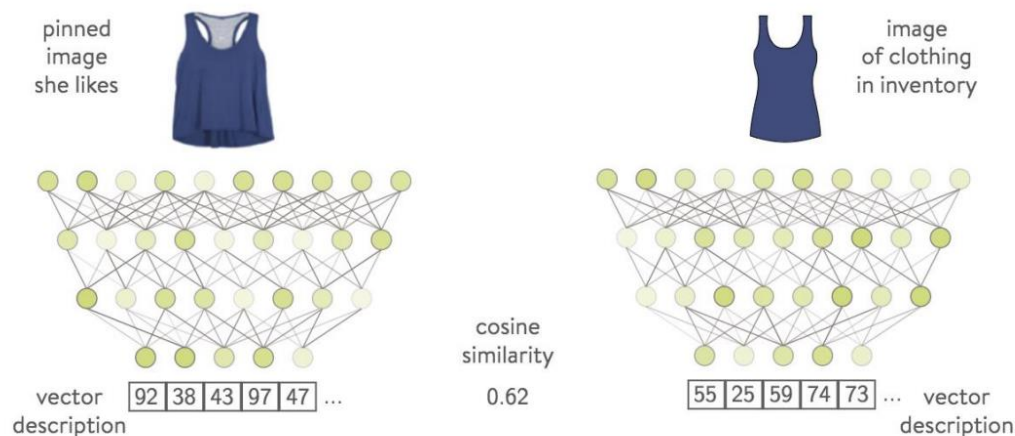


Figure: Stitch Fix data-algorithm process in big data analytics (Colson et al., n.d. cited in Du, 2019)

In addition to the adoption of big data in the NPD process in highstreet brands, luxury apparel retailers are also taking advantage of the opportunities brought on by big data. Luxury German retailer and manufacturer, Montblanc increased sales by 20% after the implementation of big data analytics software (Jain, Bernal and Jain, 2018). Video analytics in their brick-and-mortar retail stores generated data maps demonstrating customer behavioral patterns whilst shopping. Customer preferences could then be gleaned from this, and their strategy adapted to match in quick response. Thus this suggests that big-data is beneficial for understanding consumer preferences.

The successful integration of big data in the NPD process is dependent on findings remaining stable at time of product commercialization. However, the fleeting nature of fashion trends makes this contentious. Gaimster (2012) and Israeli & Avery (2018) support the idea that fashion preferences of consumers are relatively stable thus existing and historical data is suitable for future product developments and launches (Cited in DuBreuil and Lu, 2019). There is further support that the evidence-based approach of big data improves accuracy of market understanding due to its less subjective nature (DuBreuil and Lu, 2019). DuBreuil and Lu (2019) also found that the use of big data in fashion trend forecasting - a crucial market research strategy in the

fashion and apparel industry - was statistically similar with traditional and existing trend forecasting methods at the 95% confidence level. However, Lake (2018) admits that the fashion retail industry is ‘crowded, fickle and rapidly changing’.

6.3 CIDC Case: Gap Inc.

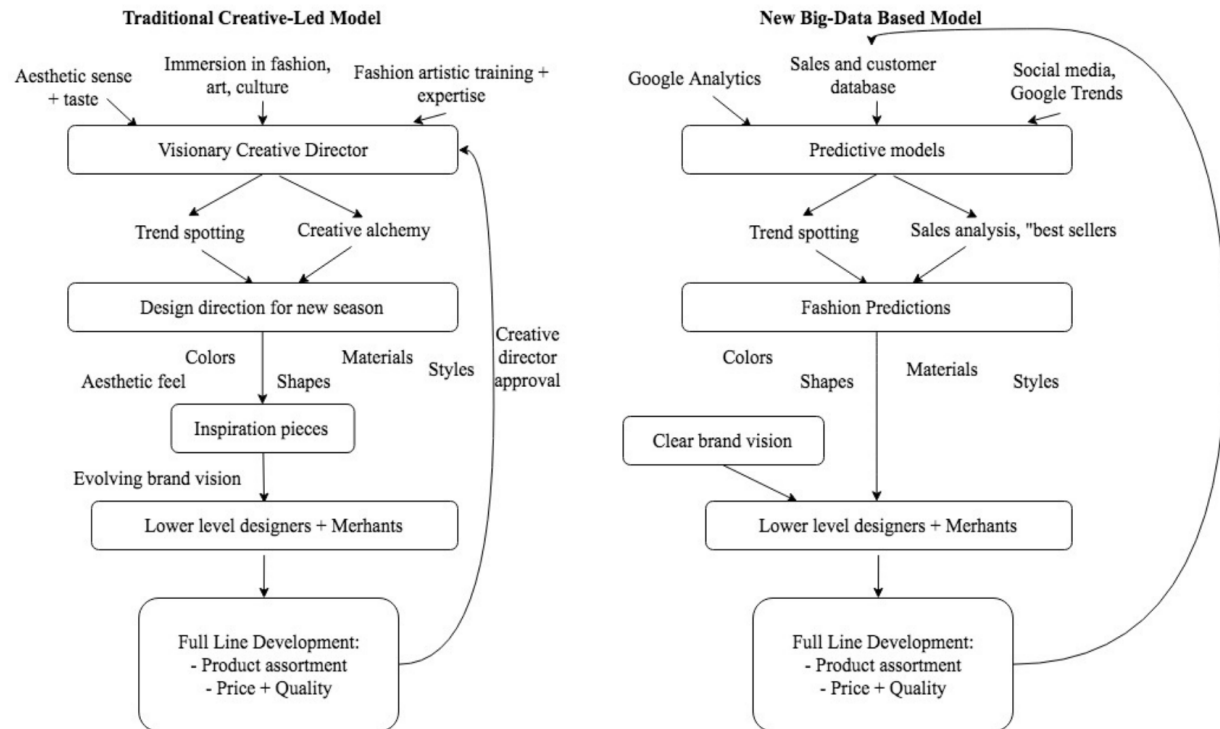


Figure: Gap Inc. Brands design process (Israeli & Avery, 2018 cited in Du, 2019)

Gap Inc. uses an omnichannel shopping database to streamline customer experience and collect data seamlessly across platforms and channels. Customers benefit from a tailored and simple shopping experience with the option of choosing their preferred media platform, whereas Gap Inc. benefits from the increased access to consumer data. Criticisms of Gap Inc’s previous, traditional, creative-led model include being governed by creative instinct instead of evidence, and conflict between the creative directors’ seasonal vision and customers’ aesthetic sense (Israeli & Avery, 2018 cited in Du, 2019). In addition, approval of concepts can be time-consuming and overly bureaucratic, thus rendering the process more inefficient. By incorporating a data-mining approach to use evidence found in Big Data, Gap Inc. was able to shorten their design cycle which is beneficial to improving consumer preference as new products can be tested in the market and adjusted much quicker. The Big Data that Gap Inc. uses is collected from social media, Google Analytics, their own channels and platforms and other customer databases. The real-time statistics provide the length of time consumers spend on each site/platform, what they are browsing, how long they are browsing for, their behavior (i.e. how many sites they visit on average before making a purchase selection), their engagement and

interaction and their consumer trends. Other points of note include improvements in stock management of new products as demand can be more accurately forecast with real-time analytics (Du, 2019). However, key criticisms of the feasibility and application of big data in NPD is the dilution of creativity, brand authenticity and uniqueness towards one driven by mainstream interests. Gap Inc. has decided that this is of lesser importance because it is not a design-led brand, and instead, is one tailored towards consumer lifestyle. Whereas the traditional model was proactive in proposing new apparel ideas, the big data-driven model is reactive to market trends, and therefore may appear behind current trends due to the lag time in production (Kenny, 2018 cited in Du, 2019).

6.4 CIDI Case: Burberry Group Plc

Burberry, a British fashion brand that produces high end clothing, accessories, fragrances and other fashion related products, is one of the early adopter of integrating big-data and customer involvement into its product strategy. In 2012 Burberry implemented their co-creation strategy with a digital platform called 'Burberry World' and a physical implementation of 'Burberry World Live' within its own Regent Street retail location in London, a 'part event space, part innovation hub, part store', providing customers with a 'digitally-advanced brand experience for the first time' (Consumer Value Creation, 2015). 'Burberry World', a series of applications developed by Salesforce.com make interactions between sales, service personnel, and consumers possible by communicating in a 'mini-community'. Through a program called Chatter, 'the employees can not only have access to traditional CRM-related transactional data, they can see an aggregation of their customers' social media posts and activities as well' (Consumer Value Creation, 2015). Customers are also able to participate in upcoming fashion shows, place orders directly off the fashion shows and make suggestions to designs for upcoming collections. Combining with the scope for applications of big-data of 'stored trends' which are the direct preferences expressed by customers that can be used for product development, customer engagement with the provision of data demonstrates strong potential and viability.

6.5 Challenges with Big Data in the Apparel Industry

Big data analytics is a complicated process and errors may occur. High dimensionality of data incur risks of incidental correlations being identified where there appears to be statistical significance when there is none. Fan, Han and Liu (2014) state that 'high dimensionality also gives rise to incidental endogeneity, a phenomenon that many unrelated covariates may incidentally be correlated with the residual noises. The endogeneity creates statistical biases and causes model selection inconsistency that lead to wrong scientific discoveries'. Due to this high dimensionality of big data, noise accumulation is high, and it may be difficult to extract the key data from surrounding outliers. This also increases the risks for spurious correlations. Thus, incidental endogeneity may occur, leading to false inferences whereby a correlation is found between predictors and outliers (residual noise). As this modelling is not reflective of the consumer market, it becomes misleading in NPD. Thus, this is counterproductive of the aim of having an evidenced and data-driven design model. To overcome this, more sophisticated analytics and heavy investment in research and development may be needed. Computer scientist

and professor at Cornell university Kavita Bala admits that this remains a ‘new and challenging field’, but does confer that it poses opportunities for ‘both retailers and consumers’ (cited in Cao, 2018).

In addition, the ‘massive sample size of Big Data fundamentally challenges the traditional computing infrastructure’ (Fan, Han and Liu, 2014). As the size of big data grows, the technology must match its pace in development. Big data is highly dynamic and difficult to store in a single or centralized database, yet if the full potential of big data is to be exploited, all of the data must be accounted for in the analyses. This presents obstacles in data storage and apposition for analysis.

Response from professionals in the apparel industry also remain skeptical. Natalie Nudell, fashion historian and professor at the Fashion Institute of Technology, New York (FIT) proclaims that it is ‘hard to imagine that AI algorithms can produce anything avant-garde or creative on purpose’ (cited in Cao, 2018). Business reporter Sissi Cao (2018) also comments that using algorithms for creative design purposes is ‘overly ambitious’ and ‘unconceivable’ due to the absence of human cognition. Bala remains that ‘designers will continue to be the driving force for creativity’ (ibid).

7. Discussion

The success of big data utilization of big data in NPD is dependent upon the performance of the other areas of business activities of finance, operations and human resources management. A restraint on the effectiveness of big data in NPD is the quantity and quality of financial and human resources available to the organization. A limited response after the utilization of big data in NPD could be wrongly attributed to the new method instead of the limited resources of the firm to collect, analyze and interpret the data. Data analytics is a growing field and requires skilled expertise to navigate, which requires adequate human resource skills to hire or invest in existing talent. The integration of NPD may also require shifts in organization structure. Big data analytics requires skills in data science and computing, which may see an introduction of data and computer scientists as well as IT professionals within the apparel sector. The expansion of this may even require a new technology department and Chief Technology Officer to oversee progress. At apparel retailer Stitch Fix, they created a Chief Algorithms Officer position to manage their data analytics team.

However, the overall application of big data in NPD appears promising, with early adopters such as Stitch Fix and Amazon experiencing success. However, the concern that data-driven design erodes creativity (Choi, 2016) persists within fashion designers and thus, may suggest why early adopters are not design-led apparel retailers and cater more to the mass market instead of a particular style. Thus, preliminary findings may suggest that the incorporation of big data analytics in NPD is more appropriate for non-design apparel retailers.

Customer-driven NPD is infrequently studied in current NPD literature (Tiedemann, Johansson and Gosling, 2018). Particularly in fashion design, the existing literature demonstrates a lack of consensus on the effectiveness of utilizing big data analytics (DuBreuil and Lu, 2019). Thus, its potential is yet to be determined but further, sophisticated understanding could aid identify its benefits and use in the design process. 'Customer involvement, customer co-creation and customer input into the design process is still in its infancy' (Tiedemann, Johansson and Gosling, 2018), and big data is one method to which enhanced customer engagement could be utilised to strengthen the NPD process. The lack of empirical studies in the area of big data in the apparel NPD process reveals an opportunity for further study to improve upon existing models in apparel product development. This study aims to enrich and advance the understanding of big data's current and potential role in NPD. Hence, providing an initial framework towards the future integration of NPD in apparel design to guide future product development innovation.

Table 2: Overview of Important Dates & Milestones

Table 3: Project Plan

[illegible]

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