

ABSTRACT

YU, YANAN. *The Digital Printing Market Deciphered* (Under the direction of Drs. Marguerite M. Moore and Lisa P. Chapman).

Digital printing represents a core innovation that is currently revolutionizing the global decorated apparel business. To date, few empirical and trade research focused on the marketing impacts of digital printing which discourage the relevant stakeholders to efficiently and effectively integrate this innovation into their strategic scope. Therefore, this dissertation is motivated by persistent gaps among scientific discourse regarding the lack of exploration into digital printing from marketing and management perspectives in the fashion domain. This dissertation aims to establish a fundamental understanding of the nature of the digital printing business environment through three unique studies.

The first study presented in Chapter 1 focuses on a sub-category of digital printing, Direct-to-Garment (DTG) printing technology. The first study aims to explore the influential indicators for the DTG market using social media based, data-mining driven Social Network Analysis. Simultaneously, it demonstrates application of a group of novel computational techniques (i.e., Crimson Hexagon, Python, Gephi) to capture, analyze, and visually depict data for strategic insight into the fashion industry. The findings reveal insights into DTG printing technology networks including the dominant apparel categories, the primary competitive approaches and growing market niches for DTG business.

The second study presented in Chapter 2 aims to identify digital printing diffusion patterns in the U.S. to establish a predictive user profile for digital printing technology (DPT) employing social media-based analytics along with data mining and traditional statistical modeling. The results indicate that the visualized DPT diffusion pattern depicts an s-shaped curve, which highlight the propensity that as new technology evolves over time. Additionally, the outcome profile suggests that likely DPT adopters reside in locations that reflect higher levels of education (bachelor's degrees or higher), relatively young populations (i.e., between 19-34 years of age), proportionately higher incomes generated from art and design occupations, but lower levels of household incomes.

The third study presented in Chapter 3 aims to conceptualize a comprehensive framework for business models used by fashion e-commerce print-on-demand (POD) platforms through direct empirical observations. This study draws on the seminal business model literature to apply the formal business model value dimension concept as the unit of analysis. Active online POD

business models are identified and described in terms of value proposition, value creation, value delivery and value capture. The study implies a number of managerial recommendations that are presented in order of the unique dimensions. Given the novelty of the field, the outcomes of this study serve as a guide for prospective POD marketers to build value and recognize opportunities for their own entrepreneurial activities.

The final validation (Chapter 4) presents the findings of an online focus group including three participants with considerable expertise in digital printing. This focus group aims to provide reflection on the results of the three studies in this dissertation. In general, all participants agree that the findings of this dissertation are consistent with their unique perceptions of the digital print market.

To conclude, the inter-related studies in this dissertation provide an illustrative blueprint for digital printing business in the fashion industry including identification of the key indicators, generation of a likely user profile, and identification of feasible business models. In addition, this dissertation serves as a model for examining un-defined, emerging technology that is not understood among brands or consumers.

The Digital Printing Market Deciphered

by
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CHAPTER 1

SOCIAL NETWORK ANALYSIS OF AN EMERGING INNOVATION: DIRECT-TO-GARMENT PRINTING TECHNOLOGY

Introduction

Social media is increasingly recognized as a rich data source through which tech savvy fashion brands pursue marketing strategy including: building customer relationships, responding to market changes, promoting brands, creating viral marketing and ultimately capturing a larger audience (Mohr, 2013; Geissinger and Laurell, 2018; Nash, 2019). There were approximately 247 million U.S. social media users as of 2019 (Clement, 2020). The increasing interaction among individuals and communities among social media environments creates opportunities for marketing researchers to gain insight into target groups. Recent empirical studies of social media in the fashion context focus on employing primary data to identify trends and examination of consumer interaction using traditional methods such as surveys and interviews (e.g. Kang and Kim, 2017; de Lenne and Vandenbosch, 2017; Nash, 2019). However, complex, user-generated social media data, which are valuable for problem solving in fashion contexts, presents challenges for research designs that rely on conventional methods (Tsou, 2015). Therefore, data-mining driven Social Network Analysis (SNA) provides an innovative approach for exploring large-scale dataset generated among engaged social media users.

Data-mining driven SNA refers to the analysis of massive volumes of user-generated data that integrates computational intelligence included but not limited to big data analytics and machine learning (Copeland *et al.*, 2019). This innovative approach provides researchers unprecedented access to large, user-generated data which can reveal insightful patterns of communication among members of social networks, identify patterns for marketing strategy, and provide direction for subsequent predictive models (Zhao and Min, 2018). Nevertheless, likely due to SNA's requirement for extensive computational skills, few marketing researchers implement this method to investigate complex interaction patterns within fashion networks.

To explore how to sufficiently and systematically apply data-mining driven SNA for examination of fashion related topics, we are among the first to demonstrate the application of innovative computational techniques among social media datasets within the fashion domain. This study aims to build an SNA for examining an emerging technology that is not well-defined or understood among brands or consumers. Specifically, interaction among engaged users of Direct-

to-Garment (DTG) printing technology provides the focal context for this research. The benefits of this research are twofold. From an academic perspective, we employ the logic of graph theory to leverage SNA within the fashion domain. Furthermore, we demonstrate a process for adapting computational techniques to capture, analyze, and visualize large scale, user-generated datasets from social media, which provides an analytical example for scholars interested in emergent topics that lack existing empirical knowledge. Additionally, we demonstrate use of centrality indices as a means for interpreting key influencers within these dynamic networks. From a practical perspective, this research generates contextual knowledge for DTG users which depicts evolving marketing structures over the three year period thereby providing insight into the product related opportunities and challenges, design influences, technological alternatives, and growing market niches for DTG. We bridge the gap between knowledge and practice, shedding light on how to harvest, organize, and analyze pertinent user-generated information from social media data to support the strategy making among DTG businesses.

Literature Review

SNA and Graph Theory

Barnes (1954) is commonly credited for developing the original *social network* concept defined as, “a network of relations linking social entities, or of webs and ties among social units emanating through society” (Wasserman and Faust, 1994, pp.10). Social Network Analysis (SNA) is not a formal theory, but rather a broad strategy for investigating social structures (Otte and Rousseau, 2002). The SNA is rooted in sociology and social psychology and incorporates inputs from multiple disciplines that facilitate sophisticated technical approaches including statistics, mathematics, computer engineering for its contemporary applications (Brandes *et al.*, 2013). The SNA integrates numerous important concepts of modern network theory including: cliques and communities, small-world networks, and clustering coefficients (Proskurnikov and Tempo, 2017). However, Graph Theory represents the prominent theory for guiding empirical SNA inquiry (Otte and Rousseau, 2002; Kilduff and Tsai, 2003; Hanneman and Riddle, 2005). Recent SNA research from various fields employed graph theory to facilitate identification of complex social connections among individuals within groups including healthcare and medicine (Ribeiro *et al.*, 2017), information science (Dehmer *et al.*, 2017), psychology (Clifton and Webster, 2017), education (Kondakci *et al.*, 2018) and economics (Lovrić *et al.*, 2018).

Graph theory which originated in the mathematics field, models pairwise relations between

objects (Biggs *et al.*, 1986). In the 1960s, as an upsurge of interest in the mathematics of network analysis arised, graph theory was adopted by sociologists (e.g. Coleman, 1964; Harary *et al.*, 1965) as a straightforward mechanism to represent social network structure (Scott, 1988). The graph theory framework requires two basic elements: a set of socially relevant *nodes* (also known as points, units, vertices, actors, attributes) connected by a set of *edges* (also known as lines, arcs, ties, interactions, relationships) representing social relations among these elements (Scott, 1988; Newman, 2005; Cioffi-Revilla, 2014). Directed and undirected graphs are distinct. The edges in a directed graph follow a fixed direction (one-way paths), while the edges in an undirected graph can be traversed in either direction (two-way paths) (Cielen *et al.*, 2016). The selection of specific graph direction depends on data structure and the research purpose. Graph direction affects construction of the adjacency matrix which is required for representing data structure within computer memory (Singh and Sharma, 2012). The adjacency matrix of undirected graphs is symmetric while that of directed graphs is asymmetric (Hanneman and Riddle, 2005).

Graph theory utilizes various centrality indices to measure the impact of nodes for unique research contexts that solves the central task of SNA, the interpretation of patterns exhibited within the network (Newman, 2005). Centrality provides a basis of interpretation for network analysis through which nodes with high centrality represent dominant components within the network. Hence, social network researchers generally regard centrality as equivalent to power (Mizruchi, 1982; Mintz and Schwartz, 1985). Freeman's (1978) seminal work focusing on centrality in social networks suggests that the impact of nodes can be evaluated through various indices: degree centrality, betweenness centrality, and closeness centrality.

According to Freeman (1978), degree centrality measures the number of edges incident to a single node to determine its dominance in the network. Put simply, nodes with more connections are more influential within the network. In a directed graph, there are two versions of the degree centrality measure, *in-degree* and *out-degree*. In-degree is the sum of the edges received by a node while out-degree is the sum of the edges sent out by a node. In sociology, in-degree is often characterized as a form of popularity, and out-degree as gregariousness (Campennì and Cecconi, 2019). Freeman (1978) defines betweenness centrality as the average differences between the relative centrality of the most central point and that of all other points. Betweenness centrality is calculated as: $C_B(i) = \sum_{j \neq k} g_{jk}(i) / g_{jk}$, where $g_{jk}(i)$ = the number of shortest paths connecting node j and node k passing through node i , and g_{jk} = total number of shortest paths. Stated otherwise,

betweenness centrality measures the number of times a node lies on the shortest path between other nodes; higher value indicates that a node lies on a considerable fraction of shortest paths connecting pairs of nodes (Kumar *et al.*, 2014). Betweenness centrality is a measure of the degree to which a node serves as a bridge. The nodes with high betweenness centrality have considerable control over information passing through the network. As betweenness functions as a junction for communication within the network, removing nodes with high betweenness indices from the network disrupts communications (Borgatti, 1995). Finally, closeness centrality is the inverse of the sum of the length of the shortest paths between a node and all other nodes in the graph (Freeman, 1978). Closeness centrality measures the speed that information spreads from one node to another and is prominently expressed in a highly connected network due to the narrow range of variation (Disney, 2014; Bihari and Pandia, 2015; Rodrigues, 2019).

Social Media Based SNA in Fashion

Interests in social media based SNA have grown rapidly in recent years due to the exponentially increasing social media usage. With the ability to efficiently facilitate the sharing of comments, opinions, and ideas with family, friends, and organizations, social media is currently used by one-in-three people in the world (Ortiz-Ospina, 2019). The proliferation of social media impacts both academia and industry, as the data contained in social media are valuable for problem solving in these contexts. The social media environment attracts diverse demographics, which in turn, provides marketers with an unprecedented platform to reach consumers and establish interactive, long-term relationships (Kelly *et al.*, 2010; Hanna *et al.*, 2011). The interactivity among members of social media networks, referred to as word-of-mouth (WOM) occupies a central role in a given brand's ability to succeed within contemporary markets and represents the focus of a growing stream of research (De Valck *et al.*, 2009; Phan *et al.*, 2011).

Within the fashion field, social media research can be broadly categorized under two approaches to data collection. The first approach includes work that employs primary data to examine the influence of social media on consumer perceptions using traditional methods such as quantitative surveys (e.g. Kang and Kim, 2017; de Lenne and Vandenbosch, 2017) and qualitative interviews (e.g. Nash, 2019). The second approach includes emerging research which leverage on secondary data readily available among social media. For example, Geissinger and Laurell (2018) captured 3,449 user-generated interactions among seven datasets to examine the formation of fashion brand constellations during Stockholm's fashion week using the *Lissly* monitoring tool.

Subsequently, they used content analysis to identify and map references to fashion brands for each respective dataset. Escobar-Rodríguez and Bonsón-Fernández (2017) generated a similar study, using content analysis to examine relationship building efforts for fashion retailers among 2,326 Facebook posts. User-generated data collection overcomes a number of shortcomings associated with traditional primary data collection. The capture of user-generated data facilitates analysis of dynamic interaction among geographically dispersed respondents and also potentially reduces bias (Cuomo and Maiorano, 2017). Primarily researcher bias, commonly associated with instrument development and data collection, is eliminated among user-generated data. Further, users generate data organically, which provides first-hand data that reflects their thoughts free from researcher influence (Salganik, 2017). Though application of content analysis to large user-generated datasets requires considerable time and cost burden for the researcher, Tsou (2015) points out that the challenges associated with big data analysis demand non-conventional data collection approaches. Therefore, social media research requiring large datasets is well suited for inputs from computational data mining.

Data mining is defined as the action of extracting or mining knowledge from large amounts of data (Han *et al.*, 2012). Many researchers demonstrate the analytical advantages that computational intelligence techniques provide, such as machine learning algorithms, due to their ability to identify important features and draw conclusions among large and imperfect datasets (Abonyí *et al.*, 2005; Iqbal *et al.*, 2018). Further, increasing accessibility and sophistication of computational technology provides an unprecedented opportunity for fashion researchers to analyze large social media datasets to generate insights for the field. For example, Park *et al.* (2016) use Instagram data to predict the popularity of fashion models based on observed data from spring-summer 2015 employing *Vader*, a sentiment analysis machine learning algorithm. The researchers conclude that SNA provides a potential alternative for predicting models' face popularity in the fashion industry compared to existing approaches to model selection. Using a different approach based on hashtags, Zhao and Min (2018) identify key influencers and dominant clusters among Twitter users over a three week period surrounding the 2017 Paris Haute Couture Fashion Week. The researchers employed Twitter Application Programming Interface (API) to capture tweets containing three chosen hashtags: #pfw, #haute couture and #chanelhaute couture. Subsequently, the hashtags were converted, calculated and visualized as three individual cases using *Python* and the *Gephi* algorithm. The study outcomes provide dynamic network visualization of the three cases

for each analyzed hashtag, thereby, identifying influential fashion icons, luxury brands and themes during Paris Haute Couture Fashion Week.

Despite the analytical promise reflected in these recent applications of computational intelligence techniques, research into social media based data mining for the fashion industry remains limited. Systematic research that incorporates empirical investigation of these tools among a diversity of fashion contexts is necessary to establish clearer understanding of their applicability.

Application in Fashion Innovation, Direct-to-Garment

Direct-to-Garment (DTG) printing technology is the focal context of this research. DTG printing represents an important innovation in global apparel markets using novel technologies and is recognized for its market potential. From a technical standpoint DTG refers to the process of printing digitally on apparel or other assembled products, using aqueous ink jet technology (Chandavarkar, 2013). Kornit Digital reports that for 2018 the total decorated apparel market totaled \$15USD billion, and predicted the market to expand to \$25 billion by 2023. The report also indicates that current digital printing technology accounts for five percent of the decorated apparel market, suggesting substantive growth potential.

The flexibility of DTG is a common driver for adoption in the fashion industry. Specifically, DTG is noted for its advantages in sustainability, print on demand, quick response, customization and inventory reduction (Samir, 2019). However, market intelligence for DTG is lagging its textile counterpart, roll-to-roll printing, due to the fragmented nature of production (Provost, 2019). In addition, DTG represents a relatively new apparel decoration approach compared to traditional screen printing and embroidery (Comb, 2019). The lack of market insight related to DTG suggests a need for systematic inquiry into this novel approach to inform practitioners and scholars.

Summary

Due to the emergent nature of DTG and a lack of corresponding empirical knowledge, this research aims to provide an overview of the features of this innovation using an inductive approach. Data-mining driven SNA provides a powerful technique for exploring emergent phenomena using existing textual data generated among engaged social media users. Based on existing computational intelligence techniques, we propose two guiding objectives:

ROI: To adapt computational techniques to capture large user-generated datasets from social media and convert these data for SNA.

RO2: To visually depict key indicators (i.e. nodes, edges and communities) among DTG networks over the past three years guided by graph theory.

By achieving the research objectives, this study demonstrates a process for researchers challenged by emergent topics that lack antecedent knowledge. The SNA method supports discovery of complex interaction patterns within visualized networks that are not otherwise evident. In addition, foundational knowledge revealing the key structures of the DTG domain, provide stakeholders first time insight to guide their respective marketing strategy and implementation efforts.

Methodology

Twitter provides the data for this analysis due to its high active user volume (i.e. averaged 320 million monthly active users in 2018). Additionally, Twitter has been widely demonstrated as an effective social platform for influencer and trend identification in fashion and apparel related research (Lee *et al.*, 2017; Zhao and Min, 2018). Hashtags represent the focal unit of analysis for the study due to their utility demonstrating information flow of key indicators related to DTG. Hashtags are commonly adopted to identify information patterns because standard algorithms for data extraction are unable to recognize slang, acronyms, incorrect spelling or grammar commonly among users' social media narrative (Rosa *et al.*, 2011; Bruns *et al.*, 2013). Researchers suggest that hashtags operate as keywords on Twitter providing an approximation of narrative text that is generalizable (e.g. Small, 2011; Bansal *et al.*, 2015). A common assumption of hashtag analysis is that multiple hashtags occurring in the same tweet describe similar topics.

Crimson Hexagon, an Artificial Intelligence (AI) social media analytic software, is employed to capture tweets including #dtg from September 2016 to September 2019. The intent of the three year sample scope was to identify key indicators of DTG. The study follows guidance for qualitative sampling from Charmaz (2006) who asserts that adequate data collection should be indicated through demonstration of saturation among observed data. That is, new topics fail to emerge with the addition of additional data. Crimson Hexagon was selected due to its capability for accessing historical data and its ease of use for researchers and marketers who lack computer programming knowledge. Next, the hashtags organized by year were extracted from each tweet and presented as initial nodes for the three networks. Subsequently, the edges between nodes were established based on hashtag co-occurrence within tweets. A matrix which presents the co-

occurrence frequencies of hashtags in the same tweet was developed using *Python 3.7.2*. Information flow and social relations around DTG technology are represented by the edges.

Pyle (1999) suggests that data preprocessing is significant in the data-mining process. Analyzing data that has not been carefully cleaned can generate misleading results. Thus, data preprocessing was applied to remove irrelevant hashtags, either auto-generated by systems (e.g. the suffix #https://) or too broad to consider for co-occurrence with other tags to be meaningful (e.g. #happyfriday, which is a hashtag used on Fridays to recommend other users to follow). Furthermore, hashtags with the same meaning but different spelling (e.g. singular and plural expression) are merged to simplify the dataset. For example, #t-shirt, #tshirt, #tee, #tees, #teeshirt, #teeshirts, #tshirts were combined into #tshirt. Inappropriate or inconsistent cleaning can impact data reliability. To mitigate this threat, three researchers screened the data individually for irrelevant and redundant hashtags, and discussed disagreements until an interrater reliability of 90 percent was achieved. An overview of the total volume of the conversations including #dtg, number of nodes, and number of edges is shown in Table 1. Because the study uses undirected networks, in- and out-degree is not relevant for differentiating nodes in the #dtg networks.

Table 1. Overview of tweet volume, nodes and edges for #dtg

Time period	Total volume of the conversation	No. of nodes	No. of edges
2016.09.13-2017.09.12	1154	1086	5788
2017.09.13 -2018.09.12	1606	2464	22659
2018.09.13 -2019.09.12	2300	2865	24836

Gephi network analysis and visualization software was applied to visualize DTG networks and roughly categorize the nodes into communities based on the matrix generated by Python for three years (2016-2019). Degree centrality and betweenness centrality measures were applied for visualization among each of the three years. To control the inherent complexity of each network which include thousands of nodes and the edges, degree range limitations were applied to the core structures of DTG networks. Additionally, the Force Atlas layout algorithm was used to improve the output visualization effect.

Results and Discussion

Overall Findings

Visuals for the three resulting DTG networks on Twitter for the time periods of September 13 to September 12 for 2016-17, 2017-18, and 2018-19 are presented in Figure 1, Figure 2, and Figure 3, respectively. The top 15 nodes based on degree centrality and betweenness centrality are presented in Table 2. Note that closeness centrality did not differentiate nodes in the visualized networks and was therefore not interpreted. The size of each node in the visualized networks is based on the value of betweenness centrality (i.e. Figure 1, 2, 3). Similarly, the size of each label in visualized networks is based on the value of degree centrality. Larger size indicates the higher value.

Influential and instrumental nodes within each of the DTG networks are identified for initial interpretation. Freeman (1978) stated that nodes which possess higher degree centrality are characterized as influential within the network. Furthermore, Freeman (1978) explained that the nodes which possess higher betweenness centrality as instrumental, functioning as a junction for communication within the network (Newman, 2005). In the present study, the ranking of betweenness centrality among the top 15 nodes is similar to that of degree centrality, with a few exceptions. For example, in 2018-19, #custom functions more effectively as a junction compared to #embroidery although the latter indicates higher degree centrality (Table 2). Deeper interpretation of the dominant nodes is undertaken in the next section.

Because #dtg was used to extract the sample tweets, this hashtag reflects the highest degree centrality and is adjacent to all remaining hashtags for the three networks. Further, #tshirt possessed second highest degree and betweenness centrality among the networks which is logical as t-shirts represent a highly preferred product category for DTG technology. According to Credence Research (2018), the global custom t-shirt printing market is expected to exceed US\$10 billion by 2025 at a compound annual growth rate (CAGR) of 6.3 percent through the forecast period 2017 to 2025. In addition to the two prominent nodes, the following hashtags represent nodes with relatively high degree centrality and betweenness centrality among all three visual networks: #custom, #screenprint, #directtogarment, #dtgprint, #fashion, #design, #shirt, #embroidery and #apparel. Although the nodes are sorted uniquely within each year's network, they are considered to be impactful because their presence is replicated across the three yearly networks and their structure suggests logical junctions within the DTG conceptual space. Further,

removal of these nodes from their respective networks disrupts communication resulting in a breakdown of network structure and loss of information.

Table 2. Top 15 nodes with their degree and betweenness centrality indices

2016-2017		2017-2018		2018-2019	
Node	Degree	Node	Degree	Node	Degree
#dtg	1,085	#dtg	2,463	#dtg	2,864
#tshirt	423	#tshirt	1,099	#tshirt	1,171
#fullcolor	220	#screenprint	611	#dtgprint	840
#color	208	#custom	611	#screenprint	796
#apparel	196	#dtgprint	555	#printing	628
#custom	193	#printing	554	#apparel	479
#screenprint	171	#directogarment	552	#embroidery	469
#directogarment	164	#design	492	#custom	451
#dtgprint	160	#clothes	398	#fashion	444
#design	144	#embroidery	381	#directogarment	383
#fashion	134	#fashion	364	#design	359
#etsy	111	#shirt	351	#shirt	303
#shirt	104	#apparel	300	#clothes	265
#embroidery	99	#smallbusiness	297	#dtgprinter	232
#ecommerce	85	#bellacanvas	281	#tshirtdesign	227
Node	Betweenness	Node	Betweenness	Node	Betweenness
#dtg	480,417	#dtg	2,272,003	#dtg	3,135,151
#tshirt	38,631	#tshirt	229,232	#tshirt	266,629
#fullcolor	9,381	#screenprint	59,669	#dtgprint	153,262
#apparel	8,600	#custom	57,317	#screenprint	109,315
#custom	8,430	#dtgprint	56,000	#printing	71,324
#color	6,186	#printing	50,961	#custom	34,503
#directogarment	5,254	#directogarment	46,956	#fashion	33,762
#screenprint	5,247	#design	31,869	#apparel	33,536
#dtgprint	4,894	#embroidery	24,107	#embroidery	30,702
#design	2,980	#clothes	21,934	#directogarment	20,308
#fashion	2,745	#fashion	18,766	#design	17,389
#shirt	1,758	#shirt	13,894	#shirt	17,118
#embroidery	1,580	#apparel	12,674	#clothes	9,984
#etsy	1,264	#smallbusiness	10,932	#tshirtdesign	7,848
#tshirtprinting	857	#bellacanvas	10,824	#dtgprinter	7,494

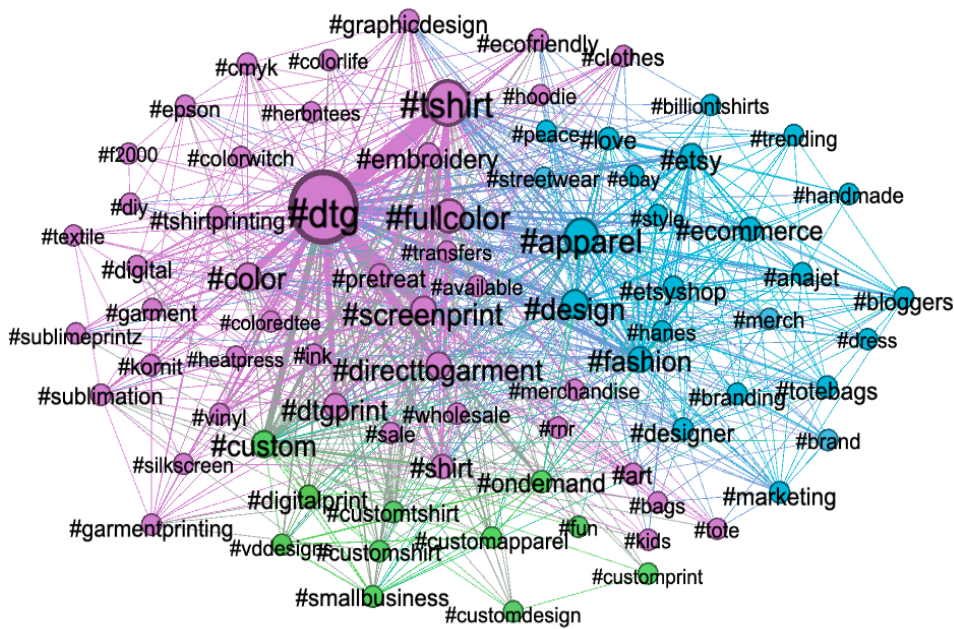
The appearance of #custom among the top 15 nodes suggests supporting evidence for the statement that customization is a leading factor driving the growth of the DTG technology

(LeDrew, 2018). With the elimination of the cost and time needed to develop screens, DTG, enables custom printing, or one-offs. While screen printing continues to dominate volume driven t-shirt decoration, DTG requires no minimum order and enables a printer to offer on-demand customization (Gifford, 2019). The consistent presence of #embroidery and #screenprint nodes among the networks, indicates their relevance to the DTG concept which can aid in searching for related DTG insights in additional forums outside of Twitter. According to Grand View Research, embroidery and screen printing accounted for approximately 40 and 25 percent, respectively, of global decorated apparel market share in 2018. In contrast, dye sublimation and digital printing collectively account for approximately one quarter of the market. Due to the novelty of DTG printing within this market, #dtg is closely tied to the predominant, traditional apparel decoration methods. Therefore, Twitter users who are interested in apparel decoration but have no knowledge of DTG technology can naturally discover DTG related tweets to explore this printing alternative. Notably, DTG is also hashtagged as Direct-to-Garment (i.e. #directtogarment) and DTG printing (#dtgprint) by Twitter users. Additional significant nodes (e.g. #fullcolor, #color, #ecommerce, #etsy) which only ranked among the top 15 in an individual year are later discussed in the community analysis. For researchers and marketers seeking knowledge of DTG, nodes with highest degree and betweenness centrality value provide a path for insight into this technology (Table 2).

Community Analyses

Three distinct hashtag communities emerged in the visual network for 2016-17 (Figure 1). The weight of an edge grows proportionally to the frequency of co-occurrence among unique nodes on the two ends of this edge, as such the central term (i.e. #dtg) generates the strongest edges. The largest community is identified by the color pink and encompasses unique product categories, apparel decorating approaches and various aspects of machinery, color and technology. The product categories that emerge within the analysis include: #tshirt, #shirt, #hoodie, #garment, and #tote. Alternative apparel decoration approaches include: #screenprint, #embroidery, #sublimation, #heatpress and #silkscreen.

Figure 1. Visualized 2016-2017 #dtg network
 (Degree>15, 79 Nodes, 781 Edges)



The pink community also presents additional information regarding DTG technology. A set of nodes related to color emerge including: #fullcolor, #color, #colorlife, #cmyk, #pretreat, and #ink. A second set of nodes related to specific printing equipment emerges including: #epson, #f2000, and #kornit. The composition of the pink community appears logical due to fact that color processing is a recognized advantage and in some cases challenge for digital printing. A primary advantage of DTG over screen printing is the flexibility for manipulating colors to accommodate vastly different graphic designs with minimal downtime (LeDrew, 2018). However, a noted shortcoming of DTG is lack of brightness when inks (#ink) are not adequately opaque or inkjet heads become clogged (Age and Dilworth, 2006). Additionally, DTG requires garment pretreatment (#pretreat) for graphics with white ink for better color performance (Combs, 2019). In terms of printer manufacturers, Epson (#epson) first entered the DTG market in 2013 with an inkjet printer SureColor(R) F2000 (#f2000). The CMYK (#cmyk) term does not refer to a printer manufacturer but rather represents the industry color model for printing (cyan, magenta, yellow and black). This color model is currently used by both Epson and Kornit (#kornit) for their inkjet printers. The network analysis suggests that the sets of nodes for color and printer are highly interconnected reflecting the relationship of these technologies in application. Notably, #ecofriendly also appears in the pink community which likely reflects the attribution of

sustainability directly to the environmental claims associated with printing technology and color processes within this production context (Samir, 2019).

The blue community which is second largest among the network, reflects marketing and retailing related nodes (e.g. #marketing, #ecommerce, #merch, #branding, #ebay, #trending, #etsyshop, #hanes) as well as design related nodes (e.g. #design, #designer, #style). In particular two specific nodes emerge within the blue community: Merch by Amazon (#merch) and Hanesbrands (#hanes). Merch by Amazon refers to a growing on-demand ecommerce platform for customized t-shirt printing. Hanesbrands (#hanes) is a global leader in blank t-shirt production which supplies the DTG print market (Textile Word, 2020). This community offers an overview of the primary marketing interests in the segment. Emergent nodes suggest that e-commerce is an important driver in this market with multiple references to unique digital platforms (i.e. Etsy, E-bay and Merch by Amazon). For novices seeking insight into market organization and information, the blue community identifies key resources for consideration.

The green community which is the smallest among the network, reflects dimensions of customization (e.g. #custom, #customtshirt, #customshirt, customdesign, #customprint, #ondemand). Notably, there are overlaps among communities, which is common to network analysis. For example, the #totebags node emerges in blue community, while similar nodes including #tote and #bags emerge in the pink community. Recall the co-occurrence of hashtags in the same tweet is the standard used to build the network analysis through establishing a matrix in Python. Unless otherwise directed through additional programming, the system rules for hashtag affiliation generates duplications.

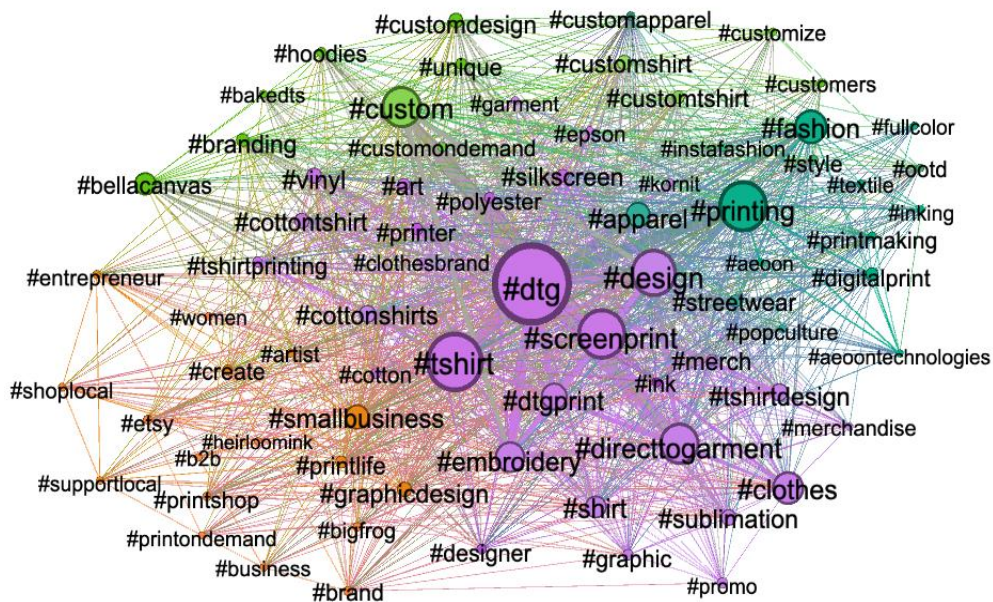
In the 2017-18 #dtg network visualization (Figure 2), the purple community is largest, indicating the highest degree and betweenness centrality. In contrast to the largest community for 2016-17 (pink), the nodes related to product category for the more recent network refer to distinct fibers including: #cottonshirt, #cottontshirt, #cotton, and #polyester. Cotton t-shirts are traditionally considered as comfortable, affordable options for consumers. However, rising demand for polyester shirts due to softness and ease of care represents a notable trend in the apparel market (Vantrease, 2016). Traditionally, DTG performs better on natural fibers such as cotton which is receptive to water-based inks. However, the digital printing industry recently engaged in the development of applications to polyester. For example, Kornit introduced technology capable of digitally printing on 100% polyester fabric, suggesting a potentially significant growth

opportunity for the industry (Chen, 2019).

Three additional communities of note emerged from the 2017-18 network. Among these relatively smaller communities, nodes generally relate to fashion, customization and business. The fashion community (dark green) includes the following nodes: #fashion, #ootd (outfit of the day), #instafashion (instagram fashion), #style, #popculture, #streetwear and #apparel. The organization of this community suggests that consumers consider DTG as an emerging fashion trend, reflected in their actions including sharing daily outfits and style inspiration across different social media platforms. Similar to the green community from 2016-17, an emergent community among the 2017-18 network also represents customization (light green). However, the more recent 2017-18 analysis generated a unique, dedicated hub that represents business, clustered around #smallbusiness (orange). The orange community encompasses the following related nodes: #b2b (business to business), #supportlocal, #business, #entrepreneur, #shoplocal, #printshop and #printondemand. This is consistent with Provost (2019)'s research which suggests that the DTG market is currently fragmented with many small companies generating low production runs.

Figure 2. Visualized 2017-2018 #dtg network

(Degree >50, 75 Nodes, 1,323 Edges)

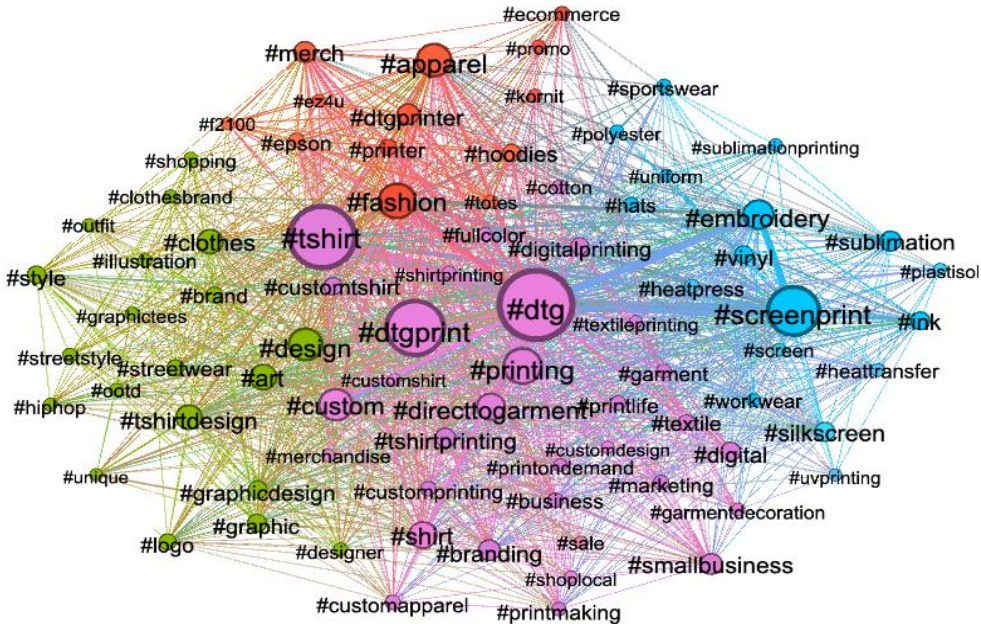


Compared to the two previous networks, the nodes within the 2018-19 #dtg visual network are more tightly interconnected because this data generated the highest number of edges among

the three. Though the 2018-19 visual network (Figure 3) bears similarity to the earlier versions, this network reveals several new structures of note. In contrast to previous years, the nodes for #screenprint, #heattransfer, #sublimation, ##heatpress and #vinyl emerged relatively independent (blue community) from the central #dtg community (pink). The blue community encompasses the alternative techniques for DTG printing in fashion and apparel and is clustered around the #screenprint node. Additionally, within the blue community new satellite nodes emerged around #screenprint including: #plastisol (an ink for screen printing), #uvprinting (a method utilizing ultraviolet light to dry ink) and #sportswear. Interestingly, the #polyester node emerged in the blue community, while #cotton remained in the central community. The divergent arrangement of polyester and cotton into different communities reveals the unique technologies required for printing on natural versus synthetic fibers and is therefore not surprising.

Another notable shift in the 2018-19 network is the emergence of a unique community clustered around the #design node (green). The green community encompasses: #graphicdesign, #designer, #art and #tshirtdesign. Further, the green community subsumed nodes for #style, #ootd and #streetwear which appeared in the #fashion and #apparel community in the previous year. The emergence of this community suggests more attention among Twitter users to design related issues within the DTG realm.

Figure 3. Visualized 2018-2019 #dtg network
(Degree >50, 82 Nodes, 1,520 Edges)



Conclusions and Implications

In the era of data rich business and social environments, data-mining driven SNA provides a powerful technique for researchers and marketers to investigate information flows among complex, abstract, or novel topics using large, user-generated datasets. The outcomes of this research suggest implications for academic and practical application. In terms of academic implications, the findings provide an example for mining knowledge from social networks guided by graph theory through methodical demonstration of a novel analytical application in the fashion domain. This study is among the first to provide a data-based inquiry using a data mining approach to build foundational knowledge for an emerging fashion technology. The research design and subsequent findings demonstrate the case for using social media data for research in the constantly changing fashion context. Although the enormous volume of user-generated data is widely characterized as the next frontier for exploration and prediction of fashion related phenomena, few researchers leverage these tools for inquiry. From an academic standpoint, we consult graph theory to interpret social network interactions in the fashion domain through the application of analytical methods derived from computer science, thereby facilitating discovery that is theoretically grounded and analytically novel. Graph theory facilitates the identification of otherwise opaque connections among social actors which are central to online markets. As social media continues to expand its reach as a popular tool for communication, the importance of capturing marketing insights from these qualitative networks will continue to grow and the present work provides an academic approach to capturing dynamic communication and engagement in electronic WOM. Likewise, this study illustrates a method that overcomes disadvantages of traditional data collection including resources required to collect primary data and mitigation of various forms of bias. Overall, this study contributes to research through extension of graph theory and accompanying analytical tools for discovery in the fashion context.

Study findings generate practical implications that are interpretable from both the full study scope as well as the yearly findings. From a marketing standpoint, the outcome of this research reveals three areas related to DTG that hold up over time including: the dominant apparel category for this technology, the primary competitive approaches to apparel decorating, the market niches that currently appear to drive the growth of DTG in the apparel and fashion industry, thereby providing stakeholders a guide to identify and assess the competitive DTG domain.

The 2016-17 network reveals discourse focused on technical challenges related to DTG

including issues associated with digital printing processes. Specifically, Twitter users express specific issues related to pre-treatment that allows white ink washability and full color images on a variety of colored shirts. It implies pretreatment is the significant step for color management of DTG printing. Second, this network reveals the importance of e-commerce as a business model for the DTG context, which continues to be the leading market platform for DTG. Simultaneously, the concept to position DTG apparel as eco-friendly also emerged in the 2016-17 network. These two key indicators suggest that the DTG stakeholders could maximize the number of potential consumers through investment in online retailing and expand efforts to promote the advantages of DTG printing for environmental sustainability.

The most popular blank t-shirt choices for DTG printing, Hanesbrands and Bella Canvas, were identified in the 2016-17 and 2017-18 networks. This particular finding not only provides the DTG retailers with two highly recognized blanks brands from hundreds of options, but also demonstrates the opportunity for fashion brands to engage customers within self-defined social media communities. Additionally, in the 2017-18 network, discourse related to business approach expanded with the emergence of unique hubs for small business and business-to-business within the same community. This suggests that DTG printing ventures appear to be suitable for individuals pursuing small businesses that may include business-to-business opportunities.

The 2018-19 network, which is the most complex among the three, reveals an additional layer of depth for the decoration community directly through emergence of: #sportswear, #uniform, and #workwear. This finding implies that while DTG is tapping into the apparel decorating industry, screen printing, sublimation and heat transfer continue to be widely used, particularly for products made primarily of polyester such as performance apparel and athletic uniforms. Interestingly, the 2018-19 network topics revealed that graphic design for the t-shirt market draws on inspiration from street culture and hip hop culture. The emergence of street culture within the greater DTG network provides anecdotal evidence of flexibility that DTG provides for design customization. Given the fluid nature of street culture, DTG facilitates expression capability for new ideas without requiring substantial development. The typical interest of young consumers in street culture suggests market opportunities for brands pursuing customization strategies.

Limitations and Future Research

A number of challenges must be confronted when applying data-mining driven SNA particularly those related to data and analysis. At a minimum, extensive computational skills and

knowledge of suitable programming languages (i.e., R, Python and Julia) are required to successfully develop and apply the method across different fields. Thus, we encourage fashion educators to formalize this education process to prepare further fashion researchers for the world of big data. Further, potential challenges related to data security may interfere with future efforts to access social media data. A number of well-known social media platforms are in the process of establishing rigorous permission reviews for access to their respective APIs; this action restricts individual researchers' capability to access the large scale data (Schröder, 2018). Additionally, with particular regard to the network models, the Gephi algorithm introduces potential limitations. The algorithm simply categorizes nodes into clusters based on co-occurrence among hashtags, which carries the assumption that multiple hashtags occurring in the same tweet represent a similar approximation of content (Rosa *et al.*, 2011). Though this method is effective for identifying potentially important elements in the DTG environment including technologies, stakeholders and marketing inputs, the visual DTG networks do not reveal subtleties in social networks due to space limitation.

The models generated for this analysis are built around a single central node (#dtg). Due to the newness of the concept and limited existing guidance in the literature, anchoring the networks around the #dtg node demonstrates a logical first step for exploring the domain. In light of the knowledge revealed through this baseline effort, additional analysis that incorporates new findings into model generation is a logical next step. For example, a comparative network analysis focusing on printing technology alternatives modeled around nodes for screen printing, sublimation and heat transfer should provide greater depth of information. Further, to delve even deeper into the social network narrative, combining network analysis to identify clusters of common interest can improve identification of targets for content analysis for follow up research.

This study demonstrates application of SNA to an underexplored but important topic with potential impact on the global fashion and apparel industry. The findings inform directions for a general understanding of the domain of DTG. Additional application of network analyses as well as other data mining approaches following empirical processes are necessary to advance analytics in the marketing discipline.

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CHAPTER 2
PROFILING DIGITAL PRINTING TECHNOLOGY ADOPTION IN THE FASHION
INDUSTRY:
A NEW APPROACH TO EXPLORING INNOVATION DIFFUSION

Introduction

The global decorated apparel market, which refers to printed or embellished products, was valued at USD 24.2 million in 2017 and is projected to reach USD 50.1 million by 2024 with a compound annual growth rate (CAGR) of 11.5 percent (Value Market Research, 2020). Digital printing technology (DPT) represents a core innovation that is currently revolutionizing the global decorated apparel business (Combs, 2019). In contrast to conventional printing methods such as screen printing, DPT automates the process by using digital files to direct inkjet printers to transfer complex designs to textile substrates including fabric and garments (Chandavarkar, 2013). This technology facilitates customization by printing graphics with complex color requirements in on-demand settings. Digital printing for textiles and apparel was recognized by Arthur (2017) as a driver of growth in the global decorated apparel market with expected annual increases of 25 percent up to 2019. Unfortunately, empirical and trade research that focuses on the marketing impacts of DPT lags the demand of this technology. Lack of fundamental understanding of the nature of the DPT business environment hampers the ability of relevant stakeholders to efficiently and effectively integrate this innovation into their strategic scope.

Due to the emergent nature of DPT and the lack of corresponding empirical attention, exploratory research into the context is warranted. To build a foundational understanding of the opaque DPT market, social media provides a useful source for capturing its discourse among dispersed users of this technology. In recent years, social media has become an important tool to explore target market identification which facilitates segmentation and subsequent marketing actions due to its exponentially increasing usage (Chinchanachokchai & de Gregorio, 2020). In 2019, approximately 79 percent of the U.S. population is engaged in at least one social networking platform (Clement, 2019). As such, social media increasingly provides a rich data resource for capturing consumer insights among institutional buyers and end-users from diverse backgrounds. Simultaneously, user-generated data of social media provides advantages through the capability to capture geographically dispersed respondents in an expeditious manner, ultimately reducing time and monetary costs (Tsou, 2015). Further, user-generated social media data is unbiased, reflecting

user thoughts free from researcher influence (Salganik, 2017). Despite the promise that user-generated social media data holds for marketing researchers in the fashion domain, integration of these data into inquiry in the context is very limited. A few recent fashion studies exemplify integration user-generated social media data into their methodologies including Geissinger and Laurell's (2018) trend analysis effort surrounding Stockholm fashion week and Koivisto and Matilla's (2018) effort using visual data from Instagram to investigate content co-creation in the luxury context. However, the integration of complex user-generated social media data into company decision making remains underexplored.

The purpose of this study is to identify DPT diffusion patterns to establish a predictive user profile for DPT using social media based data analytics. Specifically, social media interaction among Twitter users engaged in DPT dialogue provides the research context for this study. This research contributes to academia and industry. From an academic standpoint, the design draws on theoretical direction from Rogers' (2003) diffusion of innovations theory to conceptualize a comprehensive empirical model of DPT adoption. Additionally, the analytical approach demonstrates integration of social media analytics along with data mining and traditional statistical modeling to address a question with limited antecedent knowledge. Through application of the theory and the novel empirical approach the outcomes provide an initial knowledge base for practitioners to identify and understand the nature of DPT adoption in the U.S.

Literature Review and Theoretical Framework

The Diffusion of Innovations Theory

Business practitioners and researchers have long been interested in the determinants of innovation adoption to explain how, why, and at what rate an innovation disseminates. The origin of the diffusion inquiry is controversial. Everett Rogers (1962) is widely recognized as the first scholar to popularize diffusion of innovations theory by synthesizing and criticizing the important findings from previous diffusion studies. Rogers (1962) originally defined an innovation as an idea, practice, or technology that is perceived as new by an individual or other unit of adoption. More recently, Rogers' (2003) characterizes the innovation process as the collective dissemination of an innovation through communication channels over time within a social structure. Diffusion of innovations has become a transdisciplinary theoretical framework applied in diverse areas including sociology (Manzo et al., 2018), management (Bianchi et al., 2017; Trischler, Johnson, & Kristensson, 2020), political science (Boushey, 2016), geography (Fadly & Fontes, 2019), and

health (Lin & Bautista, 2017) providing contextual insight into diverse research questions.

Diffusion of innovation research broadly focuses on understanding what drives adoption of an innovation. Rogers (2003) highlights the drivers into two categories: attributes of innovations and characteristics of innovators. Numerous diffusion studies investigate the effect of innovation attributes drawing on Rogers' (2003) framework, which commonly classified attributes as: relative advantage, compatibility, complexity, trialability, and observability (e.g. Lin & Bautista, 2017; Park, Lee, & Kim, 2018). Simultaneously, substantial research examines adopter's characteristics including age, gender, education and income as their behavior change catalyst on innovation adoption based on Rogers' (2003) framework (e.g. Rojas-Méndez, Parasuraman & Papadopoulos, 2017; Deepak & Himanshu, 2018). Additionally, potential determinants of diffusion also expanded to include environmental contexts. Wejnert (2002) demonstrates that the environmental variables of social systems such as geographical settings, societal culture, and political conditions can modulate diffusion. In contrast to Rogers' (2003) study placing an emphasis on the members of a social system at individual or organizational levels, Wejnert (2002) suggests considering characteristics of innovators at a population level. Likewise, McEachern and Hanson (2008) also assert that understanding the diffusion process cannot focus on individual characteristics alone, but should consider a variety of social, political, and geographic variables.

Awareness of the time element impacting diffusion is also recognized by Rogers (2003). Innovations are rarely adopted instantaneously. Rather, diffusion of innovations takes place gradually over time. Therefore, Rogers (2003) suggests that the rate of adoption tends to follow an S-curve distribution, in contrast to past research which generally suggests that adoption of an innovation follows a normal, bell-shaped curve when plotted over time on a frequency basis. Further, Rogers (2003) indicates that the temporal dimension is easy to overlook in behavioral research. Thus, Vargo, Akaka, and Wieland (2020) suggest that a broader lens for exploring how diffusion enables innovation dissemination through iterative and recursive feedback loops over time.

Social Media: A New Communication Channel

Rogers (2003) categorizes communication channels into mass media channels (e.g. radio, television, newspapers) and interpersonal channels. Mass media channels enable information transmission from a few individuals to reach broader populations. On the other hand, interpersonal channels involve face-to-face exchange between two or more individuals

which is more effective in persuading an individual to adopt a new idea (Rogers, 2003). The emergence of social media has created a new communication avenue that simultaneously expands the communication range and strengthens the communication effect. Social media usurped traditional communication channels in creating connections and facilitating individuals to share their opinions to both friends & family and large public audiences (Shawky et al., 2020). To date, the popularity of social media communication, often referred to as online word of mouth (WOM), has transformed the nature of human interaction in modern society (Chen, Fu, & de Vreede, 2017; Appel et al., 2020).

Academics suggest that social media provides a novel approach to achieving customer engagement, spreading awareness of products, and understanding contemporary marketing (Gligor, Bozkurt, & Russo, 2019; Sahaym, Datta, & Brooks, 2019; Dessart, Veloutsou, & Morgan-Thomas, 2015). In the fashion domain, many researchers employ primary data to examine the influence of social media on consumer perceptions using traditional methods such as quantitative surveys (e.g. Kang & Kim, 2017; de Lenne & Vandenbosch, 2017) and qualitative interviews (e.g. Nash, 2019). Meanwhile, a few fashion studies which leverage readily available user-generated data sourced from social media have emerged (e.g. Escobar-Rodríguez & Bonsón-Fernández, 2017; Geissingner & Laurell, 2018). Although both primary and secondary data can provide insight to inform future business decisions and actions, an increasing number of researchers began to endorse user-generated data. They suggest that compared to primary data, user-generated data facilitates analysis of dynamic interaction among geographically dispersed respondents and also potentially reduces researcher bias (Salganik, 2017; Cuomo & Maiorano, 2017). Furthermore, user-generated social media provide opportunities for exploring novel market developments. Liu, Jiang, and Zhao (2019) suggest that user-generated data are particularly useful for examining emerging phenomena about which little is known. Additionally, Rogers (2003) claims that if individuals were informed about technology's advantages and disadvantages, their uncertainty for adoption would be decreased, which in turn, can increase their adoption intention. The existing user-generated narratives on social media provide direct access to adoption consequences, and are therefore valuable for investigating complex DPT diffusion over time. Considering the novelty of DPT and the research scope, we employ user-generated data for the study.

Digital Printing Technology: A Fashion Industry Innovation

There are multiple factors that have driven growth of the DPT business. From a supply

chain perspective, DPT uses digital files as an input which eliminates the time and cost of making fixed plates, thereby reducing the lead time for garment printing (Chandavarkar, 2013). Consequently, DPT enables fashion designers to respond in real-time to the point of sale to take advantage of rapidly changing market trends. In addition, DPT eliminates the risk and expense of maintaining inventory as no minimum order is required (Samir, 2019). From a marketing perspective, DPT is capable of customizing complex graphics, which caters to increasing demand for personalized garments (LeDrew, 2018). From an environmental perspective, DPT has relatively low energy costs reducing impact on the environment which satisfies growing demand for sustainable printing (Ding et al., 2019). From a business perspective, a digital printing service can easily be operated at any location and has low barriers for operators to enter the market. DPT's flexibility for short production runs, a short learning curve and low capital investment provides more opportunities for individuals pursuing small business or ecommerce opportunities (Provost, 2019). Despite the novelty that DPT brings to the global decorated apparel industry, fundamental understanding of the emerging DPT market remains unexplored. Therefore, this study is among the first to provide a fundamental, empirical understanding of the DPT business environment by achieve the following objectives:

RO1: To capture and visually depict the pattern of DPT diffusion in the U.S. market between 2010-2019.

RO2: To investigate the impact of adopter characteristics (i.e., internal factors) and their local business culture (i.e., external factor) on DPT diffusion at the state level in order to establish a predictive profile.

Methodology

Twitter provides the social media data source for exploring DPT diffusion due to its high active user volume (i.e. averaged 320 million monthly active users in 2018). Twitter's interactive feature enables access to real-time data which reflects customer-innovation interactions (Liu, Shin, & Burns, 2019). Additionally, academic researchers increasingly use Twitter as a data source to investigate fashion related phenomena (e.g. Lee et al., 2017; Zhao & Min, 2018).

To address the first research objective, *Crimson Hexagon*, an artificial intelligence (AI) driven social media analytic software, was used to capture tweets for the digital print hashtag

(#digitalprint) from 2010 to 2019 in the U.S. market. Though the software is capable of capturing social media inputs as early as 2008, examination of the data suggested that substantial tweet activity did not begin until 2010. Therefore, the ten-year scope was selected for analysis. Hashtags provide the focal variable for the study because they operate as keywords on Twitter and provide an approximation of narrative text that is generalizable (Bansal, Bansal, & Varma, 2015). Twitter users who do not provide geographic information were excluded from the study. *R* statistical software was applied to transform, clean, and quantify the occurrence of tweets.

Occurrence frequencies over time were subsequently plotted to visualize the dissemination curve, assuming that tweet frequency serves as a proxy variable for technology adoption. Using proxy variables can provide a useful tool for researcher investigation into novel topics that are neither well-defined nor generally accepted (Houstou, 2004). As such, proxies are widely used by social scientists in various disciplines to understand the diffusion of innovations (e.g. McEachern & Hanson, 2008; Hogset & Barrett, 2010; Magnusson, Wastlund, & Netz, 2016). Considering DPT’s novelty, it is reasonable to assume that locations with high DTP discussion volume are more interested in and familiar with this technology and are consequently more likely to adopt DPT. Next, the data were organized into different regions according to user-provided geographical information. *Tableau* software was used to visualize and examine geographical distribution and tweet density in each U.S. state over the past ten years. The resulting DPT diffusion pattern was compared to Roger’s recommendation that innovation diffusion typically follows an S curve.

Logistic regression was used to investigate the predictors of DPT adoption on the nominal dependent variable. Specifically, the study uses binary logistic regression which is appropriate for the dichotomous dependent variable (i.e., 1= likely to adopt DPT, 0= unlikely to adopt DPT). The measure for DPT adoption is determined for each state in the U.S on a yearly basis. In cases where DPT tweet frequency is above or equal to the national average for an individual year, the state is categorized as *likely to adopt*. In contrast, if a state’s DPT tweet frequency is below the average for an individual year, it is categorized as *unlikely to adopt*. The logistic regression approach allows both continuous and discrete predictors. The logistic model with multiple predictors is expressed as:

$$\text{Ln}\left(\frac{P}{1-P}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_x X_x$$

where *P* is the probability of the outcome of interest (i.e., likelihood of DPT adoption), β_0 is the *Y*

intercept, β_s are the regression coefficients for a set of predictors X_s that are estimated by the maximum likelihood estimation.

A logistic regression model was generated to examine the impact of internal and external factors on DPT adoption. Demographics are classified *internal* factors within the study while environmental variables are considered as *external*. The model examined the impact of six demographic variables on likely adoption: working status (i.e., percentage of full-time employment), financial status (i.e., household annual income), gender (i.e. percentage of females), ethnicity (i.e., percentage of Caucasians), education (i.e. percentage of bachelor degree or higher), and age distribution (i.e. percentage of youth ages from 19-34). The demographic data for each state of U.S. from 2011 to 2018 was sourced from the U.S. Bureau of Economic Analysis (<https://www.bea.gov/>) and U.S. Census Bureau (<https://www.census.gov/>). In addition, based on previous research on DPT among social media networks in the U.S. which suggests that users are engaged in art and design communities (Yu, Moore, & Chapman, 2020), an external proxy variable for states with relatively greater incomes generated among art and design related occupations (i.e., annual art and design annual income, ADI), was integrated into the model. The ADI data for each state was also sourced between 2011-2018 from the U.S. Bureau of Labor Statistics (<https://www.bls.gov/>). Note that the data for 2010 were not captured due to lack of DPT activity on Twitter (i.e, 3 total tweets). Additionally, the data after 2018 are not yet available.

To further examine the impact of the predictors on DPT adoption, decision tree analysis was applied to the focal variables. Decision tree analysis generates a hierarchical model which parses observations into adoption categories based on the predictor variables (i.e., likely, unlikely to adopt). Decision trees complement logistic regression due to the ability to capture nonlinear and interactive relationships among predictors automatically (Namazkhan, 2020). *R* was employed to generate the decision tree analysis using the *rpart* classification algorithms. To evaluate tree reliability, a *k*-fold cross-validation was executed to effectively improve out-of-sample generalization (Blockeel & Struyf, 2002). *K*-fold cross-validation is a robust resampling procedure for estimating model accuracy among datasets with size limitations (Raschka, 2018). The researcher determines the *k* metric which defines the number of unique iterations performed for cross-validation. While traditional cross-validation for decision trees typically defines a single test and training dataset for comparison, the *k*-fold approach randomly generates multiple models to determine error rates, thereby optimizing the efficiency of the available data (Kassambara, 2018).

A priori model settings for this study include: $k=10$, and a minimum of 30 per terminal node.

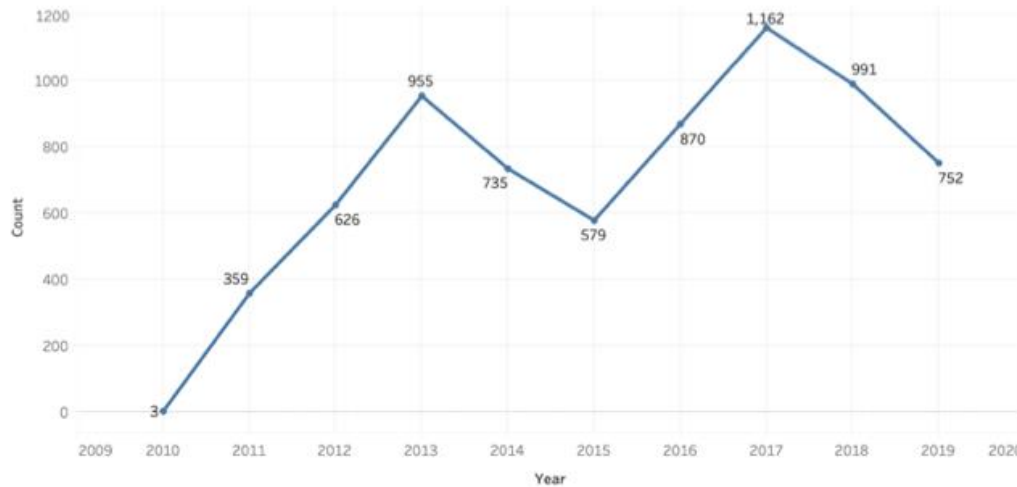
Results

Research Objective One

The diffusion pattern for DPT adoption based on annual cumulative tweets ($n=7,032$) over the ten-year period (2010-2019) is graphically depicted in Figure 4. Recall that Roger's (2003) theory suggests that the diffusion process tends to follow an S-curve. The observed pattern for DPT tweet volume suggests a non-linear distribution which supports use of the proxy variable to predict adoption likelihood.

Yearly visualizations for the geographical distribution at the city level of DPT are presented in Appendix A. Twitter users in the District of Columbia and Massachusetts were among the earliest to show interest in DPT with three relevant tweets in 2010. The discussion of DPT on Twitter appreciably emerged in 2011. During 2011, New York state (Albany, New York City, Rochester) reflected the highest discussion volume overall, while additional discussion hubs emerged simultaneously among U.S. cities including: Massachusetts (Boston), Connecticut (Stamford), Florida (Miami, Orlando, Tampa), Illinois (Chicago), Colorado (Denver) and California (Irvine, Los Angeles, San Francisco). As DPT discussion increasing in these initial locations, discourse gradually expanded to new regions including the West Coast (e.g. Oregon-Portland, Washington-Seattle), the East Coast (e.g. Virginia-Norfolk, Pennsylvania-Philadelphia), the Midwest (e.g. Missouri-Kansas City; Ohio-Cincinnati) and the South (e.g. North Carolina-Raleigh, Texas-Austin, Dallas, Houston; Georgia-Atlanta; Tennessee-Nashville). The data indicate that Twitter discussion of DPT reached a notable peak in 2013 ($n=955$). After which annual discussion volume began to decline and did not exceed the 2013 volume until 2017 ($n=1,162$). From 2017 to 2019, the data suggest that Twitter users engaged in DPT discourse emerged among increasingly dispersed locations within states. For example, DPT discussion in California expanded from initial hubs in Los Angeles and San Francisco to San Diego and San Jose. Likewise, DPT discussion in Florida expanded from Orlando and Miami to Fort Lauderdale, Sarasota, and St. Petersburg.

Figure 4. Discussion volume of DPT on Twitter, 2010-2019



Research Objective Two

Historical data (2011-2018) for fifty-one U.S. states, totaling 408 observations over the eight-year scope (i.e., 51 per year) were examined using logistic regression. Variance inflation factors (VIF) for the predictor variables indicate coefficients below the common threshold (i.e., $VIF < 3.0$) (Petter, Straub, & Rai, 2007; Cenfetelli & Bassellier, 2009) suggesting no evidence of multicollinearity.

The seven-predictor logistic regression model indicates statistical significance ($\chi^2 = 125.327$, $p < .001$). Additionally, an accompanying Hosmer–Lemeshow test which compares observed values with expected values, indicates a non-significant result ($\chi^2 = 8.048$, $p = 0.429$) providing additional evidence of reasonable fit for the logistic regression model. Classification indicators suggest relatively high prediction accuracy for DPT adoption (cutoff value of .50) with an overall correct prediction rate of 75.5 percent (64.6% likely to adopt, 84.1% unlikely to adopt). Additionally, the receiver operating characteristic (ROC) curve illustrates acceptable discrimination accuracy for the binomial model. Widely used among marketing researchers, ROC can be reflected by the area under the curve (AUC) coefficient (de Langhe, Fernbach, & Lichtenstein, 2016). The AUC is coefficient is .799 (S.E., .022, 95% C.I. = .756, .842) for the logistic regression model.

Table 3 presents the regression coefficient, the Wald test and the odds ratio $\text{Exp}(B)$ for each predictor in the logistic regression model. A forward stepwise method was employed for

predictor selection. The results demonstrate four significant predictors of adoption likelihood including three internal predictors and the single external predictor. Among the internal predictors percentage of youth population (PY), percentage of bachelor degree or higher (PBH), household annual income (HAI) emerged as significant predictors. To be specific, controlling for other variables, the model suggests that a single point increase in PY is 1.444 times more likely to adopt DPT; a single point increase in PBH is 1.204 times more likely to adopt DPT. Further, for each one thousand dollar increase in ADI, there is a 1.125 times greater likelihood of adopting DPT. Interestingly, the model suggests a negative association between HAI and DPT adoption. Accounting for other variables, for each one thousand dollar increase in HAI, there is a 0.942 times lower likelihood of adopting DPT. Additionally, while the bivariate linear test showed significant differences in the percentage of full-time employment (PFE), percentage of females (PF) and percentage of Caucasians (PC), the parameters of these variables are not significant in the full regression model. In particular, PFE and PC generate relatively smaller effect sizes in the full model and thus add little predictive power in the company of the additional predictors.

Table 3. Model regression coefficients, the Wald test, significance, and Exp(B).

Variables	B	S.E.	Wald	Exp(B)	95% C.I. for Exp(B) Lower	95% C.I. for Exp(B) Upper
Percentage of full-time employment (PFE)	-.004	.005	.674	.996	.987	1.005
Percentage of females (PF)	.209	.200	1.092	1.232	.833	1.823
Percentage of Caucasians (PC)	-.001	.010	.015	.999	.980	1.018
Percentage of bachelor degree or higher (PBH)	.186***	.047	15.598	1.204	1.098	1.320
Percentage of youth (PY)	.367***	.105	12.337	1.444	1.176	1.772
Household annual income (HAI)	-.060**	.026	5.176	.942	.895	.992

Table 3 (continued).

Art & design occupation's annual income (ADI)	.118***	.033	12.337	1.125	1.054	1.200
Constant	-25.179**	11.801	4.552	.001		

Notes: Level of significance: * $p < 0.10$, ** $p < 0.05$ and *** $p < 0.001$; Nagelkerke $R^2 = 0.354$.

The decision tree analysis indicates an overall accuracy rate of 77.9 percent (82.7 % likely to adopt DPT, 75.5 % unlikely to adopt DPT). Variable selection is built into the decision tree process, which automatically filters out predictors with relatively less predictive power (Rao et al., 2019). The decision tree identifies the same four significant predictors as the logistic regression model. The model's root node which represents the most influential classification variable was identified as ADI, which provides the basis for subsequent model splits among the predictors (Figure 5, Table 4). Specifically, the first split based on ADI indicated that income values above and below \$37,000 USD discriminate between adoption and non-adoption likelihood. Cases that include an average ADI of less than \$37,000 USD per year (N=135) are classified as unlikely adopters. These cases formed a terminal node in the tree which can be observed on the rightmost side of Figure II. Note, that a terminal node does not provide additional discrimination among variables and therefore ceases splitting within the tree hierarchy. Interpretation of the model proceeded with the cases reflecting average ADI equal to or above \$37,000 USD which can be observed on the left side of the tree. The ADI predictor split a second time indicating that cases above and below average ADI of \$52,000 USD discriminate between adoption likelihood. Cases that include an average ADI above or equal to \$52,000 USD per year (N=37) form a second terminal node and are classified as likely adopters.

The remaining cases with an average ADI between \$37,000 and \$52,000 USD (N=236) split a third time based on PBH. Among these 236 cases, states with an average PBH lower than 0.26 (N=33) yield a third terminal node and are classified as unlikely adopters. Alternatively, cases that include an average PBH equal to or exceeding 0.26 (N=203) split a fourth time based on HAI. Cases that include an average HAI less than \$51,000 USD (N=37) form a fourth terminal node classified as likely adopters. Conversely, cases that include an average HAI equal to or exceeding \$51,000 USD (N=166) occupy the final split based on PY. Heretofore, the last two terminal nodes

are generated. One includes cases with an average PY less than 0.21; the other includes cases with an average PY equal to or exceeding 0.21. The former node represents unlikely adopters (N=55) and forms a fifth terminal node, whereas the latter node represents likely adopters (N=111) and forms a sixth terminal node. Table II provides a summary interpretation of each significant split in the decision tree hierarchy for predicting adoption likelihood for DPT.

Figure 5. The decision tree

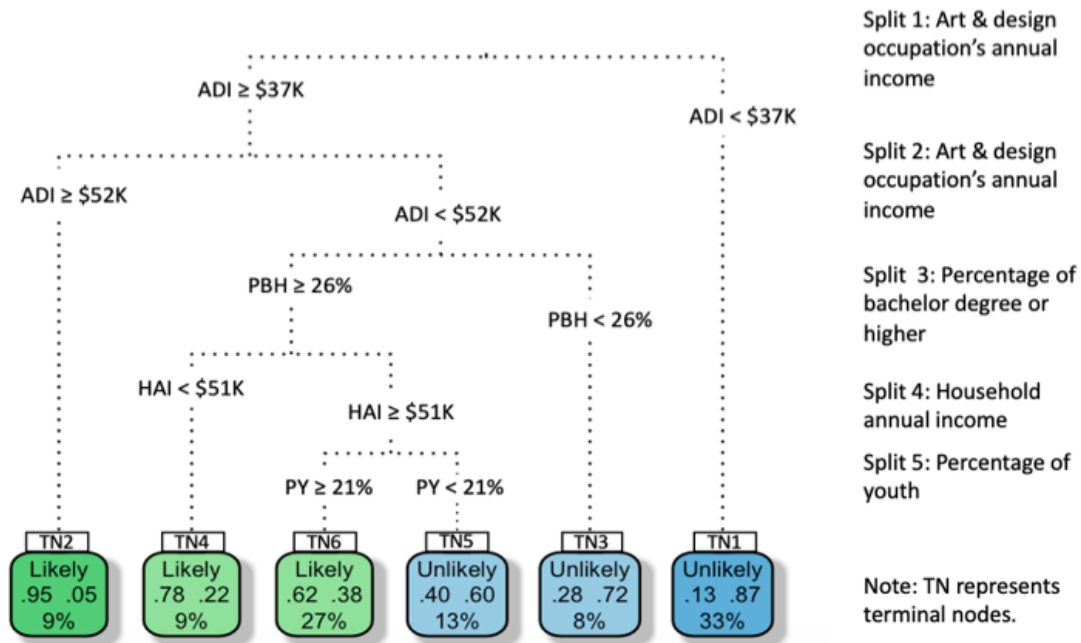


Table 4. Decision paths derived from the obtained decision tree

Terminal nodes	Decision paths associated with different outcome
1	If art and design occupation's annual income $\geq 52,000$ then the observation is likely to adopt DPT.
2	If art and design occupation's annual income $\geq 37,000$ but $< 52,000$, percentage of bachelor and higher degree ≥ 0.26 and household annual income $< 51,000$ then the observation is likely to adopt DPT.
3	If art and design occupation's annual income $\geq 37,000$ but $< 52,000$, percentage of bachelor and higher degree ≥ 0.26 , household annual income $\geq 51,000$, and percentage of youth ≥ 0.21 then the observation is likely to adopt DPT.

Table 4 (continued).

4	If art and design occupation's annual income $\geq 37,000$ but $< 52,000$, percentage of bachelor and higher degree ≥ 0.26 , household annual income $\geq 51,000$, and percentage of youth < 0.21 then the observation is unlikely to adopt DPT.
5	If art and design occupation's annual income $\geq 37,000$ but $< 52,000$, percentage of bachelor and higher degree < 0.26 then the observation is unlikely to adopt DPT.
6	If art and design occupation's annual income $< 37,000$ then the observation is unlikely to adopt DPT.

Discussion and Implications

The visualizations generated for ROI (2010-2019) reveal insights into DPT diffusion in the U.S. over time through depiction of the dissemination patterns. From a general standpoint, the line graph (Figure 4), based on annual DPT cumulative tweets as the proxy variable for DPT adoption, suggested an upward trend with a non-linear trajectory. The S-shaped innovation curve highlights the propensity that as new technology evolves over time, the profits generated by the innovation gradually rise until the maturity stage. Additionally, the visual plot for DPT adoption provides a baseline for potential adopters to assess their relative positions along the curve and consider the implications of their current position. Likewise, the yearly geographical distribution visuals (Appendix 1) enable researchers to instantly capture dissemination trends based on geographical locations. Identified regions with the highest DPT discussion volumes likely provide market opportunities for stakeholders engaged DPT marketing and distribution. However, given the non-linear nature of innovation adoption, continuity of observed trends cannot be assumed. That is, adoption reflected in a single location may wane over time. To further understand adoption of DPT consideration of adopter profiles offers guidance.

This paper applied two complementary approaches to model the predictors of likely DPT adoption. Conventional logistic regression is first used to examine statistically significant predictors, while decision tree analysis further investigates the predictors using a comparatively more flexible data mining approach that can provide additional insights for broader interpretation. This study does not aim to provide an either-or choice between logistic regression and decision tree analysis, rather, both analyses were employed to offer unique insights to inform comprehensive theory-building and predictive profile-construction. In this research, decision tree analysis serves to mitigate the potential for interpretation bias that can be common to regression

models by overcoming hyper-focus on single predictor weights such as beta coefficients. The results indicate absolute consistency between the significant variables in the logistic regression model and the decision tree. This observed consistency is not always likely to occur due to the unique assumptions and operations of the two approaches (e.g. Bencic, Sarlija, & Zekic-Susac, 2005; Namazkhan, Albers, & Steg, 2020). In this case, the consistent results can be regarded as measured validation of the importance of the significant predictors (i.e., household annual income-HAI, percentage of bachelor degree or higher-PBH, percentage of youth-PY, art and design annual income-ADI) predicting DPT adoption. In addition, the association between each significant predictor and DPT adoption is the same in both approaches. PBH, PY, and ADI are positively associated with DPT adoption, whereas HAI is negatively associated with DPT adoption. The greatest difference between the two models is that PY indicates the strongest effect on DPT adoption in the logistic regression, whereas ADI illustrates the strongest effect in the decision tree.

The results provide a profile of likely adopters connected to their geographic location at the state level. The outcome profile suggests that likely adopters reside in states that reflect high levels of education (bachelor's degrees or higher), relatively young populations (i.e., between 19-34 years of age) and proportionately higher incomes generated from art and design occupations. Interestingly, both analytical models reveal that states with relatively higher household incomes are less likely to adopt DPT. This is contrary to Rogers (2003) theoretical view which asserts that wealth tends to positively correlate with innovativeness based on Cancian's (1981) work. However, several studies suggest equivocal findings related to the income-innovation relationship. For example, Tunali and Sahan (2016) indicate that innovations in EU countries work to the detriment of people with higher incomes. Aghion et al. (2019) find that only the top one percent of U.S. incomes at the state level are positively correlated with innovation, while the remaining 99 percent indicate only weak or negative correlations.

The outcomes of this research suggest implications for practical and academic application. In terms of practical implications, this study provides significant potential for DPT stakeholders to capitalize on knowledge for strategic planning. The profile of likely adopters benefits DPT stakeholders in global fashion supply chains including: print houses, printer manufacturers, ink manufacturers, textile and apparel manufacturers, fashion brands and retailers. Stakeholders invested in DPT from various supply chain positions can use the profile to effectively target respective efforts within this undefined market space including media placement, product

placement and additional promotional efforts.

This research reveals several insights that can inform entrepreneurs and additional stakeholders interested in pursuing DPT driven businesses. These entities appear to be more active among states with thriving art and design communities which implies that localized networks likely offer advantages for small businesses with limited resources. In fact, the support of local networks for innovation is an area of study in entrepreneurship (Lazzeretti & Capone, 2016). Therefore, engagement in art and design communities could be an important input for entrepreneurs who are interested in DPT. Additional insights derived from the results suggest that DPT is of higher interest among educated individuals who likely understand the complexities of these technologies and may have skills that better prepare them for leveraging the advantages of DPT in their target markets. Additionally, younger individuals suggested higher levels of interest in DPT reflecting their generation's (i.e., Generation Z, Millennials) growing demand for customized fashion products which has been noted as a major driver of DPT business adoption (Arthur, 2017; O'Connell, 2019)

In terms of academic implications, this research provides a model for integrating social media analytics along with data mining and traditional logistic regression to establish a cursory understanding of an undefined market opportunity. The novelty of DPT as a research topic requires a mixed-methods approach to generate a robust empirical analysis. In this case, complementary research techniques accomplished a more detailed profile of likely DPT users than would have been possible using a single technique. Second, this research capitalizes on the richness of user-generated social media data to provide a context for empirical inquiry guided by diffusion of innovations theory. The data approach overcomes inherent difficulty associated with capturing responses among broad, geographically dispersed populations over a considerable time span. Third, as a result of various informatics advances, business research is transitioning to an increasingly data driven pursuit. In contrast to existing work that discusses the conceptual potential for using big data applications at a phenomenological level (e.g. Mazzei & Noble, 2017; Tabesh, Mousavidin, & Hasani, 2019), this study demonstrates active application of these techniques (i.e., Crimson Hexagon, Tableau, R) to establish a baseline description of an emerging market innovation among temporally dense and dynamically complex data.

Limitations and Future Research

Future business research on user-generated social media data is promising. In this study,

the likelihood of DPT adoption was assumed based on Twitter discussion volume. Although user-generated data enables researchers to analyze geographically dispersed observations across the U.S. over the past decade, limitations of the study should be noted. First, Twitter may skew towards smaller businesses or individuals seeking input from the community. Thus, more than one single social media platform is recommended to collect comprehensive data for future research. Second, there are numerous sources of noise in social media datasets, including robots, and non-relevant conversations (Tsou, 2015). As such, considerable data preprocessing was required to prepare the data for analysis. A logical follow up study to confirm a DPT user profile could employ targeted surveys to DPT communities with sampling approaches based on demographics as well as level of art and design generated incomes. A traditional survey approach would overcome the limitation associated with using a proxy for likely adoption by capturing actual adoption behaviors.

From a conceptual perspective, although the demographic predictors investigated in this study are commonly used by retailers to segment markets due to their capability in diagnosing group homogeneity (Moore & Carpenter, 2010), motivational factors such as dogmatism (Rogers, 2003), hedonism (Tchetchik et al., 2020) and perceived ease of use (Veríssimo, 2018) that impact on an individual's innovation adoption were not examined. Future work considering motivational factors to predict innovation adoption would provide a richer understanding of DPT adoption. Additionally, only a single external predictor was examined in this study due to difficulty capturing adequate environmental data required for the study's scope. Additional external variables such as political conditions for small businesses should be taken into consideration.

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CHAPTER 3

FASHION PRINT-ON-DEMAND ONLINE PLATFORM BUSINESS MODEL ANALYSIS

Introduction

In *The State of Fashion 2019* report, written in partnership with The Business of Fashion, McKinsey & Company forecasted that on demand was one of the top ten trends defining the fashion industry agenda (McKinsey & Company, 2019). Fashion customization is on the rise with 29 percent of U.S. consumers reporting that they have experienced personalizing products, suggesting a corresponding willingness to pay a premium for customized apparel (YouGov, 2018). Simultaneously, *printing*, one of the most widely used garment decorating applications, increasingly contributes to global customized apparel market growth, which was valued at USD 3.4 billion in 2019 and is expected to register a compound annual growth rate of 9.6 percent from 2020-2027 (Grand View Research, 2020). While conventional screen printing technology continues to dominate the current apparel decoration market, digital printing technology, especially its subcategory Direct-to-Garment (DTG) printing technology, is recognized for its potential to disrupt traditional supply chains by automating the printing process, facilitating apparel customization, and reducing production lead time (Chandavarkar, 2013; Yu, Moore, & Chapman, 2020, LeDrew, 2018). Nowadays, the fashion industry is witnessing increasing capabilities for customization facilitated by advanced printing techniques which underpin emerging *Print-on-Demand* (POD) businesses.

Print-on-Demand (POD), also referred to as custom print, is an order generated business model in which blank products are not processed until the company receives an order, allowing prints of single or small quantities (Kleper, 2000). In the fashion domain, POD is capable of customizing complex, multi-color graphics, which caters to increasing demand for personalized garments among young generations (O'Connell, 2019). Although POD is recognized as an increasingly influential fashion trend, research into its market opportunities has yet to materialize. We are the first researchers to empirically investigate fashion POD business models. Due to the emergent nature of POD business and the lack of corresponding empirical attention, exploratory research into the context is warranted. Furthermore, e-commerce is accelerating given the changes in buying behaviors due to the COVID-19 crisis (Deloitte Research, 2020). Therefore, the current

study focuses on investigating POD platforms' business models exclusively within the e-commerce channel.

This study is motivated by gaps in research attention to the structure and performance of fashion e-commerce POD business models. This study aims to develop a comprehensive and parsimonious framework for business models used by fashion e-commerce POD platforms through direct empirical observation. We contribute to both academic and industry insights. From an academic standpoint, we review the business model concept and its constituting value components' literature in the past two decades and synthesize with variables under fashion POD business context to establish a theoretical framework for future POD business analysis. Further, we present a methodological approach by integrating qualitative content analysis and quantitative multiple correspondence analysis to investigate an emerging business with limited antecedent knowledge. From a practical perspective, the outcomes provide a valuable knowledge base for practitioners to understand various fashion e-commerce POD business models and serve as a guide for prospective POD marketers to build value and recognize more opportunities for their own entrepreneurial activities.

Literature Review

Theoretical Underpinnings of Business Models

A good business model is fundamental to every successful organization (Magretta, 2002). Business model emerging as a new unit of analysis is relatively recent, with much of early research appearing in the mid-1990s (Morris, Schindehutte, & Allen, 2005; Al-debei & Avison, 2010; Zott, Amit, & Massa, 2011). Over the past two decades, many authors have offered definitions of the term "business model". Scholars employed classification methods to discover the characteristics of business models and developed the concept's general definition by synthesizing different points of view presented in earlier research. For example, Shafer, Smith and Linder (2005) defined a business model as "a representation of a firm's underlying core logic and strategic choices for creating and capturing value within a value network" (p. 202) by employing a classification method that captured inputs between 1998-2002. The authors underscored the central role of value in competitive differentiation (Shafer et al., 2005). Morris et al. (2005) synthesized nineteen studies from 1996-2002 to propose the following definition, "A business model is a concise representation of how an interrelated set of decision variables in the areas of venture strategy, architecture, and economics are addressed to create sustainable competitive advantage in defined

markets” (p. 727). This represented a strategic framework for conceptualizing a value-based venture. Al-debei and Avison (2010) employed content analysis using twenty-two existing business models from 1998-2008 and identified value proposition, value architecture, value network, and value finance as the primary dimensions of the business model concept, using quality assurance (i.e., number of citations and publication source) as criteria. Zott et al. (2011) systematically analyzed for 103 articles published in leading academic and practitioner-oriented management journals during the period 1995-2010 and defined the business model concept from a holistic perspective which “involves simultaneous consideration of the content and process of doing business” (p.1037). The authors also emphasized that the business model concept has received increasing attention from scholars and business strategists interested in explaining firms’ value creation, performance, and competitive advantage (Zott et al., 2011).

To date, there exists no consensus regarding the definition of business model, however, it is evident that the concept plays a vital role in analyzing today’s complex, turbulent business environment. In the past five years, empirical discourse tends to focus on the value themes that comprise business models based on existing work which conceptualizes the business model as a concise representation of a firm’s underlying core logic for creating value for its stakeholders (e.g. Chesbrough & Rosenbloom, 2002; Magretta, 2002; Shafer et al., 2005; Morris et al., 2006; Johnson, Christensen, & Kagermann, 2008; Teece, 2010). In other words, the centrality of value in the business model literature emerged from the existing conceptualizations of the concept (Zott et al., 2011). Furthermore, scholars developed a set of sub-themes to represent the most prevalent business model components related to different conceptual values. These components serve as a means for interpreting intangible value dimensions to establish a consolidated business model. Table 5 presents a synopsis of significant perspectives regarding business models values and their relevant components from 2014-2020. Though the business model literature varies by context, existing studies indicate a growing consensus that value proposition, value creation, value delivery and value capture are the primary value dimensions to construct the business models concept (see Table 5).

Table 5. Components of business models

Author(s), Year	Value Themes	Key Components
Bocken et al., 2014	Value proposition Value creation Value capture	Products, services, market positioning Core activities and processes Revenue expansion, operational efficiencies
Tongur & Engwall, 2014	Value proposition Value creation Value capture	Products and services (i.e., premium brand, reliability, engine power, energy efficiency, drivability, and prestige) Technology improvement (i.e., development and manufacturing of trucks built around the diesel engine powertrain) Sales of trucks, with after-sales of services as add-ons
Landau, Karna, & Sailer, 2016	Value proposition Value creation & delivery Value capture	Product portfolio Through developing an activity system that comprises design, assembling, promotion and sale, after sale services Through charging customers a price premium and sometimes by financing the purchase
Velu & Jacob, 2016	Value proposition Value creation Value capture	Product Distribution and promotion Through the difference between buy and sell prices for the securities and through transaction fees or credit guarantee fees for each transaction
Holzmann et al., 2017	Value proposition Value creation Value capture	Products and services (i.e., all around service, expertise, financial profit, quality, reliability, training and support) Technologies used, the integration of external partners into the value chain, and communication channels Revenue sources, payment methods

Table 5 (continued).

Saebi, Lien, & Foss, 2017	Value proposition Value delivery Value capture	Products/services Through establishing closer links with partners, using new suppliers, or engaging in reorganization Whether reduced or increased prices because of the crisis
Cao, Navare, & Jin, 2018	Shopper value proposition Retail value chain	Price, quality, range of products Conception of products, production, procurement, logistic, retail concept (e.g. providing diversified services, accessibility, price), information system, relationship with suppliers/consumers
Howell, Beers, & Doorn, 2018	Value capture Value proposition Value creation	Lead time advantages, competitive advantages, exchange value (profit) Frugal engineering Use value or willingness to pay, human capital increase
Garcia Martin, Schroeder, & Bigdeli, 2019	Value creation Value delivery Value capture	Production, human input, resource and activity integration Problem-solving, intellectual input, reduction of risk and uncertainty Economic outcomes and offering format
Weerawardena et al., 2019	Value proposition Value creation Value capture	New products or solutions developed in response to identified market opportunities Network-focused learning capacity (e.g. research and development activities) New ways to generate income, generate private and public funding
Gamble et al., 2020	Internal value creation External value creation	Quality of core product or service, reliability, brand loyalty, differentiation from competitors, firm size factors Suppliers (knowledge acquisition, partnership), competitors (service customization), distributor (service quality), stockists (safeguarding routes to market)

Table 5 (continued).

Kullak, Baker, & Woratschek, 2020	Value proposition Value creation process Value capture mechanisms	Content of special event Open platform for integration of internal and external resources Sponsorship association, public funding, donation
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Value Dimensions

Value proposition is defined as the value of products or services that the company offers to the chosen customer segment (Magretta, 2002; Al-debei & Avison, 2010). Scholars tend to describe the value proposition through a brand's product or service portfolios, including but not limited to, quality, price, and other leading advantages (e.g. Bocken et al., 2014; Tongur & Engwall, 2014; Landau, Karna, & Sailer, 2016; Velu & Jacob, 2016; Holzmann et al., 2017; Saebi, Lien, & Foss, 2017; Cao, Navare, & Jin, 2018; Weerawardena et al., 2019). The value proposition also serves as the statement to persuade customers to choose a company's offering over its competitors. Company value propositions that are comparatively unique to competitors are more likely to capture consumers and, in turn, facilitate a position of advantage in competitive markets (Bititci et al., 2004; Ucakurk et al., 2011).

Value creation refers to the process of value generation among network actors (Bowman & Ambrosini, 2000; Tongur & Engwall, 2014). Value creation is also recognized as the structure of the value chain required for realizing the value proposition (Saebi et al., 2017). Traditionally, a company's internal actions and efforts have been emphasized as integral to value creation (Kullak, Baker, & Woratschek, 2020). Internal value creation activities typically include: invention, innovation, research and development and production (Chesbrough & Rosenbloom, 2002; Shafer et al., 2005; Tongur & Engwall, 2014; Weerawardena et al., 2019). Increasingly, contemporary literature demonstrates value creation comprises not only internal actors but also external actors through the integration and exchange of resources (Bocken et al., 2014; Holzmann et al., 2017). Additionally, customers can be involved in specific value creation activities where the provider's expertise and customer's input are instrumental in delivering products or services with higher use value (Sjödin et al., 2020).

Value delivery is described as the manner by which a company delivers value to consumers (Teece, 2010; Gassmann, Frankenberger, & Csik, 2013). Well-proposed and well-created values

could not be captured if the company is not able to effectively transfer these values to willing consumers. The concept of value delivery refers to the physical delivery method in some research contexts. For example, Teece (2010) used Netflix to explain the business model for DVD rental in the U.S. Netflix pioneered delivery of DVDs by mail using a patented, subscriber-based online system as well as an expedited physical delivery provided by the U.S. Postal Service. Netflix provided a convenient alternative to consumers that eliminated the need to visit rental centers and enabled Netflix to achieve reasonable success. Alternatively, Slater (1997) defined the concept of value delivery as a critical process for companies to understand customers' demand in order to provide them with the necessary products or services to fulfill the value proposition. For example, Garcia Martin, Schroeder and Bigdeli (2019) operationalized measures of customers' usage experiences as one of the factors to evaluate value delivery dimension. Although the term "value delivery" is not directly used in some literature, many scholars imply an effective and efficient communication channel is critical to facilitate consumer awareness of the value proposition in order to better deliver proposed value and entice customers to pay for this value (e.g. Macdonald et al., 2011; Alghisi & Sacconi, 2015; Holzmann et al., 2017).

Nevertheless, the unique nature of value propositions may cause difficulty when differentiating between value creation and value delivery in certain contexts. Hence, some researchers integrated value creation and value delivery into a single process that reflects how value is provided to the customer (e.g. Markides, 2006; Velu & Jacob, 2016; Holzmann et al., 2017). Additionally, some researchers assessed value creation and value delivery simultaneously when the value proposition is based on intangible outputs because they assume that value is embedded at the moment of service delivery (e.g. Macdonald et al., 2011; Raja et al., 2013; Garcia Martin et al, 2019). Indeed, because business model values are inextricably linked, their boundaries or components are occasionally blurry due to the similarity of key actor configurations.

Finally, value capture defines how the company captures corresponding economic returns in relation to the value it has created for its customers (Shafer et al., 2005; Johnson et al., 2008). A firm's revenue is mainly generated by selling output in established markets and captured through various payment methods (e.g. Landau et al., 2016; Velu & Jacob, 2016; Holzmann et al., 2017; Garcia Martin et al, 2019). Value capture can also be more broadly defined as the activities a company performs to absorb created value, including risk management and cost structure, and

dividing the gains with contributing actors in the value chain (Dyer, Singh, & Hesterly, 2018; Möller & Shahnavaz, 2020).

Print-on-Demand Platforms in Fashion Business

A POD e-commerce platform is simply an Internet site that provides custom printing in single or small quantities to consumers. Most POD platforms use dropshipping to handle order fulfillment for content creators (also recognized as consumers). The POD e-commerce platforms provide entrepreneurial opportunities at various points along the value chain. One of the core advantages of POD business is producing fashion products only when customers place an order. This approach allows POD platforms to operate with minimal initial investment in inventory which reduces financial risk. POD platforms provide a range of benefits to relevant stakeholders in the value chain for the content creator including artists/designers and consumers. Artists and designers need an intermediary to promote their work to the largest possible number of consumers. POD sites satisfy this need by providing broad, global market exposure. Additionally, most POD platforms fulfill customer orders as a third party for artists/designers' own brands. That is, artists and designers not only exploit POD platforms' resources for marketing and promotion but also rely on POD manufacturing and transportation capabilities to create and deliver the products so that they can focus on the creative process. From the consumer perspective, POD platforms provide a solution for consumers who want something "unique". Senanayake and Little (2010) stated that the strategy of pure customization cannot be achieved until the customer integrated into the design process. POD increases customer integration into the product development process, advancing from "tailored" customization (i.e. the company presents a product prototype and then adapts it to consumer's demand) to "pure" customization (i.e. consumer's demand penetrate deeply into the design process, where the product is truly made to order) (Lampel & Mintzberg, 1996). Current examples of POD based business include Cafepress, Redbubble, Merch by Amazon.

Unlike other e-commerce businesses which primarily focus on providing digital platforms to connect sellers and buyers, the multiple services with unique features provided by POD platforms contribute to their complexity from an analytical perspective. This proposed research is motivated by the need to investigate how POD platforms market their offerings through unique business models in the fashion domain. We draw on the seminal business model literature to apply the formal business model value dimension concept as our unit of analysis through identifying and

describing active POD business models in terms of value proposition, value creation, value delivery and value capture.

Methodology

Sample Selection and Description

Due to the fragmented nature of the emerging POD industry, we employed an exploratory sample selection approach by integrating objective social media data analysis and subjective communications with industry experts. We first collected 5,955 tweets from July 1, 2019 to June 30, 2020 from Twitter that include the keyword *print on demand*. After removing the noise and retweets, we identified the most prevalent POD online platforms based on frequency. Although Twitter has become an increasingly important data source for scholars to investigate fashion related phenomena (e.g. Lee et al., 2017; Zhao & Min, 2018), Twitter may skew towards smaller businesses or individuals seeking input from the community (Yu et al., 2020). Therefore, to ensure the diversity of business models, we subsequently modified the sample list through consultation with two experienced industry experts with considerable experience in the POD industry.

Twenty-one POD online platforms that offer fashion product printing in the U.S. were identified (see Table 6). Nineteen POD platforms headquartered in the U.S. were originally selected along with two POD platforms headquartered in Germany and Australia with active operations in the U.S. The sample POD platforms were founded between 2000 and 2015, with thirteen platforms (62%) emerging more recently (2011-2015). Additionally, the size of the platforms can be classified into four segments according to number of employees: more than 500 employees (n=5), 201 to 500 employees (n=5), 50 to 200 employees (n=8) and less than 50 employees (n=3).

Table 6. Sample overview

POD platforms	Country of headquarters	Year founded	Number of employees
1 (Printful)	USA	2013	>500
2 (Cafepress)	USA	2014	201-500
3 (Redbubble)	Australia	2006	201-500
4 (Zazzle)	USA	2005	>500
5 (Teespring)	USA	2011	201-500
6 (Threadless)	USA	2000	50-200
7 (Gearlaunch)	USA	2013	50-200

Table 6 (continued).

8 (Bonfire)	USA	2011	50-200
9 (Spreadshirt)	Germany	2002	>500
10 (TeePublic)	USA	2013	<50
11 (Sun Frog)	USA	2012	50-200
12 (Merch by Amazon)	USA	2015	>500
13 (Rush Order Tees)	USA	2002	201-500
14 (Custom Ink)	USA	2000	>500
15 (Society 6)	USA	2009	50-200
16 (Printify)	USA	2015	50-200
17 (Gooten)	USA	2012	50-200
18 (Scalable press)	USA	2012	201-500
19 (Teelaunch)	USA	2012	<50
20 (Print Aura)	USA	2012	<50
21 (Pixels)	USA	2006	50-200

Coding Procedures

Secondary data sources were used to capture value data for each platform. These data were gathered from multiple sources including: platforms' websites, company profiles and press releases in public media. The qualitative data were analyzed using Mayring's (2000) deductive-inductive approach. This approach applies a priori, deductive theoretical categories to guide categorization of new data using induction. In the context of this study, the taxonomy of values are provided by the business model literature which provides a framework for organizing the inductive qualitative data generated to address the research objective. Three researchers independently coded the qualitative data and resolved disagreements to achieve an overall minimum interrater-reliability of 95 percent.

Based on the deductive framework, we organized each platform's value data under the four defined dimensions. The unique platform data for each value were inductively coded within each value dimension (Table 7). The content analysis generated ten product and service oriented variables for value proposition (i.e., uniqueness, reliability, accuracy, expertise, creativity, efficiency, flexibility, accessibility, return policy, and sustainability). Furthermore, value creation comprises two sub-themes that contribute a total of five variables: the printing technologies used including DTG, screen printing and alternative printing technology, and production methods

including internal and external printing facilities. The value delivery also comprises two sub-themes that generates a total of seven variables. One sub-theme related to communication channels including operational guidance and customer support (i.e., live chat, email, social media); the other sub-theme related to physical delivery variables including speed, options and international shipping. Additionally, value capture comprises three sub-themes that amount to a total of seven variables: integration with third party ecommerce platforms, revenue sources (i.e., transaction-based revenue, design service revenue, shop service revenue), payment methods (i.e., credit card, PayPal, alternatives). After the coding process was completed, the codes were interpreted dichotomously (presence-absence) for subsequent analysis. In addition, we used the number of employees as supplementary variables named E1 (>500), E2 (201-500), E3 (50-200), and E4 (<50) to explore if company size affects POD business model values.

Table 7. Coding guide

Values	Codes	Meaning
Value proposition	Uniqueness	Allow consumers to create customized design
	Reliability	Check for printability and removing errors
	Accuracy	Simulate design on selected product before printing
	Expertise	Provide professional design assistance to craft a better print outcome
	Creativity	Sell of designs created by artists/designers
	Efficiency	Promise to print within 48hours or provide expedited print service
	Flexibility	Provide different fashion products with different materials, e.g. cotton t-shirts, blended t-shirts; hoodies, caps, totes
	Accessibility	Accept more than one digital file type
	Return Policy	Accept returns/exchanges for any unsatisfactory reasons
	Sustainability	Have sustainability certification, e.g. Oeko-Tex™, Worldwide Responsible Accredited Production
Value creation	Direct-to-Garment (DTG)	Use DTG printing technology
	Screen printing technology	Use screen printing technology
	Alternatives printing technology	Use other printing technologies (e.g., sublimation, heat transfer)
	Internal print facility	Own in-house printing facility
	External print facility	Integrate external print partners into the value chain

Table 7 (continued).

Value delivery	Operational guidance	Provide detailed operational guidance for customers
	Live chat	Provide live chat for customer support
	Email	Provide email for customer support
	Social media	Provide any social media for customer support
	Express delivery	Offer an Express Delivery option that prioritize the order to the front of the waiting queue
	Delivery flexibility	Offer more than one carrier options
	International shipping	Offer international shipping (besides Canada)
Value capture	Integration	Direct connection with third party e-commerce platforms (e.g. Etsy, Ebay, Shopify)
	Transaction-based revenue	Revenue streams include transaction-based revenue
	Design service revenue	Revenue streams include design service revenue
	Shop service revenue	Revenue streams include shop service revenue (e.g. registration, monthly fee, advertising, verification fee)
	Credit/debit card	Payment methods include credit/debit card
	PayPal	Payment methods include PayPal
	Alternatives payment method	Payment methods include alternatives (e.g. bank transfer, Apple pay)

Multiple Correspondence Analysis (MCA)

The MCA is often considered to be a counterpart of principal components analysis applied to categorical variables rather than continuous variables (Cadoret, L  , & Pag  s, 2011). MCA is a statistical technique that can reduce multidimensional data through analyzing the associations between variables and individuals, which enables identification of the predominant variables of each value dimension in POD business context (Audigier, Husson, & Josse, 2017). Additionally, MCA enables visual interpretation of the biplots among cases and variables based on locational proximity (Greenacre, 1994; Husson et al., 2011). The MCA results enable us to divide 21 POD platforms into homogeneous groups based on each unique value dimension by maximizing the inertia of the projected scatter plot on a new coordinate basis. In the new coordinate space $I \times J$, the Euclidean distance d^2 between two POD platforms i and l is defined as:

$$d_{MCA}^2(i, l) = \frac{1}{J} \sum_k \frac{I_k}{I_k} (x_{ik} - x_{lk})^2$$

, where I_k denotes the number of objects in the group k (Cadoret et al., 2011). RStudio version 1.3. was used to generate the MCA in this study.

Results and Discussion

The eigenvalues for each value dimension are presented in Table 4. Following the threshold of Esmaelian et al. (2017), if the first two dimensions account for 50 percent or more of the total variance, a two-dimensional plot suffices for a reasonable approximation of the data point locations. The results in Table 8 indicate that all four values can be represented by two-dimensional plots. Thus, two-dimensional plots for value proposition, value creation, value delivery and value capture are presented in Figure 1, Figure 2, Figure 3, and Figure 4, respectively. The row points (i.e., POD online platforms) are represented by black dots, while the column points (i.e., variable categories) are represented by red triangles and the supplementary variable is represented by green triangles. The distance between any row or column points indicates similarity or dissimilarity. A platform that is on the same side of a given variable category has a high value for this variable category; a platform that is on the opposite side of a given variable category has a low value for this variable category. Appendix 1 illustrates each variable representation for the unique values. Points farthest from the origin represent stronger discrimination compared to those closer to the origin.

Table 8. Eigenvalues and variance of dimensions

		Dim.1	Dim.2	Dim.3	Dim.4
Value proposition	Eigenvalues	0.372	0.214	0.134	0.116
	% of var.	37.237	21.380	13.400	11.554
	Cumulative % of var.	37.237	58.617	72.017	83.571
Value creation	Eigenvalues	0.419	0.302	0.176	0.104
	% of var.	41.855	30.229	17.564	10.352
	Cumulative % of var.	41.855	72.083	89.648	100.000
Value delivery	Eigenvalues	0.363	0.238	0.162	0.100
	% of var.	36.347	23.809	16.200	9.983
	Cumulative % of var.	36.347	60.157	76.356	86.340

Table 8 (continued).

Value capture	Eigenvalues	0.342	0.272	0.176	0.138
	% of var.	34.221	27.202	17.621	13.758
	Cumulative % of var.	34.221	61.423	79.045	92.803

Value Proposition

Initially, ten variables represented the value proposition component. However, because each POD platform provides differentiated fashion products to consumers (e.g., different fabrics and styles), the variable *flexibility* cannot distinguish dissimilarity among platforms. Similarly, because all POD platforms accept digital design files in multiple formats, the variable *accessibility* cannot distinguish dissimilarity among platforms. Thus, eight variables were applied in the MCA for value proposition. The MCA results indicate that dimension one is best explained by a combination of uniqueness ($\eta^2=0.68$), reliability ($\eta^2=0.60$), accuracy ($\eta^2=0.59$), and expertise ($\eta^2=0.57$), while dimension two is best explained by a combination of creativity ($\eta^2=0.65$) and return policy ($\eta^2=0.69$). Further, the scattered distribution of the black points in Figure 6 illustrates that the POD platforms provide relatively different services. This observed distribution is consistent with previous literature (Bititci et al., 2004, Ucakturk et al., 2011) which suggests that brands should develop relatively unique value propositions to increase the likelihood of attracting target customers. Although Figure 6 presents a relatively dispersed distribution, the following insight can nevertheless be drawn from the visual.

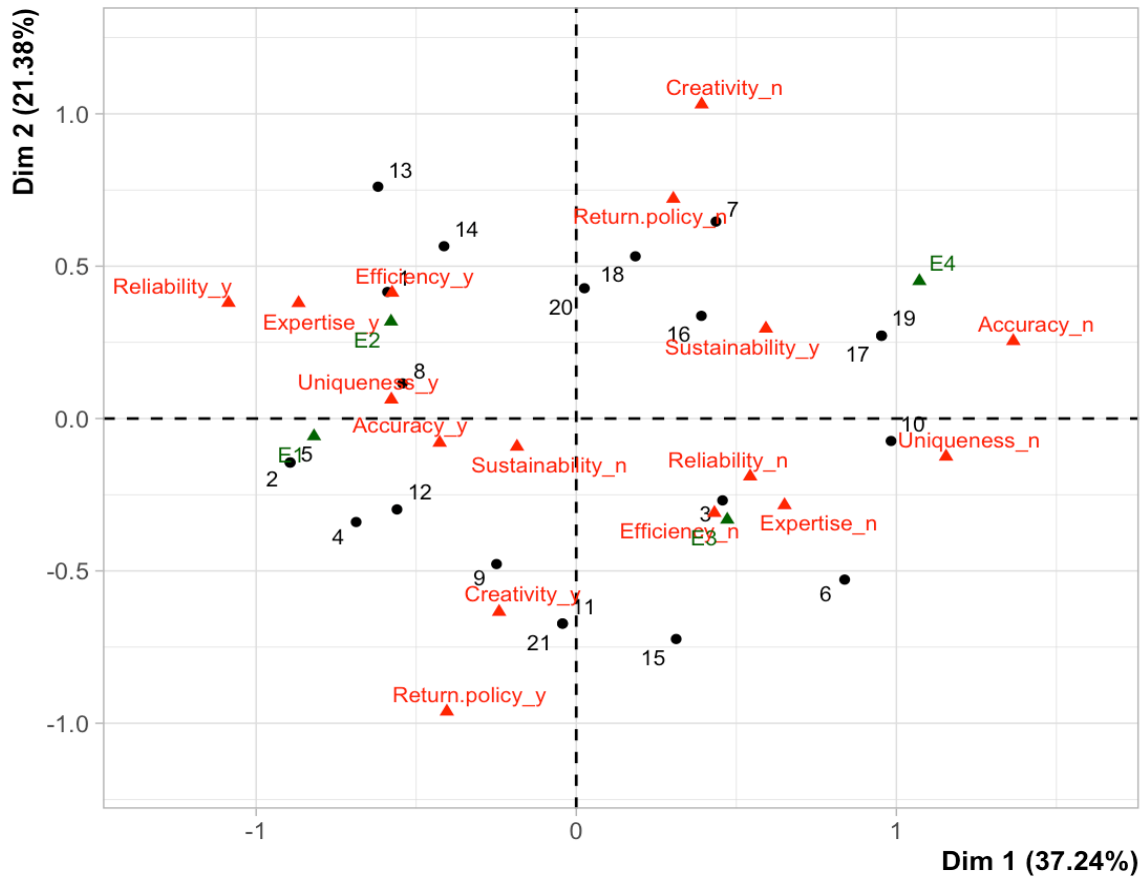
In terms of value proposition, platforms 2 and 5 are identical to each other, and suggest proximity to platforms 1, 4, 8, and 12. This group of platforms is located on the same side of the horizontal axis (i.e., Dim 1) with variable categories uniqueness_y, reliability_y, accuracy_y and expertise_y. This finding suggests that these six platforms not only allow end consumers to create customized design, but also improve their value proposition through offering printability checking, design simulation, and professional design assistance services. Contrarily, platforms 17 and 19 are also identical and suggest proximity to platform 10. This group is located on the other side of the horizontal axis with variable categories uniqueness_n, reliability_n, accuracy_n and expertise_n. This finding suggests that these three platforms do *not* provide customized design and relevant value added services. This finding implies that although previous literature (e.g. O'Connell, 2019) emphasized that customizing complex graphics is one of the core competitive advantages for POD

business, it is not the only way to address the value proposition.

Platforms 11 and 21 are identical and indicate relative proximity to platforms 9 and 15. This group of platforms is located on the same side as *creativity_y* and *return policy_y* on the vertical axis (i.e., Dim 2). This finding indicates that this group's value proposition is explained by the services of selling designs created by artists and designers and accepting returns or exchanges for any unsatisfactory reasons. This finding implies return costs for platforms that sell original graphics designed by professionals are lower compared to platforms that provide one-of-a-kind customization graphics that are difficult to resell. In contrast, the group of platforms on the opposite side of the vertical axis which do *not* sell existing designs created by artists and designers and do *not* provide unconditional returns or exchanges. The variables *efficiency* and *sustainability* do not explain adequate variance for either Dim 1 or 2, and are therefore not interpreted.

Additionally, the supplementary variable *company size* is relatively associated with Dim 1 ($\eta^2=0.50$) than Dim 2 ($\eta^2=0.10$) in terms of value proposition (see Appendix 2). Figure 1 depicts that variable categories E1 and E2 which are located on the same side with the presence of variables *uniqueness*, *reliability*, *accuracy* and *expertise*, while E3 and E4 are located on the opposite side with the absence of these variables. Meanwhile, E1 and E4 are further from origin compared to E2 and E3. In general, this finding implies that larger firms tend to emphasize end-user customization in their respective value propositions.

Figure 6. Value proposition variables MCA



Note: The suffix “y” indicates the presence of variables; the suffix “n” indicates the absence of variables.

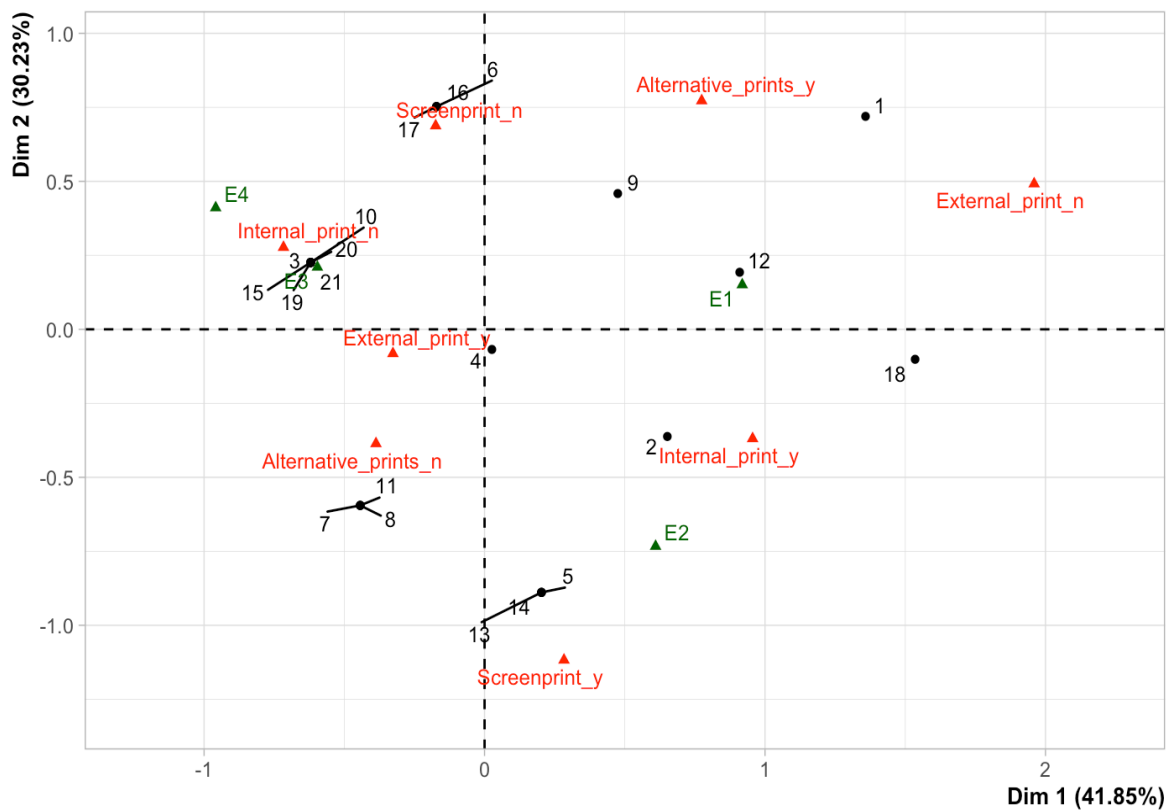
Value Creation

Five variables represented the value creation component initially. Because all sample platforms adopt DTG as a predominant printing technique, the *DTG* variable is excluded for MCA analysis. The first dimension is best explained by a combination of variables: *internal print facility* ($\eta^2=0.69$) and *external print facility* ($\eta^2=0.64$), while the second dimension is best explained by the variable *screen printing technology* ($\eta^2=0.77$). Platforms 3, 10, 15, 19, 20, and 21 are identical in terms of value creation. These platforms are located on the same side with variable category internal print_n and external print_y, which suggests that this group of platforms does *not* have in-house printing facilities and relies on external facilities to print. Notably, variable category external print_n is further from origin compared to external print_y, which implies that external print_y is not an effective discriminator due to sample platforms’ widespread use of external printing

facilities in their value chains. Note that only three sample platforms do not use external partners for printing. Moreover, the number of platforms on both sides of the vertical axis is roughly equal; platforms located on the negative side offer screen printing services. This finding implies although DTG is widely adopted as a predominant printing technique for POD business, many POD online platforms did not abandon screen printing technology, but use it to serve large-volume orders.

In addition, the supplementary variable *company size* indicates a relatively strong influence on Dim 1 ($\eta^2=0.57$) (Appendix 2). The results suggest that variable category E3 and E4 are located on the same side with internal print_n and external print_y, while E1 and E2 are located on the opposite side of Dim 1. This finding suggests that platforms with fewer employees are more likely to integrate external printing facilities into their production line.

Figure 7. Value creation variables MCA

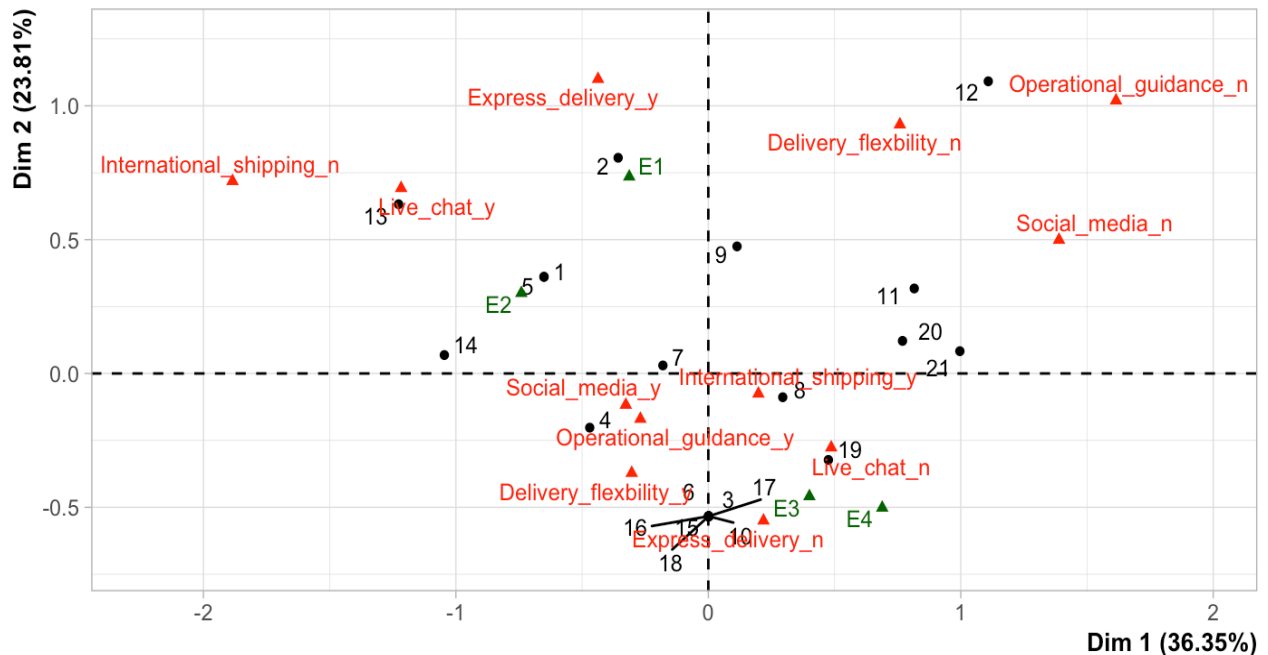


Value Delivery

Six variables represent the value delivery component with the exclusion of *email* which is used by all sample platforms for customer support (Figure 8). The first and second dimensions are

each best explained by the variable *live chat* ($\eta^2=0.59$) and *express delivery* ($\eta^2=0.61$). In terms of value delivery, platforms 3, 6, 10, 15, 16, 17, 18 are homogeneous and indicate relative proximity to platforms 8 and 19. This group of platforms is located on the same side as *express_delivery_n* which suggests they do *not* offer express delivery options that prioritize consumer queuing order. Meanwhile, variable categories *express_delivery_n* and *live_chat_n* are closer to origin compared to *express_delivery_y* and *live_chat_y*. This finding implies that platforms which offer express delivery and live chat are in the minority among the sample. Interestingly, although the majority of platforms offer more than one delivery option, USPS emerged as the most common carrier choice, followed by UPS, Fedex and DHL. Additionally, the supplementary variable *company size* does not appear to impact the value delivery component as its effect size to Dim 1 ($\eta^2=0.28$) and Dim 2 ($\eta^2=0.27$) are both relatively low.

Figure 8. Value delivery variables MCA

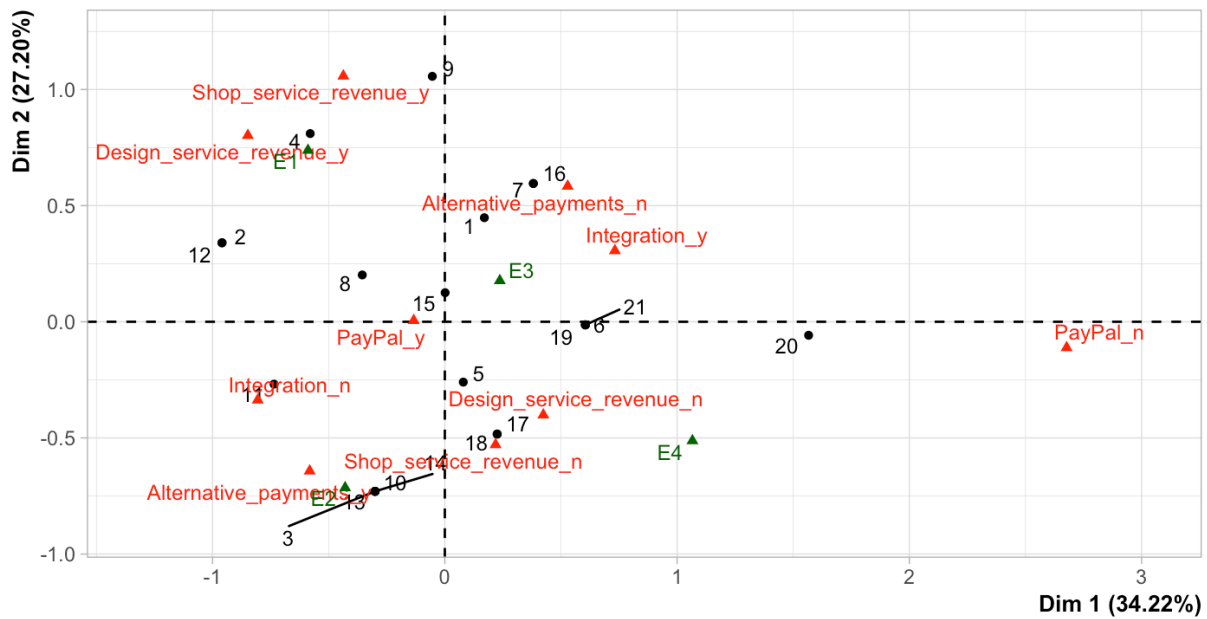


Value Capture

The value capture component initially generated seven explanatory variables, however two variables: *transaction-based revenue* and *credit/debit card* were eliminated from the analysis due to their respective widespread adoption among all sample platforms. Dim 1 is primarily described by *integration* ($\eta^2=0.59$), while Dim 2 is primarily described by *shop service revenue* ($\eta^2=0.56$).

Platforms on the same side with the variable category *integration_y* (e.g. platforms 1, 7, 16) are directly connected with third party e-commerce platforms such as Etsy, Ebay, or Shopify. These POD platforms provide convenience for designers and artists who have an existing online store. Consumer orders from other ecommerce platforms can be channeled to the POD platforms. Additionally, platforms 2, 4, 9, 12 are located in the quadrant which indicates the presence of variables related to shop service revenue. This finding suggests that this group of PODs' revenue stream includes shop service, such as monthly fee and advertising fee. Again, the supplementary variable *company size* does not impact value capture among the sample data (Dim 1, $\eta^2=0.31$; Dim 2, $\eta^2=0.30$).

Figure 9. Value capture variables MCA



Conclusions and Implications

This study is among the first to provide an empirical understanding of fashion e-commerce POD businesses. The business model literature that leverages value dimensions provides theoretical guidance for pursuing the research objective. Specifically, four value dimensions are adopted to analyze POD business models using a deductive-inductive approach, thereby facilitating discovery that is theoretically grounded and practically guided. This study contributes to the business model literature by providing a comprehensive, yet parsimonious, theoretical framework to facilitate identification of otherwise disorganized or uncategorized activities among

POD businesses. Simultaneously, the present work demonstrates application of the value centrality theoretical approach to the analysis of business models in non-transparent emerging market contexts. Consistent with previous literature that demonstrates value dimensions are concise representations for business model conceptualization (Magretta, 2002; Teece, 2010), this study provides evidence that POD business models can be clearly described and efficiently analyzed through the four focal value dimensions. Further, the value centered approach provides an accessible theoretical basis for formulating managerial basis through identification of unique dimensions that can be easily altered for strategic leverage.

The study implies a number of managerial implications that are presented in order of the unique dimensions. In terms of the value proposition, fashion POD business can be generalized into two models: *end consumer service model* (i.e., consumers customize the graphic/design) and *professional service model* (i.e., designers and artists upload well-developed designs and consumers can choose the product styles). Each model suggests corresponding value added services. The end consumer service model is comparatively more likely to provide printability checking, design simulation and assistance services to improve the consumer design experience, while the professional service model is more likely to provide a lenient return policy to improve consumers' shopping experience. The findings suggest that POD platforms which conform to an end consumer service model tend to undertake activities that provide technical and design support for novice creators with limited resources. The centrality of technical support for generating customized POD products suggests that platforms which serve individuals without formal design training or infrastructure benefit from these critical services. Therefore, these POD platforms should emphasize services that assist their customers in the design and production process. In contrast, the professional service model which caters to experienced designers focuses on providing efficient business support.

The emergence of distinct models illustrates the diversity of emerging POD platforms. Platforms that follow the end consumer model demonstrate core competencies in providing services that allow consumers to successfully transfer their design concepts into an acceptable customized product. For platforms that follow a professional service model, the core competencies appear to arise from a dedicated return policy for balancing consumer service expectations and business profits. Although findings suggest that a lenient return policy is closely associated with the professional service model, marketers must remain vigilant in efforts to reduce returns overall

due to their negative impact on profitability. Moreover, the findings indicate that the end consumer service model is significantly impacted by company size, while the professional service model is not impacted by size. A likely explanation for this finding lies in the logic that professionals need less design assistance, which reduces the platform's labor needs. Startup POD platforms should consider the importance of labor resources required for markets driven by individual customization services to ensure they can provide competitive support services.

In respect to the value creation dimension, findings suggest that a hybrid printing approach represents a trend among POD businesses. "Hybrid" not only refers to the combination of internal and external printing facilities but also refers to the combination of screen printing and DTG printing technology. From the printing facility perspective, a hybrid manufacturing system is able to increase the POD platform's printing capability and simultaneously decrease production costs (e.g. lower capital and labor cost, shorter setup time, higher average margins per order). However, an approach that requires external production runs the risk of oversimplifying the process and ultimately decreases print quality due to a lack of control. Hence, we recommend that POD platforms using hybrid printing systems develop an effective monitoring tool to exert control over external printing processes. From the printing technology perspective, although previous studies demonstrated that DTG is currently revolutionizing the apparel decoration market by facilitating customization, reducing inventory and energy, and lowering production lead time (Combs, 2019; Yu et al., 2020), the findings illustrate that nearly half of POD platforms continue to use conventional screen printing technology particularly for large volume orders. Thus, we suggest that POD platforms integrate both DTG and screen printing technology to increase their flexibility and serve a broader market. This flexibility can be particularly useful for platforms that cater to different market tiers ranging from large orders for mass markets to niche customization. Therefore a POD's core target market needs should be considered when integrating hybrid approaches into the process.

In terms of the value delivery dimension, provisions of live chat and express delivery services are important to enhance POD platform's competitiveness by providing consumers both psychological and physical value during delivery. Given the dominance of POD in e-commerce, delivery expectations among consumers are likely to be particularly sensitive. Thus, we suggest that online POD platforms focus their efforts to prepare personnel with customer service training that delivers excellent consumer experiences. Additionally, offering express delivery options that

prioritize production for urgent orders is likely to increase a platform's competitiveness. This option can be particularly beneficial, given the fact that many platforms do not currently provide this service. However, the strategic decision to offer a given service should not interfere with serving other target markets. For example, a platform that caters to diverse consumer groups should ensure order fulfillment for ordinary orders when integrating expedited services. Thus, providing express delivery should increase a POD platform's production capacity which can be achieved by adopting hybrid printing facilities. This interpretation demonstrates the interrelatedness of the four focal value dimensions when developing a competitive POD business model.

In terms of the value capture dimension, POD platforms primarily generate transaction-based revenue, therefore additional sources of profit should be identified, particularly among shop services and third-party e-commerce integration. Additionally, the findings suggest that compared to value proposition and value creation, company size does not consistently impact value delivery and value capture dimensions. Therefore, value delivery and value capture can serve as sources of competitive advantage for small POD businesses with less labor intensive processes. One conjecture of this phenomenon is that technical obstacles hinder the improvement of value delivery and value capture related activities rather than labor quantity. For example, an application programming interface (API) developer is required for integrating a POD platform with other third-party e-commerce platforms to synchronize their operation workflow. Thus, we suggest that potential POD entrepreneurs emphasize technical expertise in the early stage of team building.

Limitations and Future Research

The first limitation of this research arises from limitations associated with data visualization. Although all four values meet the Esmaelian et al. (2017) threshold (i.e., first two dimensions account for 50 percent or more of the total variance) and are thus reasonable to be represented by two-dimensional (2D) plots, three-dimensional (3D) plots are capable of explaining variance in greater depth. Unfortunately, 3D plots that require dynamic rotation for effective interpretation cannot be effectively presented in 2D publishing formats. Additional limitations associated with MCA are also notable. Although the MCA algorithm seeks explanation of maximum variance among the data, the technique can potentially fail to capture features in raw data that may be influential.

Due to the exploratory purpose of this study, the sample size is relatively small. Future

studies with larger samples are necessary to validate the result of this study. Furthermore, the findings are based on secondary data released in public media including company websites and other professional business data providers. Primary research using individual or focus group interviews with industry experts would be particularly useful for corroboration and expansion of the study's findings.

This research generated practical implications for POD businesses from the platform perspective based on the provision of value dimensions to their respective markets. Based on the findings related to the identification of the *professional service model*, platforms that follow this model tend to calibrate services for artists and designers through support services such as lenient return policies. Entrepreneurial artists and designers should seek PODs that provide opportunities for interaction and feedback to optimize the creative process. For future research, as important stakeholders in the POD market, designers and artists perspectives on the process should be considered. For example, examination of relationships between POD platforms and designers can provide insight into best practices. Additionally, future research can expand the scope of this study through consideration of POD business opportunities whereby consumers commission artists/designers to work together in a participatory design process.

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CHAPTER 4

FINAL VALIDATION

An online focus group, including three participants with considerable expertise in digital printing technology, was conducted on April 23rd 2021 to provide insight into the findings of the three studies in this dissertation. In this sense, primary data collection is designed for validation purposes. The first participant is a Senior Vice President of Research and Development at an on-demand, digital printing company with more than twenty years of professional experience in digital printing. The second participant is currently a Product Line Manager in the world's foremost manufacturer of screen-printing, hybrid and digital equipment for the graphic and textile industries. This individual has more than ten years working experience in the digital print industry. The third participant is a surface design and color specialist who has been engaged in digital printing for more than five years. During the focus group, the discussion mainly focused on whether the participants agree or disagree with the presented findings and their suggestions for future research. In general, all participants agree that the findings of three studies are consistent with their unique perceptions of the digital print market. Participants' perspectives on the research are presented according to each study.

Study One

All participants agree that the novel research method employed in the first study (i.e. social media based, data mining driven SNA) provides an effective approach for data collection and analysis given the lack of understanding of the DTG market. They agree that the ability to analyze a large volume of user-generated data provides useful insights into this emerging market. However, participants pointed out an important limitation associated with this approach. That is, the inability to distinguish the source of the information (i.e., whether the information is generated by vendors, manufacturers or the end users). Nevertheless, participants ultimately agree this data is adequate for the exploratory goal of the study (i.e., to identify fundamental market characteristics of DTG). Additional research that focuses on unique user perspectives in the DTG market is necessary to develop deeper insights into the competitive dynamics of this evolving market.

Study Two

In Study Two, which focused on establishing a likely user profile, the first discussion question centered on the non-linear volume of DPT Tweets from 2010-19. Participants provided several potential explanations for comparatively large volumes of DPT discussion observed in

years 2013 and 2017, respectively. One participant mentioned that we should further investigate the behavior of specific vendors, especially current industry leaders, as they hold special events such as new product or new technology launch events (e.g. HP Wide Format printer, single pass technology). Meanwhile, participants indicated that trade shows are not likely to explain the peaks in volume since trade shows occur annually. Further, one participant speculated that economic conditions such as employment rate in the printing sector may correlate to the DPT discussion volume. These suggestions provide directions for subsequent exploration into the technology's diffusion.

The second discussion question focused on the likely user profile generated based on the results of the logistic regression and decision tree analysis. One participant indicated that the positive impact of education on DPT adoption identified in this study is inconsistent with their experience. From the respondent's perspective (i.e., equipment manufacturer), DPT operations do not tend to be carried out in locations with highly educated individuals. But this participant agrees with the remaining characteristics of the profile, particularly that DPT is more likely to be adopted in locations with large youth populations. Additionally, they also suggest that inclusion of a rural/urban variable can be helpful to examine whether urbanization impacts DPT adoption. The other two participants did not dispute the current likely user profile.

Study Three

In Study Three, the first discussion question focused on the sample list validation. The participants generally agree with the current sample list. They all stated that the sample list includes the popular POD platforms which provide print services for finished fashion products such as Redbubble, Cafepress, Merch by Amazon, Printful and Printify. In terms of the primary findings associated with the four value dimensions, participants indicated that general consistency with their work experiences. One participant pointed out that the hybrid printing approach identified through the model's value creation dimension, represents a clear trend according to their company's internal research.

Another participant agreed with the identified models (i.e. end consumer service model & professional service model) but suggested that future research should consider the potential impact of cost on these model classifications. This respondent explained that in their experience, artists and designers expect higher print quality compared to end-users and thus, the product cost for businesses following a professional service model is likely higher than end consumer service

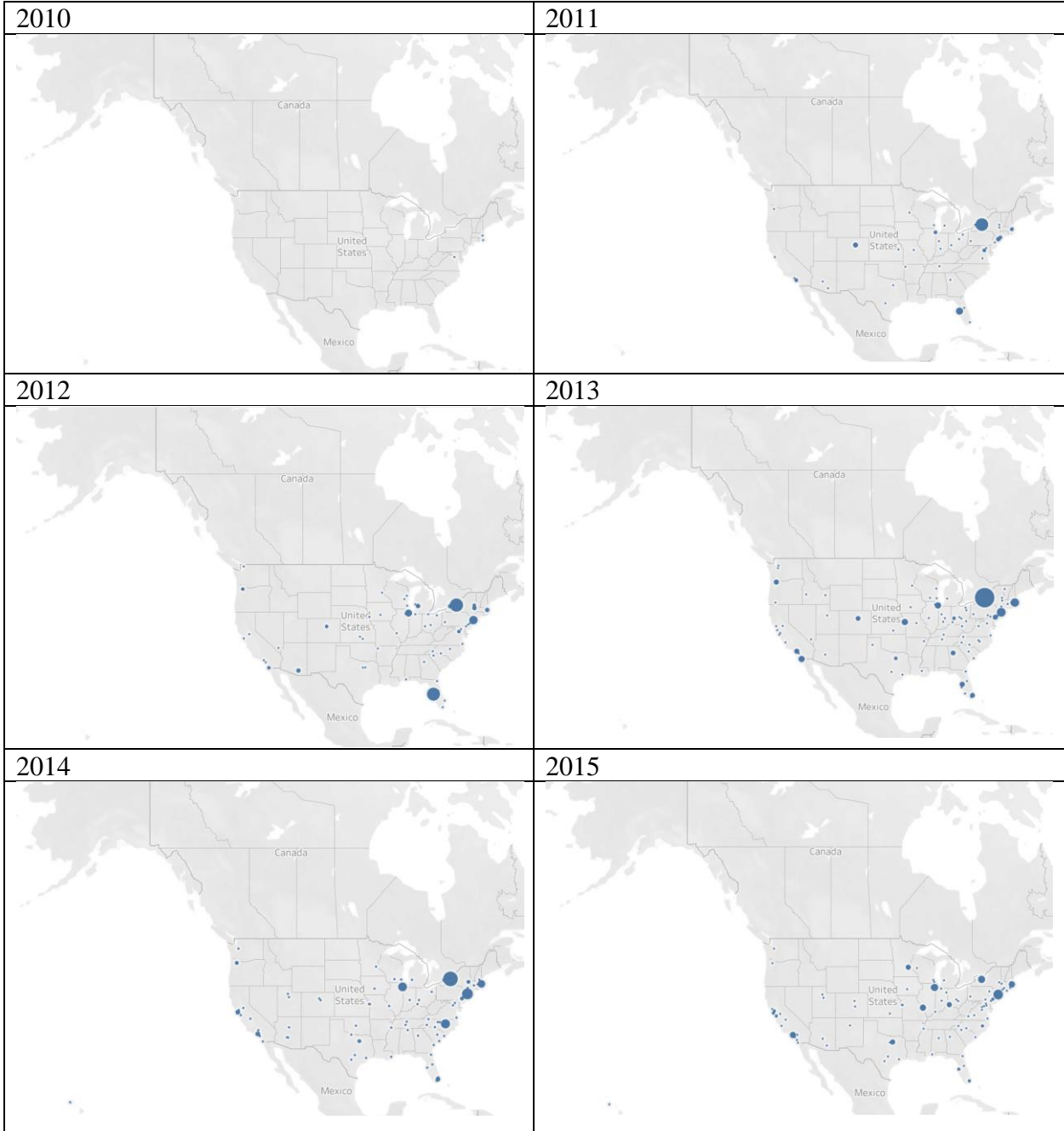
model. However, not all participants agree with her point. Another participant mentioned that the product cost for end consumers should be much higher based on a costlier distribution channel. Interestingly, participants also indicated that the two models appear to be converging in recent months. Therefore, more research on these two identified models is recommended for future researchers.

Additional directions for POD research emerged from the discussion. One participant suggested exploring the business model of on-demand companies which provide digital textile print services. Another participant suggested that future study should focus on one specific type of garment POD business model analysis (e.g. t-shirts print, swimming suits print, yoga pants print, etc.) to obtain more detailed business model information. Overall, the participants agree that as an early effort to examine POD business, the current study provides enlightening information into this opaque, under researched industry.

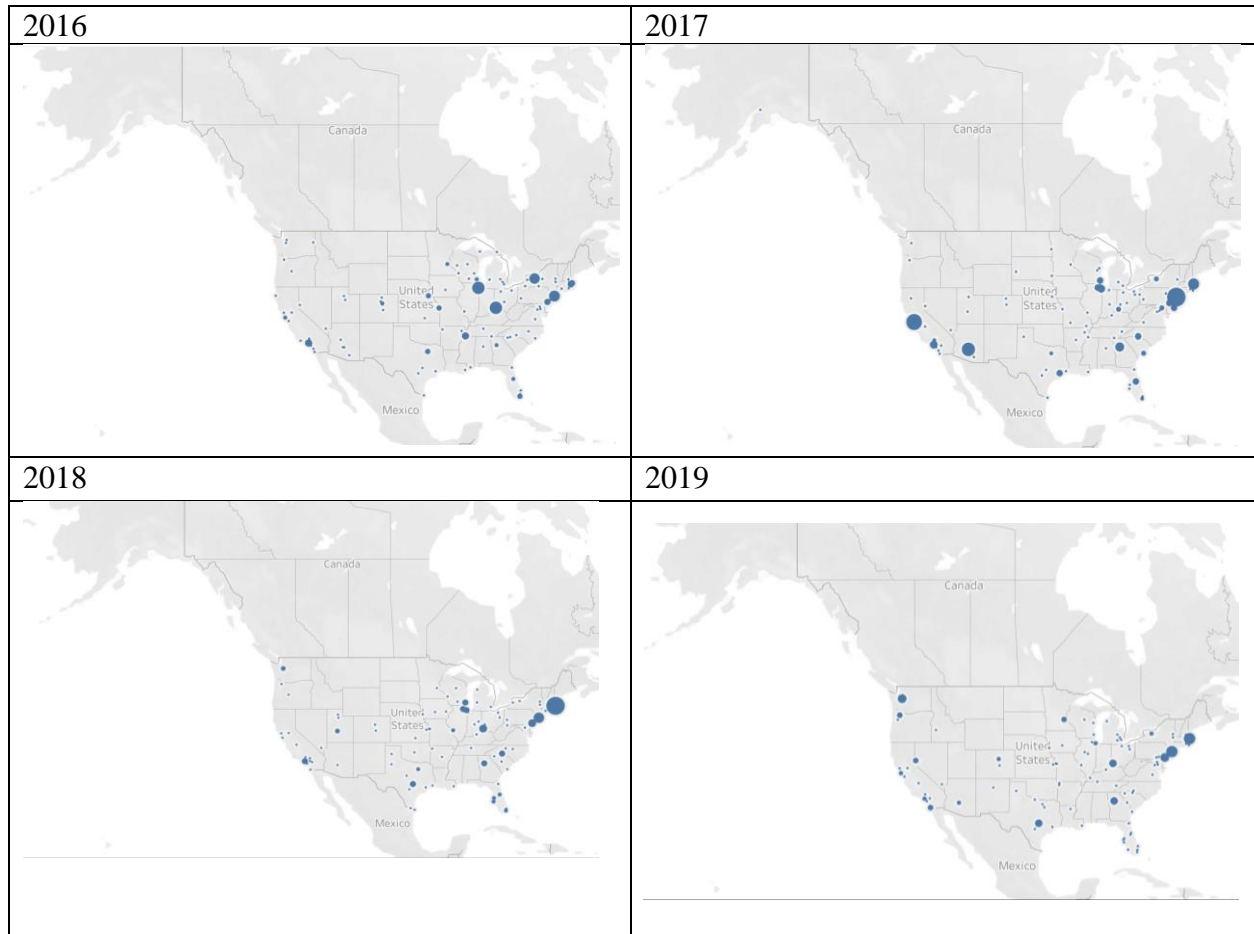
To conclude, this dissertation provides an illustrative blueprint for digital printing commerce in the fashion industry including identification of key indicators, generation of a likely user profile, and identification of feasible business models. As the participants confirmed, the digital printing business is in a complex structure with several tiers. For example, one company can take on contract work by other contractors. Simultaneously, the fragmented but large-volume small sized businesses make the context more complicated. Therefore, this dissertation presents a guideline for digital print commerce from a general perspective suggesting directions for future study that can collectively contribute to a more comprehensive framework to better inform strategy and analysis in this increasingly competitive market.

APPENDICES

Appendix 1. Geographical Distribution of DPT, 2010-2019



Appendix 1 (continued).



Appendix 2. Variables Representation for Four Value Dimensions

