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SOCIAL MEDIA SENTIMENT ANALYSIS: THE CASE OF DIGITAL LUXURY FASHION SHOWS

by
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ABSTRACT
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Luxury brands have often been hesitant to embrace social media to a full extent, however, the COVID-19 pandemic prompted many to adopt digital strategies. Designers and their teams reinvented fashion show presentations and, for the first time, virtually streamed their collection, in different themes. So far, there has been no analysis of people's perception on these digital shows.

This study aims to provide a general understanding of these virtual strategies, to perform sentiment analysis on the user-generated comments from social media channels and then suggest digital social media strategies for the different fashion show themes.

This research fills an arising gap in the literature regarding digital marketing strategies and luxury brands.

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To Michel, Fadia, Mona, Youssef & Rebecca

CHAPTER 1

INTRODUCTION

Luxury fashion brands have always resorted to fashion shows in order to showcase their products in a way that would generate an experience for their customers and mainly create bonds with their audience and potential consumers. This bond is intended to create a relationship between the fashion brands and the consumers as it becomes an important aspect of the essence of luxury fashion shows. Luxury brands set their runways with criteria to showcase their products, manifested in a pattern of messaging that reveals emotions, heritage, craftsmanship and uniqueness. This messaging generally requires live interaction with the audience to promote an interactive experience. This is why luxury fashion brands were initially reluctant in the past to transition to a digital showcasing approach for the fear of losing this direct human connection. That is the essential factor of the pathway towards building an establishment that takes the audience into consideration by transforming observers into consumers. However, the COVID-19 pandemic forced the hand of luxury brands to change their approach out of necessity and a worldwide natural shock. According to Tikanoja (2021), prior to the pandemic, there was a desire to build a more responsible future for the sector, but the outbreak hastened the eventual technological transition. This manifested a turning point for luxury brands, as they were obliged to resort to a full transition of their fashion shows, moving from a full live and interactive fashion show, to adopting digital strategies in order to showcase their collections. Therefore, luxury fashion brands find themselves with the conundrum of having to replicate this bond they highly value with their consumers in a digital setting. It is no longer a question of whether or not to incorporate internet technology into one's business plan; rather, it is a matter of how to do so most effectively (Porter, 2001).

Luxury brand managers can no longer truly control consumer perceptions (Granot et al., 2013). For example, Heine and Berghaus (2014) explain how the digital world is already discussing their brand – with or without their participation. As a result, they recommend that luxury brands' social media campaigns focus on maximizing favorable consumer-to-consumer communication and coverage across digital channels. To achieve this, luxury brands have to adopt certain digital marketing strategies that dictate how their collections are showcased, and through which channel this showcasing must be transmitted to their viewers and potential consumers.

This paper is the first examination of consumer sentiment towards digital fashion shows to date. The literature related to digital strategies based on the sentiment analysis conveyed towards luxury fashion shows is still underdeveloped, extremely scarce and needs further extensive research. Thus, this study fills a considerable gap in the literature regarding digital marketing strategies to be adapted per channel for luxury fashion runways.

Therefore, the aim of this study is to assess the sentiments conveyed by audiences towards the digital luxury runways and propose a digital strategy to be adopted while the luxury brands showcase their collections. This study will also propose an efficient digital marketing approach to be implanted across different touchpoints. In other words, the main aim of this research is to evaluate the audience's reactions towards different themes of fashion shows presented using each of the following media platforms: YouTube, Instagram and Facebook. Consequently, the analysis of the audience's reactions to the digital fashion shows on each platform is used to derive a virtual show strategy for luxury brands to follow over the mentioned channels. The coordination of this investigation decision-making and the customer-centric perspective will expand the current scope of the digital marketing strategy related to digital luxury runways.

CHAPTER 2

LITERATURE REVIEW

2.1. Evolution of Luxury Fashion Shows

The arrival of fashion ushered in a modern era in which a need for innovation, coupled with rapid shifts in taste toppled a long history of well-established dressing habits and the value placed on clothing. Fashion historians attribute the origins of fashion shows to the English designer, Charles Frederick Worth who, in the mid-1860s, revolutionized the relationship between the client and the dressmaker, whereby designs were introduced to the clients via a “defilé”, as opposed to the dressmaker going to the client. The introduction of the designs was straightforward and traditional without any music. The lack of theatricals and music indicated the strict purpose of the “defile”, which was mainly to sell the clients. However, in 1901, the fashion scene changed as another English designer, Lady Duff Gordan, introduced the first fashion show. She displayed her “Gowns of Emotions” through models that walked down the stage in a choreographed manner, embellished with theatrical innovations such as lighting, music and scenery (Klerk, 2021). This was indicative that it was not just about displaying the dresses, but rather focusing on creating an experience, one that reflected the values and emotions behind the garments. This, then introduced the principles of presenting fashion to a wider audience of the same social class upon invitation, which reflected the exclusivity of those fashion shows. Thus, in this format, we witnessed how the stage signified a barrier between the spectator and the models along with the seating allotment of the audience.

As fashion became more accessible and normalized to individuals of all income levels, designers exhibited their designs in department stores, whereby there was a plethora of space available. These parades deemed necessary to reinforce and publicize the designer's trends. Fashion historians categorize this period as the tipping point for modern fashion as they gained popularity, but all was built on the foundations set by the designers of the 19th century. Nevertheless, the location of the fashion show was not regarded with importance until the 1960s, when designers became more imaginative with the location and environment to further polish a client's experience. When Balmain, in 1965, introduced the collection in a wine cellar and Paco Rabanne in a Crazy Horse Saloon, this insinuated the agility of the theatrical fashion show to adapt to the location at hand. Therefore, as the times progressed, designers became interested in the theatricals of the fashion shows in attempts to further develop the customer experience.

Before the introduction of social media, the designers and fashion houses decided upon what should be shared to the public, thus reinforcing the exclusivity aspect of fashion shows. The spectators of this visual phenomenon were only those who were invited, while everyone else, not a part of this elite society, was excluded. However, since globalization accelerated the interrelation of the world and of different cultures, designers were now able to use social media to further expand their visibility and reach a wider audience. As a result, fashion shows are now considered an international experience. This emergence of social media did not change the mere purpose of fashion shows; however, it did contribute to the evolution of the theatricals and visual presentations in order to suit the changing world. Fashion shows have always been intended to be a way to sell an experience to customers, but this man-made experience is still required to be of economic value. Consequently, the guests invited are those who have a significant number of followers on social media to share their fashion show experience; therefore, exposing fashion shows to the vast public. The exclusivity of fashion shows remains, as invitations are limited, but the visual experience is translated online.

It is evident that the pandemic of the Covid-19 virus forced designers and fashion houses to rethink the way fashion shows have been delivered in the past decade, as social distancing has become the new norm. The occupation of space within the physical location has to adapt to this new custom, but this is no longer sufficient to support the size of the audience. Tikanoja (2021) argues that originally there was a desire to build a more responsible future for the sector prior to the pandemic, but the outbreak of the pandemic hastened the eventual technological transition.

The incorporation of technologies in the fashion field had a huge impact on its market during the corona virus outbreak. In fact, during the confinement, fashion lovers were easily able to instantly watch on social media platforms, the opening of the 2020 spring fashion season without putting themselves at risk of exposure to the virus. Brands that adopted the new normal were rewarded with a considerable amount of money and are now considered one step ahead of the other competitors. This breaks down the geographical barrier that pre-pandemic fashion shows had on spectators who could not attend, but since the customer experience and theatricals were now translated virtually, whereby the audience can be fully immersed in the show at the comfort of their own homes. This newly found virtual innovation in the fashion field leaves room for many questions to be answered regarding future ideas on how to build on this evolving customer experience.

2.2. Viewers/Consumers Emotions Vis-à-Vis Fashion Shows

In order to achieve competitiveness, fashion retailers focused on employing emotional branding in order to connect with their customers, due to the increasing need for the customer to forge an emotional connection with the brands. Emotional branding establishes itself as a crucial factor, at the base of the process of cultivating brand loyalty, which is described as a long-term, dedicated, and influencing relationship used to highlight consumer-brand bonds (Fournier, 1998).

With the evolution of social media and complementing technologies, fashion shows have advanced in an exponential way. As a result, Denegri-Knott and Molesworth (2010) argue that digital virtual consumption can be perceived as a kind of product realization of the virtual nature, but where users are less limited by the constraints and laws of physical tangible consumption (Jung, et al., 2021). In addition, those shows are buildt on the satisfaction of consumers, as Lee and Leonas (2018) shed light that when the value of enjoyment and emotion is recognized, the shopping experience emerges as a critical topic in the retail sector. The results of Atwal and Williams (2017) show that they need to move away from the features-and-benefits model promoted by conventional approaches, to customer interactions in a modern era, with new customers.

Traditional fashion shows provided a limited connection with customers as they were restricted to the view from their own seats. This prohibited the full integration of the customer into the entire experience. With virtual fashion shows, the emotional connection with the brand is amplified, as customers have the opportunity to feel thoroughly immersed in the entire journey.

2.3. Luxury Brands: Dior, Chanel, Louis Vuitton, Hermès, Valentino

Some of the most well-known luxury fashion brands to discuss are Dior, Chanel, Louis Vuitton, Gucci, Hermès, and Valentino. Dior is a French brand whose target audience is known as "Chardonnay Girls" who are young students and professionals characterized as being open, energetic, sharing cultures, having good looks, and high career aspirations (Darbinyan, 2020). Dior's audience is spread across social media platforms with 35.9M followers on Instagram (Dior, 2021), 17.6M likers on Facebook (Dior, 2021), and 1.05M subscribers on YouTube (Christian Dior, 2021). Another French luxury brand is Chanel, which usually targets young independent women of the upper class. These women are mainly between 30 and 35 years and are nick-named "Balancers" (Darbinyan, 2020). Balancers are intellectual, optimistic and ambitious people who try to always balance work and personal life (Darbinyan, 2020). Chanel has 44.3M followers on Instagram (Chanel, 2021), 23M likers on Facebook (Chanel, 2021), and 1.82M subscribers on YouTube (Chanel, 2021). Furthermore, the French Louis Vuitton brand targets women aged between 30 and 50 years with high annual incomes and are known as "Actualizers" (Darbinyan, 2019). Actualizers are prestigious trendsetters and important clients who are given access to purchase exclusive collections from seasonal catalogues. They tend to buy for quality rather than necessity and are family oriented (Darbinyan, 2019). Louis Vuitton's market on social media is distributed as 44.2M on Instagram (Louis Vuitton, 2021), 24M likers on Facebook (Louis Vuitton, 2021), and 555K subscribers on YouTube (Louis Vuitton, 2021). The famous Italian luxury brand, Gucci, focuses on extravagant women between the ages of 18 and 30 years known as "Hedonists" (Darbinyan, 2019). Hedonists are people who like to have fun and enjoy every moment in life by partying and going out. They are considered impulsive and tend to purchase items based on their labels in order to stand out (Darbinyan, 2019). Gucci's audience is mainly on Instagram with 44.2M followers (Gucci, 2021), followed by Facebook (20M likes) (Gucci, 2021), and YouTube (725K subscribers) (Gucci, 2021). Hermès is a French luxury brand whose audience ranges from teenagers to young adults that are known to have a liking for unique and differentiated products that cannot be owned by everyone (Tran, 2012). Therefore, they tend to have a high income and look for quality upon purchase. Hermès' target audience on social media is 10.7M on Instagram (Hermès, 2021), 3.4M on Facebook (Hermès, 2021), and 150K on YouTube (Hermès, 2021). Finally, Valentino, the Italian luxury brand, focuses on women between the ages of 25 and 40 years who are characterized by elegance, femininity, and modernity. They can be considered entrepreneurs with an interest in exclusivity and innovation. Valentino's followers are 14.7M on Instagram (Maison Valentino, 2021), 3M on Facebook (Valentino, 2021), and 64.8K subscribers on YouTube (Valentino, 2021).

2.4. Fashion Brands' Digital Strategy

Fashion shows represent a powerful digital communication tool because of their effective and relevant content, so the need for going digital has never been more paramount because it is affecting the brands' value chain and is creating more opportunities (Achille, Remy, & Marchessou, 2018). Therefore, luxury fashion brands have adopted digital strategies in the past couple of years in order to keep up with the growing pace of the ever-evolving market. Luxury 4.0 allows brands to take responsive decisions to changes in customer demands without jeopardizing the unique craftsmanship and individualization of the luxury item (Achille, Remy, & Marchessou, 2018). For example, Louis Vuitton resorted to handwritten notes delivered to a each customer, in order to recommend travel bags for their journey to New York City (Achille, Remy, & Marchessou, 2018). These recommendations could be implemented by digitization, where every customer's profile is segmented and targeted to reflect individualism, exclusivity and authenticity in the brand's products. Burberry's collaboration with Google created the "Burberry Booth" where people are filmed dancing to the same song of the brand's television advertisement, Cosmic Dancer. These videos are then sent to consumers to be shared on YouTube or other social media platforms (Achille, Remy, & Marchessou, 2018).

The COVID-19 pandemic was the turning point for many luxury brands to adopt digital strategies (Achille & Zipser, 2020). Thus, many luxury brands who have not been selling on online shopping platforms collaborated with Amazon in September 2020 and developed an exclusive platform, called "shop in shop", accessible only for a selected audience (Deloitte, 2020). Furthermore, showing empathy during the pandemic with customers through social media was an approach most luxury brands followed in order to better understand customers' needs and keep them engaged. For example, Louis Vuitton entertained customers in isolation or quarantine by taking them on a journey of virtual cultural exhibitions, such as 1980s photos of the French photographer Jean Larivière (Deloitte, 2020). This campaign was followed with a hashtag called #SpiritofTravel on Instagram (Grilec, Vukusic & Dujic, 2020). Chanel also utilized Instagram, Facebook and Twitter to publish "The Sound of Chanel" music list on the Apple Music platform with the objective of entertaining people in isolation, and performed a live concert on Instagram (Grilec, Vukusic & Dujic, 2020). Another creative strategy implemented in light of COVID-19 was Gucci's, which was in the form of a new application that was launched, which includes games, emojis, stickers and other sources of entertainment as well as virtual try-ons. Gucci also created a playlist on Spotify for consumers to enjoy while cooking in quarantine (Deloitte, 2020). Therefore, luxury fashion brands have shown their resiliency, having been able to successfully adapt to the hardships brought upon the fashion market by the pandemic. Their embrace of the digital means shows that they are aiming to combine the physical and digital experiences or ‘phygital’ for the long run.

2.5. Engagement with Video-Content Related Posts on Social Media

Consumer engagement refers to the interaction between consumers and brands in terms of cognition, affection, and activation. Cognition is represented by the thoughts surrounding a particular brand, affection reflects the emotional connectivity with the brand, and activation means the behaviors and time consumption related to the brand (Bazi, Filieri & Gorton, 2020). Revenues from online purchasing are expected to grow even more and increase by 20% in 2025 (Bazi, Filieri & Gorton, 2020). Therefore, providing the right social media content can drive customer loyalty, trust, and satisfaction, eventually increasing brand growth and performance. Videos tend to be the most engaging type of social media posts for they grab the attention of users five times more than a still post (Durante, 2020). Also, it was revealed by two-thirds of social media users, that brands posting video content were most engaged with (Rahal, 2019). Users tend to watch videos for entertainment as well as interesting content from brands they follow, where it has been shown that more than 50% of consumers are interested in videos from brands they love (Rahal, 2019).

There are several motivators for consumer engagement with social media posts including videos. To begin with, perceived content relevancy, such as engaging with luxury brands to be knowledgeable about the latest products and events, is a main driver for high engagement (Bazi, Filieri & Gorton, 2020). Videos representing luxury fashion shows have been seen by a great number of customer. For example, the Hermès Men's Winter 2021 collection had 121K views and 136 comments on Instagram (Hermès, 2021) and 30.5K views on YouTub/e (Hermès, 2021). Moreover, Chanel's behind the scenes of the Fall-Winter 2021/22 collection had 13.3M views and 1,225 comments on Instagram (Chanel, 2021) and on Facebook, likes reached 15K, 422 comments, and 3.9K shares (Chanel, 2021). Louis Vuitton's video of the Fall-Winter 2021 fashion show received 617K views and 1,050 comments on Instagram mostly reflecting followers' adoration of the new collection (Louis Vuitton, 2021), 32.9K likes, 2K comments, and 2.8K shares on Facebook (Louis Vuitton, 2021), and 2.1M views, 9.7K likes, and 954 comments on YouTube (Louis Vuitton, 2021). Furthermore, videos on social media related to the COVID-19 pandemic which are also linked to consumer relevancy received a great amount of engagement, such as Louis Vuitton's rainbow videos intended to lift the spirits of followers where this video had 405K views and 370 comments (Louis Vuitton, 2020). A second example is Chanel's Instagram video about a playlist to accompany people while staying home, which received 287K views and 148 comments (Chanel, 2020). These compassionate videos contributed to a high customer engagement because they affect the "expectations" theme of the EEE customer mindset, which is emotions, employment, and expectations (Klaus & Manthiou, 2020).

According to the 2020 report published by Edelman Trust Barometer, brands can affect 65% of customers based on their response to the COVID-19 pandemic and more than one-third of consumers started to purchase from and follow a brand because of their empathy and creativity during the pandemic (Klaus & Manthiou, 2020). Another reason for customer engagement is the post's quality especially when it comes to attractive and creative content (Bazi, Filieri & Gorton, 2020). In addition, celebrities play a huge role in engaging customers on social media because they are perceived as credible and reliant sources for giving advice and setting trends (Bazi, Filieri & Gorton, 2020). For instance, Gucci presented "The Beloved Show" hosting several celebrities wearing Gucci's new items. Harry Styles, the English singer and songwriter, was the guest for one of the shows and received 1M views and 1,908 comments on Instagram (Gucci, 2021), while on Facebook, the video received 1.3K likes, 36 comments, and 178 shares (Gucci, 2021). Consumer engagement towards luxury fashion brands' social media posts provides insights on customers' interests and shows brand loyalty. This demonstrates how social media is a very good starting point to set up a marketing strategy based on the data provided from previous posts and their subsequent feedback.

2.6 Examination of Sentiment Towards Digital Fashion Shows

One method to explore user engagement is to examine the audience sentiment towards brands and campaigns through sentiment analysis (Meenaghan et al., 2013). Sentiment analysis, also known as polarity analysis or opinion mining (Mostafa, 2013), is the study of people's emotions, feelings and attitudes toward a brand, product, campaign, or other property (Liu, 2012). As a subfield of natural language investigation and processing, the practice has recently proven to be an effective tool across a variety of industries and disciplines, including politics, economics, healthcare, marketing and urban planning (Roberts et al., 2018; Yu and Wang, 2015), with the goal of analyzing individuals' emotions, opinions, perceptions or attitude towards certain topics.

Understanding and analyzing attitudes, as well as assigning valence to consumer statements on social media posts that align with positive, neutral, or negative attitudinal states, are all part of the sentiment analysis process. The successful evaluation of sentiment presents a powerful performance indicator of brand's digital marketing strategy. Textual data is coded as positive, neutral, or negative (Liu, 2012; Pang and Lee, 2008), to assess and aggregate consumers' attitudes toward a phenomenon. As a result, sentiment analysis via social media provides scholars and practitioners with a significant opportunity to investigate users' feelings and emotions (Cooke and Buckley, 2008). A significant proportion of social media discussions have been found to be related to expressions of opinion or sentiment about products or brands (Jansen et al., 2009); social media users regularly share feedbacks, emotions, and attitudes, allowing brands to identify specific consumer impressions as well as analyze longer-term trends and optimize their advertising efforts (Mostafa, 2013).

For luxury brands, the mining of consumer sentiment and response to the digital fashion shows campaigns is an untapped resource. Therefore, this study aims (1) to analyze the audience's reactions to the digital fashion shows streamed across different social media platforms used and (2) to derive a digital fashion show strategy for luxury brands to follow across the studied channels.

CHAPTER 3

DATA PREPARATION

When Luxury brands streamed the collection over online venues, audiences interacted with the streamed videos, highlighting their preferences, and discussing their dislikes over online mediums through comments posted in public. To better understand the user generated feedback, we will study the sentiment of the comments conveyed towards the virtual fashion shows streamed. The first step for that is to collect audience's comments across several social networks. In this thesis, we decided to focus on Facebook, Youtube and Instagram. We have also decided to focus on the following luxury brands: Hermès, Dior, Chanel, Valentino, Gucci, and Louis Vuitton.

3.1. The Different Types of Digital Fashion Shows

After examining the video posts (in terms of form and setup) of the different fashion brands, we can classify these videos under three thematic categories: (1) Normal runways with special configuration, (2) Artistic shows, and (3) Performance shows.

- *Normal Runways with Special Configuration:* Normal runways are the typical, most well-known form of fashion shows, where models walk dressed in the clothing created by the designer, but this time it is streamed digitally. Special setups and themes are adopted, helping the audience dive in the thematic inspiration behind the collection launched. Luxury brands settled on mythology partly to explore alternative representations (WWD, 2020). For example, CHANEL opened their runway to a white background with a giant C-H-A-N-E-L sign, resembling the Hollywood sign, accompanied with a perfect cinematic

90-second package skimming across the Hollywood flats, diving into a Hollywood pool, and soaring over the Hollywood Hills, and then the catwalk began (WWD, 2020). Additionally, Gucci livestreamed "The Epilogue" collection and campaigned at the Palazzo Sacchetti in Rome. Images of the look book were superimposed in the video with a narrative feature at the beginning and end of the video. On the other hand, Louis Vuitton staged at the Louvre's Denon wing where models mingled with ancient Roman, Greek, and Etruscan sculptures (Vogue, 2020). To present their 2020 collection, Valentino staged a live performance at Cinecittà Studios outside Rome and created 15 white gowns, as tall as 16 feet, worn by the models.

- *Artistic Shows*: Collections during artistic shows are presented in the form of a short film where designers reinvent their ways of presenting fashion, by incorporating surreal, abstract, and metaphysical themes. For example, Dior reunited with Italian director Matteo Garrone to stage their haute couture collection in a luxurious short film entitled "Le Château du Tarot" (Vogue, 2020). It was released online on the first day of Paris Couture Week and is based on a 15th-century deck of tarot cards designed for the Duke of Milan. It depicts a young woman - who switches her appearance between feminine and masculine- undergoing several tests to gain self-knowledge. (WWD, 2020). The film combines the fantasy of the Italian director with the savoir-faire of the French fashion house.
- *Performance Shows*: Luxury brands collaborated with singers and musicians presented their digital collection accompanied with live music performances. Valentino, for example, paraded their collection in the Milan's Piccolo Teatro,

by assembling their models to the live singing performance of Cosima featuring the Orchestra Sinfonica di Milano Giuseppe Verdi (Forbes, 2020). Another performance show was Louis Vuitton's men's Spring/Summer 2021 collection entitled "Message in a Bottle", during which Lauryn Hills performed a 20-minute set for the 2021 line.

Table 1 below shows all the vides released by the 6 brands with their corresponding thematic category.

Brand	Video Title	Video Type
Chanel	Fall-Winter 2021/22 Haute Couture Show	Normal Runway with Special Configuration
	The CHANEL 2020/21 Métiers d'art Show	Normal Runway with Special Configuration
	The CHANEL Cruise 2020/21 Collection	Normal Runway with Special Configuration
	The CHANEL Cruise 2021/22 Show	Normal Runway with Special Configuration
	The CHANEL Spring-Summer 2021 Ready-to-Wear Show	Normal Runway with Special Configuration
	The Fall-Winter 2021/22 Ready-to-Wear Show	Normal Runway with Special Configuration
Dior	Dior Autumn-Winter 2020-2021 Haute Couture	Artistic Runway
	Dior Cruise 2022 Collection	Performance Show
	Dior Haute Couture Autumn-Winter 2021-2022	Normal Runway with Special Configuration
	Dior Men's Summer 2022 Show	Normal Runway with Special Configuration
	Disturbing Beauty	Normal Runway with Special Configuration
	The mystical beauty of Spring-Summer 2021 Haute Couture	Artistic Runway
Gucci	Epilogue	Normal Runway with Special Configuration
Hermès	Men's Winter 2021 collection	Normal Runway with Special Configuration
	Women's Fall-Winter 2021 collection	Normal Runway with Special Configuration
	Women's Spring-Summer 2021 collection	Normal Runway with Special Configuration
Louis Vuitton	LVFW21 Fashion Show	Normal Runway with Special Configuration
	LVMenSS21: Message in a Bottle	Performance Show
	LVSS21 Fashion Show	Normal Runway with Special Configuration
Valentino	ACT Collection	Performance Show
	Code Temporal	Normal Runway with Special Configuration
	Valentino Collezione Milano	Performance Show
	Valentino Des Ateliers	Performance Show

Table 1: Table shows the classification of the digital videos under the three thematic categories

3.2. Data Collection

Web scraping is a new method of collecting online data. The term refers to the automated process of accessing websites and downloading specific information from each one (Kienle et al., 2004). Web scraping, which enables the creation of large customized data sets, is already used for scientific and commercial purposes in a variety of fields, including marketing, industrial organizations, and inflation measurement (Cavallo & Rigobon, 2016).

We can use data collected from a website such as an e-commerce portal or social media channels to better understand customer behaviors and sentiments. However, obtaining this type of information on a large scale is typically difficult using traditional data collection methods or using the Application Programming Interface (API) offered by social media platforms such as Twitter, YouTube, and Facebook .

Selenium is a web-based automation tool that is an open source. The Python programming language is used with Selenium for sending standard Python commands to different browsers, despite differences in their design. Using Selenium, we created three scraping python tools that collect all the comments under the URL of any open source video streamed on the official channels of the studied brands posted on Youtube, Instagram and Facebook. The scraping tool went over each comment posted under the video and collects the username, the comment itself, and the date posted and sets it into a data frame. Additionally, the corresponding name of the luxury brand, the online medium from which it was generated, and the video title of the show were added to each comment using Python codes.

3.2.1. Dataset

Using the tools we built, we scraped 23 videos of digital fashion shows for the 6 luxury fashion brands (Chanel, Dior, Gucci, Hermès, Louis Vuitton, and Valentino) across Facebook, Instagram and Youtube. The final dataset consisted of 24,319 comments.

3.2.2 Identifying and Classifying Comment Types

The thorough examination of all comments allowed us to distinguish 5 different types. Each type is reflected with examples from the dataset in Table 2:

- *Show Configuration Comment Type*: Audiences who have highlighted their feedback related to the theme adopted or technicalities used while watching the digital show.
- *Emotional Connection Comment Type:* Audiences convey their emotions towards the brands or video streamed and such type of feedback shows the level of influence a brand name has on the minds of consumers.
- *Geographical Reach Comment Type*: While the video is streamed live, people highlight their geographical location (i.e where they are watching the show from).
- *Referral/Tagging Comment Type:* People who tag and refer the show to others, therefore increasing brand visibility across channels.
- *Collection Comment Type:* Commenters express what they like and dislike about the collection launched. It shows how much customers are satisfied. It is both a seasonal and a personal taste that varies, from seasonal collection to seasonal collection, and from one person to another.

Comment Features	Description	Example
Show Configuration Features	Comments conveyed by the audience highlighting feedback towards the theme of the show observed and details used in the configuration of the runway. It represents a technical connotation.	"Splendid location "," The green screen key nearly mess up the show" ," not good seeing walls through humans"," I'm sorry, but this is how fashion should always be presented!! Not on some boring, lifeless runway Dior. Keep it going in this direction🙂✨" ," Awful format. Convulted editing"
Emotional Connection Feature	Comments showing the emotional connection towards the video/brand without targeting a specific criterion in the show. It represents an emotional connection towards the brand.	"Love it❤️😍😍🔥🔥", "Absolutely Divine!" "Dior always perfection prestige bravo Dior", "Dior never disappoints me"," CHANEL À JAMAIS !🌹PATRIMOINE FRANÇAIS ᴄᴘ" ," Goodbye elegance, goodbye style, goodbye proudness. So sad"," *THIS IS NOT THE TRUE CHANEL"," Gucci only Gucci!!"*
Referral/Tagging Feature	Refer the show by the audience to their contacts	"@chanchanfiona so beautiful❤️"
Geographical Reach	Audience members mention their respective geographical location. This is done when the show is streamed live	"Hello from Germany"," Hello i'm from Vietnam =))))"," Halo from New York", "Hello from Sweeden", " Hello from Philippines"
Collection Features	Comments conveyed to express the perception of the audience relating either generally to the collection, or to specific items in the collection. It is a seasonal feature that varies from one person to another	"What a fabulous collection...💖❤️❤️❤️", "Hermès clothings look like a fricking MESS.", "BEAUTIFUL real clothes, high fashion, adore it 💘🌸💖"," Zara .. and H&M .... ??? Sorry i dont shop there"," Leggings 👎", "*Do not like the dresses or shoes!" "*

Table 2: Table shows the definitions of the comment types along with examples from the dataset

3.3. Data Pre-Processing

3.3.1. Data Cleaning

Before performing sentiment analysis on the data, pre-processing measures were needed. The aim is not only to transform unstructured data into structured, but also to clean data from anomalies that could obstruct the performance of the algorithms. Text pre-processing in general is an important step in data mining because it converts data into a usable format for ML techniques helping to improve the performance of the classifier and speed up the classification process.

Table 3 lists the text pre-processing tasks we have performed on the raw data, and their descriptions. Prior the data cleaning process, our dataset consisted of 24,319 comments scrapped from 23 videos of digital fashion shows for 6 different luxury fashion brands. After the data cleaning process, the dataset is composed of 21,424 comments scrapped from 23 videos of digital fashion shows for 6 different luxury fashion brands.

Step	Technique	Description
1	Separate Emojis from Raw Text Data	To avoid removing emojis during the cleaning process, and because emojis are powerful indicators of user sentiment, we separated the emojis from the text and combined them at a later stage
2	Lower Text	The main reason for changing the text to all lowercase is so that words like “Dior” and “dior” are not treated differently.It contributes to reducing the number of words that the dictionary must hold at any given time
3	Removal of @mention	It makes it easier to remove user mentions because they don't provide any relevant information about the text sentiment
4	Removal of URL	It is done in order to remove any URLs from the comment. It includes the removal of URLs beginning with HTTP, https, and …
5	Removal of Punctuation	Taking out all punctuation and non-alphanumeric words from the original text.
6	Removal of Hashtag	Removing hashtags from the text
7	Removing Whitespace	Because whitespace adds no meaning to the text, it is removed for computational reasons
8	Tokenization	It is the process of splitting each sentence into tokens. The following tokens are then used to build a vocabulary. The set of distinct tokens in the corpus is referred to as the vocabulary
9	English and French Comments	Removed all comments that are non-English and non-French.
10	Negation	Apostrophes used for negation are present in the text data for example, "didn't" for "did not". This can alter the meaning of a word or sentence. As a result, we must replace these apostrophes with the standard lexicons
11	Stop Words Removal	Words like "a," "an," and "the" add no meaning to the text. As a result, those words have been removed. It improves the text's precision (Savaliya and Philip, 2017)
12	Lemmatization	The process of converting words to their root meaning is known as lemmatization. It reduces the total number of words and improves computational speed
13	Combine Final Text with Emojis	Combined the finalized cleaned text form with the emojis into one array

Table 3: Table summarizes the different steps performed during the data cleaning process

3.3.2. Creating Features from Text – The TF-IDF Algorithm

The main interest lies in this phase of the content analysis. To effectively analyze a large number of social media data, it is necessary to use the appropriate feature information to represent the content of a piece of comment. As a result, feature selection is especially important for text information. Despite significant advances in machine learning, TF-IDF is still used in the majority of information retrieval systems. According to Pang & Lee (2008), the frequency of these terms plays an important role in identifying important information. The TF-IDF provides useful information in the pre-processing phase by evaluating the frequency of useful words, which simplifies the sentiment detection process.

The TF-IDF algorithm is widely used in text information processing for feature selection. It is a weighing matrix that is used to determine the significance of a term (count + weight) to a document in a dataset. For example, it is used by Facebook's DrQA, a tool developed and open-sourced by the Facebook AI research team, that answers questions by reading Wikipedia articles.

TF-IDF is made up of two metrics: term frequency (tf) and inverse document frequency (IDF) (idf). Eq represents the TF-IDF relationship (1).

$$\mathrm{tfidf} = \mathrm{tf}(t, d) \times \mathrm{idf}(t, d) \tag{1}$$

Term Frequency (tf) is denoted here and is calculated from the count (c), term (t), and document (d) and represented as t f (t, d) = ctd. The frequency of occurrence of words to a binary feature is converted using 1 (present in document) and 0 (not present in document) (not present in document). Averages and logarithms can be used to normalize the frequencies. Eq (2) computes the inverse document frequency (idf) for a word w in document text (t)

$$\mathrm{idf}(t, d) = 1 + \log \frac{T}{(1 + \mathrm{df}(t))} \qquad (2)$$

T denotes the total number of documents in our corpus, and df (t) denotes the number of documents containing the term t. The product of two measures will aid in calculating tfidf. The final TF-IDF metric, as given by Eq(3), is calculated using Euclidean's normalized form. The Euclidean norm is represented by ||tfidf|| in this case.

$$\mathrm{tfidf} = \frac{\mathrm{tfidf}}{||\mathrm{tfidf}||} \qquad (3)$$

3.3.3. The Final Cleaned Dataset

Following the data cleaning process, the dataset size narrowed down from 24319 comments to 21424 comments. Table 1 summarizes the total number of comments generated for each video streamed by the luxury brands and across different online mediums.

Brand	Video Title	Platform	No Comments
Chanel	Fall-Winter 2021/22 Haute Couture Show	Instagram, Facebook	**1,866**
	The CHANEL 2020/21 Métiers d'art Show	Instagram, Facebook, Youtube	**3,235**
	The CHANEL Cruise 2020/21 Collection	Instagram, Facebook, Youtube	**943**
	The CHANEL Cruise 2021/22 Show	Instagram, Facebook, Youtube	**1,180**
	The CHANEL Spring-Summer 2021 Ready-to-Wear Show	Instagram, Youtube	**1.130**
	The Fall-Winter 2021/22 Ready-to-Wear Show	Instagram, Facebook, Youtube	**2,139**
Dior	Dior Autumn-Winter 2020-2021 Haute Couture	Instagram, Facebook, Youtube	**2,592**
	Dior Cruise 2022 Collection	Instagram, Facebook, Youtube	**1,255**
	Dior Haute Couture Autumn-Winter 2021-2022	Instagram, Facebook, Youtube	**925**
	Dior Men's Summer 2022 Show	Instagram, Facebook, Youtube	**561**
	Disturbing Beauty	Instagram, Facebook, Youtube	**1,072**
	The mystical beauty of Spring-Summer 2021 Haute Couture	Instagram, Facebook, Youtube	**1,554**
Gucci	Epilogue	Instagram, Facebook, Youtube	**183**

Hermès	Men's Winter 2021 collection	Instagram, Facebook, Youtube	**188**
	Women's Fall-Winter 2021 collection	Instagram, Facebook, Youtube	**73**
	Women's Spring-Summer 2021 collection	Instagram, Facebook, Youtube	**206**
Louis Vuitton	LVFW21 Fashion Show	Instagram, Facebook, Youtube	**1,438**
	LVMenSS21: Message in a Bottle	Instagram, Facebook, Youtube	**1,494**
	LVSS21 Fashion Show	Facebook, Youtube	**2,737**
Valentino	ACT Collection	Instagram, Facebook, Youtube	**902**
	Code Temporal	Instagram, Facebook, Youtube	**859**
	Valentino Collezione Milano	Instagram, Facebook, Youtube	**474**
	Valentino Des Ateliers	Instagram, Facebook, Youtube	**1,304**
Total			**21,424**

Table 4: The total number of comments collected for each video after data pre-processing

CHAPTER 4

SENTIMENT ANALYSIS ALGORITHMS

The aim of this study was to assess the polarity/sentiment conveyed by audiences towards the digital luxury runways across Facebook, Instagram and Youtube. Sentiment analysis is a machine learning tool that examines text for polarity, ranging from positive to negative.

In this study, we chose to apply and compare two different approaches: Supervised Machine Learning and Lexicon-based.

The machine learning algorithm, at a first stage, learns how to detect sentiment without human intervention by training the algorithm with examples of texts and emotions. At a second stage, a new dataset is fed into the machine learning algorithm to judge the performance of this model and whether it correctly classifies the sentiment conveyed for each feedback. In this study, several machine learning algorithms, including logistic regression, support vector machine (linear and radial basis function), Naive Bayes, and Random Forest are tested. Those algorithms are known to produce consistent, repeatable decisions and outcomes.

The lexical approaches seek to map words to emotions by compiling a lexicon or 'dictionary of sentiment.' We can use this dictionary to evaluate the sentiment of phrases and sentences without having to look at anything else. The second aim of this study was to derive a digital fashion show strategy for luxury brands to follow over the studied channels by analyzing the audience’s reaction on each platform that is used. For the lexicon approach we have decided to use VADER (Valence Aware Dictionary for Sentiment Reasoning), a rule-based algorithm (Hutto & Gilbert, 2014) that employs a sentiment lexicon that was developed using a combination of qualitative and quantitative methods and is designed specifically for microblog-like content.

4.1. Machine Learning Approach

4.1.1. Naïve Bayes (NB) Classifier

Naïve Bayes (NB) Classifier is a probabilistic classifier that is based on Bayes' theorem and is particularly useful when the inputs have a high dimensionality. Its underlying probability model is known as an "independent feature model". As a machine learning probabilistic approach, Naive Bayes works well for dealing with changing training sets. It has demonstrated good, fast accuracy and can be used to verify sentiment analysis (G. Feng and J. Guo, 2015).

4.1.2. Support Vector Machine (SVM)

The Support Vector Nachine (SVM) is a well-known method for supervised learning in sentiment analysis, and there have been numerous studies on its use in classifying sentiments feedback on social media evaluation. SVM is based on the principle of structural risk minimization. It is also known as a discriminative classifier and is defined by the 'best' separating hyperplane. Using the SVM model, feature vectors extracted from social media comments' documents are represented as points in feature space. The feature vectors are then mapped so that a large gap is visible to perform linear classification. In our dataset, feature vectors are labeled with three categories, C = {Positive, Negative, neutral} and the training classifier creates a model that assigns new feature vectors to both defined categories. The classifier receives input in the form of two arrays, with array X having a two-dimensional size [sample number, feature vectors] to handle training data and array Y having a two-dimensional size [category label, sample number] to handle classification data.

4.1.3. Random Forest (RF)

Random Forest (RF) is a classification algorithm that can be used to detect sentiment and emotion in numerically significant data. It is a type of automatic learning technique. The concepts of random subspaces and "bagging" are combined in this algorithm. The decision tree forest algorithm is trained using multiple decision trees that are fed slightly different subsets of data. It is one of the best classification algorithms, capable of accurately classifying large amounts of data. It is a classification and regression ensemble learning method that constructs a number of decision trees during training. Every tree that is built will cast a vote for a data point and it calculates the decision tree classifiers' majority voting.

4.1.4 Logistic Linear Regression

This is a well-known classification algorithm that belongs to the Generalized Linear Models class. The logistic regression model is used to model the probabilities describing the outcome of a trial (Pedregosa, F., 2011) This algorithm is also known as the Maximum Entropy algorithm.

4.2. Lexicon-Based Approach

4.2.1 Valence Aware Dictionary for Sentiment Reasoning (VADER)

For this approach we have decided to use VADER (Valence Aware Dictionary for Sentiment Reasoning), a rule-based algorithm (Hutto and Gilbert, 2014) that employs a sentiment lexicon that was developed using a combination of qualitative and quantitative methods and is designed specifically for microblog-like content. It is a lexicon- and rule-based sentiment analysis tool that can handle words, abbreviations, slang, emoticons, and emojis commonly found in social media (Hutto and Gilbert, 2014). It is typically much faster to apply than machine learning algorithms for it does not require training models. Each body of text generates a sentiment score vector with negative, neutral, positive, and compound polarities. The polarities of negative, neutral, and positive are normalized to be between 0 and 1. The compound polarity can be thought of as an aggregate measure of all other sentiments, normalized to a range of -1 (negative) to 1 (positive).

4.3. Performance Metrics

There are several performance criteria that are commonly used to evaluate the performance of classification models, including accuracy, recall, and specificity.
False positives, true positives, and false negatives are computed when evaluating classification. True positives (TP) are the number of positively predicted samples that are correct; false positives (FP) are the number of times the actual class is not equal to c but the predicted class is; and false negatives (FN) are the number of times the actual class is equal to c but the predicted class is not.
When evaluating the results and comparing the various techniques, the following metrics are used:
The proportion of predicted positives that are correctly predicted as positives is referred to as precision score. Precision is defined as the ratio of True Positives comments to the Sum of True Positives comments and False Positives comments as represented in Eq (1)

Precision Score $= \frac{TP}{TP+FP}$ Eq (1)

The proportion of actual positives that are correctly predicted as positives is referred to as recall score. Recall is defined as the ratio of True Positives comments to the sum of True Positives comments and False Negatives comments as represented in Eq (2)

Recall Score $= \frac{TP}{TP+FN}$ Eq (2)

The harmonic mean of precision and recall scores is used to calculate the F1 Score as represented in Eq (3). It is a metric for determining a model's accuracy on the dataset. The F_1 score ranges from 0 to 1, with 0 being the lowest and 1 being the highest

F1 Score= $2\,\frac{Recall*Precision}{Recall+Precision}$ Eq (3)

4.4. Building the Classification Models

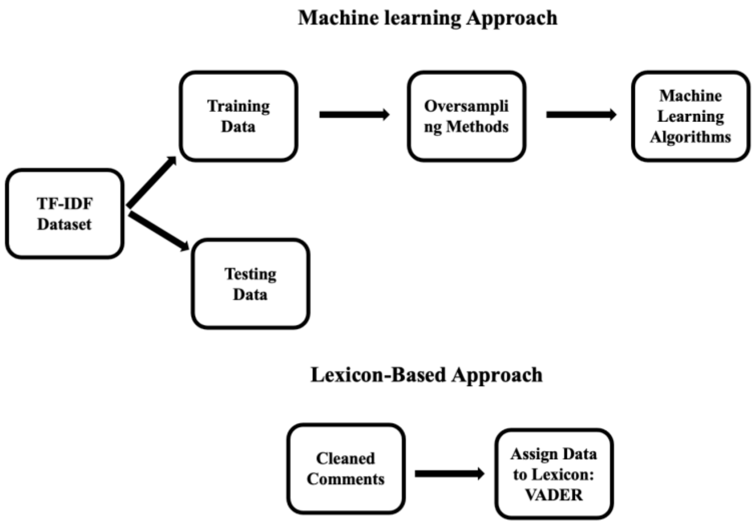

Figure 1: Flowchart that summarizes the main steps in building and training the models

The same process mentioned in Fig.1 was applied to build the machine learning algorithms including logistic regression, support vector machine (linear and radial basis function), Naive Bayes, and Random Forest. First, after extracting the features from the comments scraped using TF-IDF method, the dataset is split into 80% training (17,139 comments) and 20% testing (4,285 comments).

The training dataset has high imbalance of 14,181 positive comments, 2,146 neutral comments and 812 negative comments. The imbalance problem is tackled in order to improve the supervised algorithm's learning. Random oversampling approach is used to deal with the imbalanced training dataset. The aforementioned machine learning models are applied on the training dataset.

As for the lexicon-based approach, VADER sentimental analysis maps lexical features to emotion intensities, which are known as sentiment scores. A comment's sentiment score can be calculated by adding the intensity of each word in the comment array.

The classification results of both approaches, the machine learning approach and lexicon-based approach, are represented in Table 5.

Support Vector Machine (RBF) gave the best classification performance among all supervised learning approaches with the Precision and Recall scores. SVM (RBF) scored 91.70% Precision score, 90.69% Recall score and 91.19% F1 score. While the lexicon-based algorithm, VADER, yielded 85.36% precision score, 74.36% recall score and 79.48% F1 score. Therefore, we can conclude that the support vector machine algorithm largely outperformed the lexicon-based algorithm VADER.

Algorithm	Precision	Recall	F1 Score
Logistic Regression	90.81%	89.99%	90.40%
Multinomial Naïve Bayes Classifier	90.66%	60.18%	72.34%
Random Forest	89.90%	90.41%	90.15%
Support Vector Machine	**91.70%**	**90.69%**	**91.19%**
VADER Lexicon	85.36%	74.36%	79.48%

Table 5: Table shows the classification performance of the studied models

Additionally, Table 6 shows a qualitative comparison of the results of the tested algorithms. It should be noted that the table does not include the original comments, but rather the cleaned and tokenized version of the sample. Inappropriate and stop words have been removed. It is clear that the selected ML – Support Vector Machine (RBF) outperform the lexicon-based algorithm VADER.

We can notice also from Table 6 that prior to applying the machine learning models, we labelled all the dataset manually and attributed for each comment one of the following sentiments: positive, negative, or neutral. These human-labelled sets of data are required to evaluate the accuracy of all sentiment analysis algorithms as well as act as an input with the purpose of training the machine-learning sentiment analysis algorithms (Thelwall et al., 2018).

Comment	Manual Labelling	Selected ML Algorithm	VADER
['amazing', 'thank', 'nico', 'greatings', 'colombo', 'lot', 'love', 'flower', 'creativity', 'flower', '❤', '🌈', '🌻', '🌹']	positive	positive	positive
['beautiful', 'concept', 'collection']	positive	positive	positive
['couture', 'really', 'ugly', 'sad', 'dior', 'does',’not, know', 'make', 'beautiful', 'dress', 'anymore']	negative	negative	negative
['watched', 'live', 'yesterday', 'mind', 'blowing']	positive	positive	
['chanel', 'zara', 'video', 'production', 'look', 'cheap', 'clothes', 'pretty', 'dull']	negative	negative	positive
['lv', 'concept', 'uglier', 'better', '😂', '😂', '😂']	negative	negative	positive
['magnific', '🔮', '✨', '🙏', '□', '✨']	positive	positive	positive
['so', 'boring', 'nothing', 'special']	negative	negative	negative
['spectacular', 'transfixed', 'entire', 'video', 'image', 'narrative', 'unfolded', 'mesmerized', 'extraordinary', 'gown', 'dior', 'dreamiest', 'renaissance', 'imagery', 'opulence', 'elegance', 'italian', 'opera', 'ending', 'image', 'ultimate', 'tarot', 'card', 'will', 'never', 'look', 'tarot', 'same', 'eye', 'adore', 'actor', 'portraying', 'male', 'female', 'lover', 'eye', 'magical']	positive	positive	positive
['going', 'decided', 'watch', 'second', 'time', 'figuring', 'feel', 'collection', 'now', 'seen', 'easier', 'digest', 'still', 'say', 'whether', 'not', 'like', 'one', 'thing', 'sure', 'nicolas', 'way', 'ahead', 'virginie', 'mgc', 'dare', 'not', 'say', 'name']	neutral	neutral	positive
['yo', 'happened', 'chanel', 'like', 'every', 'collection', 'so', 'disappointed']	negative	negative	negative

Table 6: Table shows a qualitative comparison between the manually labeled output, the selected machine learning algorithm, and the lexicon-based classifier

4.5. Tuning the Selected Classifier

Knowing that the SVM classifier gave the best results, we then worked on adjusting the model's hyper-parameters to improve its accuracy. To achieve this objective, we performed Grid-Search with K-fold cross validation technique.

4.5.1. Grid-Search for SVM Hyper-Parameters

To obtain more accurate results, hyper parameter tuning is an important task in SVM (Duarte & Wainer, 2017). The kernel (K) is a hyper-parameter of the SVM model. It converts the original data space into a new space with a higher dimension. SVM uses kernel techniques to optimize the margin between different sentiment classes. It specifies whether a linear, polynomial, Radial basis function (RBF) or sigmoid separation should be implemented to separate positive, negative, and neutral data points. Accordingly, the four different kernels were tested in the previous section and therefore the RBF kernel achieved the highest performance measurement scores.

SVM (RBF) has the following hyper-parameters that demonstrate their significance by improving the model's performance: *Regularization (C) and Gamma* (ϒ):

- *Regularization (C)*: The Regularization parameter (termed often as C) optimizes how much to avoid misclassifying the training dataset. For large values of C, the optimizer will select a smaller-margin hyperplane if it does a better job of correctly classifying all the training sentiment scores. A very small value of C, on the other hand, will cause the optimizer to seek a larger margin separating hyperplane, even if that hyperplane misclassifies more points. Therefore, C manages the trade-off between a smooth decision boundary and correctly classifying training points.
- *Gamma Parameter* (ϒ)*:* Gamma determines how much curvature is needed in a decision boundary. It specifies the extent to which a single training example has an impact. If gamma is very high, the decision boundary will be based solely on sentiment points that are very close to the line, essentially ignoring those points that are very far from the decision boundary. This results in a more curvature boundary. If the gamma value is low, even the farthest points receive significant weight. This results in a more linear boundary.

To optimize the SVM (RBF) algorithm, we must first determine the best combination of its hyper-parameters (C and ϒ). Grid-Search is essentially an optimization model for hyperparameters. It is a technique for evaluating various combinations of the hyper-parameters to determine the optimal pair of values that help the algorithm achieving maximum accuracy. Therefore, the following C and ϒ values were assigned to the grid-search: C= [1, 10, 100, 1000] and ϒ= [1, 0.1, 0.01, 0.001, 0.0001].

4.5.2. K-fold Cross Validation

According to P. Refaeilzadeh (2009), cross validation is a method for testing multiple models under a specific classifier with a subset of input data. The cross-validation procedure can help to avoid overfitting (Hawkins, 2004).

First the dataset is split into 80% training and 20% testing. The training data is divided into ten equal-sized and randomly selected subsets. One subset is kept for validation, while the other nine are used for training. The models' accuracy is assessed on the test fold, and the process is repeated until each subset serves as the test fold, and the score is calculated on that fold. The final cross validation score is calculated by averaging the scores of all ten subsets.

4.5.3 Results

Based on the values given to C and ϒ, the grid-search optimizer selects C=1 and ϒ = 1 as optimal hyper-parameters values for the pair of hyper-parameters for the SVM (RBF) model. Afterwards, the SVM (RBF) to which the selected optimal hyper-parameters values were assigned (C=1 and ϒ = 1) is trained using the k-fold cross validation technique.

After tuning the SVM (RBF) model using grid-search and k-fold cross validation techniques, the comparative results of the performance measurements for the non-tuned and tuned model are represented in Table 7. We can conclude that the tuning steps helped improve the model's performance and increase its Precision score, Recall score and F1 score to reach in our case 92.06%, 90.97% and 91.51% respectively.

Algorithm	Precision	Recall	F1 Score
Support Vector Machine (RBF)	91.70%	90.69%	91.19%
Support Vector Machine (RBF) - Tuned	92.06%	90.97%	91.51%

Table 7: Table shows the comparative results of the performance measurements for the non-tuned and tuned SVM (RBF) algorithm

CHAPTER 5

ANALYSIS & FINDINGS

We will start by observing the positive, negative, and neutral comments by type of show and by social media channel. Table 9, 10 and 11 show the break down in percentages, and Table 12 in count.

5.1. Normal Runway with Special Configuration

All of the studied brands; Dior, Chanel, Louis Vuitton, Gucci, Hermes and Valentino, launched at least one digital normal runway show with a special configuration. The reception of this type of show across the three social media platforms is very dynamic in the sense that it varies greatly from platform to platform.

Out of the three platforms, the Normal Runway shared on Instagram shows the highest positive feedback, with a total of 97% of the comments revealing a positive sentiment. The positive feedback generated by Instagram audiences ranks the emotional connection feature in first place with a weight of (51%). The collection feature, which is the seasonal and taste dependent feature, follows the emotional feature, raking in (42%) of positive comments. Also, coming in third, the show configuration feature makes a (4%) positive impact on Instagram audiences. However, both the negative and the neutral feedback compile to 1% and 2% respectively representing a negligible weight.

Sentiment Classification	Normal Runway with Special Configuration			Artistic Runway			Performance Shows		
	YouTube	*Facebook*	*Instagram*	*YouTube*	*Facebook*	*Instagram*	*YouTube*	*Facebook*	*Instagram*
Positive	**79%**	**62%**	**97%**	**98%**	**77%**	**91%**	**87%**	**42%**	**96%**
Negative	**19%**	**4%**	**1%**	**1%**	**1%**	**0%**	**12%**	**2%**	**0%**
Neutral	**2%**	**34%**	**2%**	**1%**	**22%**	**9%**	**1%**	**56%**	**4%**

Table 8: Table shows the distribution of sentiment across the three studied channels for the different types of fashion shows

Comment Feature Analysis	Normal Runway with Special Configuration			Artistic Runway			Performance Shows		
	YouTube	*Facebook*	*Instagram*	*YouTube*	*Facebook*	*Instagram*	*YouTube*	*Facebook*	*Instagram*
Show Configuration Feature	14%	5%	4%	82%	6%	4%	17%	2%	5%
Emotional connection Feature	23%	22%	51%	6%	68%	86%	5%	25%	30%
Collection Feature	42%	35%	42%	10%	3%	1%	65%	15%	61%
Total	**79%**	**62%**	**97%**	**98%**	**77%**	**91%**	**87%**	**42%**	**96%**

Table 9: Table shows the distribution of positive sentiment across the three studied channels for the different types of fashion shows

Comment Feature Analysis	Normal Runway with Special Configuration			Artistic Runway			Performance Shows		
	YouTube	*Facebook*	*Instagram*	*YouTube*	*Facebook*	*Instagram*	*YouTube*	*Facebook*	*Instagram*
Show Configuration Feature	3%	0%	0%	1%	0%	0%	3%	0%	0%
Emotional connection Feature	4%	1%	0%	0%	1%	0%	0%	1%	0%
Collection Feature	12%	3%	1%	0%	0%	0%	9%	1%	0%
Total	**19%**	**4%**	**1%**	**1%**	**1%**	**0%**	**12%**	**2%**	**0%**

Table 10: Table shows the distribution of negative sentiment across the three studied channels for the different types of fashion shows

Comment Feature Analysis	Normal Runway with Special Configuration			Artistic Runway			Performance Shows		
	YouTube	*Facebook*	*Instagram*	*YouTube*	*Facebook*	*Instagram*	*YouTube*	*Facebook*	*Instagram*
Referral/Tagging Feature	2%	12%	2%	1%	20%	9%	1%	17%	4%
Geographical Reach Feature	0%	22%	0%	0%	2%	0%	0%	39%	0%
Total	**2%**	**34%**	**2%**	**1%**	**22%**	**9%**	**1%**	**56%**	**4%**

Table 11: Table shows the distribution of neutral sentiment across the three studied channels for the different types of fashion shows

Comment Feature Analysis	Normal Runway with Special Configuration			Artistic Runway			Performance Shows		
	YouTube	*Facebook*	*Instagram*	*YouTube*	*Facebook*	*Instagram*	*YouTube*	*Facebook*	*Instagram*
Sentiment Classification									
Positive	2,670	2,393	6,922	1,208	1,261	293	664	502	1,814
Negative	624	165	77	9	19	0	89	28	4
Neutral	63	1,301	171	8	358	30	7	671	73
Positive Comment Analysis									
Show Configuration Feature	465	201	260	1010	95	12	129	20	87
Emotional connection Feature	782	868	3,623	71	1,106	278	41	300	571
Collection Feature	1,423	1,324	3,039	127	60	3	494	182	1,156
Negative Comment Analysis									
Show Configuration Feature	86	6	5	6	3	0	26	2	1
Emotional connection Feature	120	28	14	0	10	0	0	11	0
Collection Feature	418	131	58	3	6	0	63	15	3
Neutral Comment Analysis									
Referral/Tagging Feature	49	437	168	4	325	30	6	207	71
Geographical Reach Feature	14	864	3	4	33	0	1	464	2

Table 12: Table shows the distribution of sentiment across the three studied channels for the different types of fashion shows

On YouTube however, only 79% of comments are categorized by the algorithm as positive. Youtube audiences admire the collection feature giving it a weight of (42%) followed by the emotional connection feature (23%). Thirdly, the configuration feature yields (14%) of the positive feedback.

Conversely the negative comments amount to a staggering 19%, which is the highest negative input out of all the platforms for this show model. The negativity triggers three features: the collection feature yields the highest negative output reaching (12%), putting it at first place followed by the emotional connection feature showing a high

(4%) of negativity. Finally, (3%) of negative feedback is towards the configuration of the show. As for the neutral feedback, it accounts for 2% of the total feedback received.

Comments on Facebook reveal 62% positive feedback. The split of positive feedback is firstly conveyed by Facebook audiences towards the collection feature (35%) followed by the emotional connection feature (22%) and lastly the show configuration feature yields a modest weight of (5%).

On the other hand, a negligible weight of only 4% of the reviewed portion is negative. The neutral feedback for a normal runway with a special set up on Facebook is a high 34%. It must be noted that the high input of neutral feedback on Facebook reflects, in its entirety, referrals (12%) where people tag each other as a form of notification of the event and geographical reach (22%), where people communicate the location from where they are viewing the show when the video is streamed live.

5.2. Artistic Shows

Out of the reviewed brands, Dior is the only major luxury brand that streams a form of Artistic Runway. Dior put out two artistic videos entitled "Dior Autumn-Winter 2020-2021 Haute Couture" and "The Mystical Beauty of Spring-Summer 2021 Haute Couture." This type of show is received in the same manner by the audiences of all three platforms, which means that the variation in opinions across all three platforms is extremely minimalistic for this type of fashion show.

These two videos receive positive-sentiment feedback in 91% of the total comments inspected on Instagram, with no negative feedback whatsoever. As for the remaining 9%, it is manifested in a neutral manner. Positive comments on Instagram trigger the emotional connection feature ranking it first with a high (86%). The show configuration and collection feature stand second and third place yielding (4%) and (1%) respectively. However, the highest weight of positive feedback is seen in the input gathered from YouTube exceeding all other types of runways, with the two mentioned videos amassing a positive feedback share of 98% of total input, with only 1% seen as negative. The remaining 1% is purely neutral feedback. The positivity spread by Youtube audiences puts the show configuration feature (82%) first, followed by the collection feature (10%) and finally the emotional connection feature (6%).

In retrospect, under the same videos on Facebook, 77% of the comments are manifested positively. The emotional connection features come in first reaching a high (68%), followed by the show configuration feature and collection feature respectively yielding (6%) and (3%) positivity. Additionally, a mere 1% of comments posted under this show are negative. Facebook generated the highest percentage of neutral feedback, with 22% of the comments seen as neutral. This is a pattern shared with the previous set of data, however, the only difference is the fact that the entirety of the neutral comments on Facebook, for the Artistic Runways, are in the form of people tagging other people (20%) and mentioning their geographical location (2%).

5.3. Performance Shows

Performance runways are shows that are accompanied by live music performance(s). All the major luxury brands incorporated some sort of musical performance along their show, with the most notable of the bunch being Valentino and Louis Vuitton. Valentino debuted two collections, “Valentino Collezione Milano” and “ACT Collection,” while Louis Vuitton streamed men's Spring/Summer 2021 collection called “Message in a Bottle” under the same theme. This type of digital show is received in different ways across the social media platforms observed, so there is a clear and noticeable variation in opinions between the audiences of each platform.

Following the same analytical pattern, Instagram generates high positive returns, as 96% of the comments showing positivity, with no negative signals. What remains is neutrality, with the last 4% of the total comments showing a neutral sentiment. The positivity conveyed by Instagram audiences triggers the collection feature firstly with a (61%) weight, followed by the emotional connection feature yielding (30%). Lastly the show configuration feature acquires (5%) positivity.

However, YouTube shows a hight percentage of positive feedback, with 87% of the comments having positive affirmation. Based on the positivity generated, the collection feature receives (65%) of the positive comments followed by the configuration feature (17%) and then the emotional connection feature (5%).
Of the total feedback generated, 12% of the weight shows negativity. This negativity was focused primarily towards the collection feature (9%) followed by the configuration feature (3%). As for neutral comments, they add up to1%.

Lastly, Facebook has the lowest percentage of positive comments with only 42%. The positive feedback is conveyed towards the collection feature (25%) followed by the emotional feature (15%) and then the configuration feature (2%).
In addition, only 2% of the comments are negative. The bulk of the comments are neutral, with a massive 56% of the entire input manifesting pure neutrality. The pattern in neutrality comes in the form of referrals (17%) and geographical reach (39%).

CHAPTER 6

IMPLICATIONS

From a scholarly perspective, this paper fills a gap in the literature regarding digital marketing strategies to be adapted per channel for luxury fashion runways. This investigative, decision-making and customer-centric perspective expands the current scope of the digital marketing strategy related to digital luxury runways to reach a more developed and integrated marketing approach that should be embraced per channel.

This paper is the first examination of consumer sentiment towards digital fashion shows to date. The literature related to digital strategies based on the sentiment analysis conveyed towards luxury fashion shows is still underdeveloped, extremely scarce, and needs further extensive research. Furhermore, this study fills a considerable gap in the literature regarding digital marketing strategies to be adapted across different touchpoints for luxury fashion runways.

From a managerial perspective, the goal of this work is to assess the audience reaction towards different themes of fashion shows presented using each of the following media platforms: YouTube, Instagram and Facebook. Secondly, the analysis of the audiences' sentiment towards the digital fashion shown on each platform was used to derive a virtual show strategy for luxury brands to follow over the channels mentioned. The importance of this research is to convince marketers that not all videos showcased suit the audiences of all channels. Therefore, this research has shed the light on understanding how the different types of fashion shows could be directed towards the specific audiences of different social media platforms. Furthermore, it demonstrates the feasibility of leveraging the negative and neutral feedback and adopting a multi-show approach and not just a multi-channel strategy, thus, making the digital luxury fashion runways appealing to all tastes.

6.1. Managerial Implication 1: Focus on, Leverage and Address the Negative Feedback

All three sentiments affect current and future showcases in one way or another. Positive feedback dictates the effectiveness of the online mediums in the promotion process of fashion shows. On the other hand, negative feedback highlights ineffectiveness in the transmission of the digital show, pinpointing the inconsistencies observed by the viewers. It it is a referral criterion and a contagious feature generating more negativity:

> *"I had to come to the comment section to see if it is just me that is rather disappointed with how unidentifiable the Chanel DNA has become. The designs... everyone is right about them being incredibly lackluster. I just can't." (CHANEL audience, YouTube)*

Negative feedback helps in identifying what needs to be changed and offers a map for the rectification of inconsistencies. Accordingly, luxury brands should harness the power of negative feedback and perceive it as a chance to improve, resulting in a positive impact. Therefore, marketing managers should consider adopting a data-driven approach by looking closely at the negative comments and seizing the constructive feedback.

On Youtube, the normal runway with special configuration and performance shows yields a high 3% negative feedback towards the configuration of the show each. However, the configuration is related to technicalities and doesn't have to do with customer satisfaction, so, the better the configuration, the better the message is conveyed. Therefore, luxury brands must work on the technical details that are an obstacle and that drive people to express their negative feedback. Additionally, on Youtube, the emotional connection comments show a high 4% of negativity for the normal runway with special configuration. The emotional interaction conveyed by the luxury brands during this type of show is not well received by the audiences of this channel. According to previous studies, emotional connection with the consumers leads to a positive impact on the brand equity (Park et al. 2010). Therefore, to develop stronger brand relationships, marketers are under pressure to include a higher level of emotional content in their marketing communications on Youtube. Indeed, establishing an emotional connection with customers is an effective strategy for a brand's long-term success (Schmalz and Orth 2012). Furthermore, on Youtube, the normal runway with special configuration and performance shows amasses the highest negative collection comments reaching 12% and 9% respectively. On Facebook, the negative collection comments accumulate to 3%. Considering that collection is a seasonal feature and taste dependent, in order to decrease this negativity, luxury brands must open up to co-creation. This forces them to see the changes in taste of their consumers and understand consumers' motivation to share. Consumer empowerment via social media is here to stay, and luxury brands must involve their customers in "product design". There is now a greater emphasis on not only acknowledging but also harnessing customer co-creation (Morgan, 2010).

6.2. Managerial Implication 2: Adopt a Multi-Show Approach

The artistic runway type of show is received in the same manner by the audiences of all three platforms, generating the highest positive sentiment out of all the other types of shows, with a minimalistic yet negligible level of negative feedback. Simultaneously, data shows that the normal runways with special configuration and performance shows are admired by Facebook and Instagram audiences generating a maximum of 1% negativity for each comment type but also mark the highest proportion of negative feedback on Youtube. We can conclude that Dior, the only luxury brand streaming artistic runways, this creative and imaginary type of show, succeeds in promoting this digital fashion show, increasing its exposure and amplifying its visibility across all three studied channels. Indeed, creativity is a necessary component for achieving extraordinary results. Adding creativity has a positive impact on attention (Yang & Smith, 2009), attitude toward the brand and message (Ang et al., 2014), online sharing behavior (Southgate, Westoby, 2010), and purchase intentions (Yang & Smith, 2009).

Therefore, a good strategy we recommend for brands to test is to adopt a multi-show approach by (1) launching a collection with an Artistic Runaway format on the 3 channels that will generate a positive first impression and constructive negative feedback and then (2) launching the collection with a Normal Runaway with Special Configuration or with a Performance show, first on Facebook and Instagram, then on Youtube.

This strategy revolves around bridging the gap between the brand and its audiences. It is about creating, at a first stage, a customer experience based on brand storytelling through the artistic runways, reflecting mystery and magic, followed by a normal runway with special configuration or performance show.

6.3. Managerial implication 3: Leverage Neutral Feedback

Neutral feeedback observed and collected in this study has mainly functioned as an amplifier of brand visibility, due to it originating from two sources: the referral/tagging comments and geographical reach comments. The referral tagging comment is simply a method for the audience to willingly increase brand visibility by referring the show to other audiences. The Geographical reach comment indicates the location of the audience manifested when the show is streamed live. Accordingly, we suggest that marketing teams write codes to collect referrals and tags for working on targeted promotions not only on the audiences that showed interest but also on those who were tagged and referred. Furthermore, scraping geographical reach comments and applying geo-analysis techniques allows managers to identify the countries from which spectators of live shows are, and also areas where they are not. Consequently, luxury brands' marketing teams can consider initiating country-targeted brand-awareness paid ad campaigns when live shows are on.

CHAPTER 7

CONCLUSION

This research study aimed to explore the strategies that luxury fashion brands could use for digital fashion shows and proposed approaches to enhance the digital fashion show experiences for spectators. This study observed user feedback over three studied social media channels, which is an ultimate indicator of success for the digital screenings of the 3 types of fashion shows. Findings of this research have shed the light on how luxury brands should address and harness negative feedback, how they could adopt a multi-show-multi-channel digital fashion show strategy, and how to leverage and benefit from the neutral feedback for marketing. The importance of this research is to show that not all digital fashion show themes suit the audiences of all channels but the managerial recommendations proposed above provide a good framework to address that challenge.

This study is not free from limitations. Future studies could qualitatively measure the degree of responses and effectiveness of each suggested digital strategy. More types of fashion shows can be studied, and additional social media platforms can be taken into consideration. The range of brands studied can be expanded to examine a wider scope of luxury fashion brands or the luxury fashion industry in general.

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