

## Brand Engagement on Social Media Platforms: A study in Luxury Fashion Brands



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## Abstract

Social media nowadays is a fundamental element for all companies in terms of strategy, as well as a key indicator of their success. Social media touchpoints are the channels through which consumers interact with brands, express their likeness or their aversion, create brand loyalty and get engaged with multiple products. From a simple “like” on Facebook to a “retweet” on Twitter or a “comment” on Instagram, consumers can express their opinion about brands and interact with them. Hence, it is crucial for companies to enhance their online existence in a way that they achieve the optimal results in terms of customer loyalty and brand engagement. This study aims to provide some insights to companies and marketers who get their hands dirty with online strategies by analyzing how different message characteristics in different platforms (Facebook, Twitter, and Instagram) have an impact on brand engagement as well as the impact of each platform. Some characteristics are the post content type, if a video or a picture is included in the post, the use of action words or hashtags. In total, 13 brands from the luxury fashion industry are analyzed and 150 posts were studied. The results indicate that social media and post characteristics have a different effect on brand engagement levels. Specifically, Facebook is stronger effecting the share button, Instagram forces people to like more, and Twitter empowers the comment option. Moreover, hashtags seem to have a positive effect on likes and shares, while picture or video included posts influence positively all the levels of brand engagement. Implications of the findings are further discussed.

*Keywords: Social Media, brand engagement, brand posts, interaction, fashion luxury brands*

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# 1 Introduction

Every day we interact with brands in different social media platforms such as Facebook, Twitter, and Instagram, therefore creating a relationship with these brands, and we are already aware of that. But have we ever wondered how our likes, shares or comments influence this relationship? Are the companies aware of how the post type, the words they use and the type of content they adopt have a different impact on brand engagement with customers? The main goal of the first chapter is to introduce the subject of the research to the readers. Firstly, the background and context of this study are discussed, and then the importance of the research objectives are described.

## 1.1 Background and Context

Social Media nowadays have formed a different way of social interaction. Customers use online platforms to communicate, discuss, argue and exchange information. That interaction can be expressed with pictures, videos, texts other types of media. Users can express their complaints regarding a product easily with a simple comment under the company's post, can show their likeness with a "like" or they can suggest the product to their friends with a "share". In that way, they share experiences online about the brands they use, therefore creating a relationship with those brands. This relationship can significantly affect brand engagement and brand loyalty as also purchase likelihood. This is the reason companies have started to integrate traditional and social media. A blend of these two types is media is when marketers focus on both capturing attention via reach (traditional media) and continuing attention via engagement (social media) (Hanna, Rohm & Crittenden, 2011). While internet based media can give the marketers the ability to move consumers from awareness to engagement, they cannot replace traditional media. The use of both tactics can enable the creation of experiences that can lead to attention and influence (Hanna, Rohm & Crittenden, 2011). Therefore, more and more companies seem to follow the trend of social media and implement online marketing strategies as a way to reach their customers. Hence, the online marketing expenditures have increased the last years, meaning that companies have realized the importance of operating online.

The most heavily used social media channel by companies is undoubtedly Facebook, with more than one billion users. In Facebook companies can create their own brand pages where they can post pictures, videos to advertise their products (Kabadayi & Price, 2014). Consumers on the other side can like, comment, or share the brands' posts. When they do one of the above it is also visible to their friends, leading to an increasing word of mouth. Likes can be an asset for the company and an indicator of how well the company performs both online and offline. Specifically, the value of each consumer that likes a brand on Facebook has increased an average of 28% over the past years (PR Newswire, 2013)

## 1.2 Importance and Research Objectives of the study

Although the advantages of social media platforms have been extensively studied, the impact of different social media platforms on brand engagement has not yet been investigated. Facebook is the online tool that researchers have been focused more, as it's the largest social networking site together with MySpace, according to Wikipedia. Additionally, as it is heavily used, it is the one that almost every company and user is familiar with. Kaplan and Haenlein (2010) have classified the Social Media considering two dimensions; self-presentation and self-disclosure. Social networking sites such as Facebook are scoring better than content communities in terms of these two aspects. Benefits of Instagram which is gaining ground as well as those of Twitter, have not been given that attention. The relationship between word of mouth communication and Twitter has been researched by Jansen et al (2009), showing that a big percentage of tweets are highly associated with brands as they contain the name of a brand, product or service (Zhang, Jansen & Chowdhury, 2011). Furthermore, Zhang and Jansen have studied how the consumers engagement relates with the business engagement on Twitter with online word of mouth communications, and found out that there is a high correlation. Even though how diffusion is created is studied in their article, no attention has been given in how different post characteristics lead to brand engagement. Additionally, how different post characteristics influence people's likelihood to like, comment or share a post on those 3 social media types is not yet investigated by scientific literature.

The main question of the current research is:

- How can brands increase their brand engagement levels on Facebook, Twitter and Instagram and which platform is more favorable for each level?

In order to answer the main question, the following sub-questions should be answered:

- Is there a significant difference on social media platforms for brand engagement levels?
- Which social media type is more favorable for brand engagement in terms of likes?
- Which social media type is more favorable for brand engagement in terms of comments?
- Which social media type is more favorable for brand engagement in terms of shares?
- Does the use of hashtags have an impact on brand engagement levels?
- Does the use of action words have an impact on brand engagement levels?
- Does the picture or video included in posts have an impact on brand engagement levels?

### 1.3 Contribution

As social media is a fundamental part of the marketing strategies that companies implement nowadays, there is a considerable body of literature related to this subject. Many researches have focused on what drives people to join virtual communities such as Networking sites (Kaplan & Haenlein, 2010), what are their motivations and incentives. Moreover, Nadkarni & Hofmann (2012), studied what are the main factors that lead people to use Facebook. They suggest that most of the users have the need to belong and self-present, therefore they create profiles in Facebook. These two needs are driven by demographic, cultural and personality traits such as extraversion, shyness, narcissism, neuroticism and self-esteem (Nadkarni & Hofmann, 2012). In addition, Habibi, Laroche & Richard (2014), have investigated how brand communities established on social media platforms achieve brand trust among consumers. More specifically, it is found that three relationships (customer-brand, customer-product and customer-company) influence positively brand trust through brand communities while

customer-other customers' relationship has the opposite effect on brand trust. (Habibi, Laroche & Richard, 2014). This research will contribute to the existing literature by examining more in depth how different social media platforms affect brand engagement, as Instagram or Twitter for example have not given that attention. Moreover, how different post characteristics in those three platforms influence people to like, comment or share are studied. The results of this study have various implications for marketers who want to implement the optimal online marketing strategies for their brands. Knowing what engages fans more, marketers can perform the efficient tactics to create closer relationships with their customers.

## 2 Literature Review

### 2.1 Social Media

Hanna, R., Rohm, A., & Crittenden, V (2011) note that are hundreds of social media platforms (e.g., social networking, text messaging, shared photos, podcasts, streaming videos, wikis, blogs, discussion groups), through which customers interact with products and services. Marketers must focus on both capturing and continuing attention via engagement. Mike DiLorenzo, director of social media marketing and strategy for the NHL stated that “Social networks aren’t about Web sites. They’re about experiences” (Wyshynski, 2009). These experiences arise when marketers can incorporate reach, intimacy, and engagement into the company’s overall integrated marketing communications strategy through the interconnectedness of online social media combined with traditional media. Furthermore, expected increases in social media expenditures by the end of 2010 imply that marketers, indeed, recognize the need to be involved in social media. Key performance indicators in measuring success can be traditional metrics (e.g. Facebook likes), or downstream metrics (e.g. sales to the extent is possible), both showing the brand lift and engagement. Social networking sites are one of the most popular social media categories. Examples are Facebook, Twitter, Instagram. In those media people can share information and connect with brands in multiple ways. They are joining social media platforms for social, psychological, informational and entertaining reasons.

#### 2.1.1 Facebook

Facebook has been established as the most commonly used social media platform throughout the years. Brands have leveraged the key benefits of Facebook to promote their products and get closer to their customers. By liking, commenting and sharing Facebook wall posts, online users create a relationship with brands and are getting engaged to products. Kabadayi & Price (2014) have studied different factors that affect consumers’ liking and commenting behavior. The study is focused on three personality traits (neuroticism, openness to experiences and extraversion) and their relationship



with the digital consumer behavior. The customers studies are classified into two types depending their mode of interactions; the broadcasters and the communicators. The study showed that broadcasters are the ones that companies should focus to better engage with their brands but communicators are the ones that are more active on Facebook pages in a meaning that they like and comment more (Kabadayi & Price, 2014). Although there are several studies with focus on Facebook and how brand engagement is accomplished, no literature review exists about how different message characteristics on Facebook lead to higher brand engagement levels, as well as how this social networking site is compared to others regarding fans likability to interact with brands.

### 2.1.2 Instagram

Instagram is the most fast growing social media platform where users post photos and videos. It is a relatively new form of communication that has attracted millions of people and has seen a rapid growth among users. Apparently, little research has been made. Hu, Manikonda, and Kambhampati (2014) analyze Instagram in a both qualitative and quantitative perspective and provide insights about different types of Instagram users, popular photo categories and generally about Instagram content. The research though is mostly related to photos and not specific characteristics such as hashtags or action words. This study aims to examine more in depth the relationship between brand engagement and Instagram in terms of post content. As Instagram is gaining ground in the social media arena, the results are of high significance for companies who want to catch up with the trend and perform online in the most optimal way.

### 2.1.3 Twitter

Twitter was founded by Jack Dorsey, Biz Stone, and Evan Williams in 2006 (Sagolla 2009). It is a functional and popular social media platform and a means through brands connect with customers. ‘‘It provides the basic social media functions such as owing a profile page, connecting with people and sharing multimedia information’’ (Zhang, Jansen & Chowdhury, 2011). The potential impact of the diffusion in Twitter community on the business engagement in terms of online word of mouth

communication was investigated by Zhang, Jansen and Chowdhury (2011). Noticeably, Twitter is highly correlated with brands, as about one fifth of tweets contain the name of a brand, product or service (Jansen, Zhang, Sobel & Chowdury, 2009). The above study showed that the brands' engagement in word of mouth communication is the main factor for consumers' brand engagement. Moreover, consumers tend to communicate and engage more with businesses that have a big number of followers, as the business following number is a predictor for its follower number. In addition, retweeting as business engagement response indicator, is shown to have an impact only for consumers with a second- degree relationship to the business (Zhang, Jansen & Chowdhury, 2011).

The results indicate that businesses should try to be the most active they can on Twitter, and more specifically in a frequency of tweeting at least once every 1.5 to 4 hours per day (Zhang, Jansen & Chowdhury, 2011). A strong presence on Twitter can have a positive impact on brand engagement followed by effective advertising strategies.

## 2.2 Brand engagement

Hoffman and Fodor (2010) studies how companies can measure the ROI of the social media marketing. Companies instead of emphasizing their marketing investments and calculating the returns in terms of customer response, they should begin with focusing on what motivates consumers to use social media and then measure the social media investments that customers make as they engage with the brands. This means that returns from social media investments will not always be measured in dollars but also in customer behaviors. There are three social media objectives that are further discussed in the paper; brand awareness, brand engagement and word of mouth. In this study, brand engagement will be discussed. According to them, there are two types of engagement; personal and social-interactive, and engagement with the media context increases advertising effectiveness (Calder, Malthouse & Schaedel, 2009). Engagement is defined as an antecedent to outcomes such as usage, affect, and responses to advertising. More simply, being engaged means being connected to something. The fundamental insight is that engagement comes from experiencing a website in a certain way. To understand engagement, we need to understand the different experiences that consumers have in connecting with the site. The relationship between customer

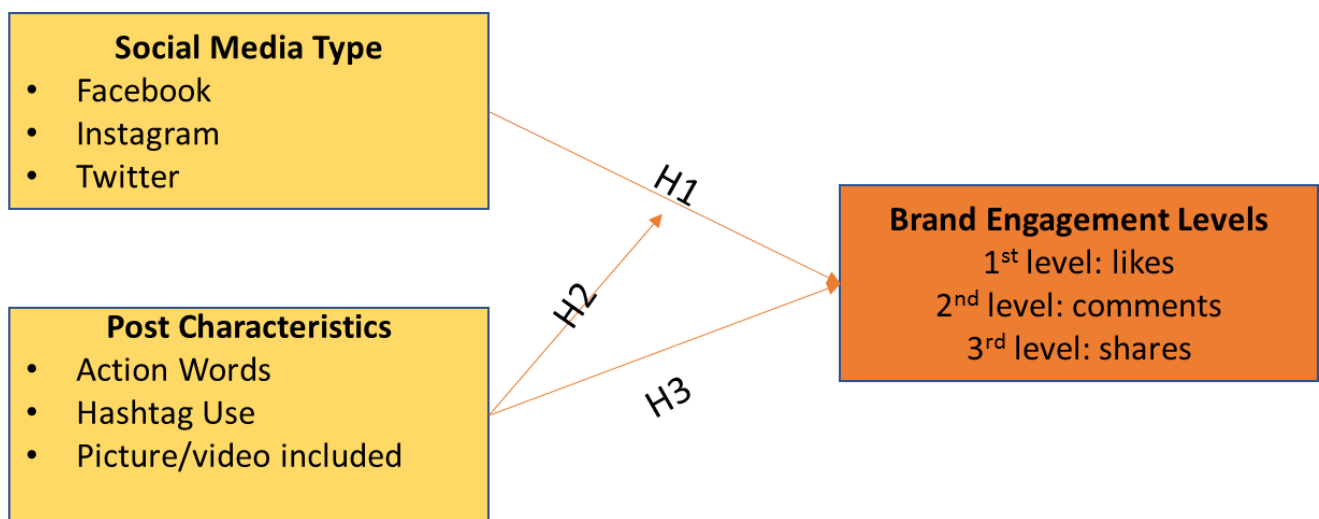
engagement and advertising effectiveness are further explained and it is later concluded that online media do involve a distinct form of engagement and that this engagement has its own impact on advertising effectiveness (Calder, Malthouse & Schaedel, 2009).

### 2.3 Post Characteristics

Post characteristics are components that brands use in their messages to make them more attractive. They can be drivers for brand post popularity and therefore create brand awareness, trust and engagement. So far research has showed that there is a number of post characteristics that enhance the salience of brand posts (de Vries, Gensler & Leeflang, 2012). Such characteristics are the vividness of brand posts (colors, pictures), how interacting the posts are, whether the posts are informative or entertaining, the position of the brand post as well as the share of positive or negative comments on posts. Since Instagram and Twitter are platforms that have seen growth the last years, there is no research regarding the post characteristics on these types of media. Moreover, the hashtags that are extensively studied in this paper is a new element that digital marketers use, therefore it is interesting to see its effect on brand engagement. Another aspect that is not given attention and is examined in the study is how the same post characteristic behaves in different media. If for example the use of action words in Facebook is useful while on Twitter useless. All these aspects will be measured in that study and consequently, marketers will have a clearer image of how to use each brand post characteristic in each platform.

## 2.4 Conceptual Model and Hypotheses

Previous chapters gave insights about the relationship between the dependent and independent variables, which can be visually demonstrated in the above conceptual framework. Based on the literature given, we can infer what the direction of this relationship is but first we need to answer the following questions: Why should different social media platforms have different effect? Why should different post characteristics should influence differently the online behavior of consumers?



Firstly, social media type and post characteristics are defined as the independent variables. Regarding our dependent variable, likes, comments and shares are classified as the different levels of brand engagement. The reason for this classification is the time and effort that the online user puts in each of them. Likes, defined as the first level of brand engagement, can be done with one click, do not appear in the user's timeline (Facebook and Instagram) and do not demand any effort. Comments demand more time as the user needs to type in a message, therefore show bigger engagement with the brand in the post. Writing a comment means that the customer is triggered by the message and wants to react. Shares, the third and last level of brand engagement shows the biggest association with the brand, compared to the other two levels. Sharing a post shows a connection between the user and the brand/message and it can be shown on the

user's timeline. Therefore, when a brand fan shares a post is most engaged than simply liking or even commenting on it.

Phua, Jin & Kim (2017), gave theoretical explanations of why consumers use different social media to connect with brands. Multiple social networking sites give different advantages to users in terms of different gratifications, such as, affection, engagement, or identification (Phua, Jin & Kim, 2017). The above study examined whether gratifications in social media are different between different social media platforms and more specifically Facebook, Instagram, Twitter and Snapchat. Moreover, studies that have used the UGT method, a framework that demonstrates why people reach different media to cover their needs (Katz et al., 1974), have showed that customers login in different platforms for entertainment, informational or social reasons. From the above we can lead to the first hypotheses of the study:

*H1: Social Media Platforms have different impact on brand engagement levels*

As we have classified the brand engagement levels in three categories: likes, comments and shares, we can further analyze the 1<sup>st</sup> hypotheses as follows:

*H1.1: Instagram has the highest brand engagement in terms of likes:*

Instagram, as it a visual image based social networking site where people can mainly post pictures or videos, is more frequently used by users as a style guide (Phua, Jin & Kim, 2017). Hence, as our study examines luxury fashion brands, we expect a higher possibility in likes than the other two media.

*H1.2: Twitter has the highest brand engagement in terms of comments (retweets)*

Twitter, being a microblogging site, makes people feel that they are part of a large brand community (Phua, Jin & Kim, 2017). Brands make updates very often and allow followers to retweet their posts, make questions as well they spread word of mouth. Being such an interacting platform, we expect higher levels in this level of brand engagement.

*H1.3 Twitter has the highest brand engagement in terms of shares*

As explained in H1.2, people perceive Twitter as a large brand community where they can share brand related objectives and interact with brands (Phua, Jin & Kim, 2017). Therefore, we expect higher brand engagement for shares compared to Facebook. A

reason for this can also be that in Facebook, the share option can be visible to more people (friends, friends of friends) hence users may feel less comfortable to share things.

Berger & Milkman (2009), investigated why specific part of online content become more viral than others. Their study focused on emotional aspects, altruistic purposes or self enhancement reasons. For example, users may share content to give information to others or appear knowledgeable. Eventually, they found out that positive content becomes more viral than negative. Additionally, sharing is social media can lead people to create connections with their followers, and force the feeling of belonging in a community. Consequently, in a similar way, this study supports that there are some post characteristics that drive likes, comments or shares higher. Hence, we can assume that:

*H2: Post Characteristics have impact on brand engagement levels*

For each of the post characteristics we have:

*H2.1 Hashtag use in posts have a positive impact on brand engagement levels*

As hashtags are an online tool of making the message more viral, we expect that hashtags will have a positive impact on all brand engagement. Through hashtags, users can learn more about a specific brand as by clicking on it, they can direct to all the posts made with this specific hashtag. Online users can also include hashtags in their posts as they make them funnier, more interacting and on trend.

*H2.2 Action words have a positive impact on brand engagement levels*

Words like ‘‘Click Here!’’ or ‘‘Visit the Site’’ make posts more interacting to online users. Therefore, we expect that people tend to like, comment or share more posts that contain action words.

*H2.3 Picture or videos included posts have a positive impact on brand engagement levels*

Since our study includes luxury fashion brands that address our aesthetic intention, we expect that images and audio have a positive effect on all three brand engagement levels.

## 3 Methodology

This chapter aims to present the methodology used in order to answer the research questions. It initially describes which data were used and the collection method. Then, it presents in detail how each of the message characteristics was evaluated, some examples of posts, as well as some valuable quantitative information. Next follows the empirical model that was used to analyze the data.

### 3.1 Data Collection Method

In order to see how the different social media platforms have an impact on brand engagement levels as well as how the post characteristics affect the possibility for people to like, comment or share, 150 posts in total were tested and empirically analyzed. Specifically, 50 same posts in the 3 social media (Facebook, Twitter, and Instagram) were measured in terms of likes, comments, shares, and retweets as also in terms of post characteristics like action words, use of hashtags or use of a picture or video. These posts were published from 13 luxury fashion brands during the period of March-April 2017. The reason why the luxury fashion market was chosen is because there is a lot of interaction with customers as it is an industry that is always on trend as well as is changing over time. Moreover, fashion is an attractive topic for both female and male and most of the luxury fashion brands operate online. The brands that were studied are: Manolo Blahnik, Prada, Dolce & Gabbana, Fendi, Chanel, Gucci, Louis Vuitton, Louboutin, Armani, Versace, Dior, Juicy Couture and Valentino. One of the main goals of this study is to examine if the same message in different social media platform has a different effect on brand engagement levels. As brand engagement levels, 1st level is the likes, 2nd level is comments, and 3d level is shares. The above can be influenced by post characteristics that are also analyzed. A use of hashtag can make the brand visible to multiple users, a video can raise the interaction with customers as it is more vivid, an action word can push the consumer to search and learn more about the brand and therefore enhancing brand engagement. Table 3.1 below summarizes the brands used, the number of page likes and followers in each social media platform as well as the number of posts used for each brand.

| Number | Brand           | Page Likes Facebook | Instagram Followers | Twitter Followers | Number of Posts |
|--------|-----------------|---------------------|---------------------|-------------------|-----------------|
| 1      | Manolo Blahnik  | 255.770             | 1.900.000           | 205.828           | 9               |
| 2      | Prada           | 6.093.443           | 12.600.000          | 800.084           | 9               |
| 3      | Dolce & Gabbana | 11.007.566          | 13.800.000          | 4.732.403         | 12              |
| 4      | Fendi           | 2.461.738           | 7.400.000           | 435.282           | 12              |
| 5      | Louis Vuitton   | 19.333.858          | 17.400.000          | 6.258.972         | 12              |
| 6      | Channel         | 19.193.127          | 22.200.000          | 12.937.127        | 9               |
| 7      | Gucci           | 16.038.972          | 15.400.000          | 4.411.333         | 15              |
| 8      | Louboutin       | 3.290.695           | 9.933.712           | 2.700.119         | 15              |
| 9      | Armani          | 8.139.001           | 8.413.019           | 3.178.578         | 9               |
| 10     | Versace         | 4.764.631           | 9.452.830           | 3.719.240         | 15              |
| 11     | Dior            | 15.976.564          | 15.871.897          | 7.592.187         | 15              |
| 12     | Juicy Couture   | 2.462.119           | 566.192             | 153.218           | 9               |
| 13     | Valentino       | 2.652.688           | 9.043.276           | 1.872.897         | 9               |

Table 3.1: Summary of page followers/fans per brand

## 3.2 Data Description

### Social Media Platform

We have studied and analyzed 150 posts in 3 different social media platforms. These 150 posts consist of 50 same posts across 3 different social media. The scope of this study is to examine if the same message in Facebook, Twitter and Instagram has a different impact on brand engagement as well as the effect of the post characteristics. Even though from the literature Facebook is supposed to be the most common online tool for companies to operate, we will see that Twitter and Instagram are also very highly used and important.

### Hashtags Use

Hashtags are a tool that companies use in order to reach a bigger consumer segment. Using the symbol ‘#’ and then typing a word or phrase can make the message visible to everyone that is searching for this specific word or phrase. Below you can find some examples:

“ gucciPhotographed by @dianelreare and styled by @joannahillman, a lurex shirt and pants with ruffle details from **#GucciSS17** seen in @harpersbazaarus.



**#GucciEditorials**” (Gucci, post on Instagram, March 9 2017, print screen is available in the appendix)

“ ROUGE COCO GLOSS. Simply irresistible. Take a look at the whole colour range. **#ILoveCoco** “ (Chanel, post on Facebook, March 4, 2017)

“Having fun whilst making a delicious meal in Napoli for the #DGTropicoItaliano Pasta shoot Photo by Morelli Brothers <http://bit.ly/2nIyWJc>”(Dolce & Gabbana, post on Twitter, March 28, 2017)

Table 3.2 shows the number of posts that included hashtags for each brand

| Number | Brand           | Posts with Hashtags Facebook | Posts with Hashtags Twitter | Posts with Hashtags Instagram |
|--------|-----------------|------------------------------|-----------------------------|-------------------------------|
| 1      | Manolo Blahnik  | 0                            | 1                           | 3                             |
| 2      | Prada           | 3                            | 3                           | 3                             |
| 3      | Dolce & Gabbana | 4                            | 4                           | 4                             |
| 4      | Fendi           | 1                            | 4                           | 4                             |
| 5      | Louis Vuitton   | 0                            | 4                           | 4                             |
| 6      | Chanel          | 1                            | 2                           | 3                             |
| 7      | Gucci           | 5                            | 5                           | 5                             |
| 8      | Louboutin       | 2                            | 1                           | 2                             |
| 9      | Armani          | 0                            | 3                           | 3                             |
| 10     | Versace         | 3                            | 3                           | 3                             |
| 11     | Dior            | 3                            | 5                           | 5                             |
| 12     | Juicy Couture   | 2                            | 2                           | 3                             |
| 13     | Valentino       | 0                            | 3                           | 3                             |

Table 3.2: Summary of posts with hashtags per brand

### Action words

Companies often use action words to encourage people act and engage with their brands. Expressions like ‘visit the site’, ‘take a look at the latest collection’, ‘shop this at’ are some phrases that companies use. Some examples are found below:

“We are an idea of mine. **Shop #PradaEyewear at <http://bit.ly/2mnqjjC>** “ (Prada, post on Twitter, March 14, 2017, print screen available in the Appendix)

“Timepieces to watch this season. **Find more models on** Armani.com/EmporioArmani. Emporio Armani Spring Summer 2017 advertising campaign captured by Lachlan Bailey.” (Armani, post on Facebook, March 23, 2017).

maisonvalentinoSneakers go punk. **Meet the new #VPunk Sneakers collection** by #PierpaoloPiccioli (Maison Valentino, post on Instagram, April 25, 2017)

Table 2.2 shows the number of posts that included action words for each brand

| <b>Number</b> | <b>Brand</b>    | <b>Posts with Action Words Facebook</b> | <b>Posts with Action Words Twitter</b> | <b>Posts with Action Words Instagram</b> |
|---------------|-----------------|---|--|--|
| <b>1</b>      | Manolo Blahnik  | 0                                       | 0                                      | 0  |
| <b>2</b>      | Prada           | 3                                       | 3                                      | 2  |
| <b>3</b>      | Dolce & Gabbana | 0                                       | 0                                      | 0  |
| <b>4</b>      | Fendi           | 2                                       | 2                                      | 1  |
| <b>5</b>      | Louis Vuitton   | 4                                       | 3                                      | 1  |
| <b>6</b>      | Chanel          | 1                                       | 1                                      | 0  |
| <b>7</b>      | Gucci           | 1                                       | 0                                      | 1  |
| <b>8</b>      | Louboutin       | 2                                       | 0                                      | 2  |
| <b>9</b>      | Armani          | 3                                       | 3                                      | 2  |
| <b>10</b>     | Versace         | 4                                       | 4                                      | 1  |
| <b>11</b>     | Dior            | 1                                       | 2                                      | 1  |
| <b>12</b>     | Juicy Couture   | 2                                       | 2                                      | 2  |
| <b>13</b>     | Valentino       | 3                                       | 3                                      | 3  |

Table 3.3: Summary of posts with action words per brand

### Picture or Video Included

All the posts that were studied had a picture or a video included together with the message. In social media, posts that contain pictures and videos make the message more interacting, vivid, and thus companies get closer to the user. Most of the times, pictures are more often used than videos but as the results will indicate, videos have a bigger effect in brand engagement.

The table below shows the number of posts that included a picture as also the ones that included a video for each brand. As long as the same posts were studied for the 3 platforms, only one table is needed to be created

| <b>Number</b> | <b>Brand</b>    | <b>Posts with Pictures</b> | <b>Posts with Videos</b> |
|---------------|-----------------|----------------------------|--------------------------|
| <b>1</b>      | Manolo Blahnik  | 1                          | 2                        |
| <b>2</b>      | Prada           | 1                          | 2                        |
| <b>3</b>      | Dolce & Gabbana | 3                          | 1                        |
| <b>4</b>      | Fendi           | 3                          | 1                        |
| <b>5</b>      | Louis Vuitton   | 3                          | 1                        |
| <b>6</b>      | Chanel          | 0                          | 3                        |
| <b>7</b>      | Gucci           | 4                          | 1                        |
| <b>8</b>      | Louboutin       | 4                          | 1                        |
| <b>9</b>      | Armani          | 2                          | 1                        |
| <b>10</b>     | Versace         | 3                          | 2                        |
| <b>11</b>     | Dior            | 1                          | 4                        |
| <b>12</b>     | Juicy Couture   | 2                          | 1                        |
| <b>13</b>     | Valentino       | 1                          | 2                        |

Table 3.4: Summary of posts with pictures and videos per brand

#### Days since post

This variable will also be added to the model. The post studied were published from the brands the period March - April 2017. However, the number of likes, comments and shares measured were until the day of their recording by the researcher. So, days since post are referring to the difference between the day that the posts were made and the recording day. That can influence their total number since more recent posts had less time on the brand pages so may have received less likes, comments, or shares from the older ones.

#### Total Page likes/followers

The total likes of each brand page as well as the number of followers are needed in order to compare the number of likes, comments and shares a post gets in an equal base. This is because some brands are more popular than others and may have much more page likes or that a social media platform may attract more traffic than others. Thus, each of the number of likes, comments and shares per post was divided with

the total number of page likes and used as the dependable variables. As total page likes/followers, the numbers that were used were the ones at the day of the recording. This may have influenced the results as the total page likes/followers is changing every single day, therefore it may affect the number of likes, comments or shares a post has. The number of brand fans on each of the 3 social media, Facebook, Titter and Instagram, are shown in the table 3.1.

Due to the fact that the quotients of the likes/comments/shares to the total page likes were between 0-1, they were log transformed (natural logarithm). While the transformation took place, the  $(\text{page likes}+1)/\text{total page likes}$  was used as the equation in order to take into consideration posts that received 0 comments or shares. From now on, when mentioning the words likes, comments, shares in the statistical analysis we refer to the log transformed ratio of them divided by the total page likes of each brand.

### 3.3 Empirical Model

In order to test the effect of the 3 social media in brand engagement levels, the impact of different post characteristics on likes, comments and shares as well as the interactions of social media with these characteristics, a linear regression model was used.

According to Janssens et al. (2008) regression analysis is a method which is used to examine how the dependent interval-or ratio-scaled variable and one or more independent interval-or ratio-scaled variables are correlated. To elaborate, this technique tries to explain the variation in one dependent variable as much as possible on the basis of the variation in a number of relevant independent variables. The general form of the regression model is expressed as follows:

$$Y = b_0 + b_1X_1 + b_2X_2 + \dots + b_nX_n + \varepsilon$$

Where Y = dependent variable

$X_i$  = independent variable

$b_i$  = parameter to be estimated, coefficient

$\varepsilon$  = disturbance term (error)

In this study, our aim is to measure the effect of Facebook, Instagram and Twitter as well as the impact of post characteristics on likes, comments and shares, which are defined as brand engagement levels. The comments correspond to retweets on Twitter and the shares to replies.

Some of the variables are expressed by nominal variables, so the creation of dummies was essential for this study. Dummy variables can take the value of 0 or 1. The value 0 demonstrates the absence of the post characteristic while the value 1 indicates the presence of the attribute. Dummy variables are used as devices to sort data into mutually exclusive categories so the number to be created is equal to the number of possible answers for the nominal variable minus 1 (Gujarati 2003, Janssens et al., 2008). For this study, 5 dummy variables should be created:

- 2 dummies were used to indicate the type of social media

Facebook serves as the baseline category

- D1= Twitter, it takes the value 0 when the post is not on Twitter and the value 1 when the post is on Twitter
- D2= Instagram, it takes the value 0 when the post is not on Instagram and the value 1 when the post is on Instagram
- 1 dummy variable measuring the existence of hashtags
- D3= hashtags use, it takes the value 0 when there is no hashtag included in the post and the value 1 when there is use of hashtag (s)
- 1 dummy variable measuring the existence of pictures or videos
- D4= picture or video included, it takes the value 0 when there is a picture included in the post and the value 1 when there is a video
- 1 dummy variable measuring the existence of action words
- D5= action words included, it takes the value 0 when there is not a use of action words in the post and the value 1 when there is

In the study 3 linear regression were studied, each one for the different level of brand engagement: likes, comments and shares. For the shares model, only Facebook and Instagram were used because in Instagram shares are not applicable. Therefore, the study contains 3 dependent variables that will be measured and are affected from some independent variables. The number of independent variables is different in the last regression analysis (shares model) for the reason described above.

The dependent variables are:

1. **Likes:**  $\ln(\text{post likes}/\text{page likes})$
2. **Comments:**  $\ln((\text{post comments}+1)/\text{page likes})$
3. **Shares:**  $\ln((\text{post shares}+1)/\text{page likes})$

Again, as explained before, the words likes, comments and shares in the statistical analysis are referred to the ratio between the likes/comments/shares and the total page likes of each brand that has been log transformed (natural algorithm).

For the **likes** and **comments** models the independent variables are:

1. **Days Since Post:** indicating the number of days that passed from the publication of the post and the recording of the post likes, comments and shares
2. **Hashtags Use:** dummy indicating if the post contains hashtags or not (0 for false, 1 for true)
3. **Action Words:** dummy indicating if the post contains action words or not (0 for false, 1 for true)
4. **Picture or Video:** dummy indicating if the post contains a picture or a video (0 for picture, 1 for video)
5. **Twitter\_Action Words:** tests the interaction between posts on Twitter and use of action words in those posts
6. **Twitter\_Picture or Video:** tests the interaction between posts on Twitter and picture or video included in those posts
7. **Twitter:** dummy indicating if the post is on Twitter (0 for false, 1 for true)
8. **Instagram\_Action Words:** tests the interaction between posts on Instagram and use of action words in those posts

9. **Instagram\_Picture or Videos:** tests the interaction between posts on Instagram and picture or video included in those posts
10. **Instagram:** dummy indicating if the post is on Instagram (0 for false,1 for true)

For the **shares** model, the independent variables are:

1. **Days Since Post:** indicating the number of days that passed from the publication of the post and the recording of the post likes, comments and shares
2. **Hashtags Use:** dummy indicating if the post contains hashtags or not (0 for false, 1for true)
3. **Action Words:** dummy indicating if the post contains action words or not (0 for false, 1 for true)
4. **Picture or Video:** dummy indicating if the post contains a picture or a video (0 for picture, 1 for video). All the posts in the study contained either pictures or videos.
5. **Twitter\_Action Words:** tests the interaction between posts on Twitter and use of action words in those posts
6. **Twitter\_Picture or Video:** tests the interaction between posts on Twitter and picture or video included in those posts
7. **Twitter\_Hashtags:** tests the interaction between posts on Twitter and use of hashtags on those posts
8. **Twitter:** dummy indicating if the post is on Twitter (0 for false, 1 for true)

The three models that will be tested are:

$$\text{Likes}_i = b_0 + b_1 \text{ Days\_Since\_Post} + b_2 \text{ Hashtags\_Use} + b_3 \text{ Action\_Words} + b_4 \text{ Picture\_or\_Video} + b_5 \text{ Twitter\_Action\_Words} + b_6 \text{ Twitter\_Picture\_or\_Video} + b_7 \text{ Twitter} + b_8 \text{ Instagram\_Action\_Words} + b_9 \text{ Instagram\_Picture\_or\_Video} + b_{10} \text{ Instagram} + \epsilon_i$$

$$\mathbf{Comments}_i = b_0 + b_1 \text{ Days\_Since\_Post} + b_2 \text{ Hashtags\_Use} + b_3 \text{ Twitter} + b_4 \text{ Action\_Words} + b_5 \text{ Picture\_or\_Video} + b_6 \text{ Twitter\_Action\_Words} + b_7 \text{ Twitter\_Picture\_or\_Video} + b_8 \text{ Instagram} + b_9 \text{ Instagram\_Picture\_or\_Video} + b_{10} \text{ Instagram\_Action\_Words} + \epsilon_i$$

$$\mathbf{Shares}_i = b_0 + b_1 \text{ Days\_Since\_Post} + b_2 \text{ Hashtags\_Use} + b_3 \text{ Twitter} + b_4 \text{ Action\_Words} + b_5 \text{ Picture\_or\_Video} + b_6 \text{ Twitter\_Picture\_or\_Video} + b_7 \text{ Twitter\_Hashtags} + b_8 \text{ Twitter\_Action\_Words} + \epsilon_i$$

where  $b_0$  = constant

$b_1, b_2, b_3, b_4, \dots, b_{13}$  = coefficients of the independent variables

$i$  represents a wall post

$\epsilon_i$  = error



## 4 Results

This chapter provides a detailed analysis of the results after a linear regression model is run with the SPSS program. First, the checks needed for the model are discussed and then the interpretation of each variable is presented as evaluated from the coefficients of the independent variables.

### 4.1 Linear Regression Analysis

The method used in this study is the linear regression which shows the relationship between the independent and dependent variables. With the models used, the variance of the dependent variables -likes, comments, shares- will be explained by the various independent examined variables- the wall posts characteristics.

Before we move to the analysis of the relation between the variables we must check some important assumptions, as well as the meaningfulness of the models (Janssens et al. 2008). The two most important assumptions to be tested are the independence of the residuals and the multicollinearity issue.

#### 4.1.1 Error Distribution and Multicollinearity Check

As we can observe from the histogram and the normal probability plot provided in the Appendix, the residuals are not normally distributed for any of the three modes (likes, comments, shares) as the distributions do not follow the shape of a normal curve. Furthermore, the Durbin Watson values (1.592, 1.686, 1.568) for likes, comments and shares respectively, are inconclusive and indicate that there is autocorrelation in residuals. The table of Casewise diagnostics indicates in all cases the residuals are out of the accepted limits. To fix that, the bootstrapping method was performed for all the 3 models. After bootstrapping, all the models seem accurate regarding their error distribution.

Additionally, checking the multicollinearity of the independent variables is essential. There are a number of indicators that can show the existence of multicollinearity (e.g. VIF, Tolerance or Condition index). For example, a VIF indicator greater than 10 reveals a multicollinearity problem (Myers, 1990). As we can see in the Collinearity

Statistics (Appendix) none of independent variables in all the models examined face such an issue. In addition, we can come to the same conclusion if looking at the Tolerance indicator. All the Tolerance values of the independent variables are greater than 0,1 so no strong multicollinearity exist among the variables.

#### 4.1.2 Interpretation of Results

To see if there is meaningfulness in the results, we need to check the p-value (sig.) from the ANOVA table provided in the Appendix. The number equals to zero for all the three models, indicating that they are meaningful. Since the p-value is lower than 0,001, we can predict better the dependent variables. More specifically, for the likes model  $F=29,228$  ( $P<0.001$ ), for the comments model  $F=9,885$  ( $P<0.001$ ) and for the shares model  $F=12,366$  ( $p<0.001$ ). Hence, we can further interpret the ‘‘Adjusted R Square ‘‘ and the relation of the variables placed in the ‘‘Coefficients’’ table.

In the table of ‘‘Model Summary’’ (Appendix) it is useful to examine the ‘‘Adjusted R Square’’ as it explains the variation of the dependent variable. As a result, the 65,5 % of the variation of the number of likes is explained by the variation of the ten independent variables that were included in the model. Likewise, the 37,4% of the variation of the comments and the 47,9% of the variation of shares are explained by the variation of the independent variables.

As a result, our models run by the regression analysis in SPSS indicate that the results show significant information about how users’ interaction with Facebook, Instagram and Twitter is explained by certain posts as measures by the number of likes, comments and shares. As explained above, the multicollinearity check and the independence of errors after the bootstrapping, helps us proceed with the interpretation of the results of the coefficients in order to see which social media platform has the strongest impact on the three levels of brand engagement (likes, comments and shares) as well as how the post characteristics influence members to like, comment or share on a post and toward which direction. The interpretation will be per feature for each of the three models. The summary of the results that will follow can be seen on table 4.1.

| Independent Variables    | Dependent Variables |        |          |       |         |       |
|--------------------------|---------------------|--------|----------|-------|---------|-------|
|                          | Likes               |        | Comments |       | Shares  |       |
|                          | B                   | Sig.   | B        | Sig   | B       | Sig   |
| Constant                 | -7.153              | .000*  | -11.945  | .000* | -10.651 | .000* |
| Days_since_post          | -.006               | .393   | -.004    | .631  | -.002   | .884  |
| Hashtags_use             | -.378               | .077** | -.380    | .109  | -.815   | .048* |
| Action_words             | -.199               | .503   | -.428    | .116  | -.606   | .137  |
| Picture_or_video         | -.509               | .089** | .721     | .030* | 1.616   | .000* |
| Twitter_action_words     | .047                | .911   | .318     | .496  | .657    | .260  |
| Twitter_picture_or_video | .329                | .439   | .273     | .563  | -1.170  | .046* |
| Twitter                  | -1.485              | .000*  | 2.000    | .000* | -2.573  | .000* |
| Instagram Action Words   | -.041               | .925   | .122     | .799  | -       | -     |
| Instagram_Picture_Video  | -.935               | .027*  | -.604    | .197  | -       | -     |
| Instagram                | 2.615               | .000*  | 1.749    | .000* | -       | -     |
| Twitter_hashtags_use     | -                   | -      | -        | -     | .757    | .235  |
| R Square                 | .678                |        | .416     |       | .521    |       |
| Adjusted R Square        | .655                |        | .374     |       | .479    |       |
| Sample Size              | 150                 |        | 150      |       | 100     |       |

\*p < .05, \*\*p < .10

Table 4.1: Regression Results

#### 4.1.2.1 Social Media Type

To see which social media platform (Facebook, Instagram or Twitter) has the greatest impact on brand engagement levels, Facebook served as the baseline and two dummy variables were created for Instagram and Twitter. Except for the main variables, interactions were created to measure the combinations of the social media type and post characteristics. The reason behind this is to examine in each platform which post feature is more favorable for making users like, comment or share the post. The interactions hashtags on twitter and hashtags on Instagram were excluded for the likes and comments model, and the hashtags on Instagram from the shares model, because there was a high degree of collinearity.

For the likes model, both Twitter and Instagram appear to be statistically significant compared to Facebook, with  $p < 0.05$ . To see which of the three social media platforms has the biggest impact on likes, we look at the B values. As the B value for Twitter is negative (-1.485), it helps us conclude that Twitter has a weaker influence on users on likes than Facebook, when all interacted dummies are zero. On the other hand, the B value for Instagram is positive (2.615) and therefore makes this platform stronger on the likes level than Facebook. We should also note that because Facebook is the same reference group for each of the other two dummies, we can directly compare each of the social media types to one another. Therefore, we can say that Instagram has a more positive influence than Twitter ( $2.615 > -1.485$ ). To conclude, the results above indicate that first, there is significant difference between the three social media types and that Instagram has the biggest effect on them. This can validate H1.1 hypotheses. As explained in chapter 2, Instagram is heavily used as a style guide and for fashion purposes and drives engagement. Hence, it makes sense that people tend to like more Instagram posts to express their likeliness to brands.

For the comments model, we can see that Twitter and Instagram are also statistically significant compared to Facebook, with  $p < 0.05$ . Looking at the B values in the comments model, it is clear that both Twitter and Instagram are influencing more people to comment on post, with B's equal to 2.000 and 1.749 respectively. The above helps us conclude that in the comments level, Twitter is the platform that triggers more comments, compared to Facebook and Instagram. This finding validates H1.2

hypotheses which states that Twitter as a microblogging site, makes people feel that they belong in a large community. Therefore, they feel comfortable to share and show their emotions, learn and exchange information.

Last, for the shares model as mentioned before, only Twitter was used as in Instagram the share option is not feasible. From the table above we can see that the difference between Facebook and Twitter is statistical significant, as  $p < 0.05$ . From the B value of Twitter, we can jump into the conclusion that in the shares level, Facebook has stronger impact than Twitter, therefore is more engaging to users. This finding rejects the H1.3 hypotheses. A reason for this may be that since we examine luxury fashion brands and Facebook is the platform that users have the biggest number of followers, sharing fashion posts can favor their need of being liked and ‘on trend’.

From the above we can validate our hypothesis that social media platforms have different impact on brand engagement. The interactions between the social media types and the post characteristics will be discussed in the ‘‘additional analysis’’ paragraph later.

#### *4.1.2.2 Days Since Post*

This variable was added to the model since the recording day was different from the day of the post. The reason behind this was to take into consideration posts that may later have received more likes, comments or shares. The analysis shows that there is no significant effect of the days since post to any of the brand engagement levels: likes, comments and shares, as in all three models  $p > 0.05$ . We therefore conclude that most of the posts receive likes, comments and shares the first days of their publication. Only a small number of them is received after long time has passed.

#### *4.1.2.3 Hashtag Use*

This dummy variable explained the existence of hashtags in posts (1 for true, 0 for false). According to literature, hashtags are used to attract attention and make the post visible to a larger audience. By clicking on a hashtag, a user can see all the posts made with this hashtag by the same or other brand. Therefore, companies enhance brand awareness and engagement.

For the likes model, we can see from the table above that the main effect of hashtags is significant with  $p < 0.01$ . The same happened with the shares with  $p < 0.05$ . On the other hand, the effect of hashtags on the comments level is not significant with  $p > 0.05$ . Hence, H2.1 hypothesis is both validated and rejected. For the comments, this finding can be explained since hashtags trigger more awareness and likeness of the brand advertised on the post. Moreover, as fashion brands were examined, people tend to like or share more fashion posts than commenting on them.

#### *4.1.2.4 Action Words*

A dummy was created for this variable in order to see if the use of action words has an effect on the interaction with fans on a likes-comments-shares level (1 for true, 0 for false). The dummy seems to be insignificant for all the three models, as  $p > 0.05$ . This means that the use of action words in posts do not have an impact on likes, comments and shares. This rejects the H2.2 hypothesis. The main reason for this is probably because most of the posts selected for this study had a small number of action words used.

#### *4.1.2.5 Picture or Video Included*

A dummy was created for this variable to indicate if the use of a picture or a video in a post encourages brand fans to like, comment or share (0 for picture, 1 for video). For the likes model, there is a significant effect of videos used (coded as 1) with  $p < 0.01$ . Therefore, videos have a positive impact on likes, something that validates the H2.3 hypotheses. From the B value of the variable and since picture is coded with 0, we can support that pictures affect the likes -0.509 less than videos.

The same exists for the comments model, as we can see from the table that the use of a video is statistically significant with  $p < 0.05$ . From the B value however, we can see that pictures have a stronger effect than videos as  $B = 0.721$ .

For the shares model, it is noticeable that the variable is highly statistically significant with  $p < 0.05$ , validating also the H2.3 hypothesis. Like the comments model, pictures are also here affecting more the shares than videos as  $B = 1.616$ .

#### 4.1.3 Additional Analysis

Except for the main effects of post characteristics on brand engagement levels, the interactions were also studied. It was found that the interaction of Instagram with picture or video included posts has a strong effect on the likes when picture or video included posts on Twitter enhance shares with  $p$  values  $< 0.05$  .

All the other interactions were found to be insignificant while for the likes and shares models the interactions of hashtags with social media types were found to have multicollinearity so they were excluded from the study.

## 5 Discussions and Implications

In this chapter, the results will be discussed together with some noticeable conclusions. Furthermore, the way these results can be applicable for marketers and how the last can leverage from them to implement marketing strategies will be highlighted.

### 5.1 Conclusions

This study was developed to examine the influence that different social media have in brand engagement. Users are everyday interacting in multiple ways with brands. When companies have a strong online presence, affect the relationship they have with consumers and get closer to them. The 3 different platforms that were studied are Facebook, Twitter, and Instagram. To measure brand engagement, 150 wall posts were analyzed by 13 luxury fashion brands in total. The posts for each brand were the same in each social media platform. The reason for this was to see how different post characteristics have an impact on brand engagement levels on each platform. As brand engagement levels, likes were defined as the first, comments as the second and shares as the third. For Twitter, the comments correspond to retweets and the shares for replies. For Instagram, only likes and comments were measured, as the shares option is not applicable. As we move on to the levels, the bigger the brand engagement is. To elaborate, people tend to more easily like a post on a brand fan page, as it is just a click. Commenting on it means they do devote time and are concerned about the brand. Last, when users share the post, it means they are getting engaged to it and want their friends/followers to see it as well.

Concerning the different post characteristics, the use of hashtags, action words, the picture or video included as well as they days since post were evaluated. These characteristics are the one that are more commonly used by brands and therefore have an impact on the likability to like, comment or share the post.

Regarding the social media type, the results varied. For the likes level of brand engagement, it was found that firstly, there is statistical difference between the 3 platforms, with Instagram winning the first place. It is more likely for online users to like a post on Instagram than Facebook or Twitter. This is somehow surprising as the



media that is used more is supposed to be Facebook. The reasoning behind this, though, may be that Instagram is gaining ground extremely fast and it is becoming very popular to people. Especially for the luxury fashion market, which is the one that was chosen for the study, most of the brands are operating on Instagram and post pictures and videos in a daily basis. In addition, regarding the second level of brand engagement, there is also significant difference in the three platforms, meaning that each one of them affects differently online users. It was eventually found that Twitter is the one that has the stronger impact. This was also not expected for this kind of market, as Twitter is a media that is more informative and politically oriented. The results though are indicating that there is an interaction with consumers concerning brands that cannot be overseen. Lastly, in the third model of shares, Facebook was found to be more appealing to users for this level of brand engagement. This is somehow expected, as in this level only Facebook and Twitter were considered and people are more easily to share a post on their Facebook page than writing a reply in Twitter (reply was corresponded to 'share' as it takes more concern regarding the brand in order to write a reply than retweet the post). Finally, each social media type seems to be significantly important and affects in a different way the online users.

With reference to the hashtags used in posts, the study indicated that hashtags are important when people are about to like or share the post and not comment/retweet it. Hashtags are used to create a buzz through the brand and target a larger audience. Hence, it is not surprising that they influence likes and shares, as this is the reason why they are used; to attract attention and make people interact with the brand.

As far as action words are concerned, the study showed that there is no significant impact on brand engagement levels not only as a main effect but also as interaction with the different social media types. Using action words in posts like "visit the link" or "shop the new collection" do not affect likes, comments, or shares. This can be explained in a way; the main purpose of the action words in posts is to make people make actions like visiting the brands webpage or go to the store. They are aiming to create a stronger relationship with customers, not specifically in social media but also outside of them.

Last but not least, the posts that were analyzed contained either a picture or a video. By using pictures and videos, posts are more vivid and interacting. The use of colors and

sounds are more likely to attract people's attention that's why most of the posts are including this type of characteristics, especially in the fashion industry. The results here indicate that videos are highly engaging compared to pictures in all the three levels of brand engagement. In the likes level, videos on Instagram have the strongest impact compared to the other social media. In the comments level, there is no difference between Facebook, Twitter or Instagram regarding this characteristic. Lastly, videos on Twitter are influencing significantly users to reply on posts. Finally, days since post were found to be indifferent for brand engagement levels.

To sum up, marketers that operate the brand fan pages on Facebook, Twitter or Instagram, should take into account some specific post characteristics as their use may have an impact on the brand engagement levels and the relationship with the fans. How to use the different media is of great importance, as videos are really engaging on Instagram for likes and using hashtags in all the three platforms can make users engaged.

## 5.2 Managerial Implications

Social media channels are the means through brands are approaching consumers. Having a strong online presence can achieve great results in terms of brand awareness and engagement. As long as everything is turning digital, people are spending more and more time on social media to look, shop or ask for brands. It is therefore crucial for companies and marketers to implement the optimal online marketing strategies in order to reach their fans. In that way, companies can build relationships, advertise effectively their products and expand their potential customers through social media channels. This online presence need to be designed carefully so the best results would be accomplished. According to the current study there are some directions that companies could follow to maximize interaction trough posts. There directions include some post characteristics that brand posts should involve in increasing the number of likes, comments or shares they receive.

To begin with, brands should operate in all three social media platforms. When collecting the data from the posts it was noticeable that most of the times brands were posting more on Instagram (approx. 2-3 posts per day), less on Facebook (approx. 1 post per day) and the least on Twitter (approx. 1 post per 2 days). The results showed that there is significant difference between all the three platforms, meaning that is important

for brands to operate in all of them if they want to achieve the optimal results. Being more active on Instagram can make them lose ground from Facebook and vice versa.

Furthermore, as the results indicate, marketing managers should consider using hashtags in all the 3 platforms. While hashtags were originally born in Twitter, using them in Facebook and Instagram can have also positive results. Hashtags make the messages visible to a bigger target, can give people content that is useful and can inform them about a certain topic, therefore making them get closer to it.

Additionally, as results showed, the videos in posts are significantly important for brand engagement as well. Videos are leading brand engagement as they are vivid, have sound and hence interact more with online users. In a video, a consumer can see the different features of a brand and its dimensions. He or she can learn about the brand story and get informed about various aspects. The study revealed that videos on Twitter are highly engaging, hence companies should consider using more videos on their brand posts on this media. Videos can increase likes, comments and shares, as they provide a small story regarding the brand and can provoke feelings, questions and likeliness.

By doing the above, managers can get closer to their fans and obtain a strong online presence. They can leverage from certain post characteristics and together with an active online strategy in all the 3 social media platforms, companies can get their fans more engaged.

## 6 Limitations and Future Research

After the results of the data analysis, as well as the practical implications for marketers, the limitations of this study and suggested future research will be discussed in this chapter.

Marketers and managers must take into consideration some limitations before they apply the implications of the study in Facebook, Twitter and Instagram.

To begin with, the number of brands that were studied may be limited. Only 13 brands were taken into consideration and from a specific market, the luxury fashion one. So, the results may be not that accurate. Future researchers would better to investigate the possibilities that a bigger number of brands have and from a broader market. The luxury fashion industry was chosen because people can get easily engaged with fashion (clothes, shoes, accessories), as the purchases are basically made from emotional reasons like self-confidence, prestige, and the feel of being liked. Consequently, future research could choose more product sectors for more variation. Furthermore, the period that was chosen was restricted, so a longer period could give better results.

Another limitation of the research may be that the total page likes that were used in the model as well as the number of likes, comments, and shares in the 3 social media platforms were taken the day of the recording. This may have an impact on the results, as brand pages and posts may have received more followers, likes, comments and shares the following days.

In addition, only some post characteristics were included and measured in the analysis. More post characteristics could be studied, as the use of celebrity endorsements on posts, the use of questions or the day of the post, if it is made on weekdays or weekend. There are also some other reasons a person may like, comment or share the post. This can be personal preferences, the attitude towards social media, the mood at the time the user sees the post and his willingness to share information. Word of mouth is also in the game, so a user can like a post because his friend did so. Other reasons but post characteristics that influence online users are open to future research, like social ones. Another study could investigate how much the brand likeliness comes from the word of mouth in social media. Moreover, the days and the time that the posts are made can

be studied, as for the companies to know when to post and share information about their brands.

Last but not least, as the posts were analyzed and evaluated only by one researcher, more people should participate in the evaluation in order to be more accurate. Another idea for future research could be to study how other networking sites as YouTube, Pinterest, LinkedIn lead to brand engagement.

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## Appendix

### Example of Hashtags Use



gucci Photographed by @dianelreare and styled by @joannahillman, a lurex shirt and pants with ruffle details from #GucciSS17 seen in @harpersbazaarus. #GucciEditorials

load more comments

luc.ker Flamingo

mxstr.piece 🍷🍷🍷🍷🍷🍷🍷🍷🍷🍷🍷🍷

suaveymoderna W❤️W

leterrible 🍷🍷

artofbodyweight Make a dress On a scale of one to 1000

jenpatryn 🍷🍷🍷🍷🍷

rat\_head Yes

derinseyo TAE FOR GUCCI

bpazpaz Parece un extraterrestre 🍷

grdaccessorios 🍷🍷🍷

62,116 likes

MARCH 9

Add a comment...

### Example of Actions Words Used



PRADA PRADA ✓  
@Prada Follow

We are an idea of mine.  
Shop #PradaEyewear at [bit.ly/2mnqjjC](https://bit.ly/2mnqjjC)

11:00 AM - 14 Mar 2017

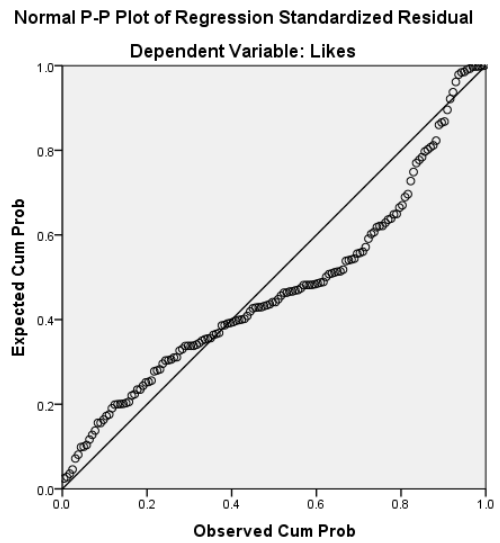
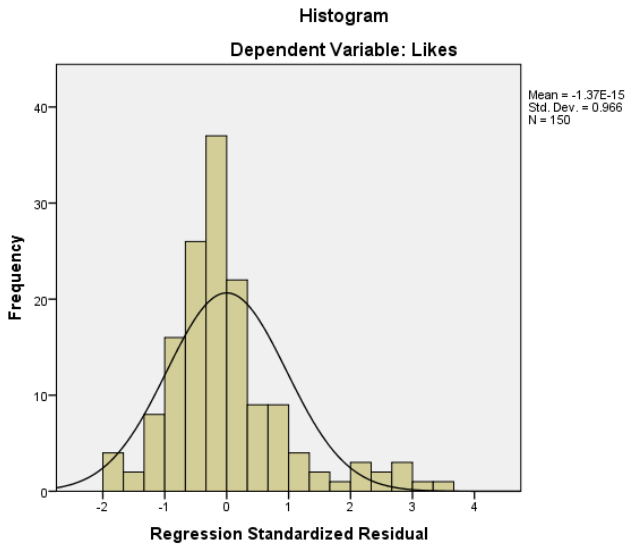
47 Retweets 121 Likes

1 47 121



# Regression Analysis Results

## 1) Likes Model



**Model Summary<sup>b</sup>**

| Model | R                 | R Square | Adjusted R Square | Std. Error of the Estimate | Durbin-Watson |
|-------|-------------------|----------|-------------------|----------------------------|---------------|
| 1     | .823 <sup>a</sup> | .678     | .655              | 1.034                      | 1.532         |

a. Predictors: (Constant), Instagram, Days Since Post, Picture or Video Included, Action Words Included, Hashtags Use, Twitter\_Action Words, Twitter\_Picture or Video Included, Instagram Action Words, Instagram Picture or Videos, Twitter

b. Dependent Variable: Likes

**ANOVA<sup>a</sup>**

| Model |            | Sum of Squares | df  | Mean Square | F      | Sig.              |
|-------|------------|----------------|-----|-------------|--------|-------------------|
| 1     | Regression | 312.749        | 10  | 31.275      | 29.228 | .000 <sup>b</sup> |
|       | Residual   | 148.734        | 139 | 1.070       |        |                   |
|       | Total      | 461.483        | 149 |             |        |                   |

a. Dependent Variable: Likes

b. Predictors: (Constant), Instagram, Days Since Post, Picture or Video Included, Action Words Included, Hashtags Use, Twitter\_Action Words, Twitter\_Picture or Video Included, Instagram Action Words, Instagram Picture or Videos, Twitter

**Coefficients<sup>a</sup>**

| Model                             | Unstandardized Coefficients |            | Standardized Coefficients | t      | Sig. | 95,0% Confidence Interval for B |             | Collinearity Statistics |       |
|-----------------------------------|-----------------------------|------------|---------------------------|--------|------|---------------------------------|-------------|-------------------------|-------|
|                                   | B                           | Std. Error | Beta                      |        |      | Lower Bound                     | Upper Bound | Tolerance               | VIF   |
|                                   |                             |            |                           |        |      |                                 |             |                         |       |
| 1 (Constant)                      | -7.153                      | .581       |                           | 12.304 | .000 | -8.302                          | -6.004      |                         |       |
| Days Since Post                   | -.006                       | .007       | -.042                     | -.857  | .393 | -.020                           | .008        | .966                    | 1.035 |
| Hashtags Use                      | -.378                       | .212       | -.099                     | -1.779 | .077 | -.798                           | .042        | .753                    | 1.327 |
| Action Words Included             | -.199                       | .297       | -.056                     | -.672  | .503 | -.786                           | .387        | .330                    | 3.032 |
| Picture or Video Included         | .509                        | .297       | .144                      | 1.713  | .089 | -.078                           | 1.096       | .329                    | 3.038 |
| Twitter_Action Words              | .047                        | .420       | .010                      | .112   | .911 | -.784                           | .878        | .311                    | 3.213 |
| Twitter_Picture or Video Included | .329                        | .424       | .074                      | .776   | .439 | -.509                           | 1.167       | .255                    | 3.925 |
| Twitter                           | -1.485                      | .407       | -.399                     | -3.651 | .000 | -2.289                          | -.681       | .194                    | 5.155 |
| Instagram Action Words            | -.041                       | .433       | -.007                     | -.094  | .925 | -.897                           | .816        | .399                    | 2.506 |
| Instagram Picture or Videos       | -.935                       | .419       | -.189                     | -2.229 | .027 | -1.764                          | -.106       | .324                    | 3.086 |
| Instagram                         | 2.615                       | .342       | .703                      | 7.638  | .000 | 1.938                           | 3.291       | .274                    | 3.650 |

a. Dependent Variable: Likes

**Casewise Diagnostics<sup>a</sup>**

| Case Number | Std. Residual | Likes | Predicted Value | Residual |
|-------------|---------------|-------|-----------------|----------|
| 1           | 2.845         | -5    | -7.71           | 2.943    |
| 2           | 2.848         | -4    | -7.13           | 2.946    |
| 15          | 3.085         | -5    | -7.87           | 3.191    |
| 16          | 2.928         | -5    | -7.78           | 3.028    |
| 18          | 2.355         | -5    | -7.17           | 2.436    |
| 21          | 2.173         | -5    | -6.97           | 2.248    |
| 62          | 2.152         | -7    | -8.98           | 2.227    |
| 68          | 3.487         | -5    | -8.98           | 3.607    |
| 95          | 2.457         | -7    | -9.27           | 2.542    |
| 118         | 2.031         | -4    | -5.66           | 2.101    |

a. Dependent Variable: Likes

**Residuals Statistics<sup>a</sup>**

|                      |                | Statistic | Bootstrap <sup>b</sup> |            |                         |       |
|----------------------|----------------|-----------|------------------------|------------|-------------------------|-------|
|                      |                |           | Bias                   | Std. Error | 95% Confidence Interval |       |
|                      |                |           |                        |            | Lower                   | Upper |
| Predicted Value      | Minimum        | -9.37     |                        |            |                         |       |
|                      | Maximum        | -4.90     |                        |            |                         |       |
|                      | Mean           | -7.44     | .00                    | .15        | -7.72                   | -7.14 |
|                      | Std. Deviation | 1.449     | .022                   | .070       | 1.331                   | 1.610 |
|                      | N              | 150       | 0                      | 0          | 150                     | 150   |
| Residual             | Minimum        | -2.031    |                        |            |                         |       |
|                      | Maximum        | 3.607     |                        |            |                         |       |
|                      | Mean           | .000      | .000                   | .000       | .000                    | .000  |
|                      | Std. Deviation | .999      | -.042                  | .086       | .782                    | 1.118 |
|                      | N              | 150       | 0                      | 0          | 150                     | 150   |
| Std. Predicted Value | Minimum        | -1.332    |                        |            |                         |       |
|                      | Maximum        | 1.754     |                        |            |                         |       |
|                      | Mean           | .000      | .000                   | .000       | .000                    | .000  |
|                      | Std. Deviation | 1.000     | .000                   | .000       | 1.000                   | 1.000 |
|                      | N              | 150       | 0                      | 0          | 150                     | 150   |
| Std. Residual        | Minimum        | -1.963    |                        |            |                         |       |
|                      | Maximum        | 3.487     |                        |            |                         |       |
|                      | Mean           | .000      | .000                   | .000       | .000                    | .000  |
|                      | Std. Deviation | .966      | .000                   | .000       | .966                    | .966  |
|                      | N              | 150       | 0                      | 0          | 150                     | 150   |

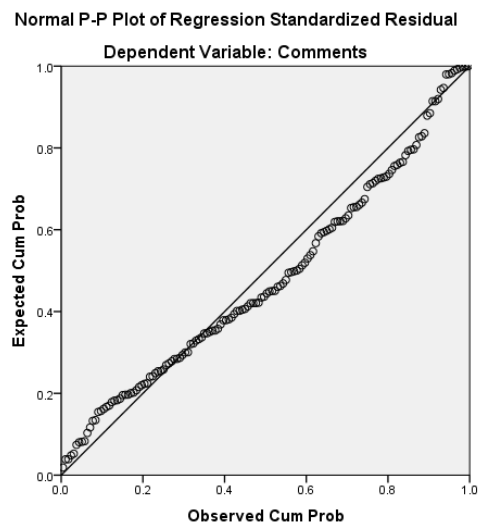
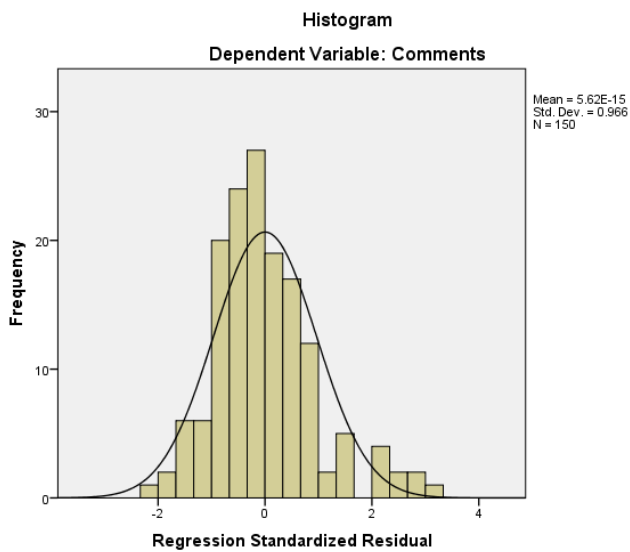
a. Dependent Variable: Likes

b. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples

**Descriptive Statistics**

|                                      | Mean  | Std. Deviation | N   |
|--------------------------------------|-------|----------------|-----|
| Likes                                | -7.44 | 1.760          | 150 |
| Days Since Post                      | 75.87 | 12.137         | 150 |
| Hashtags Use                         | .70   | .460           | 150 |
| Action Words Included                | .43   | .497           | 150 |
| Picture or Video Included            | .43   | .497           | 150 |
| Twitter_Action Words                 | .15   | .362           | 150 |
| Twitter_Picture or Video<br>Included | .19   | .396           | 150 |
| Twitter                              | .33   | .473           | 150 |
| Instagram Action Words               | .11   | .310           | 150 |
| Instagram Picture or Videos          | .15   | .355           | 150 |
| Instagram                            | .33   | .473           | 150 |

## 2) Comments Model



**Model Summary<sup>b</sup>**

| Model | R                 | R Square | Adjusted R Square | Std. Error of the Estimate | Durbin-Watson |
|-------|-------------------|----------|-------------------|----------------------------|---------------|
| 1     | .645 <sup>a</sup> | .416     | .374              | 1.161                      | 1.686         |

a. Predictors: (Constant), Instagram, Days Since Post, Picture or Video Included, Action Words Included, Hashtags Use, Twitter\_Action Words, Twitter\_Picture or Video Included, insta\_actionwords, insta\_picture\_video, Twitter

b. Dependent Variable: Comments

**ANOVA<sup>a</sup>**

| Model |            | Sum of Squares | df  | Mean Square | F     | Sig.              |
|-------|------------|----------------|-----|-------------|-------|-------------------|
| 1     | Regression | 133.271        | 10  | 13.327      | 9.885 | .000 <sup>b</sup> |
|       | Residual   | 187.394        | 139 | 1.348       |       |                   |
|       | Total      | 320.664        | 149 |             |       |                   |

a. Dependent Variable: Comments

b. Predictors: (Constant), Instagram, Days Since Post, Picture or Video Included, Action Words Included, Hashtags Use, Twitter\_Action Words, Twitter\_Picture or Video Included, insta\_actionwords, insta\_picture\_video, Twitter

**Coefficients<sup>a</sup>**

| Model           | Unstandardized Coefficients |            | Standardized Coefficients | t      | Sig. | 95,0% Confidence Interval for B |             | Collinearity Statistics |         |
|-----------------|-----------------------------|------------|---------------------------|--------|------|---------------------------------|-------------|-------------------------|---------|
|                 | B                           | Std. Error | Beta                      |        |      | Lower Bound                     | Upper Bound | Tolerance               | VIF     |
|                 | 1 (Constant)                | -11.901    | .652                      |        |      |                                 | -18.251     | .000                    | -13.190 |
| Days Since Post | -.004                       | .008       | -.033                     | -.503  | .616 | -.020                           | .012        | .966                    | 1.035   |
| Hashtags Use    | -.340                       | .237       | -.107                     | -1.434 | .154 | -.810                           | .129        | .760                    | 1.316   |

|                                      |       |      |       |        |      |        |       |      |       |
|--------------------------------------|-------|------|-------|--------|------|--------|-------|------|-------|
| Twitter                              | 1.664 | .415 | .534  | 4.007  | .000 | .843   | 2.485 | .237 | 4.220 |
| Action Words<br>Included             | -.521 | .329 | -.177 | -1.583 | .116 | -1.172 | .130  | .338 | 2.959 |
| Picture or Video<br>Included         | .815  | .329 | .276  | 2.476  | .014 | .164   | 1.466 | .337 | 2.963 |
| Twitter_Action Words                 | .581  | .449 | .143  | 1.293  | .198 | -.307  | 1.469 | .343 | 2.914 |
| Twitter_Picture or<br>Video Included | .542  | .451 | .147  | 1.202  | .231 | -.350  | 1.435 | .283 | 3.533 |
| insta_actionwords                    | .216  | .483 | .046  | .446   | .656 | -.740  | 1.171 | .404 | 2.478 |
| insta_picture_video                  | -.700 | .468 | -.169 | -1.498 | .136 | -1.625 | .224  | .328 | 3.045 |
| Instagram                            | 1.686 | .383 | .544  | 4.408  | .000 | .930   | 2.443 | .276 | 3.619 |

a. Dependent Variable: Comments

#### Casewise Diagnostics<sup>a</sup>

| Case Number | Std. Residual | Comments | Predicted Value | Residual |
|-------------|---------------|----------|-----------------|----------|
| 1           | 2.049         | -10      | -12.27          | 2.379    |
| 2           | 2.416         | -9       | -11.41          | 2.805    |
| 15          | 2.635         | -10      | -12.76          | 3.060    |
| 16          | 2.115         | -10      | -12.71          | 2.456    |
| 18          | 3.257         | -8       | -11.82          | 3.781    |
| 21          | 2.286         | -9       | -11.30          | 2.655    |
| 46          | -2.085        | -15      | -12.30          | -2.421   |
| 62          | 2.894         | -7       | -10.07          | 3.360    |
| 68          | 2.993         | -6       | -9.91           | 3.476    |
| 95          | 2.061         | -8       | -10.42          | 2.393    |

a. Dependent Variable: Comments

**Residuals Statistics<sup>a</sup>**

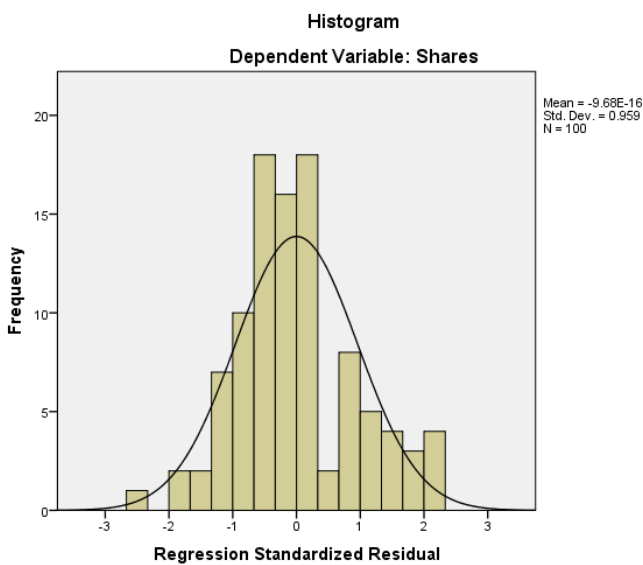
|                      | Minimum | Maximum | Mean   | Std. Deviation | N   |
|----------------------|---------|---------|--------|----------------|-----|
| Predicted Value      | -13.11  | -9.59   | -11.10 | .946           | 150 |
| Residual             | -2.421  | 3.781   | .000   | 1.121          | 150 |
| Std. Predicted Value | -2.126  | 1.588   | .000   | 1.000          | 150 |
| Std. Residual        | -2.085  | 3.257   | .000   | .966           | 150 |

a. Dependent Variable: Comments

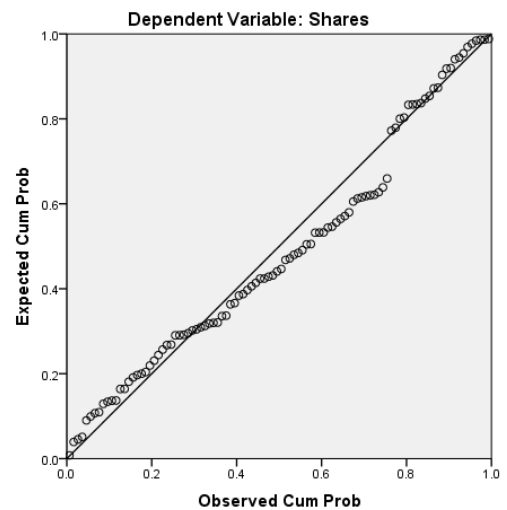
**Descriptive Statistics**

|                                   | Mean   | Std. Deviation | N   |
|-----------------------------------|--------|----------------|-----|
| Comments                          | -11.10 | 1.467          | 150 |
| Days Since Post                   | 75.87  | 12.137         | 150 |
| Hashtags Use                      | .70    | .460           | 150 |
| Twitter                           | .33    | .471           | 150 |
| Action Words Included             | .43    | .497           | 150 |
| Picture or Video Included         | .43    | .497           | 150 |
| Twitter_Action Words              | .15    | .362           | 150 |
| Twitter_Picture or Video Included | .19    | .396           | 150 |
| insta_actionwords                 | .1067  | .30972         | 150 |
| insta_picture_video               | .1467  | .35496         | 150 |
| Instagram                         | .33    | .473           | 150 |

### 3) Shares Model



**Normal P-P Plot of Regression Standardized Residual**



**Model Summary<sup>b</sup>**

| Model | R                 | R Square | Adjusted R Square | Std. Error of the Estimate | Durbin-Watson |
|-------|-------------------|----------|-------------------|----------------------------|---------------|
| 1     | .722 <sup>a</sup> | .521     | .479              | 1.411                      | 1.568         |

a. Predictors: (Constant), twitter\_action\_words, Days Since Post, Picture or Video Included, Hashtags Use, Action Words Included, Twitter, Picture or Video on Twitter, Hashtags on Twitter

b. Dependent Variable: Shares

**ANOVA<sup>a</sup>**

| Model |            | Sum of Squares | df | Mean Square | F      | Sig.              |
|-------|------------|----------------|----|-------------|--------|-------------------|
| 1     | Regression | 197.014        | 8  | 24.627      | 12.366 | .000 <sup>b</sup> |
|       | Residual   | 181.222        | 91 | 1.991       |        |                   |
|       | Total      | 378.236        | 99 |             |        |                   |

a. Dependent Variable: Shares

b. Predictors: (Constant), twitter\_action\_words, Days Since Post, Picture or Video Included, Hashtags Use, Action Words Included, Twitter, Picture or Video on Twitter, Hashtags on Twitter

**Coefficients<sup>a</sup>**

| Model |                             | Unstandardized Coefficients |            | Standardized Coefficients | t       | Sig. | Collinearity Statistics |       |
|-------|-----------------------------|-----------------------------|------------|---------------------------|---------|------|-------------------------|-------|
|       |                             | B                           | Std. Error | Beta                      |         |      | Tolerance               | VIF   |
| 1     | (Constant)                  | -10.651                     | .949       |                           | -11.226 | .000 |                         |       |
|       | Days Since Post             | -.002                       | .012       | -.011                     | -.146   | .884 | .987                    | 1.013 |
|       | Hashtags Use                | -.815                       | .407       | -.206                     | -2.003  | .048 | .498                    | 2.008 |
|       | Twitter                     | -2.573                      | .594       | -.661                     | -4.334  | .000 | .226                    | 4.423 |
|       | Action Words Included       | -.606                       | .404       | -.156                     | -1.502  | .137 | .489                    | 2.045 |
|       | Picture or Video Included   | 1.616                       | .401       | .411                      | 4.026   | .000 | .504                    | 1.983 |
|       | Picture or Video on Twitter | -1.170                      | .579       | -.245                     | -2.020  | .046 | .358                    | 2.794 |
|       | Hashtags on Twitter         | .757                        | .633       | .189                      | 1.195   | .235 | .211                    | 4.745 |
|       | twitter_action_words        | .657                        | .580       | .140                      | 1.134   | .260 | .345                    | 2.897 |

a. Dependent Variable: Shares



**Casewise Diagnostics<sup>a</sup>**

| Case Number | Std. Residual | Shares | Predicted Value | Residual |
|-------------|---------------|--------|-----------------|----------|
| 18          | 2.209         | -7     | -9.73           | 3.118    |
| 46          | -2.421        | -14    | -10.61          | -3.417   |
| 62          | 2.271         | -10    | -12.97          | 3.205    |
| 68          | 2.151         | -10    | -12.88          | 3.035    |
| 95          | 2.210         | -10    | -13.45          | 3.119    |

a. Dependent Variable: Shares

**Residuals Statistics<sup>a</sup>**

|                      | Minimum | Maximum | Mean   | Std. Deviation | N   |
|----------------------|---------|---------|--------|----------------|-----|
| Predicted Value      | -13.45  | -9.11   | -11.94 | 1.411          | 100 |
| Residual             | -3.417  | 3.205   | .000   | 1.353          | 100 |
| Std. Predicted Value | -1.070  | 2.006   | .000   | 1.000          | 100 |
| Std. Residual        | -2.421  | 2.271   | .000   | .959           | 100 |

a. Dependent Variable: Shares

**Descriptive Statistics**

|                             | Mean   | Std. Deviation | N   |
|-----------------------------|--------|----------------|-----|
| Shares                      | -11.94 | 1.955          | 100 |
| Days Since Post             | 75.81  | 12.030         | 100 |
| Hashtags Use                | .59    | .494           | 100 |
| Twitter                     | .49    | .502           | 100 |
| Action Words Included       | .49    | .502           | 100 |
| Picture or Video Included   | .43    | .498           | 100 |
| Picture or Video on Twitter | .21    | .409           | 100 |
| Hashtags on Twitter         | .38    | .488           | 100 |
| twitter_action_words        | .2200  | .41633         | 100 |