Building Your Audience With Impactful Images

An investigation which factors influence consumers to follow a brand on social network sites.

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Management summary

Reaching an audience on social network sites has become more difficult for firms. The core of social network sites lies in staying in touch with family friends and acquaintances. Therefore the question remains: why would the consumer follow a firm? Prior research discovered the motivations of consumers to follow a firm, but factors that lead to a big follower base have not yet been studied. Gaining more insight into the effect of these factors will contribute to a better understanding of consumer behavior on SNS and provide firms with knowledge to improve their marketing strategy.

We decided to fill this gap by collecting a large dataset in collaboration with the company LiveWall. We monitored the activity of Fortune 500 firms for 36 days on Instagram. Furthermore, we examined the influence of certain factors on the number of followers a firm has, which can be controlled by the firms themselves. In total, we examined three main factors, namely: frequency of posts, electronic word-of-mouth and likes of a post. In addition, we examined factors that drive the amount of likes a post receives, such as hashtags and the effect of color. Furthermore, we studied whether the factors differ in effect size for different industries.

The results confirm our expectation that the more frequent firms post an image, the more users notice the firm and the larger the increase of followers. In addition, we found that an increase in mentioning a firm in messages by the consumer, also called electronic word-of-mouth, has a positive influence on the amount of followers of a firm. When zooming in on the specific dimensions "Farbe an sich" and bright-dark contrast of the construct effect of color, we found evidence that if the values of these dimensions increase, this has a positive influence on the amount of likes a post will receive. In addition, we confirmed that the effect size of each of the above mentioned factors is influenced by the industry a firm belongs to.

Our first recommendation for firms is to structurally plan a certain amount of images, so there is a base line for the amount of posts. For example, to decide on a weekly amount of images linked with consistent activities of a firm. Second, we advise firms to take the use of colors into account when creating content and posting images, because improving the pictorial content will make advertisement more efficient and effective. Third, firms should stimulate consumers to mention the firm or brand in their message, this enhances the publicity of the firm.

Keywords: Instagram, influencing followers, image-marketing, social network sites, Fortune 500, SIC, eWOM, likes

Preface

During an internship of six months at LiveWall (i.e., marketing and social media company) and after obtaining all my courses, this thesis concludes my master in Marketing Management at Tilburg University. This research focuses on creating a better understanding of factors that influence the consumer to follow a firm.

This Master Thesis would not have been possible without the help of others. First of all I want to thank my supervisor at Tilburg University, dr. Hannes Datta. His constructive feedback, guidance and keeping me on track when needed has helped me a lot completing this thesis. I also want to thank my supervisor at LiveWall, Eelco van de Wiel and his colleague Stijn Meevis for the insights regarding the data collection and willingness to help me when necessary.

Last but not least, I would like to thank my family, friends and colleagues for their help, support and understanding throughout my entire career at Tilburg University.

I wish you all an enjoyable reading.

Sjors van den Hout.

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1 Introduction

It is very easy nowadays for consumers to communicate their questions, compliments or complaints with firms and brands. Most of them are 24/7 online accessible via social media[1]. But why would you follow them?

The study of Zaglia (2013) states that one of the more important motivations of consumers to follow a firm is their passion for the company in question. To follow a firm through social network sites (SNS) means that a consumer chooses to receive information and advertisements from them on regular basis. The goals of this new kind of advertisement do not differ from the goals from traditional advertising. Even though the new way of communication is through social media, the goals of the branded information and advertisements can still be defined as brand awareness, brand knowledge, brand purchase and loyalty (e.g., Lavidge & Steiner, 1961; Petty, Cacioppo & Schumann 1983, Liu & Shrum, 2002). However, where the purpose of advertisement is still the same, the form of communication and the consumer's role has changed.

In the past decades the marketer would communicate in a one-way direction via television, print and billboards to a relatively large target group. Nowadays, there is a two-way communication stream between consumers and brands/firms. SNS provide the consumer the choice to follow companies and receive their content. Two-way communication started with relationship marketing described by Berry (1980), but became more important when online advertisement increased. Online advertising started with banners (Sherman & Deighton, 2001) and email advertising (Phelps, Lewis, Mobilio, Perry & Raman, 2004), but developed itself rapidly through new digital concepts like interactive websites and games (Kiss & Esch, 2006). This resulted in more interaction with the firm than was possible via offline environment. The latest focus for firms is advertising on SNS and creating separate

[1] http://www.socialmediaexaminer.com/SocialMediaMarketingIndustryReport2014.pdf

strategies for each of them. However, the difference with advertising on SNS is that the consumer needs to follow a firm to receive messages/advertisements. Therefore, it is interesting to have knowledge about which factors directly or indirectly influence the number of followers a company has. While studies regarding SNS are increasing (Kietzmann, Hermkens, McCarthy & Silvestre, 2011; Park, Kee & Valenzuela, 2009), the factors that lead to a big follower base have not yet been researched. This study will examine if basic factors such as the frequency of posting (frequency), the number of mentions by other user users (electronic word-of-mouth), the categorization of a message (hashtag) and the use of color in pictorial content (effect of color) have an influence on the amount of followers a firm has.

Gaining more insight on the effect of these factors will contribute to a better understanding of consumer behavior on SNS. Companies can use this knowledge to optimize their content strategy[2] and make their posts more appealing to the consumer. This is or should be a high priority for firms and brands as a result of the increasing amount of advertising and content on consumer's newsfeeds (e.g. new messages on Twitter, Facebook or Instagram). The core in SNS lies in staying in touch with friends and family. With the up rise of an enormous supply of firms to follow it gets more difficult to gain followers as a company or to keep them interested. This study could indicate that a high bright-dark contrast in pictorial content has a better chance of being appreciated by the consumer. Information like that could let firms know to stand out in the crowd. The research will support firms to improve their pictorial content and being more visible in a crowded and competitive environment.

This study relates to previous work, because the mentioned factors have been studied, but not from the perspective we describing. For instance, Logan (2014) studied the motivations to follow a brand on Twitter and Facebook among young adults and concluded

[2] Content strategy refers to the planning, development, and management of pictorial and textual content in offline and online environment.

that perceived ease of use and peer pressure are important factors. Furthermore, the study of Hollenbeck and Kaikati (2012) found that consumers use brands on Facebook to reflect their actual or ideal self. While studies emerge regarding SNS, there are still a lot of gaps in literature and the Marketing Science Institute (MSI) still considers the domain as a research priority[3]. As previously mentioned regarding SNS advertising, it is important to create an audience for your message. This implies that the message and the content strategy of a firm should suit the audience in order for consumers to follow a brand. Therefore, an important contribution of this study is to examine which of the previous defined factors have an influence on the number of followers of a firm.

Another gap within the literature lies with analyzing online pictorial content. While firms increasingly use pictorial content online to spread a message and even some researchers state that image marketing is rising in popularity (Johansson & Wallsbeck, 2014), empirical literature is surprisingly quiet. Offline advertisement and images are extensively analyzed, for example Gorn, Chattopadhyay, Yi & Dahl (1997) found that higher levels of the color constructs chroma and value in an image will increase the likability of an advertisement. In addition, Pechman and Stewart (1988) state that higher frequency of advertising increases recall and attitude. The studies regarding images online are limited to the exposure time of banners (Sherman & Deighton, 2001) and which content received by email will be passed along more often (Phelps et al., 2004). Therefore, the second contribution of this study will give more insight in the largely unexplored pictorial content of firms on SNS.

Previous research has proven that brand type and the type of industry influences the result of many relationships in the literature (Escales & Bettman, 2003; Ang & Lim, 2006; Jang, Olfman, Ko, Koh & Kim, 2008). In addition, consumers identify themselves with different type of brands, so results in many studies differ per brand type (Hollenbeck &

[3] http://www.msi.org/research/2014-2016-research-priorities/

Kaikati, 2012). Therefore, it is important for firms to know whether the factors that influence the number of followers are generalizable across all categories a firm can belong to or differ per industry. As a result, the third contribution of this study is whether brand type influences the factors that increase or decrease the number of followers of a firm.

To test the hypotheses, we collect a large dataset with all the pictorial- and text content of 105 firms of the Fortune 500 over a time range of 36 days (see Appendix 1 for firms). The results will contribute to the understanding of the consumer and likability of online images. Furthermore, it will also support business people to increase ones knowledge about the factors that can influence their followers/reach so that they can optimize their content and content strategy.

In the following chapter, we further elaborate on existing literature and how this study contributes to it. Secondly, we describe the research method and analyze the results to answer the hypotheses. At last, we summarize the finding, assign the possible academic and managerial implications and identify the limitations and directions for future research.

2 Contributions to literature

An emerging body of research has shown how consumers respond to advertisements and how the relationship between firm and consumer has changed over the years. The first stream of studies examined traditional offline advertisements (Vaughn, 1980; Pech & Stewart, 1988). These studies are all based on one-way communication where the marketer communicates and the consumer responds (Stewart & Pavlou, 2002). The majority of these studies demonstrate how consumer's behavior changes with different factors in advertising. Holbrook and Batra (1987) studied the mediating function of emotions and how they affect the consumer's response on advertising. Other studies found that attitude towards an advertisement has an effect on consumer's choice (Shimp, 1981) and that there is an inverted U-shaped relationship between exposure and consumers attitude towards the advertising (Pechman & Stewart, 1988).

The second stream of research focused on online advertisement and the two-way communication between a firm and consumer which started to increase in importance. Some examples are Ha and McCann (2008) and Bergemann and Bonatti (2011) who compare offline with online advertisement and Burns and Lutz (2006) that investigated different kinds of online advertising formats. Other studies argue consumer’s online buying behavior (Lohse, Bellman & Johnson, 2000) and advertising effectiveness (Goldsmith & Lafferty, 2002). Several studies argue how consumer behavior differs in online settings. The communication change from one-way to two-way created a more active role of the consumer than before. The importance of this change is supported by Duncan and Moriarty (1998), who suggest that communication (rather than persuasion) is the foundation for the relationship between a firm and consumer. At last, the study of Stewart and Pavlou (2002) proposes that interactive media enables firms to better monitor consumer’s behavior, while this was difficult to do with traditional media.

The third stream of research concerns online advertising, but focuses on SNS. The advent of SNS increased electronic word of mouth (eWOM) between consumers. Moreover, consumers now utilize these platforms by discussing, creating and sharing information (Kietzmann et al. 2011). Brands and products can be more easily reviewed or rated than before and the opinion of consumers is spreading faster to friends and acquaintances. With a reach of 67 million active users on Facebook alone in 2008 (Park, Kee & Valenzuela, 2009), SNS are becoming an important medium for firms to spread their message and start the interaction with their target group. There are two ways for firms to advertise or spread their message on SNS. At first, there is advertising that is similar to banner advertising where the firm purchases space on the SNS where they can put their message, also comparable with advertisement in newspapers. The other option is to create user accounts or pages with the name of the firm or brand, which are called brand pages. Brand pages enable firms to spread their message on topics they decide. Chi (2011) found that whenever consumers are given the choice between the two ways that firms can advertise on SNS, they favored the advertisement derived from brand pages. Moreover, consumers perceived the advertising originated from firms that use SNS accounts more trustworthy and less irritating (Chi, 2011). However, this type of advertising comes with an important restriction. Before two-way or even one-way communication can occur, the consumer has to follow the firm or brand. Moreover, this means that the consumer already made the decision of following the brand or firm which indicates first interest. This had led to a shift in power from first one way communication, where the firm was communicating, to two-way communication where the consumer decides whether they want to receive information from a firm.

Our study contributes to the third stream of papers and has three contributions. This study provides more insight in the rather new concept of “followship” on SNS. Moreover, followers are people who take an active interest in a particular activity, this activity can be a person, brand or firm. There are three main differences between following brand pages on SNS and following in offline environments. At first, the brand pages we previously mentioned are created by the firm, whereas the offline communities are created by consumers with passion for the brand. Secondly, these brand pages on SNS advertise for example with new products and information about upcoming events, but the consumer has to follow them before receiving the information. At last, it is much easier to be a follower on SNS, since consumers only have to click follow and can choose if they want to be a passive or active follower. Voluntary acceptance of brand messages is important for SNS, because consumers seek to interact with brands and other consumers (Chu & Kim, 2011).

Previous studies about SNS studied different aspects, such as consumer behavior between consumers (Chu & Kim, 2011; Chatterjee, 2011) and the main motivations for consumers to engage in communication with firms. Zeng, Li and Wenyu (2009) concluded that social identity and group norms are the most important motivations for consumers to engage in communication with firms on social media. Other motivations for following firms, specifically on Facebook, are willingness to learn, passion for the brand and entertainment (Zaglia, 2013). However, while motivations for following on SNS are clear and well-studied, the influence that a firm can carry out on the consumer is still unknown (Zeng et al. 2009; Zaglia, 2013). Therefore, as a first contribution, we explore which factors have an influence on the number of followers a firm has on SNS.

By analyzing textual as well as pictorial content, this study also contributes to knowledge about images in an online environment, specifically on SNS, and how consumers respond. Although a considerable amount of studies focused on images and the use of it in offline advertisement; e.g., frequency of advertising and the attitude and recall towards it, (Pechman & Stewart, 1988), which colors to use and consumers response (Scott & Vargas, 2007), rather less attention has been paid to images in online environment. This is quite strange, because the popularity of image marketing is rising and the prediction is that all the uprising SNS are based on image based content rather than text (Johansson & Wallsbeck, 2014). The studies regarding images mostly analyzed the motivations for passing along (Ho & Dempsey, 2008) or more globally the content that is passed along the most often (Phelps et al., 2004). They found that individualistic consumers pass along content more often and that content containing good deeds or jokes have the highest percentage of being passed along. Even though these studies integrated aspects of images, it still remains a gap regarding knowledge about how images are best constructed and how different constructs of images can influence a consumer to follow a firm. The study of Lothia, Donthu and Hershberger (2003) did focus more on how an image should be constructed by researching banner effectiveness.

They especially studied content- and design elements and the different click-through rates. Taking into account the increase of advertising clutter and the lack of studies concerning images on SNS, it is important to enlarge the knowledge of academic knowledge concerning pictorial content on SNS. In addition, since 70% of the marketers[4] report that they are planning to increase the use of images, image-centric content is becoming a part of most marketing strategies. Therefore, this study examines the factors that will increase image likability and create more insight in how consumers react on specific colors in images and whether it differs from previous offline studies. The results of this study will create insight in more effective images and enlarges the chance of standing out in the advertising clutter.

Finally, previous research has evidence that the brand type in most cases influences the behavior of the consumer (Escales & Bettman, 2003; Jang et al. 2008). Moreover, the study of Ang and Lim (2006) mentioned that metaphors in advertisement of symbolic products were perceived as more sophisticated and excited, but less sincere and competent than utilitarian products. In addition, Hollenbeck and Kaikati (2012) found that consumers use brands to reflect their identity and different identities seek different brands. Brand type within this study is categorized by using the Standardized Industrial Classification (SIC) and consists of ten categories. It is relevant for firms to know whether the studied factors can be generalized for all brand types or that categories may have an influence on these factors. Therefore, this study will contribute whether brand type is a moderating variable and how it differs for factors that influence the number of followers a firm has on SNS.

In summary, the recent growing interest in advertising possibilities on SNS has increased the need for knowledge of which factors, textual as well as pictorial content, have an influence on the number of followers a firm has. Furthermore, this study analyzes if these

[4] http://www.socialmediaexaminer.com/social-media-marketing-industry-report-2014/

factors are moderated by different brand types and how much it differs. Table 2.1 provides insights in the contributions of our paper relative to existing studies.

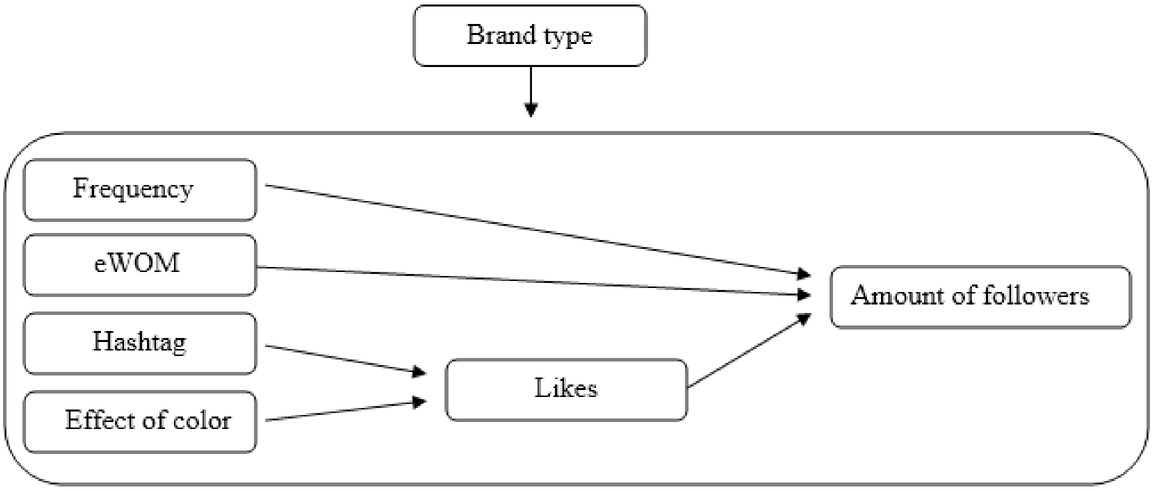
Table 2.1 Contribution to the literature

	1	2	3	4	5
Existing literature	*Factors influencing followers*	*Analyse text*	*Analyse images*	*Brand type*	*Offline/online environment*
Ambler, Loannides & Rose (2000)			**X**		**Offline**
Berger and Schwartz (2011)		**X**		**X**	**Online**
Cha et al. (2010)	**X**	**X**			**Online**
Garcia et al. (2011)			**X**		**Offline**
Gorn et al. (1997)			**X**		**Offline**
Hollenbeck & Kaikati (2012)	**X**			**X**	**Online**
Jansen et al. (2009)		**X**			**Online**
Lothia, Donthu & Hershberger (2003)			**X**		**Online**
Metha (2000)			**X**	**X**	**Offline**
Pechmann & Stewart (1998)		**X**	**X**		**Offline**
Phelps et al. (2004)		**X**	**X**		**Online**
Romero et al. (2011)	**X**	**X**			**Online**
Zaglia (2013)	**X**			**X**	**Online**
Zeng et al. (2009)	**X**		**X**	**X**	**Online**
This Thesis	**X**	**X**	**X**	**X**	**Online**

3 Conceptual framework and hypotheses

The following conceptual framework (Figure 3.1) illustrates the different constructs and hypotheses of this study. SNS enable firms to make their own corporate account, so consumers can follow them for information, interaction or other content. Some research already studied the motivation from consumers to follow one another (Zeng et al. 2009; Zaglia, 2013). However, these previous studies did not examine possible factors that firms can use to increase their followers on SNS. The motivation of consumers to follow a specific firm is difficult to influence, so this study will explore factors that influence the amount of followers that are controllable by the firm. The following constructs will be used in this study: frequency of posting, eWOM, likes, hashtag and effect of color. Taking previously mentioned literature in consideration, we will formulate two types of hypotheses. At first, the main effects will be a direct comparison between frequency, eWOM and likes on the amount of followers. However, the likes a firm receives on their posts are driven by a number of factors. Therefore, the second type of hypotheses we formulate are factors that drive the likes of the pictorial content a firm posts. We investigate if hashtags and the effect of color drive the amount of likes a post receives and if the number of likes will have a positive effect on the amount of followers. In addition, we examine if the constructs have different outcomes concerning the category a firm belongs to.

Figure 3.1 Conceptual framework



Frequency. We expect that the more frequent a firm posts an image, the larger the increase of the amount of followers will be. First by posting images, a firm creates publicity for themselves. Their followers will most likely notice the image, and as previously mentioned, a 'like' can enhance the chance of spreading the image to the followers of the one that liked the image. Second, higher frequency of advertising increases the recall of an ad (Pechman & Stewart, 1988). The increase in recall will keep the advertisement and thus the firm more top of mind of the consumer. In addition, using different advertisements increases the recall of brand names more than using the same advertisement (Unnova & Brunkrant, 1991). Third, considering that people follow on average 822 other social media users[5], it is highly presumable that a message originating from a firm can easily be lost in the crowd. That is why firms have to make sure their message will be noticed. We expect that if firms post content more frequently, the chance that the consumer notice the firm will increase. Therefore, the following hypothesis has been formulated:

H1: The amount of posts will increase the number of followers.

eWOM. Electronic word-of-mouth is an important and extensively studied construct. Some researchers focused on the impact of eWOM on sales (Chevalier & Mayzlin, 2006; Goldsmith & Horowitz, 2006), others study the impact of eWOM on the decision making process (De Bruyn & Lilien, 2008) and others studied the effect of eWOM on the attitude and the corporate website of firms (Lee, Rodgers & Kim, 2009). These studies found evidence for the impact of eWOM on sales, the decision making process and the attitude regarding a firm. SNS users have the possibility to like, comment, and share pictorial- and textual content of everything they like to share. By mentioning the firm in their posts one reveals to others their brand preference and show their persona (e.g. name and picture), which creates eWOM communication (Chu & Kim, 2011). When SNS users mention a firm, they often use a hashtag (#) followed by the name of the firm, such as: #cocacola, #JetBlue, #nike. This hashtag allows SNS to combine all the related posts about a firm or brand and will be used in this study to measure the eWOM. The use of hashtags will be elaborated later on in this study. When eWOM on SNS increases it leads to extra publicity for the firm, which raises the chances of attracting new followers. Therefore, we formulate the following hypothesis:

H2: An increase in eWOM will boost the number of followers of a firm.

Hashtag. The use of hashtags is exclusive for SNS and can be compared with keywords in academic articles. Using hashtags started on Twitter and is described as "*a string of*

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[5] http://opticalcortex.com/instagram-statistics/

characters preceded by the hash (#) character" (Tsur & Rappoport, 2012, p.1). Nowadays, hashtags are available on almost all SNS, such as Twitter, Facebook, and Instagram. While previous hypotheses were more focused on influencing the amount of followers, hashtags are expected to drive the amount of likes a post receives. Moreover, hashtags are used to provide an indication of the context and to categorize the posts, helping other users to post related content (Chang, 2010). Some examples of hashtags for sports are #fitness, #healthy, #sport, but hashtags are used for describing every context. Furthermore, hashtags can support firms in various ways. At first, it categorizes the post and adds it to every other post that used the same hashtag. This increases the posts findability on SNS, even when consumers have not followed the firm that posted the content. Secondly, hashtags can be used by firms not only to describe the post, but also to categorize themselves in the topics they want to be related to. By making the post visible in multiple categories, we think the chance of receiving more likes on the post will increase. In conclusion, hashtags can enhance the reach of a post and thus the following hypothesis is formulated:

H3: The number of hashtags increases the amount of likes.

Effect of color. The popularity of image marketing is rising and the prediction is that all the uprising SNS are based on image based content rather than text (DeMers, 2013). With the increase in value of image marketing it is important to know which images brands should use and the effectiveness of the different aspects of images. We expect that the use of different color dimensions will influence the likes a firm will receive on the pictorial content they post on SNS. Previous studies provide evidence that yellow and red draw attention, while blue and green calms the customer (Singh, 2006). The color red also makes them lose track of time. The study of Gorn et al. (1997) concluded that a higher value and chroma in an image increases likability. In addition, while studies regarding the effect of color on printed advertising have found multiple results, in online environments there is still quite a gap. A different and interesting approach to study the effect of colors within images was executed by Ploch (2013). The study of Ploch (2013) combined the art theory “Sever Color Contrast” from Itten (2003) with marketing knowledge to develop an algorithm to analyze whether different dimensions of color and sizes in movie covers have an effect on the purchase of them. Despite the fact that not all the dimensions of colors in the study of Ploch (2013) had a significant influence, the algorithm they developed is very useful for this study. Not all color dimensions are evenly important in marketing practices and not all are compatible to SNS. Therefore, we chose to use four dimensions to describe the effect of color, namely: complementarity contrast, number of colors, “Farbe an sich[6]” and bright-dark contrast. Without extensively elaborating the used art theory by Ploch (2013), each of the dimensions will be explained briefly and result in several hypotheses.

At first, the dimension complementarity contrast refers to colors that are considered opposite of each other on the color wheel (see Appendix 2), for example red and green. The more different or opposite the colors are from each other, the higher the complementarity contrast. Furthermore, complementarity contrast induces the impression of colorfulness and vividness (Itten, 2003). Our expectation is that images with a high complementarity will stand out, and as a result we hypothesize:

H4a: Higher complementarity contrast increases the number of likes.

Further, the number of colors refer to the amount of colors within the previously mentioned color wheel, with the addition of black and white. This construct is comparable with the third dimension “Farbe an sich”, which is the contrast of a few colors that cover a fair amount of the total image. “Farbe an sich” is considered high when comparable colors, that are close to each other on the previous mentioned color wheel (see Appendix 2), show dominance in a image. A high amount of “Farbe an sich” is considered to be seen as colorful, loud and

[6] There is no similar word existing in the English language, so we will use this term from now on.

powerful (Ploch, 2013). Given the dominance and loudness of these color dimensions, we expect that it will catch more attention of the SNS users. Therefore we formulate the following hypotheses:

H4b: Higher number of colors increases the number of likes.

H4c: Higher "Farbe an sich" increases the number of likes.

At last, the dimension bright-dark contrast represents a comparison of different brightness levels of color. When brightness level is mostly the same it relates colors and makes them less powerful and dominantly present. A stronger bright-dark contrast is more attention catching, because of the variety in colors (Ploch, 2013). Therefore, we hypothesize:

H4d: The higher the bright-dark contrast, the more positive the effect on likes

Besides the expectation that hashtags and the color dimensions will enhance the number of likes an image receives, we also propose that these constructs, have a positive influence on the amount of followers a firm has. The reasoning behind this expectation is that when persons like a certain image on SNS, this 'like' is mostly shown to their followers. Therefore, the more SNS users like a certain image the higher the chance of other users being directed to the SNS of the firm. This resulted in the following hypothesis:

H5: Hashtag and effect of color have an indirect positive effect through likes on followers

In addition, each firm has a different core business and thus the products they sell and the industry they belong to. It is likely to assume that the results of this study will differ for the different industry. For example, consumers will more often mention the clothes they are wearing, than the transportation they took to work. Therefore, we expect that the results for eWOM in the category manufacturing, with a firm such as Nike, would be more positive, than for the category transportation, with a firm such as Jetblue.

4 Data

4.1 Study context

We test our hypotheses on the basis of a large dataset collected on Instagram. Instagram is a free to use mobile photo sharing application that was founded in 2010. It provides users the opportunity to post, share, like and comment images. Since 2010, Instagram has reached a monthly active rate of 200 million[7] users and an average of 60 million images are being uploaded on a daily basis. As Johansson and Wallsbeck (2014) predicted that marketing will shift focus to image marketing, the importance of the platform Instagram will increase. Moreover, firms can use Instagram to connect and communicate to customers and potential customers (Bergström & Bäckman, 2013).

The firms that we used in our dataset are the Fortune 500 firms of 2013[8] (see Appendix 1 for firms). From the in total 500 firms, we excluded all the firms that did not have an official Instagram account. The remaining 105 firms were monitored within a time range from the 24 August till 29 September, 2014. The firms were divided into categories, based on the Standard Industrial Classification (SIC). SIC is a system for classifying industries by a four digit code and has ten main categories, namely: Agriculture, forestry and fishing, Mining, Construction, Manufacturing, Transportation and public utilities, Wholesale trade, Retail trade, Finance insurance and real estate, Services and Public administration. Due to the fact that we could only use firms that have an official Instagram account, there is no data for the categories Agriculture, Forestry and Fishing, Contruction and Public Administration.

The data is all publicly available and due to the usage of an application programming interface (API), we could automatically check the accounts on a daily basis. The monitored consisted of: the number of post, the amount of eWOM and the amount of followers per firm.

[7] Instagram, press
[8] http://fortune.com/fortune500/2013/

Furthermore, every post was collected, including the text and image belonging to the post and the development of likes the post got within the time period. This research method can be compared to the study of Cha, Haddadi, Benevenuto and Gummadi (2010) where they followed millions of users on Twitter to study if there are factors that identify influencers. An important aspect concerning this method is that since there is no manipulation or survey it increases the external validity and therefore the validity of our study.

4.2 Dataset and Explanation of Variables

Our initial dataset consisted of 47,484 observations that were acquired in the previous mentioned time range. To complete our dataset, we used an algorithm developed by Ploch (2013) to extract the number of colors, complementarity index, bright and dark contrast and the "Farbe an sich" from the images that belonged to our variable effect of color. To make sure the development of likes is equal for every post, our analysis concentrates on the likes that were received within one day after posting. Therefore, we excluded the likes received on each post after the one day time range. Furthermore, from the 105 firms, eighteen of them did not use Instagram within the time range of this research and were thus excluded from the analysis. If firms uploaded multiple images per day, we combined the likes and post related variables and took the average to have one value for each day within the time range. The last step for preparing our date for the analyses, was to fill in the zero values for the days there were no posts. The method we took for this was to replace the missing values into zeros. In summary, this results in a dataset that has 3134 observations including all variables and 87 firms in seven categories. Table 4.1 provides a summary of the final dataset.

Table 4.1: Descriptive statistics and variable operationalization

Variable name	N	Min	Max	Mean	SD	Operationalization
Firm						
Followers	3134	-65	50168.00	536.02	2496.30	Dependent variable; change in amount of followers
Frequency	3134	-16	18.00	.72	1.29	Change number of posts
eWOM	3134	-18	161349.00	1531.92	9394.73	Change of electronic word of mouth, measured in how often the firm is mentioned
Post						
LikesL1	3134	0	203184.00	3239.03	16863.28	Average number of likes received per day
HashtagL1	3134	0	17.00	.97	1.66	Average number of hashtags used per day
No.colorsL1	3134	0	11.00	2.30	2.74	Average number of colors per day
Compl.colorL1	3134	0	.89	.04	.10	Average complementarity contrast per day
FarbeansichL1	3134	0	4.00	.84	1.04	Average number of color coverage per day
BrightDarkL1	3134	0	.97	.12	.19	Average bright-dark contrast per day
MissingL1	3134					Identifies when the value is missing or zero
SIC category	Mining = 36 (1,1%) Manufacturing = 972 (31,0%) Transportation = 649 (20.7%) Wholesale Trade = 144 (4,6%) Retail Trade = 864 (27,6%) Finance = 181 (5.8%) Services = 288 (9,2%)					Firms belong to 1 of these categories

Notes: The firm variables are incremental values and L1 stands for lagged by 1

The dependent variable 'followers' and the independent variables eWOM and frequency are converted from cumulative to incremental data. As a result, this enabled us to monitor the change per day and leads to a dataset were all variables were equally measured. The observations of the independent variables were lagged by one day, because the data of all the variables were collected at the same time each day. Without lagging the variables, this would result in no or inaccurate causality between our independent and dependent variables.

The value of color dimensions need some further explanation, because the operationalization is slightly more complex. We used the algorithm developed by Ploch (2013) and this algorithm uses a RGB color spectrum to derive the different used color dimensions. The spectrum consists of 39 primary, secondary and tertiary colors (see Appendix 3 for RGB spectrum). To obtain the complementarity contrast for each picture, the algorithm calculated the shares of color of the total number of pixels. Each pixel was assigned to one of the 39 colors (RGB color spectrum) and then the distance between the pixels was calculated. The complementarity contrast value reaches from 0 to 1, whereas a 1 implies a high complementarity contrast. Furthermore, the colors which are used for the variable number of colors have been taken into account when they cover at least 1% of the image. In addition, for the dimension "Farbe an sich" a few colors that are comparable need to cover 20% of the image and each additional 20% will add one more "Farbe an sich" contrast. The "Farbe an sich" dimension refers to the dominance of a few colors in an image, that cover a large part of it. The last dimension bright-dark contrast, is measured by calculating the share of bright, dark and pure colors and the ration of dark colors to the total number of colors within the image. The bright-dark contrast reaches from 0 to 1, the closer to 1 the higher the contrast.

The variable 'missing', as described in Table 4.1, informs us whether the zero refers to a day were there was no post or whether the observation measured had the value zero. For example, if a firm post no pictorial content on day four it is logical the value of the constructs such as “Farbe an sich” or hashtag will be zero. However, if a firm do post an image on day six and the value of “Farbe an sich” is zero, because of no dominant colors in the image, it should not be measured the same as the zero we used to fill in the constructs when there was no post. In addition, each firm belongs to one of the seven categories and results will show whether or not the category a firm belongs to has an influence on the number of followers they have and if it influences the size effect of the previous described independent variables on the amount of followers.

5 Model

To test the hypotheses formulated in chapter three, we use two standard multiple regressions. The standard multiple regression allows us to test the predictive power of the set of independent variables and analyze the contribution of each individual variable (Pallant, 2010). In this research, we test the effect of the previously explained constructs on the dependent variable (i.e., followers). In addition, we test our expectation that likes has a mediating function between the constructs regarding the post and the dependent variable. However, the number of likes are driven by the post related variables hashtag, complementarity color, number of colors, “Farbe an sich” and bright-dark contrast. Therefore, we have to estimate a model in two stages. In the first stage, we use the construct likes as dependent variable to investigate the effect of the post related variables on our proposed mediator. We formulate this first stage of the model as follows:

$$(1)\ \text{Likes}_{i,t} = \alpha_0 + \alpha_1\text{Hashtag}_{i,t-1} + \alpha_2\text{No.colors}_{i,t-1} + \alpha_3\text{Compl.color}_{i,t-1} + \alpha_4\text{Farbe.ansich}_{i,t-1} + \alpha_5\text{Brightdark}_{i,t-1} + \alpha_6\text{Missing}_i + \varepsilon_{it}$$

The output of the first stage of the model will be used to test if the hypotheses regarding the post related variables could be accepted. It is expected that hashtags make a post more visible and thus increase the chance of likes (H_3). Therefore, the coefficient of hashtag should be positive to accept our hypothesis. To confirm whether the hypotheses $H_{4a,}$ $H_{4b,}$ $H_{4c,}$ H_{4d} concerning the amount of color and contrast used in images can be accepted, the coefficients have to be positive. To test for the remaining hypotheses, we use the predicted values of the first stage in the second stage of the model, where we test the direct effects of the constructs on the dependent variable followers. We formulate the second stage of the model as follows:

$$(2)\ Follow_{i,t} = \beta_0 + \beta_1 Ewom_{i,t-1} + \beta_2 Frequency_{i,t-1} + \beta_3 \hat{Likes}i_{,t} + \beta_4 Mining_i + \beta_5 Transportation_i + \beta_6 Wholesale_i + \beta_7 Retailtrade_i + \beta_8 Finance_i + \beta_9 Services_{i\ +}\ \varepsilon_{it}$$

The remaining hypotheses will be tested by using the output of the second stage of the model. To confirm whether the increase of posting images by a firm, changes the amount of followers of a firm (H_1), we used the incremental number of images a firm post per day. If the coefficient is positive and significant we can accept hypothesis 1. Furthermore, in our second hypothesis we stated that an increase of eWOM would have a positive effect on the amount of followers. Instagram combines all the posts regarding a specific name or word, if a hashtag is used, and gives the total number the name has been used. Therefore, to test for hypothesis 2, we compared the change of the total number of mentioned brand names (eWOM) to the change in the amount of followers for a specific brand. We expected that an increase of eWOM can influence the number of followers of a firm and thus checked if the coefficient of the variable eWOM was positive, which confirms our thoughts of H_2. To test if the post related variables that drive the mediator likes have an indirect effect on the amount of followers (H_5), the coefficient of the mediator needs to be positive. In addition, we also expected that the type of category a firm belongs to influences the chance of getting more followers. Therefore, we measured this by using dummy variables for six of the seven categories and take the category manufacturing as base level. Contrary to the hypotheses, the dummy variables only have to be significant, because the coefficient has to differ, positively or negatively, from the base level.

The focus of this research is to test which variables influence the amount of followers on Instagram. Therefore, the larger the variance within the model fit, the better this will be for our study. Beside the explaining variance within the model fit, we examined the significance of the model, by means of *F*-value ($p < .05$).

6 Empirical results

6.1 Model performance

We estimated the first and the second stage of the model, as described in chapter 5, by using a standard multiple regressions. During analyzing the first stage, it can be observed that the adjusted R^2 has a value of 0.053, which means that 5.3 % of the variance in the amount of followers is explained by stage one. Moreover, the *F*-value indicates that stage one is significant ($F = 30.021$, $p < .001$). In addition, the value of the adjusted R^2 of the second stage of the model is 0.236 and also in stage two the *F*-value is significant ($F = 108.748$, $p < .001$). Furthermore, we will extend model 1 and 2 in model 3 to analyze possible interaction effects between industry and the firm and post variables. The goal of this study is to increase knowledge about possible factors that can influence the amount of followers a firm on SNS. Furthermore, there is no violation of the multicollinearity assumption, because the values of the VIF are within boundaries for the significant variables (see Table 6.1). In the following section, we will examine the different hypotheses which are established in chapter 3. The coefficients of the total model, stage one and two, are presented in Table 6.1 and the influence of our moderator in Table 6.2.

6.2 Results of the tests

As mentioned in chapter 5, we started to analyze the first stage, which consist of the post related variables, namely: hashtag, complementarity color, number of colors, "Farbe an sich" and bright-dark contrast. Hashtags can categorize images and allow other SNS users to post related content (Chang, 2013). It is expected that the more hashtags are used describing an image, the more positive the effect will be on the likes an image will receive (H_3). However, the statistical results show a negative coefficient (β_1 = -1073.938), which is significant (p < .001), so we reject H_3. The effect of color consists of four dimensions with each their own hypothesis. At first, the complementarity contrast is expected to increase the likes of a post, when the contrast gets larger (H_{4a}). However, the linear regression indicates that this variable is not significant and has a negative coefficient (β_2 = -3212.325). As a result, H_{4a} is rejected. Furthermore, we expected that the number of colors would have a positive influence on the increase of likes. Even though the coefficient is positive (β_3 = 278.251) it is not significant, so the number of colors does not influence the amount of likes of a post. The third dimension "Farbe an sich" refers to a few similar colors, which cover 20% of the image. The expectation is that the more similar colors reaches the 20% coverage, the more effect on likes it will have (H_{4c}). The statistical results provide us with a positive and significant coefficient (β_4 = 2812.415, p < .001), so H_{4c} is accepted. This implies that if a few colors are dominantly present in an image, the amount of likes of the image increases with 2812.415 (see Appendix 5 for example). At last, the color dimension bright-dark contrast refers to the comparison of different levels of brightness of colors. Ploch (2013) stated that the higher the contrast the more attention catching the image would be. Therefore, we expected that an image with a high bright-dark contrast increases the amount of likes, compared to low bright-dark contrast. Since the coefficient of bright-dark contrast is positive and significant (β_5 = 8880.365, p < .001), we confirmed our expectation (see Appendix 6 for example).

After analyzing the first stage, we now have all the values available for stage two to examine the three main hypotheses. The first main hypothesis stated that the more frequent firms post an image, the higher the amount of followers a firm will have (H_1). Our expectation was that posting images gives the firm more exposure, because it creates the chance for SNS users to interact with the firm by liking or commenting. In line with H_1, frequency positively influences the amount of followers ($\beta_1 = 73.666$, $p < .019$). This finding implies that if frequency increases by 1 post, the amount of followers by 73.666, on average. In other words, the more images a firm posts the higher the chance of receiving more followers. Secondly, to test whether mentioning the firm's name by consumers on SNS increases the amount of followers a firm has, we interpret β_2. The coefficient concerning eWOM is positive and significant ($\beta_2 = .120$, $p < .001$), so we confirmed H_2. Moreover, this indicates that an increase of 1 for eWOM, boosts the amount of followers with 0.12. This seems a really small effect, but given the average eWOM increase of 1531.92 per day (see chapter 4.2) it would increase the amount of followers with 183.

The third main hypothesis concerned whether the predicted value of stage one has an influence on the amount of followers (H_5). This is expected, because when a SNS-user likes a certain image on SNS, this like is mostly shown to their followers. Therefore, the more SNS-users like a certain image the higher the chance of other users being directed to the SNS of the firm. We confirmed the expectation, regarding likes as mediator in our model, by using the Sobel test (see Appendix 4 for results). The Sobel test is a method for testing whether a mediator carries the influence of an independent variable to a dependent variable (Preacher & Hayes, 2008). The statistical results of this variable provides us with the size effect this mediator and the result is a positive and significant coefficient ($\beta_2 = .046$, $p < .001$). As a result, we were able to accept H_5. Moreover, this implies, given the average amount of likes of 3239,027 on an image (see chapter 4.2), that the amount of followers would rise on average with 149 per day.

Table 6.1: Estimation results

First stage regression (DV = Likes)						
Model	*Beta*	*SE*	*Std. coeff.*	*t*	*p-value*	*VIF*
Constant	574.848	584.805		.983	.326	
Hashtag	**-1073.938**	230.336	-.106	-4.662	.000	1.696
No.colors	278.251	281.323	.045	.989	.323	6.907
Compl.color	-3212.325	3775.878	-.019	-.851	.395	1.569
Farbeansich	**2812.415**	605.088	.174	4.648	.000	4.621
BrightDark	**8880.365**	2122.249	.099	4.184	.000	1.838
Missing	-479.696	628.402	-.014	-.763	.445	1.138
Second stage regression (DV = Followers)						
Constant	**531.886**	78.948		6.737	.000	
Frequency	**73.666**	31.434	.038	2.344	.019	1.380
eWOM	**.120**	.004	.450	28.710	.000	1.012
$\hat{Likes}$	**.046**	.010	.074	4.477	.000	1.423
Mining	-581.601	371.466	-.025	-1.566	.118	1.032
Transportation	**-724.263**	111.173	-.118	-6.515	.000	1.336
Wholesale trade	**-537.886**	195.413	-.045	-2.753	.006	1.104
Retail trade	**-340.859**	102.880	-.061	-3.313	.001	1.386
Finance	**-681.238**	177.036	-.064	-3.848	.000	1.124
Services	**-727.408**	147.482	-.084	-4.932	.000	1.204

Note: Numbers in bold are significant at the $p < .05$ level (two-sided).

With regard to the category dummies only the category mining is not significant. The coefficient of each of the dummy variables is negative in comparison with the base level manufacturing. The results show that the category manufacturing has the largest increase of the amount of followers and the service industry the lowest. While Table 6.1 only considers whether there are categories revealing higher amounts of followers, Table 6.2 observes possible interactions between categories and the previously mentioned factors.

Table 6.2: Estimation results extended model

	Total	*Manu*	*Trans*	*Whole*	*Retail*	*Finance*	*Services*
First stage regression (DV = Likes)							
Constant	574.85	-871.09	556.62	1786.12	1615.20	2088.57	**-68.99**
Hashtag	**-1073.94**	**-2867.53**	**-5138.47**	-311.60	365.99	**1193.43**	**-61.77**
No.colors	278.25	400.78	1452.10	34.254	80.08	88.55	**82.21**
Compl.color	-3212.33	-695.64	-18542.11	325.77	-968.15	1578.15	-177.96
Farbeansich	**2812.42**	**4757.59**	**6078.72**	1956.62	**2399.04**	2017.93	**87.04**
BrightDark	**8880.37**	**15416.39**	**12893.55**	**-1119.66**	**7789.12**	5248.07	-63.52
Missing	-479.70	2059.59	-213.47	**-2616.03**	-2137.64	**-2849.91**	**88.18**
Second stage regression (DV = Followers)							
Constant	**531.89**	238.82	243.51	94.68	**296.81**	**268.25**	**52.85**
Frequency	**73.67**	-67.19	-44.78	33.05	**122.05**	**150.85**	**-10.26**
eWOM	**.12**	**.19**	**.17**	.00	**.08**	**.08**	**.01**
$\widehat{\text{Likes}}$	**.05**	**.08**	**.07**	**.11**	**.02**	**.02**	.04

Note: Numbers in bold are significant at the p < .05 level (two-sided).

In Table 6.2 we extended the original model to investigate possible interaction effects. The sample size for mining was too small to gather any results, so we excluded it. However, the other six categories all had a significant model fit and different significant results, which confirms that there are interaction effects (see Appendix 7 for models fit). The effect size differs for “Farbe an sich” and bright-dark contrast, but overall it is present in almost each of the categories. More interesting is the negative coefficient for bright-dark in the whole trade category, which suggests that for this category a lower bright-dark contrast works better. A surprising result is that while hashtag in most categories has a negative coefficient, it is positive in the finance industry. This indicates that for each additional hashtag a firm in the finance industry adds to their post, the amount of followers will increase with 1193. Also the effect size of frequency on the amount of followers is two times larger in the finance industry compared to the average. At last, the construct number of colors has a positive coefficient in the service industry, which implies that the more colors present in an image the more likes it will receive.

7 Discussion

Prior research gives us the knowledge which motivations consumers have for following a firm or brand on SNS. The reasons are that the consumers use brands to show others their own identity and where they stand for (Zeng et al., 2009) and others follow firms because they have a passion for the brand (Zaglia, 2013). While these motivations are hard to change, previous research did not pay attention to study factors which can be influenced by firms. Therefore, we aimed to fill this gap by exploring which factors influence the amount of followers of a firm. To answer this question, we in collaboration with the company LiveWall, created API mining scripts to tap into the big data sources of the social media platform Instagram. Specifically, we collected the posts, images and eWOM of all the active Fortune 500 firms on Instagram for a time range of 36 days. As we examined multiple factors (i.e., frequency, eWOM, hashtags and effect of color) in different categories (i.e., mining, manufacturing, transportation, wholesale trade, retail trade, finance and services) , we provided a better understanding which factors influence the amount of followers of a firm and could be considered by firms to use in their marketing strategies.

7.1 Summary of main findings

There were three main factors that we expected to have an effect on the amount of followers of a firm. The number of likes a post receives, was driven by the influence that hashtags and certain color dimensions have. Questioning whether these factors also have an indirect effect on the amount of followers, we first had to test if they had an effect on the number of likes and after that whether the predicted value had influenced the amount of followers. We confirmed that, the color dimensions "Farbe an sich" and Bright-dark contrast both have a positive influence on the number of likes an image receives. Moreover, the finding implies that when these two color dimension increase, the chance of getting more likes on an image will expand. We expected hashtags to have a positive influence on the number of likes, because the assumption was that hashtags make the post of a firm more visible for SNS-users. However, the results indicate that instead of a positive influence, an increase of hashtags has a negative effect on the number of likes. In addition, we concluded that the number of likes have a positive influence on the amount followers. This finding also gives us the conclusion that, beside the positive effect on likes, the color dimensions "Farbe an sich" and Bright-dark contrast have a positive indirect influence on the amount of followers. The other two expected main effects, were the frequency of posting and eWOM. The results imply that the more frequent a firm posts an image on Instagram, the amount of followers will increase. The same result was shown for eWOM, so when more users mention a firm the larger the positive effect on the amount of followers.

In addition, we also examined whether the chance that is higher for one of the industries to receive more followers. The results indicate that the manufacturing category receives the most followers and the service industry the least. Furthermore, we examined whether there were interaction effects between industry and the previous mentioned factors. The extended model demonstrates that the effect size of "Farbe an sich", bright-dark contrast, frequency, eWOM and likes differs per category, which confirms the expectations of interaction effects. Moreover, hashtags only have a positive influence on the amount of followers in the finance category and the number of colors only have an influence in the service category.

7.2 Theoretical implications

The results of our research present several theoretical implications. At first, the results contribute to the empirical knowledge of the concept followers, which factors can influence the concept and in contrary to previous studies, we study the concept from a firm's perspective. Secondly, we compared our findings with prior research regarding frequency of advertising, eWOM and the effect of certain color dimensions. Comparing the frequency of posting on SNS with previous research on frequency of advertising in offline environment, we can suggest that parts of the proven positive influence of frequency on offline environment (Pechman & Stewart, 1988) can be generalized to SNS advertising. Furthermore, we cannot apply the believe of Unnova and Brunkrant (1991), who stated that different advertisements are more effective than using the same advertisement, because we had no comparison regarding firms using the same advertisement. We identified that eWOM on SNS increases the amount of followers of a firm, it adds to previous studies (Chevalier & Mayzlin, 2006; De Bruyn & Lilien, 2008; Lee, Rodgers & Kim, 2009) that found evidence of the impact of eWOM on numerous concepts. In addition, with image marketing increasing in importance our study found prove for color constructs that increase the likability of an image, which adds to the effect color has on images as studied by Gorn et al. (1997). Moreover, the results also confirm the expectation of Ploch (2013), whom stated that color constructs influence consumer behavior in multiple ways. Within our study we examined the amount of influence an industry has on the effect size of the constructs, which had an effect on the amount of followers. Therefore, we add to the finding previous studies (Escales & Bettman, 2003; Jang et al., 2008; Hollenbeck & Kaikati, 2012) that the industry a firm belongs to influences many relationships.

7.3 Managerial implications

This research provides several insights that have direct managerial implications. A better understanding of the factors that can influence the amount of followers on SNS results in action points that can be implemented on a short notice by businesses in all sorts of industries.

First of all, we can conclude that firms will stand out more if they post images more frequently, due to the positive effect of frequent posting on the amount of followers. Additionally, we identified that a high "Farbe an sich" and a high bright-dark contrast increases the amount of likes a firm receives on a post. Therefore, we advise firms to take this into account when creating content and posting an image (see Appendix 5 and 6 for examples). As a result of the improved pictorial content, advertising on SNS will become more efficient and effective. Promoted content that is attractive for the target audience leads to more clicks towards the website and/or more engagement for the same costs per mille[9] (CPM). Moreover, if firms improve their pictorial content by using the right proportions of previous mentioned color dimensions, it could lead to more engagement from their followers, which results in an increase of the organic reach[10] of the content and page.

Furthermore, we expected that including more hashtags in a post would positively influence the amount of likes a post receives. However, results indicate a negative influence of hashtags on the number of likes for all categories, except the finance industry. Therefore, we suggest that post derived from firms, should not include multiple hashtags, with the exception of firms that operate in the finance industry. A possible explanation could be that consumers not often follow firms in the finance industry and that hashtags make their posts

[9] Costs per thousand viewers of a certain advertisement.
[10] Organic reach is the total number of unique persons who were shown the post through unpaid distribution.

visible in the categories they want to be related to, for example sport events they sponsor. In addition, since eWOM increases the followers of a specific firm, we advise firms to stimulate SNS-users to mention firms in their messages. A possible action a firm could consider is organizing competition were the consumer should posts the best picture while using the brand. As a result, the firm will receive more publicity and increase their amount of followers.

This study also concludes that the influence of the factors mentioned above is not equally effective for each firm. The industry in which a firm operates influences the effect size of the previous mentioned factors. For example, eWOM is twice as effective in the manufacturing and transportation industry, than in the retail trade and finance industry. Posting content more frequently turns out to be twice as effective for the retail trade and finance industry, than it is for firm in the manufacturing category.

Concluding, these results could indirectly lower advertising costs, improve the reach of content and thus the awareness around a firm or brand. The insights gathered from this research can be used to improve the content and content strategy and as an effect increase the return on investment.

7.4 Future research

The limitations of our study provides several opportunities for future research. At first, our study used data from a time range of 36 days and specifically examined firms derived from the Fortune 500. By extending the given time range and using firms from all sizes, so small, midsize and large firms, we would have gathered more data, which made the data more reliable and more generalizable across all firms and categories. Secondly, as a result of only using Fortune 500 users that have an active Instagram account, the categories in which a firm belonged were not equally divided. Moreover, if we selected firms equally for each of the categories, the reliability of the results would increase. Thirdly, we used factors that are all present on multiple platforms, such as Twitter and Facebook, but we only gathered Instagram data. Therefore, future research should collect the same data for each of the platforms, so the results would be more applicable for other SNS.

Furthermore, to indicate which factors influence the likes of an image, we used the likes collected after on day. It would be interesting to collect the like development of each post and analyze whether the effect size of the factors increase or decrease over time. This study has made a start with analyzing factors that influence the amount of followers, but with a model fit of 23,6 % there are still multiple factors unknown. Some examples of factors that could be analyzed further are: the content of the image, the text that goes along with the image and other types of color dimensions. In addition, we found that the category a firm belongs to influences the effect size of factors previous mentioned, this leaves room for multiple other moderators. Some examples are mobile versus desktop computer, male versus female, different target groups, different cultures or consumer accounts versus firm accounts.

In summary, we developed a better understanding of the different factors influencing the amount of followers of firms on SNS. We found evidence that an increase of frequency in posting and eWOM boosts the amount of followers. In addition, we proved that the color dimensions “Farbe an sich” and bright-dark contrast have a positive indirect influence on the amount of followers through likes. Equally important, we find that the industry a firm belongs to influences the effect size of the proven factors that influence the amount of followers. We believe our findings offer managers new insights and help them to improve their social media strategies.

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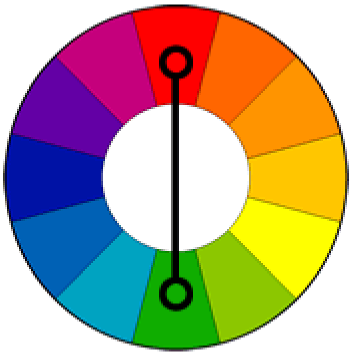
Appendix

Appendix 1: Industries and belonging firms

Mining
Chesapeake Energy
Manufacturing
Agco
Avery Dennison
Avon
Baker Hughes
Cisco
Coca Cola
Dell
Dr Pepper
Estee Lauder
Ford
General Electric
General Mills
Harley Davidson
Honeywell
HP
Intel
Land O'Lakes
Lockheed Martin
Motorola
Netapp
Nike
Northrop Grumman
Qualcomm
Ralph Lauren
Sandisk
Texas instruments
VF Outlet
Transportation & Public Utilities
AT&T
Delta
Consolidated Edison
DTE Energy
DirecTV
Disney
Dominion
FedEx
JetBlue
MetroPCS
Norfolk Southern
Southwest Airlines
Sprint
Time Warner Cable
Verizon
Viacom
Waste Management
Xcel Energy
Wholesale trade
Dole Food Company
Henry Schein
Nordstrom
Toys R Us
Retail trade
Advance Auto Parts
Autonation
Bed, Bath and Beyond
Dick Sporting Goods
Dillard's
Footlocker
Gap
The Home Depot
J.C. Penney
Kohls
Krogeo
Lowe's
Macy's
McDonalds
Office Depot
PetSmart
Rite Aid
Sears
Sherwin-Williams
Starbucks
Target
Walgreens
Walmart
Whole Foods Market
Finance, Insurance and Real Estate
Americanexpress
Citigroup
Liberty Mutual
Nationwide Iinsurance
Simon Property Group
Services
Avis Budget Group
Ebay
Facebook
Loews Hotel
Marriott Hotels & Resorts
Oracle Corporation

Appendix 2: Color wheel



Appendix 3: RGB color spectrum

Color	Color Name	Color Code (RGB)	Color	Color Name	Color Code (RGB)	Color	Color Name	Color Code (RGB)
	Bright Yellow	255-255-193		**Yellow (1)**	**255-255-0**		Dark Yellow	129-126-0
	Bright Yellow-Orange	255-240-193		Yellow-Orange	255-192-0		Dark Yellow-Orange	122-93-0
	Bright Orange	255-230-205		Orange (2)	255-128-0		Dark Orange	126-63-0
	Bright Red-Orange	255-230-221		Red-Orange	255-64-0		Dark Red-Orange	118-31-0
	Bright Red	255-230-230		**Red (1)**	**255-0-0**		Dark Red	126-0-0
	Bright Red-Violet	240-192-255		Red-Violet	192-0-255		Dark Red-Violet	93-0-122
	Bright Violet	230-205-255		Violet (2)	128-0-255		Dark Violet	63-0-126
	Bright Blue-Violet	230-221-255		Blue-Violet	64-0-255		Dark Blue-Violet	31-0-118
	Bright Blue	230-230-255		**Blue (1)**	**0-0-255**		Dark Blue	0-0-126
	Bright Blue-Green	231-255-249		Blue-Green	0-255-192		Dark Blue-Green	0-84-64
	Bright Green	221-255-221		Green (2)	0-255-0		Dark Green	0-126-0
	Bright Yellow-Green	234-255-193		Yellow-Green	192-255-64		Dark Yellow-Green	64-96-0
	White	255-255-255		Grey	128-128-128		Black	0-0-0

Appendix 4

Sobel test

	Test statistic:	*Std. Error:*	*p-value:*
Hashtag	-2.68	19503.10	0.007
No.colors	-3.10	15018.81	0.002
Compl. Color	-2.11	4668712.04	0.035
Farbeansich	2.64	50342.64	0.008
Bright-dark	-2.22	2947622.01	0.027

Appendix 5: Farbe an sich

“Farbe an sich” of 1

“Farbe an sich” of 4

Appendix 6: Bright-dark contrast

Low brigh-dark contrast (0.000839)

High bright-dark contrast (0.94741533)

Appendix 7: Model fit for all models

Model	Adjusted R^2	F-value	P-value
Total			
Stage 1	.053	30.021	.001
Stage 2	.236	108.748	.001
Manufacturing			
Stage 1	.060	13.396	.001
Stage 2	.321	.321	.001
Transportation			
Stage 1	.104	23.587	.001
Stage 2	.305	142.835	.001
Wholesale Trade			
Stage 1	.302	13.345	.001
Stage 2	.140	8.773	.001
Retail Trade			
Stage 1	.050	10.140	.001
Stage 2	.245	94.167	.001
Finance			
Stage 1	.061	12.198	.001
Stage 2	.257	100.266	.001
Services			
Stage 1	.305	26.142	.001
Stage 2	.199	24.755	.001