International Journal of Business Analytics
Volume 9 • Issue 6

Applying Machine Learning to Study the Marketing Mix's Effectiveness in a Social Marketing Context:
Fashion Brands' Twitter Activities in the Pandemic

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ABSTRACT

This study examines the effectiveness of the marketing mix practiced on Twitter across high-end and low-end fashion brands and explores whether any four Ps activities have changed across the different pandemic stages. A quantitative research method was designed to analyze text data scraped from identified fashion brands' Twitter accounts. A classification instrument was developed to group tweets based on the four Ps marketing mix. Then the developed instrument was applied to a small set of 145 tweets randomly sampled from the collected data. Logistic regression models were then trained using the sample set to predict four Ps activities on all the collected 144k tweets. The numbers of likes per tweet and frequencies of being retweeted per tweet were used to measure engagement effectiveness across brands.

KEYWORDS

Digitalization, Four Ps, Logistic Regression, SMM, Supervised Learning, Text Mining

INTRODUCTION

The ongoing "Fourth Industrial Revolution", powered by advancing digital technologies, is reshaping the fashion industry in identifying, creating, delivering, and communicating values (Bertola & Teunissen, 2018; Nobile et al., 2021). More specifically, digital transformation, or digitalization, not only facilitates online sales for all types of fashion brands (Perry et al., 2019) but also helps fashion companies adapt operation systems by reducing costs and making each step of the value chain operate faster and cheaper with more efficiency and accuracy. For instance, digitalization allows customers to enjoy omnichannel shopping experiences and enables companies to improve customer relationships through two-way communications (González Romo et al., 2017; Siddiqui et al., 2019). Digitalization transforms fashion design and production, providing designers with tools for automation, and hence enhanced design process (K. Liu et al., 2019; Särmäkari & Vänskä, 2021). Digitalization also transforms decision-making in planning and implements production with more effective and efficient workflows (Ludbrook et al., 2019). Moreover, digitalization transforms fashion culture and society, enabling creative and sustainable solutions to the preservation of artworks (Luchev et al., 2013), fashion education (Lenoir, 2019), and virtual product consumption (Segran, 2020).

DOI: 10.4018/IJBAN.313416 *Corresponding Author

Social media platforms play an essential role in fashion digitalization. Before social media, consumers adopted trends much slower and more passively. Because of social media's wide diffusion and adoption, consumers instantly access real-time content and can actively participate in fashion creation, consumption, and communication. The broad customer participation via social media platforms and social networks brings new challenges and opportunities for fashion retailers, marketers, and suppliers (Bendoni, 2017). A company's social media marketing (SMM) activities influence its brand equities and customer engagement (Bi̇lgi̇n, 2018; Godey et al., 2016). Some commonly employed SMM strategies include storytelling, electronic word-of-mouth (eWOM), customization, and celebrity endorsement for better engaging customers. Storytelling is marketer-created content that takes customers on a journey to forge stronger connections (Bendoni, 2017). eWOM is consumer-created and spread content that tends to have higher credibility, empathy, and relevance for the target audience than marketer-created sources of information (Gruen et al., 2006). Instead of broadcasting messages, the customization strategy sends individualized messages built based on consumers' profiles, better fitting the consumer's needs and increasing consumer loyalty (Zhu & Chen, 2015). Celebrity endorsement, especially for young consumers such as millennials, creates a product's immediate identity or persona and positively affects consumer attitudes and purchase intention (McCormick, 2016). Brands with different profiles and price points may use different marketing strategies to best fit their consumers' interests.

With the growing importance of social media marketing, it is critical to develop instruments for assessing the effectiveness of different social media marketing strategies. Research has employed various methods to classify and evaluate SMM activities. For instance, Kim and Ko's (2012) conducted a quantitative study to identify attributes of SMM activities and examine the effectiveness of SMM activities from the perspective of customer perceived value. Their study found positive effects of SMM activities on customer equity, including value equity, relationship equity, and brand equity. However, their measures developed based on sampled individuals' cross-sectional subjective responses have limits on providing content-oriented marketing communication or operational suggestions. Therefore, using accessible large-scale social media data to determine how to design and disseminate content to maximize customer engagement and marketing outcomes has attracted researchers' attention. For instance, Lee et al. (2014) developed an instrument with True/False questions to evaluate message contents collected from Facebook. They employed machine learning algorithms to scale the analysis to an extensive collected data set. However, there is no further testing to assess if the developed survey instrument identifies types of content (persuasive vs. informative) effectively in other social marketing contexts such as Twitter.

The classic 4Ps marketing mix framework, which has been accepted as the dominant marketing management paradigm, identifies the principal components of marketing decisions to allocate resources for delivering value and engaging customers better than competitors (Kotler & Armstrong, 2020). Even in digital business contexts, some scholars still believe that the 4Ps paradigm can adapt to the environmental changes and continue to be adequate, relevant, and applicable to contemporary marketing strategies in social media marketing contexts (e.g., Dominici, 2009; Fan et al., 2015; Lahtinen et al., 2020). However, there is very limited empirical testing to assess the effectiveness of the 4Ps marketing mix frame in a social marketing context, especially in the fashion marketing domain. Furthermore, the global pandemic has significantly influenced the fashion industry. Consumers spend more time online than ever before, and their fashion consumption has shifted or transformed into digital. It will be critical to examine how fashion brands react to the influence of the pandemic and identify effective SMM activities.

To this end, this research intended to examine the effectiveness of fashion brand SMM activities through the lens of the 4Ps marketing mix. The authors employed text mining techniques on large-scale social media data to explore brands' resource allocation to each P and understand each P's effectiveness in engaging customers. Also, this research aimed to explore fashion brands' social media practices across high-end and low-end fashion brands before and during different pandemic stages.

The next section provides a literature review and research questions followed by the methodology. The authors then provided findings and implications for fashion brands to enhance their social marketing performance. Also, the authors intended to develop and test a text mining procedure that can be applied to more research.

LITERATURE REVIEW

While traditional marketing focuses on the utilitarian view of consumption (Bagozzi, 1975), modern marketing addresses the contextual aspects of consumption, such as the symbolic nature of consumed products and experiential aspects of consumption activities, which can be more important than the product itself (Dahl, 2018). The invention and diffusion of social media technologies have changed the way people interact and communicate, allowing contextual consumption to grow exponentially. Kaplan and Haenlein (2010, p. 61) define social media as "*a group of internet-based applications that build on the ideological and technological foundations of Web 2.0, and that allow the creation and exchange of user-generated content*". Individual users are growing exponentially, and business firms and governmental organizations are also joining social networks to use the media for advertising and marketing (Kim & Ko, 2012). To increase consumer loyalty and brand values, business organizations build and maintain relationships with brand communities of brand admirer groups and brand-unrelated tribes bounded by the shared symbolic meaning of consumption experience (Dahl, 2018). For example, González Romo et al. (2017) studied five pioneering luxury brands and found that SMM efforts significantly affected brand equity in brand awareness and image perceptions. X. Liu et al. (2021) also focused on luxury brands' SSM activities. They found that activities focusing on entertainment, interaction, and trendiness increase customer engagement, while activities focusing on customization do not. Other researchers looked at the usefulness of social media from the lens of consumer characteristics. For instance, Michaela and Orna (2015) found that fashion-conscious consumers are more likely influenced by reviews posted on social media and easily discouraged from purchasing by negative opinions. Duffett (2017) found that most teenagers have become resistant to traditional marketing but favor digital interactive advertising, particularly through mobile and social media platforms. McCormick (2016) indicated that celebrity endorsements on social media are effective marketing strategies for millennial consumers.

The global pandemic has had significant influences on the fashion industry. It disrupted consumers' fashion clothing consumption, pushing them to adapt to the changing environment and move toward online shopping. In addition, consumers have changed their clothing styles and preferences, and cultivated new habits for fashion clothing consumption (C. Liu et al., 2021). With more consumers using online media for product information search, online transactions, and post-purchase sharing, SSM has become more important than ever. A systematic understanding of SSM activities and the effectiveness of engaging customers can help brands survive through the global economic crisis, adapt to digital transition, and grasp growing opportunities. The following sections discuss ways to characterize SSM activities and measure their influence.

MEASURES OF SOCIAL MEDIA MARKETING ACTIVITIES

Companies and brands interact with target audiences and potential customers through sponsored or user-generated content in different formats, including texts, images, and videos, via various SMM platforms such as Twitter, Instagram, and YouTube. To assess the effectiveness of SMM activities, it is important to understand the features or attributes of different types of SMM activities. Kim and Ko (2012) developed an SMM activity typology from a perspective of customer equity. They identified five types of SMM activities, including entertainment, interacting, trendiness, customization, and word of mouth (WOM), based on a review of related research on luxury brands' SMM from different aspects, such as attributes of two-way communication media, influences of mobile advertising, and characteristics of mobile fashion shopping. Applying Kim and Ko's (2012) developed SMM activity typology, Yadav and Rahman (2017) proposed and validated a 15-item, five-dimensional scale for classifying and measuring attributes of SMM activities. The five identified SMM activity attributes are interactivity, informativeness, personalization, trendiness, and WOM. Ebrahim (2020) narrowed SMM activities to three dimensions: trendiness, customization, and WOM. However, the perceived SMM activities are about consumers' overall aggregated feelings about a brand's SMM activities instead of specific contents of a message. It will be more efficient to determine which attribute of an SMM activity is most effective in engaging customers. For example, Ebrahim (2020) found that WOM directly influences brand loyalty and indirectly influences brand equity mediated by brand trust. An example survey question used to gauge WOM activity was "*I would like to pass along information on the company's services from its social media to my friends*". Finding out what specific attribute associated with an SMM activity motivates consumers to share and spread through their social network is very practical for fashion brands. Hence, it is of interest to explore.

Unlike the widely discussed consumer-perceived SMM activities, Lee et al. (2014) studied the effect of SMM content on customer engagement using a large-scale field study on Facebook. They found that persuasive content, such as emotional and philanthropic content, increases customer engagement, while informative content reduces engagement. For instance, messages mentioning prices, availability, and product features are less likely to be liked or shared by viewers. The instrument that Lee et al. (2014) used to categorize the content of a message is based on 14 True/False questions with a relatively high degree of consistency in categorizing message content. In order to reduce inaccuracy caused by ambiguity in questions related to persuasive content, Lee et al. (2014) introduced a majority-voting rule to increase the accuracy of the assessing results. Their research findings and implications are more specific and straightforward for a company to implement.

MEASURES OF SOCIAL MEDIA MARKETING EFFECTIVENESS

Studies on social media can be grouped into survey-based and media-based, depending on the data sources. Survey-based studies follow traditional survey protocols with structured survey questions designed to answer research questions. For example, to measure brand loyalty, Ebrahim (2020) used survey questions, such as "*I intent to keep purchasing the services offered by this company*", "*I am loyal to this company*", and "*I consider myself to be loyal to this company*". Also measuring brand loyal, Godey et al. (2016) used questions such as "*I will suggest X brand to other consumers*", "*I would love to recommend X brand to my friends*", "*I regularly visit X brand*", "*I intend to visit X brand again*", "*I am satisfied with X brand with every visit*", and "*X brand would be my first choice*". The collected survey responses are then analyzed through exploratory and confirmatory factor analysis to validate the measurement scales and hypothetical models (Ebrahim, 2020; Godey et al., 2016; Kim & Ko, 2012; Yadav & Rahman, 2017).

Because of the sharing nature of social media content, consumers' reactions to social media activities are public and accessible as second-hand data. Leading social media platforms like Twitter, Facebook, and Instagram also provide Application Programming Interfaces (APIs) for easy data download. Consumer interactions/engagements with a brand's posts are often used to measure the effectiveness of SMM activities. For example, Lee et al. (2014) used likes and comments to measure user engagement on Facebook. Also focusing on the Facebook platform, Dhaoui (2014) expanded the engagement indicators to include the numbers of subscribers, posts, likes of a post, shares of a post, comments on a post, comments made by the community members on a comment, comments made by a brand, likes of a comment, and likes of a replay to a comment on a brand's Facebook account. X. Liu et al. (2021) examined the effectiveness of SMM activities in the context of Twitter marketing. They used the sum of retweets and likes on messages posted by a brand or by following users using "@brand" as measures for assessing customer engagement. In addition, they use the total number of customer-generated messages, which include "@brand" as the indicator of customer engagement on Twitter.

RESEARCH OBJECTIVES AND THEORETICAL FRAMEWORK

Existing research has shown that SMM significantly impacts fashion consumers' shopping and consumption. However, much research is survey-based and focuses on consumers' perceptions of brands' social media activities. Results of such studies often reveal the importance of SMM. However, these findings cannot give companies specific recommendations on what content should be created and shared through social media networks, especially for those brands at the beginning stage of implementing SMM technologies. Also, the open access to online social media data creates tremendous research opportunities. In media-data-based research, Lee et al. (2014) designed an instrument (a list of T/F questions) to analyze the contents of SMM activities through largescale data scraped from Facebook. However, answers to persuasive content questions depend heavily on the answerers, which are not objective and accurate.

The global pandemic accelerated digital transformation. However, the pandemic crisis and related challenges might also create opportunities for the fashion industry due to shifts in environments, markets, and consumers' needs and wants (Liu et al., 2021, Knowles et al., 2020). Among all the foreseeable opportunities, digital is considered the biggest for the fashion industry to grow (BoF and McKinsey & Company, 2021). Fashion's digital transformation, or digitalization, is considered a promising opportunity for fashion brands to identify, create, deliver, and communicate value with their target customers. However, there is a lack of research examining how fashion brands react to this global crisis and search for effective SMM strategies to accelerate digital transformation effectively and efficiently.

To this end, this research aims to study the contents of SMM messages and their effectiveness through collecting and mining large-scale social media data. Instead of directly borrowing Lee et al.'s (2014) content instrument, the authors indent to generate a new instrument with straightforward questions. Kotler and Armstrong's (2020) classic four Ps marketing mix theory is adopted as the theoretical framework because (1) it is the root of many other marketing theories such as the 7 Ps (Rafiq & Ahmed, 1995), (2) it looks at the marketing activity from the viewpoint of marketers, and (3) it is simple, straightforward, and works as a starting point for pilot studies.

THEORETICAL FRAMEWORK

The four Ps marketing mix, the dominant paradigm in modern marketing, is considered as a set of tactical marketing tools, including product, price, place, and promotion, that a firm employs with a customized combination to engage consumers and deliver customer value (Kotler & Armstrong, 2020). Even though the business contexts have evolved fast with the diffusion and adoption of technological innovations, scholars and practitioners still consider the marketing mix paradigm applicable in the digital business context. A group of scholars considered revisionists believe that the 4 Ps paradigm needs to be reviewed and redefined to include new elements to adapt to the changing digital business landscape (Dominici, 2009). For instance, two additional Ps, people and process, were suggested to be added to adapt to the breadth and complexity of current-day marketing (Kareh, 2018). Lawrence et al. (2003) proposed to add people and packaging to the traditional 4 Ps mix. Fan et al. (2015) developed a framework for big data analytics using the marketing mix as the theoretical foundation. Their integrated framework indicates that social networks provide data for implementing and examining the Ps of people, product, promotion, and place. Another group of scholars considered traditionalists asserts that the 4 Ps model can be adapted and continue to be the dominant marketing paradigm in new digital business contexts (c.f., Dominici, 2009). They believe that digital technologies and digital business environments improve the classical marketing mix's functionality so that the 4 Ps should be maintained as the basic instrument for marketing in digital business contexts.

The authors take the conservative viewpoint of the 4 Ps and agree that the marketing mix approach is able to adapt to the new needs in a digital business context. Specifically, the new communicative capabilities enabled by the information technologies allow the marketing mix to be adapted to meet new needs, including the introduction of co-design with customers to product, the higher levels of transparency to price, the new ways to reach customers to place, and interactive capabilities to promotion (Peattie & Peters, 1997). Meanwhile, this research also integrates the revisionists' viewpoint to redefine the 4 Ps in the social media marketing context. Specifically, this research developed instrument questions that help determine if the content of an SMM activity falls in the scoop of each of the 4Ps (see Table 1). The instrument questions were developed for text data based on the reviews of sample messages. If the answer to an instrument question is yes, then the message is labeled as true to the P associated with the question. For example, suppose the answer to the question "*Does the text of a message contain a product/service's price information, sales, or discount information?*" is yes, the message is classified into price since it contains price-related content.

Table 1. The 4 Ps Marketing Mix Definitions and SMM Implementations

Category	Operational Definition (Dominici, 2009; Kareh, 2018)	Instrument Questions
Product	All the benefits before, during, and after a product or service transaction that users obtain and experience.	Does the text of a message contain information on a product's design (for example, colors, materials, motifs, and category), quality, variety, and features (for example, wrinkle-free)?
Price	The amount of money, time, and effort customers must pay to obtain the products, including regular retail prices, sales, and discounts.	Does the text of a message contain a product/service's price information, sales, or discount information?
Place	Everything that is done and necessary to smooth the process for a customer to complete the process of exchange.	Does the text of a message contain information about any selling channels, such as locations of physical stores or links to online selling pages?
Promotion	All the information and activities that communicate the merits of the products and persuade target consumers to buy	Does the text of a message link the product/brand to celebrities, events (for example, holidays), sponsorship, or collaborations?

RESEARCH QUESTIONS

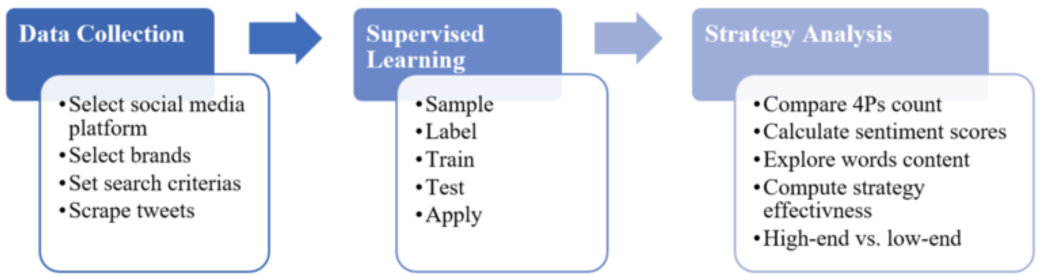
Based on the review of the relevant literature and discussion, the current research intents to address the following research questions:

1. How have fashion brands practiced the four Ps marking activities on their Twitter accounts?
2. Do SMM activities vary from time to time, especially before and during the pandemic?
3. How effective were the four Ps marketing activities in engaging consumers through Twitter?
4. Do SMM activities and their effectivenesses vary between high-end and low-end brands?

METHODOLOGY

Figure 1 plots the workflow of the methodology, which is arranged into three phases, namely data collection, supervised learning, and strategy analysis. Further explanation is given in the following sections.

Figure 1. Flowchart

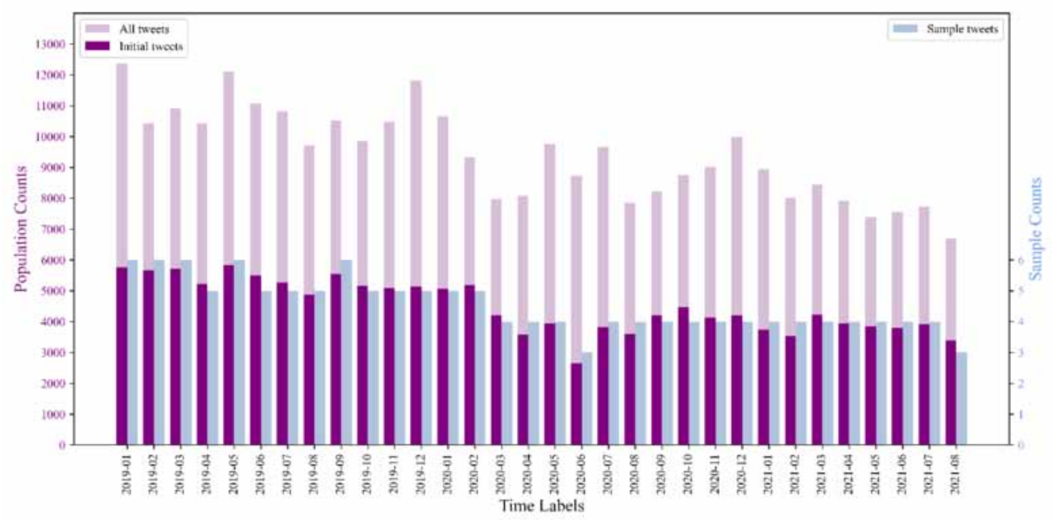


DATA COLLECTION

Twitter was selected as the social media platform to collect data for the empirical study. The reason is three-fold: (1) Twitter is one of the major social media platforms; (2) the majority of fashion brands have Twitter accounts and are constantly updating their posts and responses; and (3) while images and videos are the primary contents of Instagram, tweets captured from Twitter are more of elevator-pitch like text messages, which makes it possible to analyze with text mining techniques. Even though fashion brands tend to share images along with their text messages on Twitter because of the visual nature of fashion, this research only focused on SMM strategies through the text contents because the machine learning technique for image analysis is different from text mining techniques.

In order to capture representative data, the authors first identified the top 200 fashion accounts on Twitter based on the number of worldwide subscribers. However, some of the top 200 fashion accounts were fashion influencers instead of fashion brands. Since the authors intended to study fashion brands' SMM strategies, fashion influencer accounts were removed from the list, reducing the number of accounts from 200 to 193. For the remaining accounts, the authors scraped English tweets posted from January 1, 2019, to August 31, 2021, using python scripts. This period was selected so that the collected dataset covered one year before the pandemic and various stages during the pandemic to explore how the pandemic significantly influenced SMM implementation across fashion brands. A total of 301,239 tweets were collected. Some tweets were initiated by the fashion brands, and some were responses. The authors further filtered the tweets to only focus on the initial tweets posted by fashion brands in order to fully focus on SMM activities planned and implemented by the fashion brands. The filtration ended with 144,227 initial tweets, 46.88% of the total collected tweets. Figure 2 shows the distribution of monthly total (in light purple) and initial (in dark purple) tweet counts.

Figure 2. Population and Sample Tweet Counts by Month



SUPERVISED LEARNING

The authors first randomly sampled 145 tweets from the collected 144,227 initial tweets following the same distribution pattern (see Figure 2 in light blue) for labeling and model training purposes. Each of the 145 tweets in the training sample was reviewed and labeled following the four Ps coding method (see Table 1). A tweet may be assigned to multiple Ps based on its content. For example, "*New Balance x Junya Watanabe Man M1500 - Black / Grey* https://t.co/C4lnbpbepZ https://t.co/3AiGGL5Jbb" was labeled as product, promotion, and place marketing activities. More specifically, "*Black / Grey*" is the product information describing the color options, "*New Balance x Junya Watanabe*" is the promotion information indicating collaboration with celebrities, and the first HTML link is the place information directing readers to the online selling website.

The labeled tweets were then used to train and test Logistic Regression classification models for each type of marketing activity. Within the 145 samples, 87 (60%) tweets were randomly selected as the training set, while the remaining 58 (40%) tweets were used as the testing set to check the performance of the generated models. The Logistic Regression classifier was selected because it performs well on training data sets with small sample sizes. When training models for each marketing activity, the labeling outcomes of the SMM activity were input as Y (the dependent variable), and the vectors of the tweet' texts along with two computed features were input as Xs (independent variables). The texts of each tweet were transformed into a 200-dimension vector based on a word vector library pre-trained from 2 billion tweets (Pennington et al., 2014). When observing the sample data, the authors noticed that the numbers of HTTP links and price tags were closely associated with the price and place marketing activities. Therefore, the authors computed two additional variables to document the count of HTTP links and price tags within a tweet and added them as independent variables. Consequently, the dimension of Xs changed to 202. The generated Logistic Regression classification models' accuracies were 0.776 for product activity, 0.966 for price activity, 0.672 for place activity, and 0.793 for promotion, respectively.

The generated models were applied to predict SMM types for the rest of the tweets since it was impractical to read and manually label all 144k initial tweets. Table 2 shows tweet examples for each marketing type labeled manually and predicted by the generated classification models. Table 3 lists the initial tweet counts for each marketing activity.

Table 2. Tweet Examples Labeled by 4P Marketing Activities

Marketing Activity	Researcher Labeled Examples	Computer Labeled Examples
Product	*"**High contrast: Sweetly stitched broderie in bold hues brings an unexpected edge** to the Mini Seaton.* Explore the latest arrivals: https://t.co/E2MYaVYIRV https://t.co/pPyuVmGUKP"	*"**An oversized trench coat with kimono sleeves in beige polyfaille, worn with the Worker boot**.* Pre-order the collection: https://t.co/gzcP59GmCs #McQueenFirstLight https://t.co/yGrRkHJQjP"
Price	*"Fresh-looking denim and comfy tees are modern day essentials! #HM Ladies' tees from **PHP 299*** https://t.co/pjHFoE6fZH*"*	*"JANUARY SPECIAL: Get the Drought at only **R899.99**. Size 5-9. Shop:* https://t.co/5zsd0PXBM3.#QuitQuitting https://t.co/56JSaPIZc3*"*
Place	*"Discover our special pop-up Tabi space celebrating the iconic shoes at in the **Dover Street Market shop's outposts of NY, LA and London.** The spaces will run from Jan 11-Feb 6 in NY, Jan 12-30 in LA and Jan 12-Feb 14 in London. #MaisonMargiela #Tabi* https://t.co/1ti2zabM5E*"*	*"The Bond large tote bag in jacquard canvas with petrol blue and white #Givenchy Chaîne motif designed by #ClareWaightKeller, available **in-store and online** in selected countries.* https://t.co/Y8qp71bexU *[online link]* https://t.co/MCz8N6hqY1*"*
Promotion	*"We **partnered with stuntman Riley Harper** to showcase some of our newest Men's arrivals! Year round must haves in-store and online:* https://t.co/OLMuHXxG1V#HMMan https://t.co/pAI5ysGi8u*"*	*"After her pre-party performance, @**QueensChristine attended the @Guggenheim International Gala dinner** wearing an Haute Couture dress by Maria Grazia Chiuri. Take a glimpse of the #DiorSavoirFaire behind the design and go* https://t.co/Der3fSjFLe *for more # GIG2019's highlights.* https://t.co/InEqmRApDg*"*

STRATEGY ANALYSIS

The tweet counts distribution was used to answer the first research question. Sentiment scores evaluating the positive and negative tone of the text were calculated for each tweet using the TextBlob API (Loria, 2013/2022). The sentiment scores fall within the range of -1 to 1, with positive numbers indicating positive tones of the texts, negative numbers indicating negative tones, and 0s indicating neutral tones. A larger absolute value indicates a stronger tone. An averaged sentiment score was calculated for tweets labeled with each Ps. In addition, word co-occurrence plots (Figure 3) were generated to help understand the contents of each Ps. The word-co-occurrence plots documented the word frequency and two words' coherence. A larger font size of a word indicates a higher ratio of tweets containing the word, and a bolder and darker edge connecting two words indicates a higher frequency of the two words used in the same tweet. To examine the influence of the pandemic on marketing activities on fashion brands, the authors plotted monthly tweets count across the four marketing activities as shown in Figure 4 (product in light orange, price in orange, place in light blue, and promotion in blue). The authors then overlaid the plot with monthly worldwide covid-19 case numbers (Hasell et al., 2020) (in grey areas) to help observe the influence of the pandemic and provide responses to the second research question.

Figure 3. Word Co-Occurrence Plots for Each P

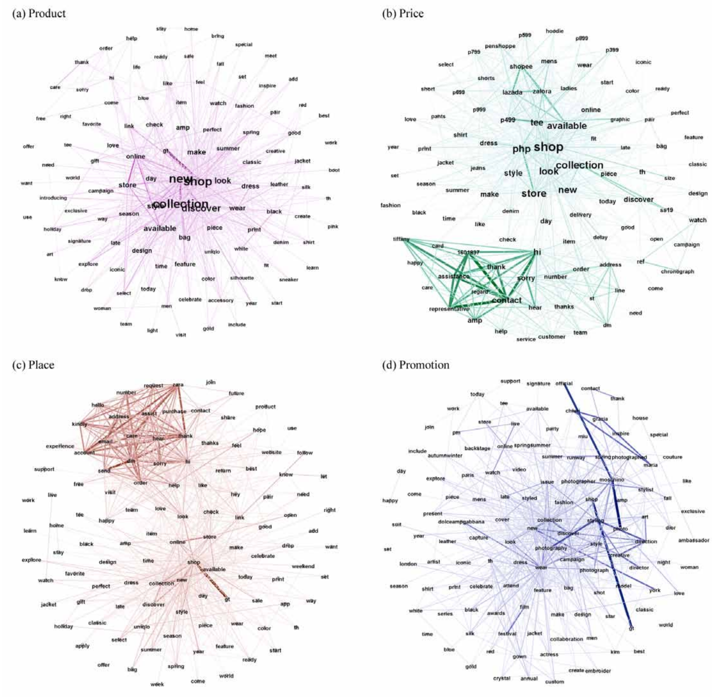
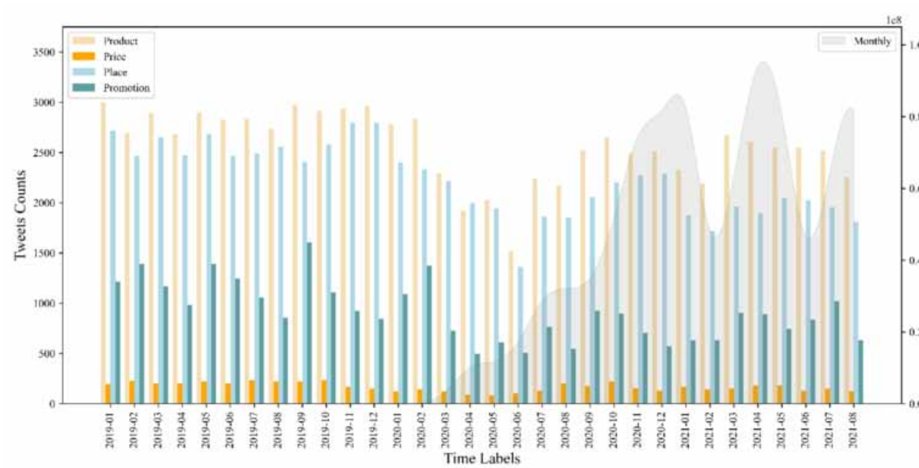


Figure 4. Monthly Four Ps Marketing Activity Counts and Worldwide Coivd-19 Cases



Since each tweet was classified into the four Ps marketing activities, the authors were able to examine the effectiveness of each of the 4 Ps activities using the measures of customer engagement as outcome indicators, which include counts of likes and retweets per tweet. A marketing activity type with higher numbers of likes or retweets was considered more effective. The effectiveness was then compared across different Ps subsets and the complete initial tweet set. Analysis results are shown in Table 3. These results provide evidence to answer the third research.

The authors then moved to examine if high-end and low-end fashion brands applied marketing strategies differently on social media. From the 193 Fashion brands' Twitter accounts, This research selected the top ten accounts for each brand category based on the number of subscribers. The authors classified a brand into high-end or low-end based on the price points of product categories such as tops, bottoms, and dresses. In this study, brands classified as high-end brands included haute couture and designer brands, with a price point of $1,000 or higher for a normal clothing piece. In comparison, low-end brands are mass market and moderate brands, with a price point of $300 or lower. Specialty brands, such as Victoria's Secret, were not considered for this research because it has no consistent reference point to compare price ranges between different product categories. Because the text mining algorithms used in this research were designed for English, Twitter accounts not using English as the communication language were filtered out. For example, even though @UNIQLO_JP ranked high based on its number of subscribers, it was not included in the low-end brand list because Japanese was used in most of its posts. The selected ten high-end fashion brands were Chanel (@CHANEL), Dior (@Dior), Burberry (@Burberry), Louis Vuitton (@LouisVuitton), Gucci (@gucci), Dolce & Gabbana (@dolcegabbana), Versace (@Versace), Saint Laurent (@YSL), Armani (@armani), and Valentino (@MaisonValentino). The selected ten low-end fashion brands were H&M (@hm), Adidas Originals (@adidasoriginals), Forever 21 (@Forever21), Tommy Hilfiger (@TommyHilfiger), ZARA (@ZARA), Vans (@VANS_66), Sidemen Clothing (@SidemenClothing), PENSHOPPE (@ PENSHOPPE), Ain't Flexin', just Texan (@TexasHumor), and Levi's (@LEVIS). Brands are listed following the orders of subscriber numbers from high to low when the data was collected.

The authors calculated the combined initial tweet counts, average likes per tweet (labeled as likes/tweet), and average retweets per tweet (labeled as retweets/tweet) for each brand group (high-end vs. low-end groups). The authors also calculated the same parameters for each Ps within the high-end and low-end groups. The likes/tweet and retweets/tweet helped the authors identify effective marketing strategies. The tweet counts for each of the four Ps subgroups allow this research to identify the similarities or dissimilarities in SMM implementation across high-end and low-end brands. The likes/tweet and retweets/tweet for each of the four Ps subgroups allow the authors to identify which type of SMM activity works better for high-end or low-end brands. Table 3 shows all the generated results providing evidence to answer the fourth research question.

Table 3. Evaluation of Four Ps Marketing Activity and Effectiveness

Accounts	Measures	Overall	Divided by Marketing Activity Type			
			Product	*Price*	*Place*	*Promotion*
All Accounts	Initial Tweet Count	144,227	81,995	5,403	71,158	29,316
	Tweet Frequency	100%	56.85%	3.75%	49.34%	20.33%
	Likes/Tweet	350	269	383	237	738
	Retweets/Tweet	84	58	95	54	201
Selected High-End Brands	Initial Tweet Count	17,027	12,126	546	4,799	7,564
	Tweet Frequency	100%	71.22%	3.21%	28.18%	44.42%
	Likes/Tweet	1,419	929	803	1163	1,996
	Retweets/Tweet	358	195	149	284	548
Selected Low-End Brands	Initial Tweet Count	13,139	6,444	1,496	7,602	1,348
	Tweet Frequency	100%	49.04%	11.39%	57.86%	10.26%
	Likes/Tweet	509	429	582	494	785
	Retweets/Tweet	114	91	203	106	247

FINDINGS AND DISCUSSION

RESEARCH QUESTION 1: PRODUCT, PRICE, PLACE, AND PROMOTION

Fashion Twitter accounts spent half of their efforts posting initial messages and the other half responding to consumers' posts. The initial posts contained various marketing content and proactive activities to engage current and new customers. In contrast, the response posts were mostly reactive activities to maintain relationships with existing customers and solve customers' problems and concerns. Fashion brands allocate resources to implementing marketing mix across the four Ps differently when planning content for initial posts. The sentiment scores of initial posts for all Ps are positive, with 0.201 for product strategy, 0.180 for price strategy, 0.193 for place strategy, and 0.171 for promotion strategy. The results are consistent with our expectations since companies want to establish good images of their brands through social media marketing. They tended to add more positive tones when practicing product strategies than implementing promotion strategies.

Quantity-wise, content about the product accounted for half of the initial posts. This type of content mainly focuses on introducing new looks, collections, styles, seasons, and product design features such as prints, colors, and silhouettes, as indicated in Figure 3-product. Place information, such as the location of a physical store, a link to online shopping sites, or both, was often combined with the product information. Adding online shopping links in tweets provides convenience to customers and helps a fashion brand convert marketing activities to direct revenues. Promotion activities, including collaborations with designers, and celebrity endorsements such as attending events wearing the brand's products (Figure 3-promotion), were seen in around 20% of the initial tweets. Such promotion activity helps engage new consumers. Unlike the high coherence between product and place information, an online selling link was usually not included when mentioning a celebrity. Price information, including a product's list price and discount percentage (such as "php", "p499", and "p999" in Figure 3-price), was only shown in less than four percent of all initial tweets, indicating that brands might not favor posting their products' prices directly.

RESEARCH QUESTION 2: BEFORE AND DURING THE PANDEMIC

The fashion brands' Twitter SMM activities show seasonal patterns, with overall tweet counts peaking in May (spring season) and December (fall season) when new styles are launched for a new season, such as summer/vacation season or winter/ holiday season. Figure 2 shows that the social media activities were very active in February and September because of the big four fashion weeks. On January 30, 2020, The World Health Organization (WHO) declared the novel coronavirus outbreak, a public health emergency of international concern (PHEIC), with its highest alarm level. On March 11, 2020, WHO declares COVID-19 a pandemic (WHO, 2021). The pandemic hit the global fashion business hard. Due to country lockdowns, pent-up demands, and budget cuts, fashion brands' SMM activities decreased sharply between February 2020 and June 2020. Starting from July 2020, the fashion brands' Twitter activities slowly grew back. However, as of August 2021, it still had not reached the pre-pandemic level.

The four Ps marketing activities distribution chart shows the negative influence of the pandemic. Specifically, the product, price, and place activities declined immediately with the hit of the pandemic. However, the pandemic's impact on the promotion activities was delayed until April, indicating that fashion brands prioritized resources to maintain long-term brand image and loyalty when coping with disasters. During the pandemic, the worldwide cases showed three waves of surging periods during the time period of our data collection. The first wave had the most significant influence and disrupted the fashion seasons the most. The seasonal activity, which always peaks in February, did not happen in 2021. Also, all the fashion shows were canceled. There was a delay, usually 1~2 months, between the peak of the Covid cases and the valley of SMM activities associated with the case peak. The second wave of case surging disrupted the spring season, which peaked in May in the pre-pandemic stage. Overall, the negative influence of the fluctuating worldwide case numbers on brands' social media activities decreases across all the pandemic stages.

RESEARCH QUESTION 3: EFFECTIVENESS OF THE FOUR PS

Among the four Ps, promotion-oriented SMM activities are most effective, with an average of 738 likes per tweet and 201 retweets per tweet. Most promotional tweets mentioned celebrities and helped the brand convert fans of the celebrities to the brand's customers. The second effective SMM activities are price-oriented, which is consistent with price in the traditional marketing context. Namely, low price and discount strategies effectively engage customers in both digital and traditional business contexts. While accounting for more than half of the total initial tweets, product and place information was the least effective in engaging consumers. This could be because the overwhelmed digital information has turned consumers numb to information that does not have an emotional connection. Therefore, fashion brands should focus on generating content with customized messages to tailor to customers' preferences and trigger their emotional responses. Overall, to engage more audiences, fashion brands should increase their promotion activities and decrease the number of posts that simply provide product descriptions and online selling links. Discounts and low prices might gain the audience's attention. However, when deciding how much SMM activities are allocated to price, a fashion brand should consider the brand's positioning, strategically balancing purpose and profit.

RESEARCH QUESTION 4: HIGH-END BRANDS VS. LOW-END BRANDS

High-end and low-end brands practiced the 4 Ps marketing mix on Twitter differently. More than 70% of high-end brands' tweets included product information, while the number was less than 50% for low-end brands. High-end brands' effort in promotion activities was four times higher than low-end brands. In contrast, almost 12% of initial tweets posted by low-end brands contained price information, almost four times the number for high-end brands. The low-end brands also put twice as much effort into place-oriented SMM as high-end brands do.

Regarding the effectiveness of the four P marketing mix in the Twitter marketing context, the overall likes per tweet for high-end brands were almost three times more than those for low-end brands. The promotion activities were the most effective way for both high-end and low-end brands. The second effective P was place for high-end brands but was price for low-end brands. Price marketing activity performed well for low-end brands because the low-price strategy often attracts their targeted price-conscious customers and motivates more consumption. However, price is the least effective P for high-end brands. Price information was more of interest to low-end target consumers. Overall, the positioning of high-end fashion brands requires more resources spent on SMM to stay active to acquire enough publicity, maintain customer loyalty, and attract new consumers. However, low-end fashion brands may use social media platforms as a tool to create direct selling, especially during holidays or special seasons. This research recommends that high-end brands save some of the resources from product-oriented SMM and put more resources on place-oriented SMM activities such as offline events based on our research findings. For low-end brands, the authors recommend an increase in promotion activities.

CONCLUSION

This research analyzed fashion brands' SMM activities on Twitter across different pandemic stages. Tweets posted by the top fashion accounts with the largest numbers of worldwide subscribers were collected from January 1, 2019, through August 31, 2021. An SMM classification instrument was developed applying the four Ps (product, price, place, and promotion) marketing mix framework to classify SMM contents. Manual labels were assigned to 145 randomly selected from the collected tweets to train logistic regression models that were then applied to predict labeling outcomes for the remaining 144k tweets. These SMM activity labeling outcomes and measures of effectiveness (likes/tweet and retweet/tweet) were used to analyze the overall performance of brands' SMM activities and examine the difference across high-end and low-end brands. Analysis results and findings responded to the raised four research questions. Overall, the findings support the argument that the 4Ps marketing mix paradigm is able to adapt to environmental changes and continues to be adequate, relevant, and applicable to contemporary marketing strategies in social media marketing contexts. However, different fashion brands need to customize their SMM activities with resources distributed across 4Ps differently to maximize outcomes in terms of engaging current customers and attracting new customers. Specifically, fashion brands might want to put the most effort into creating and posting products and place-oriented content. Considering brand positioning, high-end brands should allocate more resources to promotion-oriented SMM activities, while low-end brands should focus more on price-oriented SMM activities. Furthermore, the pandemic significantly disrupted fashion brands' SMM activities, but the salience of influence decreased as time went on. Also, the newly developed classification instrument and data analysis pipeline were tested to be effective and feasible. It can be applied in more SMM-related research using social media data. This research highlighted the importance of SMM and provided practical suggestions for companies who want to invest in or reposition SMM strategies, helping them become competitive in the post-pandemic fashion industry.

LIMITATION

One limitation of this research is the small size of the training data set used to generate the trained model, which constricted the logistic regression model's accuracy. In future research, the authors should increase the training data set size and recruit more domain experts to code and label the training data set to increase the models' accuracy and internal validity. Also, this research only studied the Twitter platform, which may not be the first choice among all social media platforms for some fashion brands. Therefore, studying other social media platforms with similar data analysis steps is also important. To make the results more generalizable, tweets from more brands' could be captured and analyzed in the future. Another limitation is related to the data format. In this research, the authors only focused on text data. Future research should put effort into analyzing non-text data such as image or video data.

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