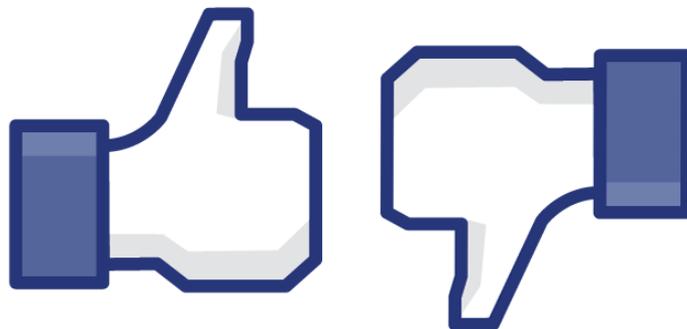


“FACEBOOK BRAND PAGES – DRIVERS OF POST ENGAGEMENT”



Erasmus School of Economics

Master of Science in Economics and Business

Specialization in Marketing

Matej Kobulský - 410022
Supervisor: Arash Yazdiha

Preface

Upon finishing this thesis, my master degree and studies will be at the end, thus I would like to thank all those people who made this achievement possible for me. First, I would like to thank for the support and everlasting motivation from my parents, without whom I would never be able to reach this point. Second, my gratitude goes to my supervisor Arash Yazdiha for valuable comments and guidelines during the formation process of this thesis. At last but not least, I would like to address deep gratitude to all my friends, both from my studies in Prague and here in Rotterdam, who kept me motivated and focused during all those years, especially Braňo, Matej, David, Milena & Rayana and many others. In addition I have to thank all the brands for providing the data necessary for the research in this thesis.

Abstract

Social media plays already a major role in brands' marketing strategy. This thesis is focused on the measurement and evaluation of brand posts' success on the most popular social media platform - Facebook, specifically on what factors drive customer engagement on Facebook brand posts. To conduct the research, Facebook insights data from two distinct fan page categories (Products & services, Media & news) were collected. The engagement rate of brand page posts was the observed metric of posts success.

Results suggest that there are several post characteristics, which influence overall customer engagement. However, different types of posts are engaged in a different way, namely by likes, comments or shares. Among factors that have the strongest positive effect over customer engagement are post vividness, posting on the weekend and posting on peak hours. Negative effect was present for number of fans, post length and hard-sell impulse. Posts corresponding to fan pages of Products and Services had a higher customer engagement over posts of Media and News fan pages. This study contributes to ongoing research in customer engagement on social media.

Key words: *social media, online marketing, customer engagement, Facebook, brand fan page, brand community*

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1. INTRODUCTION

Internet became the main communication network of our age and with a brink of social media, more people than ever are spending time online. This chapter will describe why it is necessary to study marketing on social media and describe proposed research settings.

Earlier last year I was working as a marketing manager for a small travel company and I suggested some changes for our marketing communication over Facebook, such as when to schedule the posts, how often during the week and what kind of content to post. Then my boss asked me:

“How do you know, that it will be better with your changes?”

He was right, neither have I known what was the best way, nor how to measure the success. Marketing on social media is becoming a major channel for communication of brands with their customers. People are spending more of their free time on digital devices, according to recent study (eMarketer, 2013), adults in U.S. now spend about 5 hours per day consuming digital media, while only 4,3 hours per day in front of their TV. Companies are slowly adapting to this trend by increasing their budgets for marketing on digital media, but biggest slices of budget still goes to traditional marketing on TV or press, putting TV ads on a first place with 45% in 2013 (Bloomberg, 2014).

Reasons for that may vary, first, customers like to follow new trends, especially when they provide them with higher freedom in choice of their preferred entertainment and enable direct interaction. Social media can keep their users in touch with their friends and favorite brands and allow them to share their ideas and news (Social Media Today, 2014). All this makes social media a perfect platform for marketers to communicate and interact with customers.

However, different fan pages on Facebook have different goals. While some brands aim to raise awareness of their Products and Services, other, such as news and media fan pages want to simply increase their web traffic, since they profit from online advertising.

These two fan page categories have slightly different goals on social media, therefore it is necessary to evaluate them separately.

But how do marketers capture full potential of social networks? Right now they can only rely on empirical results and recommendations of other marketers active on social media, but academic literature will give them little and very shortsighted guidelines. Understandably, like in every other economic discipline there is no “holy grail” for successful marketing on social media for exact brand and what works today may not work tomorrow. But would it be possible to observe what content of brands is more likely to be successful? How to measure success on social media? How can managers improve their results on social media? This thesis will try to provide answers to these questions.

1.1 RESEARCH QUESTION

Measuring marketing success on social media and interpretation of findings have many limitations, mainly due to continued evolution of social media platforms. This research will focus on observable and quantifiable factors that makes consumers interact with fan page posts of brands on Facebook in a form of liking, commenting, sharing or mere clicking on a post of brands' fan page.

Based on the thesis goals, research question is formulated as follows:

What are the key factors that drive consumer engagement of Facebook brand pages posts?

With additional sub questions:

- *Are there any differences within consumer engagement of Products and Services compared to Media and News fan page posts?*
- *How can we reliably measure customer engagement on social media?*

1.2 RESEARCH SETTINGS

To see effects of brands' marketing on social media, this thesis will observe currently world's most used social media and second most popular webpage in general (Alexa, 2015) – Facebook, with 1,390 million monthly active users worldwide (Social Bakers, 2015) In addition to that, Facebook is providing environment for brands to make their marketing communication via Facebook fan pages and also provides marketers with wide selection of insight data that include all key engagement statistics for data analyses. Analyses will be conducted on data from Facebook Insights provided by various brands.

Second, a proper sample of fan pages has to be selected. Research will be conducted from Facebook Insights of two types of fan pages: First type is fan page for brand promoting products or services. Goal of this fan pages is to increase awareness and sales. Second type of fan pages are various “media” and news brands which provide their fans with informational and entertaining content. Their goal is to increase website traffic and therefore revenues from online advertising.

1.2.1 Dependent Variable

Customer engagement on Facebook posts is observed in four levels: likes, comments, shares, total number of clicks and overall engagement rate is calculated by sum of users who engaged with post divided by number of users who saw the post, so called reach. Simplified formula proposed by Jadhav et al. (2013) uses total number of brand fans on posts' day instead of reach, but this method does not take into account number of fans that did not have opportunity to interact with the post. Therefore in order to standardize, this study will use metric “Reach”, also called impressions.

1.2.2 Independent Variable

Explanatory variables of this study are various characteristics of brands posts extracted from the data, which can be described in six main groups: (1) Content type represent type of the message content, for example if post contain informational or entertainment content. (2) Type of vividness will observe what media type was used to carry on the message by fan page admin, ranging from simple status up to complex video. Next, (3) Post Interactivity components will be studied, (4) Time of posting analyses day of the week and

hour in a day of post submission, (5) Text characteristics will analyze textual content of the message and (6) Fan page characteristics will observe fan page category and number of fans.

1.3 RESEARCH RELEVANCE

Growth of social media marketing makes a very interesting topic for various researchers because of the impact of social media on marketing communication. However, due to its short existence still lacks unified theoretical framework or further research guidelines. Research is often based on consumer online behavior, since interactions of customers with brands online has a much stronger impact on their behavior than traditional forms of marketing communications (Chiou & Cheng 2003). Muntinga et al. (2011) categorized three dimensions of consumers' online brand-related activities (COBRAs) as consuming, contributing and creating and three motivations for them: information, entertainment and remuneration, based on uses & gratification theory (Katz 1959; Dholakia et al. 2004). This research can be translated also on social media.

Uses and Gratification theory was used also by Goh, Heng & Lin (2013) to investigate how user and marketer generated content on social media influence purchase behavior. Their results showed a significant increase of customer purchases with increased engagement on social media. Factors of customers engagement on Facebook brand pages was investigated by Kabadayi & Price (2014). They researched three personality traits that affect consumer behavior: extraversion, neuroticism and openness to experience to broadcast message or communicate privately. Consumer engagement via likes and comments was proven to be essential for success of brands' social media strategies.

Wallace et al. (2014) took a different approach by providing typology of Facebook fans, suggesting four "fan types": the fan-atic, the utilitarian, the self-expressive and the authentic. Another research was done by Swani, Milne & Brown (2013) by evaluating strategy effectiveness on Facebook of Fortune 500 companies. They found the difference

in B2B and B2C effectiveness when posting messages with direct calls to purchase versus emotional content.

As shown above, there are several approaches used by academics to research brands and customers on social media. Very few managed to contribute into understanding the essence of successful brand post, but most of the researchers agree on importance of customer engagement in a form of liking or commenting (Bolton 2011; Kabadayi & Price 2014) and its connection to increased profitability of the brand (Enders et al. 2008; Kumar et al. 2010). Among those who tried to understand factors that drive consumer engagement are Cvijikj & Michahelles (2013), who observed how content type (entertainment, information or remuneration), media type (message vividness and interactivity) and posting time (day of the week and peak hours) influence likes, comments, shares and interaction duration, finding entertainment as leading factor of engagement and interestingly negative relationship with message interactivity. Although, their research did not took number of clicks or post length into account. Similar study was done by Vries, Gensler & Leeflang (2012) by studying impact of post vividness (picture, event or video), interactivity (media type), presence of informational or emotional content, position and valence of positive versus negative comments on number of likes and comments. While for number of likes high level of vividness was found to be significant, high post interactivity (e.g. question) was important for number of comments.

These two studies share a common limitation of overlooking the brand community size (Cvijikj & Michahelles 2013), since Extra (2011) found that the number of fans is the biggest predictor of the number of likes and comments. Therefore, this study will contribute to ongoing research by examining engagement among brand fan pages with a relative variable – “engagement rate”.

1.4 GOALS

Goal for this thesis is to contribute ongoing academic research into customer behavior towards brands on social media. Since past research proven consumer engagement on brand posts as a key benefit for a brand's social media presence (Tsimonis & Dimitriadis 2013) that translates into customer loyalty and higher purchase likelihood, this thesis will examine what factors and in what valence influence this engagement. Aim is to not only contribute to theoretical knowledge, but come up with practical managerial implications that can help marketers to successfully measure and manage brand fan pages on Facebook and other social media.

2. THEORETICAL FRAMEWORK

Purpose of this chapter is to review existing literature into studied topic, based on which are later proposed hypotheses tested in this thesis.

2.1 SHIFT FROM TRADITIONAL MEDIA

It was only a few decades ago, when British scientist Tim Berners-Lee invented World Wide Web in late 80s (Goyal 2013), but it had major impact on how society consume media. Before that, brands was able to buy advertising time on television or radio, place for public display, space in newspapers or other form of advertising which was “pushed” at the consumers (Schlosser et al. 1999). Consumers recently built immunity and skepticism towards these traditional commercial media (Bagozzi & Dhlokia 2006) and brands had to find new means of communication and interaction with their target audience (Kabadayi & Price 2014). With advent of the World Wide Web and age of digital interactivity, consumers role has shifted from being “passive recipients of information to becoming active generators of information” (Stewart & Pavlou 2002) thus creating new “pull” form of communication, when consumers can choose when, where and what advertising content they wish to consume (Schlosser et al. 1999). Moreover, these forms of interactions with brands were proven to have stronger impact on consumer behavior over traditional forms of marketing communication (Chiou & Cheng 2003).

Hoffman et al. (1995) defines World Wide Web as new alternative to mass media and highlights its potential as a marketing medium that can “change radically the way firms do business with their customers by blending together publishing, real-time communication broadcast and narrowcast”. Difference between traditional passive “One-to-many” information flow and new model for marketing communication on the web “many to many”. This new way of communication gives consumers control over information they consume and frees them from traditional passive role as receivers. They become active participants of marketing process by searching for information and engaging.

Rodgers & Thorson (2000) identified consumer motives for internet use as a key to understanding internet advertising effectiveness and in follow up study provided four primary factors: research, communication, surfing and shopping (Rodgers et al. 2007) broken into 12 sub-scales, among them highest variance was explained by sub-motives community (connecting and communicating with others), entertainment (entertain and amuse yourself) and information (research for information).

2.2 WEB 2.0 AND SOCIAL MEDIA

So called “social media” came in existence with the Web 2.0, which is according to O’Reilly (2005) “a collection of open-source, interactive and user-controlled online applications”, “that allow creation and exchange of user-generated content” (Kaplan & Haenlein 2010). Term Web 2.0 does not refer to any specific technical update of the World Wide Web, but more to a set of basic functionalities that are necessary for its functioning (Kaplan & Haenlein 2010), among them are Adobe Flash (adding interactivity and audio & video streams on web pages), RSS (Really Simple Syndication), family of web feed formats and AJAX (Asynchronous Java Script). It is considered as a platform for the evolution of social media nowadays. Other than that, Web 2.0 allows creation of User Generated Content (UGC), various forms of media content that are publicly available and created by end-users. But according to Kaplan & Haenlein (2012), “this social media revolution is nothing else than internet going back to its roots”. In early day’s internet started as a group of newsgroups created by Tom Truscott and Jim Ellis in 1980, where users could read or post bulletin-like messages in different categories. After several transformations, internet now returns to “what it was initially for – platform to facilitate information exchange between its users”.

To answer question “What is social media?” Mayfield (2008) offers several characteristics: (1) Social media encourage users’ participation, (2) most of them are open, (3) social media offer two-way communication, (4) allows communities to form and communicate effectively about shared interests and (5) connect to other sites, resources and people. Shift towards social media was described by several factors by Gillin (2007): (1) Declining

consumer response rate to conventional online marketing, (2) attractiveness due to technology development, (3) demographic shift, (4) low cost and (5) fact, that people trust user-generated content more than marketer-generated content by companies (Goh, Heng & Lin 2013). Firms benefit from presence on social media at various levels. First, companies can develop and enhance relationship with their customers (Bartlett 2013), reach and target precise audience that could not be reached otherwise (Dong-Hun 2010), gather valuable insights on customer preferences, raise brand awareness and most important increase purchase behavior and therefore boost sales (Tsimonis & Dimitriadis 2013).

Focus of this thesis will be on currently most popular social networking site Facebook with 1,390 million monthly active users worldwide (Social Bakers 2015) and also the most visited web page worldwide (Alexa.com 2015). Social media and Facebook in particular diffused exponentially compared to its predecessors. For the radio it took 38 years to gain 50 million listeners, for the television that number of viewers lowered to 13 years and the internet took only 4 years to gather 50 million users. But for Facebook, same number of participants, 50 million was reached in only one and half year (Nair 2011). Nowadays, 83% of the Fortune 500 companies are present on Facebook (Barnes & Lescault 2014) with Facebook itself on 341st place (Fortune 2015). Facebook allows companies to create and manage their own fan page, where they can post news, photos or other content to a broad audience (Gummerus et al. 2012) and let visitors engage by liking or commenting. This customer behavior “straighten the bonds that customers have with companies by turning them into engaged fans” (Wallace et al. 2012). By liking and commenting company post is transmitted to network of each engaged user, creating a powerful word of mouth.

2.3 BRAND COMMUNITIES

Muniz & O’Guinn (2001) described brand community as “a specialized, non-geographically bound community, based on a structured set of social relationships among admirers of a brand”. Brand communities are important platform for engagement behavior of consumers and firms aim to influence members’ perception about the brand and learn

from and about them (Algesheimer et al. 2005). Consumers can engage in a several behaviors, as well as in non-interactive such as reading others' comments (Tsimonis & Dimitriadis 2014), therefore presence of the comments on brand posts' is important predictor of consumer engagement. Moreover, findings of a study done by Lee et al. (2011) suggests, "that consumers can easily associate marketers' effort to build and manage online brand communities with extrinsic motives of profit exploitation and are less likely to engage in community behaviors in marketer created online brand communities". Overall, for brands it is important to provide community-building infrastructure with opportunity for users to communicate with each other beyond what is required for purchase transaction since it has positive effect on future customer loyalty and their purchase intentions (Mathwick, 2002).

2.4 CONSUMER ENGAGEMENT

Oxford dictionary offers several meanings for the verb "to engage", among them are "to succeed in attracting and keeping somebody's attention and interest" or "to become involved". All meanings have in common its behavioral focus. Engagement in media can be distinguished from mere liking (Calder & Malthouse, 2008) by stronger state of connectedness between them.

Doorn et al. (2010) defined consumer brand engagement as "customers' behavioral manifestation toward a brand beyond purchase, resulting from motivational drivers" including behaviors like WOM, recommendations, writing reviews or blogging. Empirical findings suggests that engagement presence improves consumer – brand relationship with a higher level of satisfaction (Gummerus et al. 2012). Appelbaum (2001) stated, "that a customer's brand engagement score represents the most powerful predictor of customer loyalty available", moreover Banyte & Dovaliene (2014) propose reversed direct link in relation between customer loyalty and engagement into value creation – when customers become more loyal they become more interested in greater benefit from maintaining long-term relationship and become actively involved in the process of value creation.

Doorn et al. (2010) also propose five dimensions of Consumer Engagement Behaviors: (1) Valence which can be positive or negative, (2) Form of modality, referring to different ways in which it can be expressed by customers, (3) Scope based on time and location, (4) Nature of its impact, meaning its immediacy, intensity, breath and longevity and (5) Customer goals.

Findings of Goh et al. (2013) show that “engagement on social media brand communities leads to significant increase in consumer purchases”. High customer engagement can transform them into brand advocates through Customer Engagement Cycle (Sashi 2012). Fans are referred to consumers that have high both emotional bonds (relationship with seller) and relational exchange, which is increasing with experiencing different stages of the Customer Engagement Cycle over time. Both, customer delight and loyalty are necessary for customer engagement.

Hollebeek (2011) defined customer brand engagement as “the level of a customer’s cognitive, emotional and behavioral investment in specific brand interactions” which are represented by three themes: (1) Immersion, as “customer’s level of brand-related concentration in interactions”, (2) Passion, defined as “degree of customer’s positive brand-related affect” and finally (3) Activation, “customer’s level of energy, effort and time spent on brand-related interactions”.

Therefore, based on the prior research into customer engagement and its positive effect on customer loyalty and purchase behavior, this thesis will investigate factors that influence customer engagement on social media, specifically Facebook. For brands’ success on social media, consumer engagement in form of active likers and commenters is essential strategy (Kabadayi, 2014).

2.5 USES AND GRATIFICATIONS THEORY

Users have to have utilitarian experience with media content in order to engage with it (Calder et al. 2009). Those experiences can have different causes and can vary based on medium or type of the user. Some users can value entertainment content, while others seek information. Uses and gratifications (U&G) theory (or sometimes approach) provides

functionalist explanation why people use and consume media (McQuail 1983). Four main motives were identified:

- “*Information*” – finding information about relevant event in society around the world, seeking advice, gaining knowledge or satisfying curiosity.
- “*Personal identity*” – finding models of behavior, identifying with valued others, finding personal reinforcement or gaining insight into one’s self.
- “*Integration and social interaction*” – identifying with other people and gaining sense of belonging, finding a basis for conversation and social interaction, substitute real-time companionship or connecting with the friends and family.
- “*Entertainment*” – relaxing, escaping from problems, getting cultural enjoyment, emotional release or just filling time.

2.6 CONCEPTUAL FRAMEWORK AND HYPOTHESES

In the *Figure 2.2* conceptual framework for this study is proposed. This thesis argue, that content type (information, entertainment and remuneration), post vividness (status, link, photo and video), interactivity (call to action, presence of question and hard-sell), time of posting (day of the week, peak hour), text characteristics and the fan base characteristics have an effect on customer engagement with brand’s fan page posts on Facebook.

2.6.1 Content type

Based on Uses and Gratification theory mentioned earlier, this thesis derive three motives that drive customer engagement of brands on social media. Those motives are information (by informing customers about new offers and news from the community and world), entertainment (by providing content with that pleasure or delight customers) and remuneration (content that offers some sort of reward or benefit for customers if engaged, typically in form of competition). Previous application of the U&G theory for social media show entertainment and informal content as an important factor for participation in brand communities (Dholakia et al. 2004). According to Calder et al. (2009) users engage on posts that hold higher utilitarian benefit, therefore it is hypothesized that posts with

entertaining, informal or remuneration content will have higher customer engagement. Within those three content types, Park et al. (2009) found that entertainment have a stronger effect and according to Muntinga et al. (2011) and remuneration with the least frequent motivation for engagement. Therefore, following hypotheses are formulated:

H_{1A}: Posts with entertaining content leads to a higher customer engagement.

H_{1B}: Posts including informal content leads to a higher customer engagement, but lower than entertainment.

H_{1C}: Posts offering remuneration leads to a higher customer engagement, but lower than informal and entertaining content.

2.6.2 Post vividness

Brand post's visual features can be represented as vividness, by stimulating different senses (Steuer 1992). By including more dynamic animations, colors or pictures, posts can achieve higher customer attention and therefore engagement. The more senses are stimulated at once, the more vivid message appears (Coyle and Thorson 2001), for example video stimulates not only sight, but also hearing. Posts on Facebook can consist of merely a text in a form of status or they can include a web link (appearing highlighted in different color). More vivid posts include picture and the highest degree of vividness is thought the video. Therefore this thesis formulate:

H₂: Posts with a higher level of vividness gain a higher level of customer engagement.

2.6.3 Post interactivity

Interactivity is by Liu and Shrum (2002) defined as “the degree to which two or more communication parties can act on each other, on the communication medium, on the messages and the degree to which such influences are synchronized”. Thanks to Web 2.0 platform, brands on social media are fully equipped to encourage the customers into various form of interaction with posted content. For example post can include a question which can lead customers to the interaction thought commenting. Another form of interaction can be presence of “call to action”, meaning instruction to audience that provokes some sort of action, usually link click, like, comment or sharing the post. Brands

can also offer customer interaction in for of purchase by posting “hard-sell” messages, although due to evolving “banner blindness” (Benway, 1998) in the eyes of customers, this posts may lower their engagement. Following are hypotheses:

H_{3A}: Posts including a “call to action” impulse results in a higher customer engagement.

H_{3B}: Presence of a question in posts leads to a higher customer engagement.

H_{3C}: Posts with hard-sell content will have a lower customer engagement.

2.6.4 Time of posting

It can be intuitively assumed, that time in a day and day in a week will play a role in overall consumer engagement. Study into Facebook usage by Virtu (2010) indicated lower consumer activity during weekends and higher during the peak hours in a day (between 18:00 and 22:00). Therefore it is hypothesized, that submitting posts by admin during time period with higher consumer activity will result in higher consumer engagement. Submitting more posts than one in a day shorten the top position in a news feed for individual post, so it is possible that such posting will decrease customer engagement of individual post. These hypotheses are formulated as follows:

H_{4A}: Submitting more than one post per day by fan page admin will lower individual post’s customer engagement.

H_{4B}: Submitting posts by fan page admin during the peak hours will increase customer engagement.

H_{4C}: Submitting posts by the fan page admin on weekends will decrease customer engagement.

2.6.5 Text Characteristics

Results from advertising research suggest, that message length has an effect on click thought rate (Robinson et al., 2007), therefore this thesis hypotheses that shorter posts will gain higher consumer engagement, since they can gain customer attention in shorter time. Among other observed characteristics, presence of brand name, web link and emoticon was mined from the data and agnostic hypotheses are formulated whether there

exist an effect of their presence on customer engagement. Reason for forming the agnostic hypotheses is lack of theoretical background to predict valence of such textual characteristics, but past research of Shaparenko et al. (2009) found effect of similar text characteristics on click thought rates of online advertising banners, therefore some effect is expected. These hypotheses are formulated as follows:

H_{5A}: Shorter posts will have a higher customer engagement.

H_{5B}: Presence of the brand name in the post will have an effect on customer engagement.

H_{5C}: Presence of the web link in the post will have an effect on customer engagement.

H_{5D}: Presence of the emoticon in the post will have an effect on customer engagement.

2.6.6 Fan base Characteristics

Difference in fan page category can be intuitively believed to have an effect on overall post's engagement. This thesis is focusing on two fan page types: fan pages of Products and Services brands and fan pages of Media and News brands. Media fan pages provide content with higher informal and entertaining content, therefore is assumed their posts will have a higher level of consumer engagement. Pervious research reported, that number of brand's fans is the biggest predictor of customer engagement (Extra, 2011), therefore it is important to include size of brand fan base on a day of posting. From virality studies we can conclude that message has higher potential to spread when it is served to larger audience (Kaplan & Haenlein 2011; Dobeles et al., 2007) therefore posts with higher fan base should have higher customer engagement, which is also expected according to conventional wisdom. Hypotheses are formulated as follows:

H_{6A}: Media fan pages will have a higher customer engagement.

H_{6B}: Posts of brands with a bigger fan base will have a higher customer engagement.

Following are the hypotheses presented in conceptual framework for a better overview:

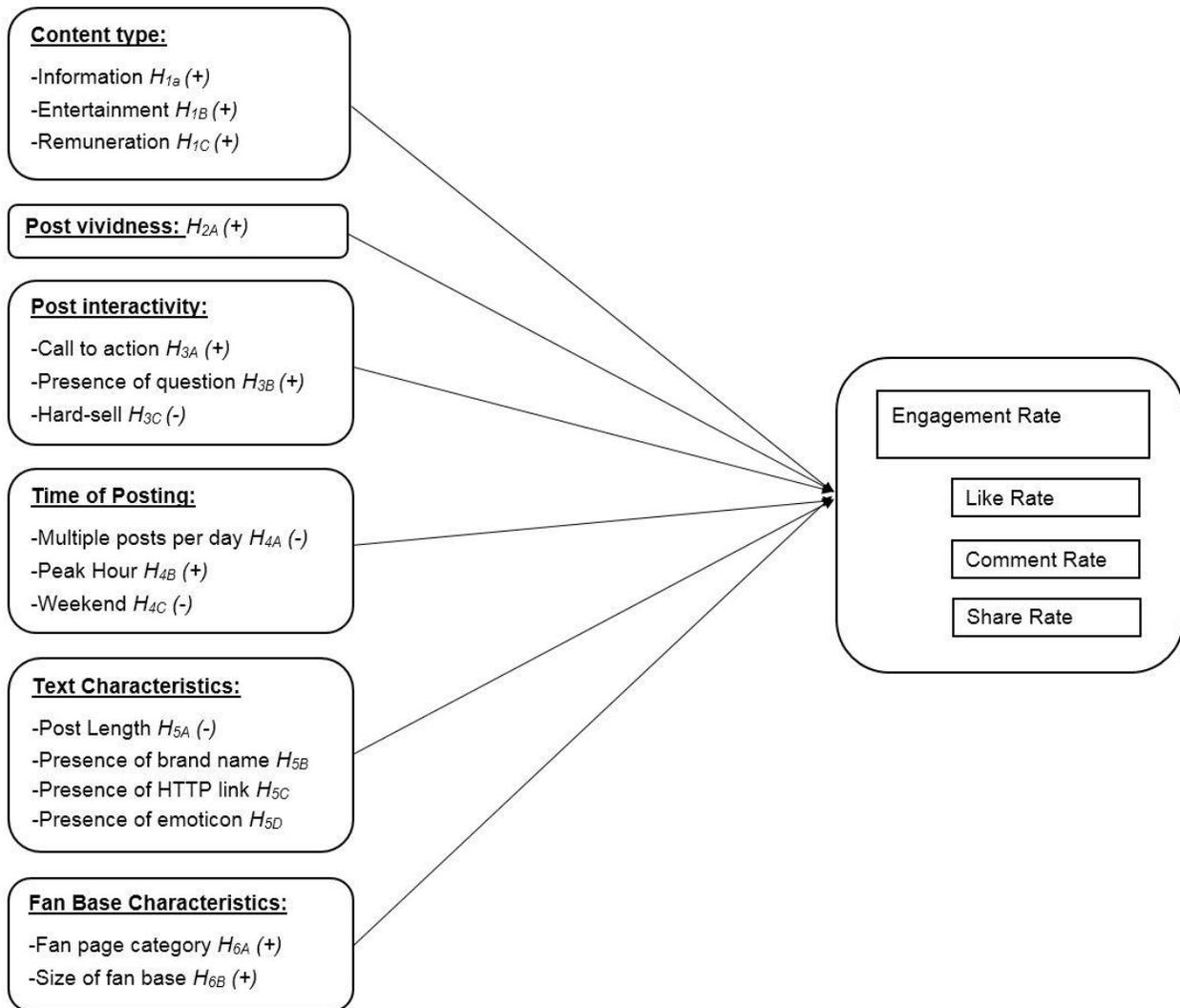


Figure 2.1 Conceptual framework

3. METHODOLOGY

This chapter will describe methodology planned for this thesis, including data collection, coding of the variables and the data analysis.

3.1 DATA COLLECTION

This thesis analyzes the data from Facebook Insights exported and provided by seven various Facebook brand pages. Due to confidentiality issue, none of the brand's name are mentioned. Admins of the Facebook fan page account have the option to export insights data of their fan page performance in maximum range of 180 days. This research collected data in a range from 5th of August 2014 to 31st September 2015, in order to capture both, summer and winter season and reduce spikes of popularity of seasonal brands. Four product & services and three media & news brand fan pages agreed to share their insight data for the purpose of this study, listed in *Table 3.1*.

Product & Services	Number of Fans	Number of posts	Media & News	Number of Fans	Number of posts
Brand A	102383	93	Brand E	4670	165
Brand B	73099	127	Brand F	29457	500
Brand C	5711	67	Brand G	27674	99
Brand D	1987	77			
SUM	183180	364	SUM	61801	764

Table 3.1 Fan page overview

Based on numbers from the *Table 3.1*, data analysis will be performed on 1,128 brand's posts on Facebook and 244,981 fans, but this number is likely to be higher, since brand posts are often engaged also by the users outside of the brand's fan base. Product and Services brands represent fan pages of common brands that sells goods and services. Among studied brands are energy drink company, sports clothing manufacturer, sport equipment manufacturer and travel agency. Media brands is chosen as an additional group of fan page due to their different goal for social media presence. While Products and Services aim to raise awareness, increase customer relationship and mainly boost the sales, media brands aim to increase traffic of their web page (mainly thought the links

to their web page content on social media). Studied media brands includes online lifestyle magazine and two online sports magazines.

Facebook Insights is a tool similar to a web analytics, which allows Facebook fan page admin to track page performance and user interaction. This tool also allows admins to export in depth data on two levels. First on daily level, measuring performance of fan page on daily basis in various metrics like total number of fans or total number of likes. This thesis will focus on second, post level data, which provides data on performance of the each individual brand post. Among collected metrics are:

- (1) *Post message* - text content of a post, number of characters
- (2) *Type of post* - presence of status, link, photo or video
- (3) *Date and time of post submission*
- (4) *Total reach* – number of people post was shown
- (5) *Total engagement* – number of people that engaged with the post in any way (likes, comments, shares and clicks)
- (6) *Likes* – number of people who liked the post
- (7) *Comments* –number of people that commented on the post
- (8) *Shares* - number of people who shared the post
- (9) *Clicks* - number of people who clicked anywhere in the post, meaning photo views, video plays or clicking on link.
- (10) *Number of fans on a day of posting*

3.2 OPERATIONALIZATION OF THE VARIABLES

Following the guidelines from Saunders et al. (2000), all data types should be entered using numerical codes to prevent errors, both quantifiable and categorical data. This study will often use so called dummy variables in order to test hypotheses. Dummy variable is

coded as 0 in order to indicate absence of given attribute and 1 indicating its presence. Following are described both independent and dependent variables of this thesis:

3.2.1 Independent Variables

Content type

In order to assign the corresponding content type to each post, manual coding is performed based on deduction, following the coding development strategy (Glaser and Strauss, 1967).

Posts labeled as “Entertainment” does not necessary contain information about the brand or its products, rather message that wants to entertain their fans with a quote, funny picture, such as:

“Enjoy the weekend and remember: take it easy :)”

Posts coded as “Information” are more common to the ordinary advertising content, informing customers about Products and Services and various news, such as:

“See more of the Brand B Winter collection at www.BrandB.eu or in the online catalogue.”

Finally, posts with “Remuneration” content offer some sort of reward or benefit for customers, often in form of various competition in which the goal is to increase customer engagement, such as:

“Last 6 days to enter our Photo Contest and win a brand new Brand C equipment.”

Post vividness

Admins of Facebook fan page can submit the posts in different media types with different degree of vividness. Status contain only textual content, therefore is assumed to have the lowest degree of vividness, Link offer slightly higher vividness with increased real estate on Facebook wall news feed, photo has high level of vividness since it offers higher visual stimulation and finally video has the highest level of vividness due to both visual

and sound stimulation. Vividness is coded on scale from 1, representing the status to 4, representing the video. It is worth mentioning, that each of these types is accompanied by textual description (e.g. Photo has the caption), which is used for testing various hypotheses.

Post interactivity

Interactivity of the posts is observed by three dummy variables that indicate presence of content that users can interact with or are lead to interaction. Presence of question is coded from text mining with value 1 if post message include question mark “?” and 0 if no question mark was present. Other two variables are coded manually, call to action variable is coded 1 if post message contain any sort of instruction that provokes a response in different way, usually liking, commenting or visiting the link, for example:

“Should we run a video contest this year? Hit LIKE button if you think so!”

Hard-sell posts are messages directed to customers with aim to sell their Products and Services, typically leading to online shopping platform or other purchase place, such as:

“Girls do it better.....especially with our Tina jackets :) Shop at www.BrandB.eu”

Time of posting

Post that is accompanied with other brand posts on given day is coded with dummy variable 1 and 0 if it was single post of a brand on given day.

Four dummy variables are created for each period of a day. Dummy for night has value 1 if posts were submitted between 23:00 – 8:00, Morning dummy for posts between 8:00 – 12:00, afternoon dummy between 12:00 – 17:00 and finally evening dummy, which is hypothesized to contain post during so called “peak hours” between 18:00 – 23:00. Other time dummies are left in the model for their controlling effect.

Posts submitted by admin on weekends has value 1, while weekday posts are coded with value 0.

Text characteristics

The number of characters of each post message is extracted with MS Excel. Post length is measured in number of character in the post and variable is log transformed for normal distribution.

Another dummy variable controls presence of Brands name in corresponding post messages, with 0 value for posts without brand name and 1 posts with brand name included.

Posts with characters “http” included in the post message are coded as 1, indicating presence of the web link, while 0 indicate no web link presence. Note, that this variable differs from Type of vividness variable “Link”, while “Link” is direct integration of landing page in Facebook platform, this variable observes presence of the link inside of post textual message, which can be included in all types of posts, like photos or videos.

Messages containing various forms of emoticons, such as “:)”, “:-P” or “:-(” are coded with dummy 1, and posts absenting those emoticons as 0.

Fan base characteristics

Different brand type (product & services or media & news) can have other unobserved differences for user engagement, therefore they are coded with dummy variable 0 for fan pages of Products and Services and 1 for fan pages of News and Media.

Size of fan base is log transformed number of fans of given fan page on a day of posting.

In conclusion, this thesis will observe effect of variables listed above on dependent variables using several multiple regression models. For clarity, coding scheme of independent variables is presented in *Figure 3.1*.

Variable	Code
Content type	<u>Dummy 1: Information</u> 0 = Not information content (false) 1 = Informational content (true) <u>Dummy 2: Entertainment</u> 0 = Not entertainment content (false) 1 = Entertainment content (true) <u>Dummy 3: Remuneration</u> 0 = Not remuneration content (false) 1 = Remuneration content (true)
Post vividness	<u>Scale based on level of post vividness:</u> 1 = Status 2 = Link 3 = Photo 4 = Video
Post interactivity	<u>Dummy 4: Call to action</u> 0 = Post without call to action (false) 1 = post with call to action (true) <u>Dummy 5: Presence of question</u> 0 = Post without question mark (false) 1 = Post including question mark (true) <u>Dummy 6: Hard-sell</u> 0 = Post without hard-sell message (false) 1 = Post containing hard-sell message (true)
Time of Posting	<u>Dummy 7: Multiple posts per day</u> 0 = single post on given day by the brand 1 = Posted along one or more other posts on given day <u>Dummy 8: Peak hour</u> 0 = Posted outside of peak hours (false) 1 = Posted during peak hours (true) <u>Dummy 9: Weekend</u> 0 = Posted on workday (false) 1 = Posted on weekend (true)
Text Characteristics	<u>Post length:</u> String (log transformed number of characters in the post) <u>Dummy 10: Presence of brand name</u> 0 = Brand name not mentioned in post message (false) 1 = Brand name mentioned in post message (true) <u>Dummy 11: Presence of HTTP link</u> 0 = HTTP link not present in post message (false) 1 = HTTP link present in post message (true) <u>Dummy 12: Presence of emoticon</u> 0 = No emoticon in post message (false) 1 = Emoticon included in post message (true)
Fan base characteristics	<u>Dummy 13: Type of fan page</u> 0 = Product & Services brand fan page 1 = Media brand fan page <u>Size of fan base:</u> String (log transformed number of brand fans on a day of posting)

Figure 3.1 Coding scheme of independent variables

3.2.2 Dependent Variables

This thesis aim to research how independent variables defined above interact with user engagement to brand posts, in a form of (1) liking the post, (2) commenting on the post, (3) sharing the post and (4) clicking on the post (opening photo, clicks on the link or video plays). Since this thesis is working from with the data coming from various fan pages, two problems emerges if simple engagement values would be used as dependent variables. First, each fan page has different fan base and pervious research found out, that size of this fan base is the biggest predictor or post engagement (Extra, 2011), hence results of such analysis would be affected by a brand fan base size. Second problem is, that not every post generates same amount of impressions (people to which post is shown on their Facebook news feed wall), mainly due to various other factors considered by Facebook formula called EdgeRank which decides which post are going to be shown and to whom. Therefore, looking only on absolute number of engagement could lead to distorted results.

First problem is often tackled with standardizing engagement by dividing post engagement with number of brand fans on a given day, this solution was used in research of Cvijikj and Michahelles (2013) in the *Figure 3.2*.

$$Engagement Rate_{OLD} = \frac{\#Likes + \#Comments + \#Shares}{\#Fans}$$

Figure 3.2 Old formula for Engagement rate

However, this thesis argues that proposed solution do not solve the second problem of not taking into consideration actual number of impressions. In this research, engagement rate is measured by dividing total number of engagement by total number of people that post was shown and therefore had the chance to engage. In the banner advertising practice, similar metric, click thought rate is broadly used and accepted. Data from Facebook Insights report collected for purpose of this study offers information about total number of the people to whom was post shown, called *Total Post Reach*. Therefore, this thesis is using this number to standardize post engagement. To overcome duplication of

individual engagement types (for example if one person could both, open the photo and like the post), unified measure Total Post Engagement included in Facebook insights data is used. This measure shows number of unique people that engaged with the post in any way. Moreover, insights data also contains information about how many people clicked anywhere in the post, which is also a valuable form of engagement that has to be taken into consideration. *Figure 3.3* shows the formula for main dependent variable of this thesis.

$$Engagement Rate = \frac{\#Likes + \#Comments + \#Shares + \#Clicks}{Total Post Reach} = \frac{Total Post Engagement}{Total Post Reach}$$

Figure 3.3 Formula for Engagement rate

In addition to this measure, this thesis is analyzing each form of engagement separately, mainly in order to discover significant differences, which could be useful in managerial practice. First, *Likes Rate* will measure how many people liked brand posts, which could be useful as a metric to measure overall post appeal.

$$Like Rate = \frac{\#Likes}{Total Post Reach}$$

Figure 3.4 Formula for Like rate

Second additional dependent variable observes posts' *Comments Rate*, which could be a valuable metric to observe word of mouth created by post or customer loyalty.

$$Comment Rate = \frac{\#Comments}{Total Post Reach}$$

Figure 3.5 Formula for Comment rate

And finally third and last additional dependent variable is *Shares Rate*, which can indicate how "viral" post message got.

$$Share Rate = \frac{\#Shares}{Total Post Reach}$$

Figure 3.6 Formula for Share rate

3.3 REGRESSION MODEL

This thesis uses quantitative data in order to find statistically significant relationship between independent and dependent variables. To text mine the data, code the dummy variables and create informal graphs and tables Microsoft Excel is used and SPSS for Windows is used to perform statistical tests.

To analyze relationship between variables, regression analysis is studying dependence of user engagement on Facebook posts characteristics. Regression analysis is the study of the dependence of one dependent (exploratory) variable on one or more explanatory variables. In case of more than one explanatory variables, this method is called multiple regression. In such method, there are multiple factors having an influence on the dependent variable, which might also influence each other. A linear regression model allows to disentangle these several factors and to determine the impact of one single factor. These effects can be attributed on the outcome variable because of the *ceteris paribus* condition, meaning that all the other factors having an impact on the outcome variable are holding constant. The β coefficients of the linear regression equation are estimated by ordinary least squares (OLS). This method estimates the coefficients in a way that the sum of the squared error terms is minimized, thus it minimizes the difference between predicted and observed values. (Stock et al. 2012)

Since this thesis is using slightly different independent variables for different fan page categories, total of twelve multiple regressions are tested.

Models for all brand fan pages observes four dependent variables y_1 = Engagement rate, y_2 = Like rate, y_3 = Comment rate and y_4 = Share rate and can be expressed as:

$$\begin{aligned} \log(y_i) = & \beta_{0i} + \beta_{1i}VividnessType + \beta_{2i}CallToAction + \beta_{3i}Question + \beta_{4i}HardSell \\ & + \beta_{5i}MultiplePosts + \beta_{6i}PeakHour + \beta_{7i}Weekend + \beta_{8i}PostLenght \\ & + \beta_{9i}BrandName + \beta_{10i}HTTP + \beta_{11i}Emoticon + \beta_{12i}FanPage + \beta_{13i}Fans \\ & + \varepsilon_i \end{aligned}$$

Where *VividnessType* is level of post vividness on scale, *PostLenght* and *Fans* are intervals and other variables are coded as dummies and error term ε_i for normally distributed error terms for all four dependent variables.

Similar models for Products and Services brands can be expressed as:

$$\begin{aligned} \log(y_i) = & \beta_{0i} + \beta_{1i}Information + \beta_{2i}Entertainment + \beta_{3i}Remuneration \\ & + \beta_{4i}VividnessType + \beta_{5i}CallToAction + \beta_{6i}Question + \beta_{7i}HardSell \\ & + \beta_{8i}MultiplePosts + \beta_{9i}PeakHour + \beta_{10i}Weekend + \beta_{11i}PostLenght \\ & + \beta_{12i}BrandName + \beta_{13i}HTTP + \beta_{14i}Emoticon + \beta_{15i}Fans + \varepsilon_i \end{aligned}$$

Where observed dependent variables are y_1 = Engagement rate, y_2 = Like rate, y_3 = Comment rate and y_4 = Share rate. Three dummy variables *Information*, *Entertainment* and *Remuneration* are present in these models, in order to observe an effect of the content type of the posts. Rest of the model is same as model for all brands, expect the exclusion of variable *Fan page*, since only one type of brand category is present in observation.

Finally, models for Media and brands with dependent variables y_1 = Engagement rate, y_2 = Like rate, y_3 = Comment rate and y_4 = Share rate can be expressed as:

$$\begin{aligned} \log(y_i) = & \beta_{0i} + \beta_{1i}VividnessType + \beta_{2i}CallToAction + \beta_{3i}Question + \beta_{4i}HardSell \\ & + \beta_{5i}MultiplePosts + \beta_{6i}PeakHour + \beta_{7i}Weekend + \beta_{8i}PostLenght \\ & + \beta_{9i}BrandName + \beta_{10i}HTTP + \beta_{11i}Emoticon + \beta_{12i}Fans + \varepsilon_i \end{aligned}$$

3.4 REGRESSION ASSUMPTIONS

There are several assumptions according to Janssens et al. (2008) which has to be satisfied in order to have valid and reliable outcome of regression analysis. Following is of important assumptions for proposed regression models:

1. All relevant variables must be taken into consideration

Failure to include all relevant independent variables can bias the regression results. This thesis will rely on intuition and previous research, as proposed by Janssens et al. (2008). User engagement on posts is effected by various subjective evaluations of individuals which cannot be quantified and used for the model, but previous research (Cvijikj & Michahelles 2013; Extra 2011) has shown that great deal of variance can be explained by similar independent variables as used in this thesis.

2. Residuals are normally distributed

In regression analysis, assumptions are that residuals of variables are normally distributed. This means that the differences between the model and observed data are most frequently zero or very close to zero and greater differences happen only occasionally (Field, 2009). This thesis have four dependent variables and two independent variables which are codes on scale and therefore needs to be tested for normality. Normality can be checked either using normal probability plots, or

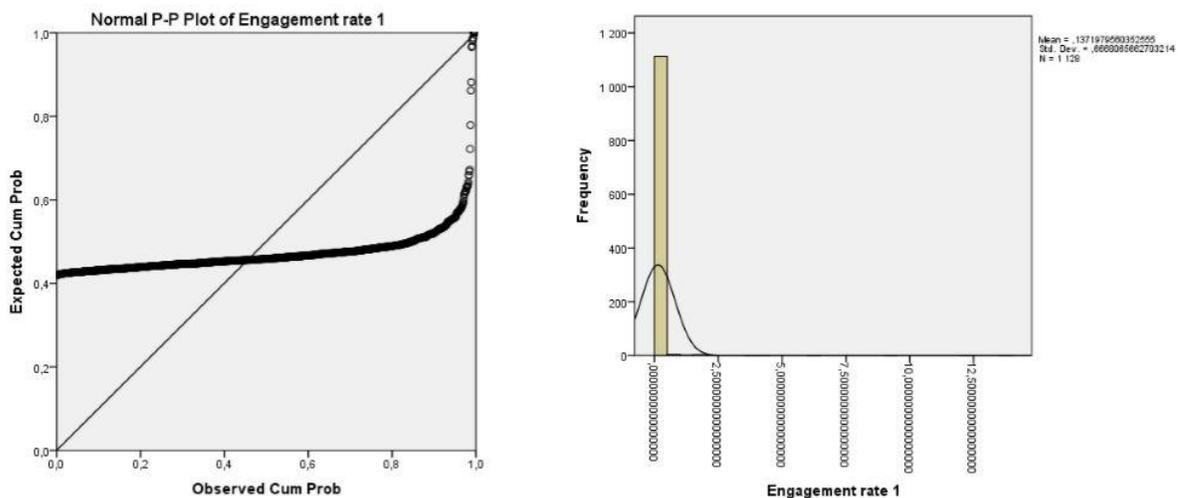


Figure 3.7 Normal probability plot for dependent variable Engagement Rate

histograms. In *Figure 3.8* can be graphs of the dependent variable “Engagement Rate”:

The straight line in P-P plot represents a normal distribution and points on graph are observed residuals. In a perfectly distributed data, all of the points should be approximately linear on the line, however this is not the case of variable Engagement Rate, which has therefore non-normally distributed residuals.

On histogram we can observe, that data of our variable are highly skewed, with significant right skew of the data. The logarithmic transformation can be used to make such skewed distribution approximately normal, which is making the patterns in the data more visible and interpretable. Results of a log transformation are shown in *Figure 3.9*, with almost normal distribution.

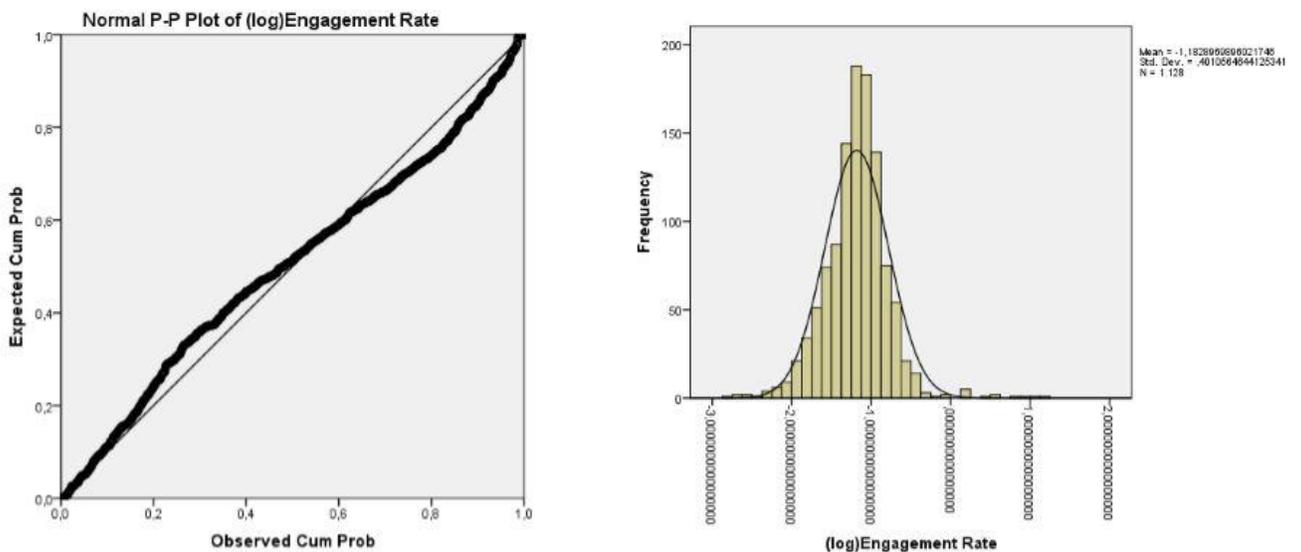


Figure 3.8 Normal probability plot and histogram for dependent variable (log)Engagement rate

All dependent variables (Engagement Rate, Like Rate, Comment Rate and Share Rate) are log transformed, as well for two independent variables Number of Fans and Post Length. For interpretation of such regressions results when dependent variable is log (with a base of 10) transformed and independent are left in their original metric state, one unit of increase in independent variable changes the dependent variable by $(10^{\text{Coefficient}} - 1) * 100\%$ while other variables hold constant. In

case of both, dependent and independent variables are log transformed, the percentage in independent variable results in (coefficient) percentage change in dependent variable, holding other variables constant.

3. Sufficient number of observation

Rule of thumb according to Janssens et al. (2008) is that model has to have at least five times as many observations as parameters to be estimated. Regression models in this thesis have 16 examined variables, meaning necessity of ($16 \cdot 5 = 80$) at least 80 observations. Model has 1128 observations, so this assumption is satisfied.

4. No multicollinearity

In regression analysis, we look at the correlations between one or more independent variables, but in order to keep clear results we have to check if those variables do not correlate between each other, or so called multicollinearity. In order to check multicollinearity we have to create cross table of variables (See *Appendix 1*). If bivariate coefficient between two variables exceeds 0.6 or more, it is a signal of collinearity problem.

After looking at the cross table four pairs of collinearity was identified: Information – Entertainment (0.799), Information – Hard-Sale (0.678), Fan page – Multiple (0.625) and Time Evening – Time Afternoon (0.625). One way how to solve this problem is to remove problematic variables from the model. By removing variables Information, Time Afternoon and Multiple this assumption is satisfied.

4. DATA ANALYSIS AND RESULTS

In this chapter the collected data will be analyzed using descriptive analysis and several multiple regression models with the help of the SPSS software. Tables and graphs will be later obtained from MS Excel. Regressions will be explained and based on results hypotheses are tested.

4.1 DESCRIPTIVE ANALYSIS

4.1.1 Exploratory variables

Explored variable of this thesis Engagement Rate have its several components, namely Likes, Comments, Shares, Clicks and Post Reach. For better overview relative numbers of each component is shown in *Table 4.1*.

	Likes	Comments	Shares	Clicks	Reach
Mean	71	5,3	2,7	351	4782
Std. Deviation	201	22,5	10,5	745	11272
Min	0	0	0	1	1
Max	3079	362	187	9859	156800

Table 4.1 Absolute number of engagement measures

From obtained data it is obvious that clicks anywhere in the post (viewing photo, video or link) is by far the most common form of the user engagement on post ($M=351$, $SD=745$). As for the other forms of engagement, Likes are more frequent ($M=71$, $SD=201$) over Comments ($M=5.3$, $SD=22.5$) and Shares ($M=2.7$, $SD=10.5$). High standard deviations of these results can be explained by the differences in the engagement count of the different brands. Average Reach of each post is 4782 unique users but more interesting is high standard deviation 11272 which can be explained by different fan bases of each fan pages and difference between organic and sponsored (paid post promotion on Facebook) post reach.

4.1.2 Brand fans

	Brand A	Brand B	Brand C	Brand D	Brand E	Brand F	Brand G	ALL
Average	99614	72880	5310	1875	4395	29150	25165	34056
Min	93514	72517	4847	1723	4304	28891	24150	
Max	102383	73139	5711	1989	4670	29462	26239	
Growth	9,48%	0,86%	17,83%	15,44%	8,50%	1,98%	8,65%	8,96%

Table 4.2 Number of fans per each brand

There is a big difference in observed brand's fan base, as well as their growth during studied period of 180 days. Brand with the lowest fan base of 1875 fans on average is Brand D and highest fan base on average has Brand A, 99614 on average. We can see a pattern that fan pages with lower fan base tend to have higher growth rate, in particular Brand C and D with growth rates over 15%, while other fan pages with bigger fan base recorded growth rate below 10%. Although there is an exception in the growth of Brand A, which is close to 10% and to prove this pattern there would have to be a study with higher number of samples.

4.1.3 Brand Posts

Brand	Type of Fan page	Nr of posts	Percentage	Avg. posts per day
Brand A	Products & Services	93	8,2%	0,5
Brand B	Products & Services	127	11,3%	0,7
Brand C	Products & Services	67	5,9%	0,4
Brand D	Products & Services	77	6,8%	0,4
Brand E	News	165	14,6%	0,9
Brand F	News	500	44,3%	2,8
Brand G	News	99	8,8%	0,6
	<u>Total</u>	<u>1128</u>		
	<u>Average</u>	<u>161,1</u>		<u>0,9</u>

Table 4.3 Brand posts overview

From the *Table 4.3* can be determined, that in general Fan pages of News brands has more posts in total and in average per day. This fact is linked to their goal in increasing traffic to their web page, while Product & Services fan pages aim to higher quality over quantity of posts. In a period of 180 days fan pages posted 161 posts on average and almost 1 average post per day.

4.1.4 Day of Posting

	Posts	Percentage	Avg. Engagement Rate	Std. Deviation
Monday	189	16,76%	0,1303	0,4927
Tuesday	203	18,00%	0,1447	0,6778
Wednesday	207	18,35%	0,1052	0,2867
Thursday	185	16,40%	0,1494	0,8786
Friday	141	12,50%	0,0848	0,0582
Saturday	86	7,62%	0,0843	0,0672
Sunday	117	10,37%	0,1632	0,3568

Table 4.4 Day of posting overview

Looking at the number of posts sorted according to day of the week, we can observe significant fall in the number of admin posts during a Friday's and a weekends. Almost 70% of posts were submitted during Monday till Thursday and Friday has the least share of admin posts. It is interesting to look at the average engagement rate per day, however these results are not sufficient to confirm the hypotheses, since their significance has to be confirmed through the regression analysis in later sections. However we can see decline of average engagement rate during Friday and Saturday and peak during Sunday, which contradicts hypothesis H_{4C}. Empirical explanation for this observations might be, that brands submit less posts at the end of the week (Friday) and on weekends, since their fan page admins are outside of working hours. Users also engage on social media less during this period, since they have various weekend activities, however at Sunday afternoon they have usually free time, hence increased average engagement rate. This finding suggests that weekends should be evaluated separated as Saturday and Sunday, rather than together.

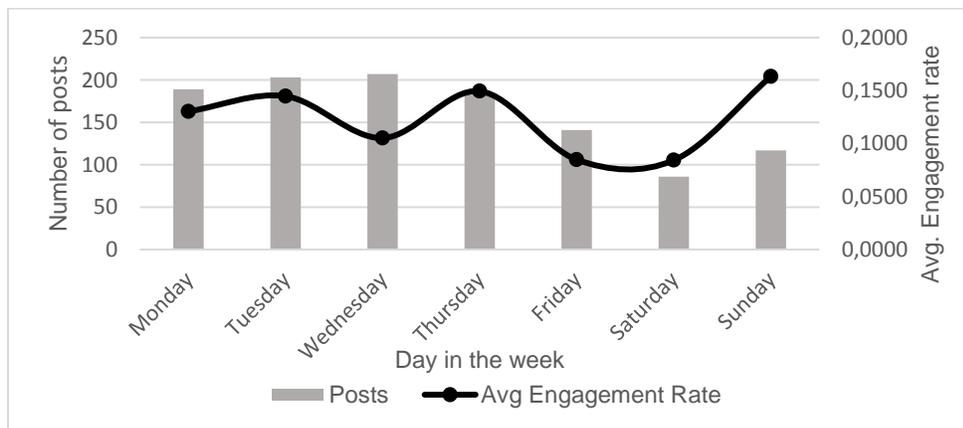


Figure 4.1 Day of posting graph

4.1.5 Time of posting

Looking at the number of posts per hours during the day, we can see low posting activity between 22:00 and 8:00 and higher posting activity during 16:00 and 22:00, with its peak at 20:00. It is worth mentioning, that some of the studied brands have worldwide audience, which means that results may be also influenced by their time zone. It could be interesting for the future research to look at geographical location and time zone of fans that engage with brand posts.

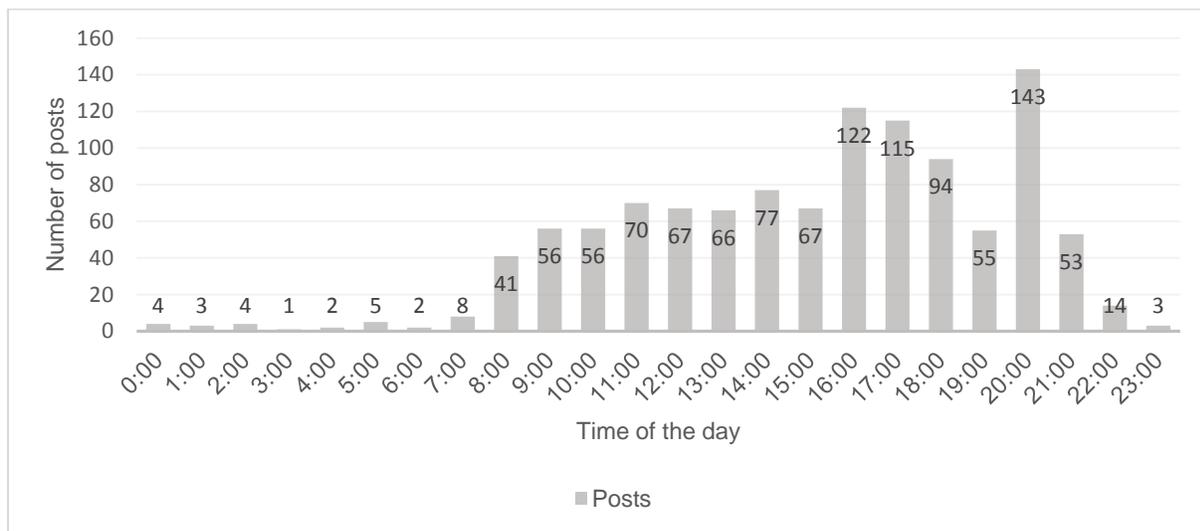


Figure 4.2 Time of posting overview

4.1.6 Content Type

		Posts	Avg. Engagement Rate	Std. Deviation
Information	Yes	158	0,1305	0,1641
	No	207	0,2756	1,2108
Entertainment	Yes	189	0,2384	1,0669
	No	176	0,1848	0,7243
Remuneration	Yes	15	0,1117	0,1066
	No	350	0,2170	0,9383

Table 4.5 Content type overview

Table 4.5 shows the amount of posts divided as Informative, Entertainment and Remuneration according to the Uses & Gratifications theory. Since posts of Media and News fan pages cannot be labeled due to their similarity as mix of information and entertainment, only posts from Product and Services fan pages are observed. As expected, there is a slightly more entertainment type of content over informal and very

few remuneration posts. Interesting observation comes from plotting average Engagement Rate into graph, which shows decrease of Engagement Rate with involving informational content into post and on the other hand increasing when including entertainment content. However, regression analysis is needed to support these finding and draw conclusions of the hypotheses.

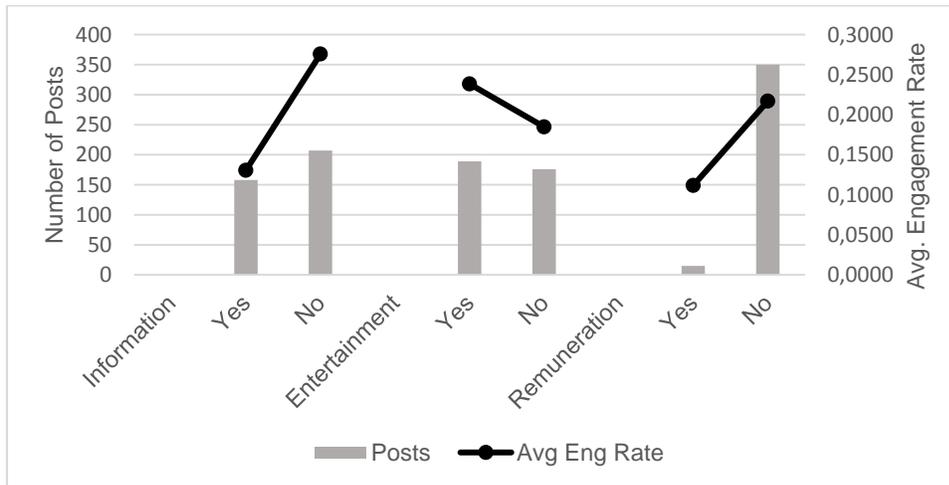


Figure 4.3 Content type graph

4.1.7 Vividness

		Posts	Avg. Engagement Rate	Std. Deviation
Status	Yes	59	0,1656	0,0895
	No	1069	0,1356	0,6846
Link	Yes	684	0,0597	0,0359
	No	444	0,2566	1,0515
Photo	Yes	377	0,2746	1,1398
	No	751	0,0682	0,0511
Video	Yes	8	0,0775	0,0283
	No	1120	0,1376	0,6692

Table 4.6 Type of vividness overview

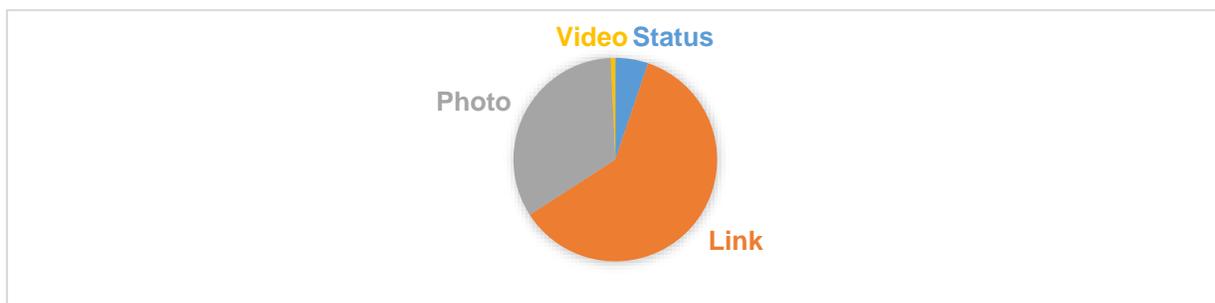


Figure 4.4 Type of vividness pie chart

Similar to content type, posts are divided by its type of vividness from low, as status up to highest form as post including video. This division was performed on all brand's posts. *Table 4.6* and pie chart in *Figure 4.6* above shows the percentage of each category. Majority of posts (60%) is in a form of Link, second most common posts (33%) are submitted as a photo, third place got posts with a Status and the last place, with only 8 occurrences are a Video posts. It is important to note, that Facebook upgraded its video uploading platform in recent months, so it is expected for this number to grow in the future. Again, average engagement rates are plotted on graph. Results suggests higher engagement rate for other than Link posts and the highest engagement rate on average for posts submitted as photo. As mentioned before, these are not final results that could be used for testing the hypotheses, but rather interesting graphic representation that can lead to hypotheses generation for future research.

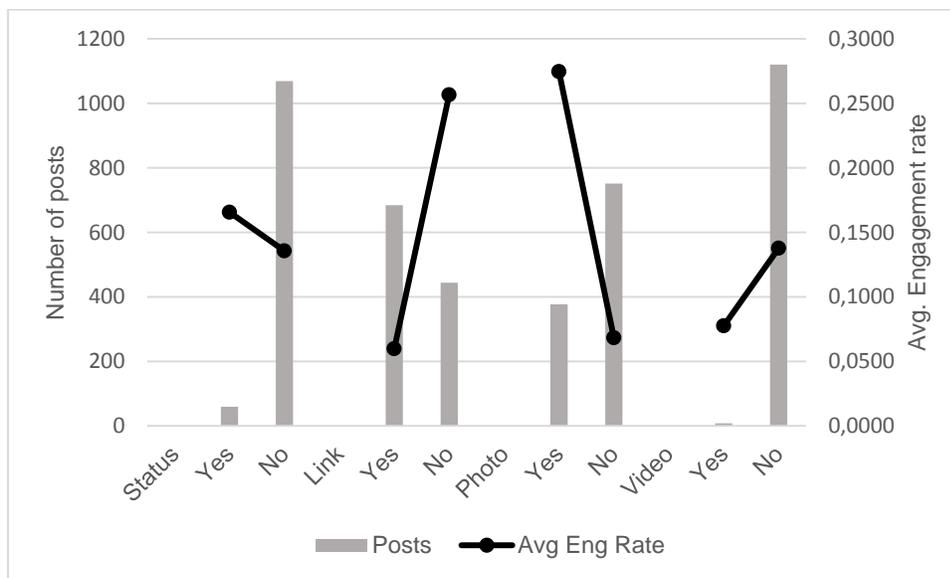


Figure 4.5 Type of vividness graph

4.1.8 Post length

Each post has different amount of characters in its text, ranging from 2 up to 1478 characters. Average number of characters is 161 and the box plot in *Figure 4.8* shows the distribution of characters volume. We can see that posts rarely exceeds 250 characters.

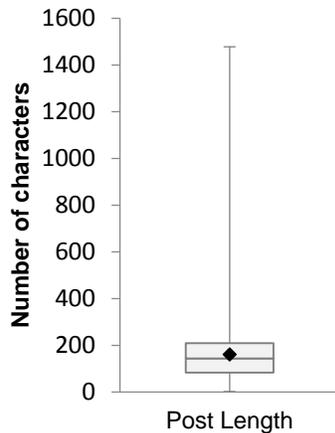


Figure 4.6 Post length distribution in box plot

4.1.9 Other

		Posts	Avg. Engagement Rate	Std. Deviation
Call-to-Action	Yes	317	0,1729	0,8739
	No	811	0,1232	0,5657
Question	Yes	198	0,0851	0,0491
	No	930	0,1483	0,7336
Hard-sell	Yes	194	0,1359	0,4749
	No	934	0,1375	0,7003
Brand name	Yes	217	0,2449	1,0900
	No	911	0,1115	0,5150
HTTP	Yes	174	0,2699	1,1814
	No	954	0,1130	0,5183
Emoticon	Yes	406	0,2019	1,0339
	No	722	0,1008	0,3014
Multiple	Single	334	0,1166	0,2343
	Multiple	793	0,1459	0,7801
Fan page	P&S	365	0,2126	0,9192
	M&N	764	0,1013	0,5008

Table 4.7 Other variables overview

The rest of the independent variables is shown in *Table 4.8* and plotted along with average engagement rate in *Figure 4.9*. There is approximately 2.6 times more posts without Call to Action than post including Call to Action, 82% of the posts do not contain question in its text and same percentage of posts do not include Hard Sell. 17% of posts contain own Brand name in its text, 15% of posts includes web link in its text and 36% of post's text include some emoticon. 70% of posts were posted along some other post by admin on a

given day and finally, three times more posts were submitted on Media and News fan pages, over posts of Products and Services brands. This result was empirically expected, since news and media fan pages tend to post various news and information more frequently than promotional posts of products and serviced brand pages. In the *Figure 4.9* posts are plotted along with their average engagement rates. Higher engagement rates had posts including Call to Action, posts including Brand Name, Web link and emoticon and posts of Product and Services fan pages. These results suggests, that higher engagement rate is achieved by including impulse for engagement, such as Call to Action or link for Web page.

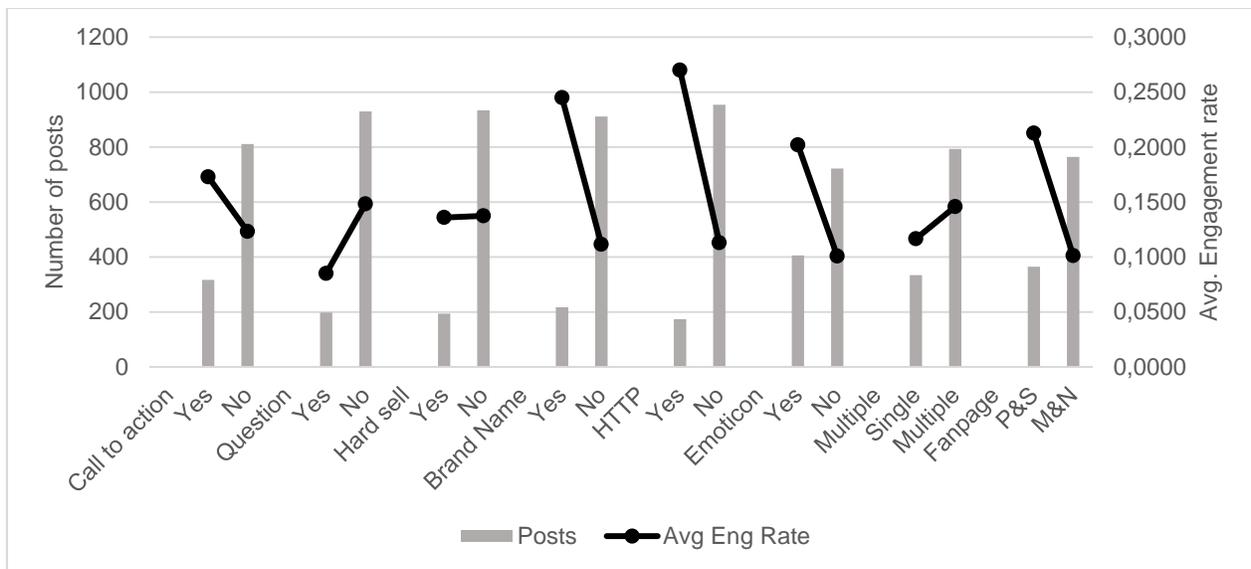


Figure 4.7 Other variables graph

4.2 REGRESSION ANALYSIS

Hypotheses are be tested using several multiple linear regression analysis, falling in the three main groups divided by the different type of brand category and within each, four models with the different dependent variables are tested: (log)Engagement Rate, (log)Likes, (log)Comments and (log)Shares. Main focus for hypothesis testing is on dependent variable (log)Engagement Rate, while other DVs are explored mainly in order to uncover some hidden variance, observe significant differences or find suggestions for further research. Following are all regressions divided on three parts, depending on the brand category. For each brand category table with ANOVA analysis and R Square value is presented for each DV and in the second table are plotted all B coefficients from all regressions. Full SPSS outcome tables can be viewed in *Appendix 2 to 4*.

4.2.1 All Brands

Dependent variable	(log)Engagement Rate	(log)Like Rate	(log)Comment Rate	(log)Share Rate
R Square	,187	,055	,087	,085
ANOVA F Value	17,062	4,307	7,101	6,885
ANOVA p value	,000	,000	,000	,000

Table 4.8 ANOVA analysis and R Square value for regression models with all brands

Analysis of the variance shows that F value for all regression models is significant at $p < 0.001$, suggesting linear relationship between the variables. Statistical significance at a .001 level means there is a 99% chance that the relationship among the variables is not due to chance, therefore there is a good fit between the data and the assumed regression models, which has explanatory power. The R Square of the first model is .187, which indicates that proportion total variability in (log)Engagement Rate that is explained by independent variables is 18.7%. There is still 81.3% of variance that could not be explained by the model, therefore there must be other variables that has influence. Model with DV Like Rate explains 5.5% of the variance, 8.7% of variance is explained for DV Comment Rate and 8.5% of variance for DV Share Rate. Full outputs from SPSS with Model Summaries, ANOVA tables and coefficients for regressions of all brands can be viewed in *Appendix 2*. Following, in *Table 4.9* is the output of the main regression model with dependent variable (log)Engagement Rate.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,433 ^a	,187	,176	,3638572845020

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	33,883	15	2,259	17,062	,000 ^b
	Residual	147,088	1111	,132		
	Total	180,971	1126			

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-,406	,131		-3,096	,002
	(log)Fans	-,195	,026	-,236	-7,646	,000
	Vividness	,154	,021	,219	7,174	,000
	Call to action	-,014	,028	-,016	-,508	,611
	Question	,047	,031	,045	1,543	,123
	Hard sell	-,092	,031	-,087	-2,945	,003
	Weekend	,058	,029	,055	2,011	,045
	(log)Length	-,130	,035	-,107	-3,709	,000
	Brand Name	-,005	,029	-,005	-,181	,856
	HTTP	-,015	,038	-,013	-,389	,698
	Emoticon	,024	,024	,029	1,032	,302
	Time Night	,517	,068	,214	7,588	,000
	Time Morning	,009	,030	,009	,319	,750
	Time Evening	,065	,026	,075	2,510	,012
	Fan page	-,144	,035	-,168	-4,077	,000

a. Dependent Variable: (log)Engagement Rate

Table 4.9 Model summary, ANOVA and coefficients outcome for model with all brands and DV (log)Engagement Rate

For simplicity and better overview, *Table 4.10* shows unstandardized Beta coefficients of all four regression models combined from the sample of all brands.

Dependent variable	(log)Engagement Rate	(log)Like Rate	(log)Comment Rate	(log)Share Rate
(log)Fans	-0,195**	-0,092*	0,036	0,139
Vividness	0,154**	0,055	-0,09	0,029
Call to action	-0,014	0,025	0,077	-0,044
Question	0,047	-0,029	0,012	-0,327*
Hard sell	-0,092*	-0,008	-0,023	0,012
Weekend	0,058*	-0,027	0,152	0,07
(log)Length	-0,13**	0,082	0,043	-0,697**
Brand Name	-0,005	0,319**	0,177	0,093
HTTP	-0,015	-0,152*	-0,048	0,015
Emoticon	0,024	-0,028	-0,875**	0,071
Time Night	0,517**	-0,088	0,431	0,119
Time Morning	0,009	0,027	0,085	-0,139
Time Evening	0,065*	0,071	0,126	0,095
Fan page	-0,144**	-0,2*	-0,042	0,541**

Table 4.10 Unstandardized coefficients outcome for all dependent variables and all brands (*)p<0.1 *p<0.05 **p<0.001

Coefficients of main observed model are in the first column with dependent variable (log)Engagement Rate since this variable is explored in the most hypotheses. Other models serve as additional source of information to increase validity of results, notice about limitations and serve as hypotheses generation for further research. By looking at standardized betas (see *Appendix 2*), we can conclude that the biggest variance is explained by fan base of posting brand (*standardized beta=-.236*). Interesting finding is, that posts with higher fan base gains lower engagement rate, meaning smaller Facebook fan pages can have more engaging users. Other results worth mentioning is higher engagement rate for posts posted at the evening and the night, higher Like Rate for posts including brand name and lower comment rate for posts with emoticons. As for the difference between brand categories, posts of Media and News brands gains lower engagement rate, but higher share rate.

4.2.2 Products and Services Brands

Dependent variable	(log)Engagement Rate	(log)Like Rate	(log)Comment Rate	(log)Share Rate
R Square	,208	,115	,077	,097
ANOVA F value	5,316	2,636	1,698	2,181
ANOVA p value	,000	,000	,041	,005

Table 4.11 ANOVA analysis and R Square value for regression models with Products and Services brands

Analysis of the variance shows that F value for all regression models is significant at $p < 0.05$, suggesting linear relationship between the variables. Statistical significance at a .05 level means there is a 95% chance that the relationship among the variables is not due to chance, therefore there is a good fit between the data and the assumed regression models, which has explanatory power. The R Square of first model is .208, which shows that proportion total variability in (log)Engagement Rate that is explained by independent variables is 20.8%. There is still 79.2% of variance that could not be explained by the model, therefore there must be other variables that has influence. Model with DV Like Rate explains 11.5% of the variance, 7.7% of variance is explained for DV Comment Rate and 9.7% of variance for DV Share Rate. For better overview of the results, *Table 4.12* shows unstandardized Beta coefficients of all four regression models combined from the sample of all brands. Full outputs from SPSS with Model Summaries, ANOVA tables and coefficients for regressions of all brands can be viewed in *Appendix 3*. Following, in *Table 4.12* is the output of the main regression model with dependent variable (log)Engagement Rate.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
	Fan page = ,0 (Selected)			
1	,456 ^a	,208	,169	,4465382377394

ANOVA^{a,b}

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	18,020	17	1,060	5,316	,000 ^c
	Residual	68,792	345	,199		
	Total	86,812	362			

Coefficients^{a,b}

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-,326	,249		-1,310	,191
	(log)Fans	-,220	,042	-,323	-5,267	,000
	Vividness	,146	,039	,208	3,738	,000
	Call to action	,105	,061	,105	1,725	,085
	Question	-,055	,064	-,046	-,860	,390
	Hard sell	,040	,077	,036	,518	,605
	Multiple	,093	,055	,087	1,709	,088
	Weekend	,085	,068	,066	1,258	,209
	(log)Length	-,116	,095	-,072	-1,221	,223
	Brand Name	-,006	,057	-,005	-,097	,922
	HTTP	-,148	,065	-,146	-2,281	,023
	Emoticon	,030	,050	,031	,599	,550
	Time Night	,511	,118	,221	4,337	,000
	Time Morning	-,016	,063	-,013	-,259	,796
	Time Evening	,204	,066	,165	3,088	,002
	Entertainment	-,007	,105	-,008	-,071	,943
	Remuneration	-,016	,165	-,007	-,100	,921

a. Dependent Variable: (log)Engagement Rate

b. Selecting only cases for which Fan page = ,0

Table 4.12 Model summary, ANOVA and coefficients outcome for model with product and services brands and DV (log)Engagement Rate

For simplicity and better overview, *Table 4.13* shows unstandardized Beta coefficients of all four regression models combined from the sample of all brands.

Dependent variable	(log)Engagement Rate	(log)Like Rate	(log)Comment Rate	(log)Share Rate
(log)Fans	-0,22**	-0,07	-0,041	-0,06
Vividness	0,146**	0,059	0,036	0,074
Call to action	0,105(*)	-0,034	-0,147	0,05
Question	-0,055	-0,018	0,015	-0,496*
Hard sell	0,04	-0,153	0,053	-0,045
Multiple	0,093(*)	0,043	0,146	0,346(*)
Weekend	0,085	0,039	0,048	0,169
(log)Length	-0,116	-0,191	0,635*	-0,528(*)
Brand Name	-0,006	0,413**	0,025	-0,014
HTTP	-0,148*	0,009	-0,081	-0,166
Emoticon	0,03	-0,315**	-0,603**	0,102
Time Night	0,511**	0,031	0,476	0,482
Time Morning	-0,016	0,097	0,256	0,455*
Time Evening	0,204*	0,231*	0,508*	-0,119
Entertainment	-0,007	-0,05	0,214	0,004
Remuneration	-0,016	-0,248	-0,014	-0,643

Table 4.13 Unstandardized coefficients outcome for all dependent variables and Products and Services brands only (*)p<0.1 **p<0.05 ***p<0.001

Number of fans is the strongest predictor also for Brands category Products and Services and most of the results are in line with regressions from all sample brands (see *Appendix 3*). The main reason for this separation of regressions was to observe the effect of Content Type, which was coded only for this category, however the effect of content types is insignificant. Among differences from general models are positive effect of Call to Action presence on Engagement Rate, opposite and positive effect of message length on comments rate and positive effect of messages posted in morning on share rate.

4.2.3 Media and News Brands

Dependent variable	(log)Engagement Rate	(log)Like Rate	(log)Comment Rate	(log)Share Rate
R Square	,189	,059	,110	,057
ANOVA F value	12,471	3,379	6,603	3,258
ANOVA p value	,000	,000	,000	,000

Table 4.14 ANOVA analysis and R Square value for regression models with Media and News brands

Analysis of the variance shows that F value for all regression models is significant at p<0.001, suggesting linear relationship between the variables. Statistical significance at a .001 level means there is a 99% chance that the relationship among the variables is not

due to chance, therefore there is a good fit between the data and the assumed regression models, which has explanatory power. The R Square of first model is .189, which shows that proportion total variability in (log)Engagement Rate that is explained by independent variables is 18.9%. There is still 81.1% of variance that could not be explained by the model, therefore there must be other variables that has influence. Model with DV Like Rate explains 5.9% of the variance, 11% of variance is explained for DV Comment Rate and only 5.7% of variance for DV Share Rate. For better overview of the results, *Table 4.14* shows unstandardized Beta coefficients of all four regression models combined from the sample of all brands. Full outputs from SPSS with Model Summaries, ANOVA tables and coefficients for regressions of all brands can be viewed in *Appendix 4*. Following, in *Table 4.15* is output of the main regression model with dependent variable (log)Engagement Rate.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
	Fan page = 1,0 (Selected)			
1	,435 ^a	,189	,174	,3099766289800

ANOVA^{a,b}

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	16,776	14	1,198	12,471	,000 ^c
	Residual	71,968	749	,096		
	Total	88,744	763			

Coefficients^{a,b}

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
		1	(Constant)	-,980		
	(log)Fans	-,068	,040	-,062	-1,713	,087
	Vividness	,168	,027	,222	6,272	,000
	Call to action	-,065	,030	-,080	-2,182	,029
	Question	,111	,033	,118	3,364	,001
	Hard sell	-,143	,036	-,139	-3,982	,000
	Multiple	-,044	,042	-,039	-1,053	,293
	Weekend	,022	,029	,026	,763	,446
	(log)Length	-,143	,035	-,144	-4,134	,000
	Brand Name	-,028	,032	-,030	-,887	,375
	HTTP	,082	,055	,054	1,490	,137
	Emoticon	,032	,025	,042	1,269	,205
	Time Night	,459	,085	,187	5,384	,000
	Time Morning	,025	,031	,029	,787	,431
	Time Evening	,008	,026	,012	,318	,750

a. Dependent Variable: (log)Engagement Rate

b. Selecting only cases for which Fan page = 1,0

Table 4.15 Model summary, ANOVA and coefficients outcome for model with Media and News brands and DV (log)Engagement Rate

For simplicity and better overview, *Table 4.16* shows unstandardized Beta coefficients of all four regression models combined from the sample of all brands.

Dependent variable	(log)Engagement Rate	(log)Like Rate	(log)Comment Rate	(log)Share Rate
(log)Fans	-0,068(*)	-0,118	0,172	0,384*
Vividness	0,168**	0,067	-0,177	-0,027
Call to action	-0,065*	0,056	0,143	-0,06
Question	0,111**	-0,019	0,011	-0,265(*)
Hard sell	-0,143**	0,042	0,103	0,145
Multiple	-0,044	0,047	0,108	0,019
Weekend	0,022	-0,043	0,081	0,003
(log)Length	-0,143**	0,162*	-0,191	-0,762**
Brand Name	-0,028	0,306**	0,224	0,132
HTTP	0,082	-0,173	-0,172	0,254
Emoticon	0,032	0,117*	-1,048**	0,041
Time Night	0,459**	-0,246	0,654(*)	-0,231
Time Morning	0,025	-0,002	0,01	-0,421*
Time Evening	0,008	0,032	-0,008	0,076

Table 4.16 Unstandardized coefficients outcome for all dependent variables and Media and News brands only
 (*)p<0.1 **p<0.05 ***p<0.001

Final set of regression models also contain similar results as regressions with full sample. However, there was find some differences, from which highlighted should be positive effect of fan base on Share Rate, positive effect of Question presence on Engagement Rate and opposite effect to other models of posting in morning. For Media and News brands posting in morning lowers the Share Rate.

4.3 TESTING THE HYPOTHESES

Hypothesis 1: Content Type

First set of hypotheses H_1 is assuming that presence of several types of content based on Uses and Gratifications theory, namely Entertaining, Information and Remuneration type and their positive effect on customer engagement.

Three dummy variables of content type was manually coded as a dummies. Since almost all of the posts of Media and News brands fan pages were of both, informative and entertainment character, this category was excluded from testing this hypothesis and variable was included only in models for category Products and Services. Presence of each dummy do not have significant effect in any of the models so there seems to be not effect of content type on customer engagement and all parts of hypothesis H_1 are therefore rejected. Limitation of this hypothesis may be the manual coding of the independent variables, where human error and subjective judgment could influenced the results. However descriptive analysis shows that on average non-informal and entertaining posts scores higher on Engagement rate, hence there might be some relationship between content type and consumer engagement, so for the further research it is recommended to dig deeper into this matter.

Hypothesis 2: Post Vividness

Posts on Facebook can be posted in various format, giving them lower or higher level of vividness, starting with low vivid Status, increasing with Link, Photo and the highest form of vividness as Video. Hypothesis H_2 is based on assumption that posts with higher level of vividness with gain higher customer engagement.

Different levels of post vividness was posted on a scale from 1 to 4 and in main regression model with all variables and dependent variable (log)Engagement rate effect is positive and significant ($B=0.154$) at 99% level ($p<0.001$). The effect is slightly higher ($B=0.168$) when observed in model for Media and News fan pages only. Therefore null hypothesis is rejected and alternative hypothesis H_2 is accepted, hence the higher level of post

vividness increases a customer engagement. It seems that fan page admins who post their messages in more vivid form achieves a higher engagement rate. Moreover, results from descriptive analysis shows that posts coded as Photo scored the highest Engagement rate on average among other content types. Limitation of this hypothesis might be low number of occurrences of category Video.

Hypothesis 3: Post interactivity

Posts on Facebook can include several means of increasing their interactivity, among observed are call-to-action impulse in post message, questions presence and hard-sell impulse. Hypotheses H₃ assumes that these impulses have a significant impact on customer engagement. For call to action and presence of question effect is assumed to be positive and for Hard-sell negative.

Variable Call-to-action was manually coded as a dummy and since its effect is insignificant in the main model, alternative hypothesis H_{3A} is rejected. It is worth mentioning that effect of Call-to-Action presence is significant in the models with separated brand categories and while for Products and Services category hypothesis is marginally significant at 90% level ($B=0.105$), therefore it comply with hypothesis H_{3A}, for Media and News category effect is significant at 95% level but with adverse effect ($B=-0.065$), meaning posts of Media and News brands have lower Engagement rate by 16.1% over posts of Products and Services brands, holding other variables constant. It can be concluded, that there is no clear valence of an effect on customer engagement when call to action impulse is included in the message, however effect is positive for fan pages of Products and Services brands. The general understanding of this results is that while users are not likely to engage on such impulses while consuming various news, some impulse leading to engage is helpful when promoting products or services on social media.

Presence of question was coded as a dummy and it is not significant for dependent variable (log)Engagement rate, thus rejecting the hypothesis H_{3B}. However, looking at model including samples from Media and News category only, effect becomes significant at 95% level ($B=0.111$). Interestingly, model with dependent variable (log) Share rate shows significant ($p<0.05$), but adverse effect ($B=-0.327$). This results could help in understanding the nature of question presence on social media posts. While question

increases engagement of Media and News posts, since it raises consumers' curiosity and attention on its informative and entertaining content, consumers have lower likelihood to share and spread the message when they are asked questions.

Last observed metric for post interactivity is presence of hard-sell impulse and is was also coded as a dummy. Presence of Hard-sell has a significant ($p < 0.05$) negative effect on dependent variable (log) Engagement rate ($B = -0.092$), thus accepting the hypothesis H_{3c}. This effect is even stronger for category Media and News ($B = -0.143$), while no significant effect was found in model for Product and services fan pages. Thus, posting message with hard-sell impulse results in 23.6% decrease in Engagement rate, keeping other variables constant. It seems that including hard-sell impulses into the brands posts lowers the consumer engagement, especially in case of Media and News fan pages.

Hypothesis 4: Time of Posting

Hypotheses H₄ are assuming, that posting message by admin at certain time affects the customer engagement. First assumption is that posting message along with other posts on a given day lowers the Engagement rate. Second, posting on peak hours will increase customer engagement and third, that posting on weekends will decrease customer engagement.

Dummy Multiple posts per day was removed from the main regression model due to multicollinearity issue with variable Fan page, thus hypothesis H_{4A} that its presence has significant negative effect on customer engagement is rejected. However there was no multicollinearity problem for models for separate fan page categories and effect of dependent variable Engagement rate is marginally significant at 90% level ($p < 0.1$) for Products and Services category ($B = 0.093$) and a bit stronger effect on supplemental dependent variable Share rate ($B = 0.346$). Thus posting more than one posts par day have an effect in the posts of Products and Services category, especially for sharing of the message.

Time of the day when post was submitted by fan page admin was divided on four dummy variables, Morning, Afternoon, Evening and Night. Hypothesis H_{4B} assumed that posting

at peak hours (represented by dummy Evening) has a positive and significant effect on customer engagement. Effect of Evening posts was found to be significant at 95% level ($p < 0.05$) for dependent variable Engagement rate ($B = 0.065$), so the hypothesis H_{4B} is considered as accepted. In addition to that, interesting results are concluded from observing variable Time night, which has even higher significant and positive effect ($B = 0.517$). High customer engagement on night hours posts (20:00 – 7:00) seems to contradict the intuition, but there could be two possible reasons that could explain this phenomena. First one is of a technical character, since there are not many posts submitted during the night, they will be in the top of the news feed of users who will check Facebook wall in the morning, making this a competitive advantage of the post. Second, if admins think that their message is so urgent that it has to be posted even during weak hours, it is by its nature type of message that would score high on user engagement. But it is also worth mentioning that descriptive analysis showed low number of observations during the Night period, so further research would be needed to clarify this findings. It seems that there are other factors that play role in post's engagement, but right timing can have positive influence.

Hypothesis H_{4C} assumes that post submitted during weekend will have lower customer engagement. Dummy weekend is significant on 95% level ($p < 0.05$) but with adverse effect as assumed ($B = 0.058$), thus hypothesis H_{4C} is not supported. Results show, that posting on weekend, when user activity is generally lower increases Engagement rate by 14.3%, holding other variables constant, therefore posting on weekend versus workday does hold significant effect. It is worth mentioning that results from descriptive analysis shows difference in average engagement rate of Saturday versus Sunday, so for further research it is recommended to observe the days separately, rather than combined in a weekend or workday category.

Hypothesis 5: Text Characteristics

There are several assumptions in hypotheses H₅ on how various text characteristics affect customer engagement. First, there is an assumption of significant negative relationship between the length of the post message and customer engagement. Second, there are

three agnostic hypotheses assuming significant relationship between presence of brand name, web link and emoticon and customer engagement.

Dummy Post length was coded as interval and negative effect on consumer engagement was assumed. On 99% significance level ($p < 0.001$) this effect is negative ($B = -0.13$), hence supporting the hypothesis H_{5A} . Results can be interpreted as follows: 1% increase of post length lowers engagement rate by 0.13%, holding other variables constant. It is worth mentioning, that effect of Post length is stronger in model with dependent variable (log)Share rate ($B = -0.697$). It seems that consumers engage more on posts with shorter message, especially for sharing of the post.

Brand name was coded a dummy and assumption that it has an effect of customer engagement. Effect on engagement rate is not significant, however effect is positive and significant at 99% level ($p < 0.001$) for model with dependent variable (log)Like rate ($B = 0.319$), thus hypothesis H_{5B} is partially accepted. It seems like amount of likes is increased when brands include their names in their post message.

Similar assumption were draws for dummy Presence of HTTP link. No significant effect was found for dependent variable (log)Engagement rate for both fan page categories combined, but when looking at model for Products and Services fan page category, this effect is significant at 95% level ($p < 0.05$) and negative ($B = -0.148$) for dependent variable (log)Engagement rate. In addition, the effect is negative and significant at 95% level ($p < 0.05$) for model with dependent variable (log)Like rate ($B = 0.152$), hence hypothesis H_{5B} is partially accepted.

Last dummy of hypothesis H_5 observes the presence of emoticon in text message and there is no significant effect on dependent variable (log)Engagement rate. Surprisingly strong negative effect ($B = -0.875$) was found significant at 99% level ($p < 0.001$) for complementary dependent variable (log)Comment rate, and for that reason partially supporting the hypothesis H_{5D} . It seems that customers are less prone to commenting on brands posts when emoticons are present in its message.

Hypothesis 6: Fan base characteristics

Last set hypotheses H_6 first assumes significant positive relationship between size of brand fan base and engagement rate. Second assumption is that posts of Media and News fan pages will have a higher customer engagement over posts of Products and Services brands.

In a model with both fan page categories combined dummy variable Fan page was added with assumption of positive and significant effect, meaning posts of Media and News having higher engagement rate. Significant effect was found at 99% significance level but in adverse, negative effect on Engagement rate ($B=-0.144$), thus rejecting the hypothesis H_{6A} . Hypothesis could be partially accepted by looking at model with dependent variable (log)Share rate, where effect is significant at 99% ($B=0.541$). Results shows us, that posts of Products and Services brands have higher engagement rate by 39.3%, keeping other variables constant.

Variable (log) Fans was coded as interval with assumption of its significant and positive effect on customer engagement. Main regression model with dependent variable (log)Engagement rate shows that this variable is significant on 99% level ($p<0.001$) but with adverse effect ($B=-0.195$), thus rejecting the hypothesis H_{6B} . However significant and positive effect ($B=0.384$) is shown in model for category News and Media with dependent variable (log) Share rate, thus partially supporting the hypothesis H_{6B} . This means that 1% increase in fan base size will lead to decrease of post Engagement rate by 0.195%, holding other variables constant. To understand this negative effect, we can assume that brands with bigger fan bases collected their fans over a longer period in time and some of them may lost interest in the brand related topics, while brands with smaller fan bases includes mostly loyal customers with a higher relative share of active and interested users. However sharing occurs when message is especially entertaining and interesting so brands with bigger fan bases holds advantage by its size and increased chances for viral behavior.

A summary of obtained results in terms of supported hypotheses is provided in *Table 4.17*

Hypothesis	Expected effect	Engagement Rate	Like Rate	Comment Rate	Share Rate
H_{1A} (Information)	(+)	Not Supported	Not Supported	Not Supported	Not Supported
H_{1B} (Entertainment)	(+)	Not Supported	Not Supported	Not Supported	Not Supported
H_{1C} (Remuneration)	(+)	Not Supported	Not Supported	Not Supported	Not Supported
H₂ (Post vividness)	(+)	Accepted	Not Supported	Not Supported	Not Supported
H_{3A} (Call to action)	(+)	Not Supported	Not Supported	Not Supported	Not Supported
H_{3B} (Question)	(+)	Partially Supported	Not Supported	Not Supported	Not Supported (Adverse)
H_{3C} (Hard-sell)	(-)	Accepted	Not Supported	Not Supported	Not Supported
H_{4A} (Multiple posts)	(-)	Not Supported	Not Supported	Not Supported	Not Supported (Adverse)
H_{4B} (Peak hour)	(+)	Accepted	Partially Supported**	Partially Supported	Not Supported
H_{4C} (Weekend)	(-)	Accepted	Not Supported	Not Supported	Not Supported
H_{5A} (Post length)	(-)	Accepted	Partially Supported**	Not Supported (Adverse)	Accepted
H_{5B} (Brand name)	(agnostic)	Not Supported	Accepted**	Not Supported	Not Supported
H_{5C} (HTTP link)	(agnostic)	Partially Supported	Accepted**	Not Supported	Not Supported
H_{5D} (Emoticon)	(agnostic)	Not Supported	Partially Supported	Accepted	Not Supported
H_{6A} (Fan page category)	(+)	Not Supported (Adverse)	Not Supported	Not Supported	Accepted
H_{6B} (Fan base size)	(+)	Not Supported (Adverse)	Not Supported (Adverse)	Not Supported	Partially Supported

Table 4.17 Summary of obtained results in terms of supported hypotheses

5. CONCLUSIONS AND RECOMMENDATIONS

This chapter will summarize all of the finding of this thesis and draw conclusions out of them. Implications for managers will be proposed, in order to help them to maximize customer engagement on social media. Finally, the last paragraph discusses the limitations of this thesis and suggestions for future research.

5.1 CONCLUSIONS

The aim of this thesis is to connect existing research on customer engagement and social media marketing, and find out what factors of Facebook posts of brands' fan pages are the main drivers of customer engagement. The reason of choosing this topic is the necessity of improving brand communication on social media, due to increasing competitiveness of brands on Facebook. The hypotheses are formulated based on existing theory concerning customer engagement, online advertising, virality and social media. The data for the hypotheses testing are collected from seven Facebook brand pages over the period of 180 days, divided on two categories: Products & Services, and Media & News. The main research question of this thesis is:

“What are the key factors that drive consumer engagement of the posts in Facebook brand pages?”

This thesis found out that there are measurable post characteristics that have influence over customer engagement. However, a low percentage of the variance is explained by those characteristics, signaling that there must be other, subjective and non-measurable characteristics of the post that have an effect. This is not a surprising finding, taking into account that valuable information would be positively received by customers regardless of the form or time it was submitted. It is the mediocre message that could achieve slightly higher customer engagement if communicated in a right way. As expected, the number of fans of a fan page was found to be a great predictor for customer engagement, but surprisingly with a negative effect. Thus, brands with smaller-sized fan base could engage a higher share of their fans, than brands with a larger fan base. It is important for fan page

admins to aim not only at acquiring new fans, but at retaining and engaging current ones as well.

Among visual and content characteristics, post vividness (starting from status with low vividness, up to video with the highest form of vividness) has the biggest effect on customer engagement. The more vivid format is posted, the higher customer engagement is attained. As expected, including hard-sell impulse into messages lowers customer engagement, thus signaling that customers engage less when confronted with advertising messages. For the category Products and Services, posts with Call-to-action impulse scored higher on customer engagement, and for Media and News category presence of the question leads to a higher customer engagement. This could be understood by looking at the nature of the posts for each category. While posts of Products and Services are generally of advertising nature, it is good to include some impulse that may motivate customers to engage. Media and News fan pages, on the other hand, usually post information and news linked to the external source. Therefore, a question may increase customer's curiosity, hence increase the likelihood of them engaging on post.

It was also proven that time and day of posting may influence customer engagement. Observed brands submitted less posts on the weekend. However, weekend posts scored higher on customer engagement. Moreover, results from the descriptive analysis showed that the peak in engagement is during the Sunday posts. Posts submitted during internet peak hours, between 18:00 and 23:00, also showed higher consumer engagement, but there is also a significant increase of engagement for the posts submitted in the night. However, the night posts had only a few occurrences, thus this finding would be considered as a limitation. This can be the perfect example of how posts can achieve high engagement nevertheless submitted in settings that are not perceived as ideal. Simply put, if admins post interesting and valuable information, it will find its listeners regardless of its presentation form or time posted.

Among type of message and time of posting, this thesis also observed how various textual characteristics influence customer engagement. Research findings suggest that lengthier posts score lower on customer engagement, hence shorter messages perform better. Moreover, including web link in the message lowers the customer engagement as well,

and surprisingly, presence of emoticon also has a strong negative effect on the dependent variable. Conventional wisdom is a possible explanation for the previously occurred phenomenon. For example, sometimes fan page admins do not have any interesting messages to post or want to forcibly increase customer attention for mediocre marketing messages, which would lead them to include emoticons. Such messages have lower customer engagement by its nature and this effect could be more of a side outcome, rather than causal nature.

Next, the first sub-question of this thesis is answered:

“Are there any differences within consumer engagement of Products and Services compared to Media and News fan page posts?”

To examine differences between observed fan page categories, three sets of linear regression analyses are performed. First, both sample pages are tested together and then each of them separately. The analyzed data suggests that there is indeed a difference between observed categories and their effect on customer engagement. Posts of category Products and Services have significantly higher customer engagement, contradicting the hypothesis H_{6A}. However, when looking at the number of post shares, Media and News fan pages have a higher rate of shares than the Posts and Services fan page category. An explanation of these results could be that while admins of Media and News throw every piece of information out in the social media space (share of posts volume confirms this assumption) hoping to create a high engagement rate on one of their posts, Products and Services fan pages admins need to lower the quantity and aim to increase the quality of individual posts. However, the Media and News category holds higher chances of users sharing its posts by nature, since it contains information or entertaining features that they might find useful to show to their friends, and thus holds the basic principles of virality.

Other differences have been found between the two categories of interest, looking at the effects of the independent variables in regression models of separate categories. Among the most interesting findings is the positive effect of post length on comment rate for Products and Services. Posting during the peak hours holds stronger effect for the Products and Services category, Call-to-action has positive effect for the Products and Services category, but negative for Media and News. Presence of emoticon is found to

have a positive effect for Like rate in the Media and News category, which is opposite to its negative effect in the overall model. Differences in independent variables can be seen in *Table 5.1* for better overview.

	Products and Services	Media and News
Fans		Positive for SR
Vividness		
Call to action	Positive	Negative
Question	Negative for SR	Positive
Hard sell		Negative
Multiple		
Peak Hour	Stronger effect	
Weekend		
Post Length	Positive for CR	Negative; positive for LR
Brand Name		
HTTP	Negative effect	
Emoticon		Positive for LR

Table 5.1 Difference between brand categories

Finally, the second sub-question is answered:

“How can we reliably measure customer engagement on social media?”

Past research proposes various metrics that measure the effectiveness on social media. In the current paper, an attempt to combine existing research from social media, online advertising and customer engagement literature is made, resulting in the metric called “Engagement Rate”.

The Engagement Rate metric observes the total number of users who engaged with the post in a form of liking, commenting, sharing or clicking, divided by the total number of people, who saw the post, or the so called “Reach”. In order to confirm the validity of the Engagement Rate, several other measures, which are components of Engagement Rate, are tested by the linear regression analysis, such as Like rate, Comment rate and Share rate. The regression models with Engagement Rate as the dependent variable are able

to explain the most variance in the model, proving that the Engagement Rate is a very good predictor of customer engagement and overall effectiveness on social media.

Interestingly, only some partial effects of independent variables are present in the models with Like, Comment and Share rate. Most of the significant effects are present in the unified Engagement Rate metric. Thus, customers engage on different types of posts in a different way. However, every form of customer engagement is combined in the proposed metric Engagement Rate, hence making it superior.

5.2 MANAGERIAL IMPLICATIONS

The results of this thesis indicate that brand fan page admins can influence the success of their posts on Facebook beyond subjective selection of information and content. First, a crucial recommendation is to utilize the “Engagement Rate” formula as a measure of success of posts on Facebook. The current research finds great differences between two categories of fan pages – Products and Services and Media and News, so it is believed that for each brand there is a different road to success. Therefore, admins must evaluate the results using the proposed formula and incorporate it into their future marketing strategies on social media such as Facebook. Additionally, the admins of a brand page on Facebook should not aim to increase only one of the components of engagement, but aim to increase all of them, since they are all a part of the overall engagement. It should be noted that different types of Facebook posts generate different type of engagement, so admins must be aware of which engagement they wish to stimulate for a given post.

Next, several direct recommendations not only for overall engagement, but for its components as well will be presented.

Likes

Higher Likes count is measure of post appeal and can improve overall reach of the posts. For higher likes on Facebook posts, admins should post shorter, likable and simple messages. Is also helps if they include the brand name, since fans like the messages

where their favorite brand is mentioned. They should include meaningful text messages, rather than simple emoticons or web links. The best time to post is in evening between 18:00 and 23:00 o'clock.

Comments

Comments count can increase word of mouth and customer loyalty. Brands that want to engage their users in a conversation can write slightly longer posts, but it still holds that the textual message has to be meaningful without unnecessary emoticons. The best time for posting is not only in the evening, but also during the night, since it can evoke users to comment in the morning.

Shares

A good way of gaining engagement is evoking the sharing of the post, since it not only creates the engagement, but spreads the message outside of the brand's fan base, thus making the post viral. Naturally, fan pages with higher number of fans have a higher chance to spread their posts though sharing. Among other factors that could influence sharing are posting shorter, comprehensible messages without any questions. Posting more messages in a day also increases the likelihood of sharing.

Overall Engagement

In order to achieve good scores on overall post engagement, admins should aim to incorporate various components into a brand's post, stimulating the several components of engagement mentioned above. For a successful social media marketing strategy, it is not of high importance in which way customers engage with the posts, but admins must be aware of which engagement type they wish to stimulate. As for general recommendations, admins should post vivid and short messages, preferably without hard-sell impulses. The best time to post is during the weekends and in the evening hours (between 18:00 to 23:00 o'clock).

Finally, main implications for admins of a specific fan page category are summarized in *Table 5.2*.

Products and Services fan pages	Media and News fan pages
<ul style="list-style-type: none"> - Post in more vivid formats - Include a Call-to-Action impulse into a posts - Submit multiple posts per day - Do not include a web link into the text of a posts - Submit the posts in the evening or during the night 	<ul style="list-style-type: none"> - Post in more vivid formats - Do not include a Call-to-Action impulse into a post - Include a question into a posts - Do not include a Hard-Sell into a post - Post shorter textual messages - Submit the posts during the night

Table 5.2 Summary of implications per specific brand category

5.3 LIMITATIONS

There are a few limitations which need to be addressed when considering the contributions of this thesis.

First, the research of this thesis is limited to selecting Products and Services and Media and News fan page categories. Other categories may have a more accurate and remarkable effect. Thus it is worth exploring other fan page categories in future research. Furthermore, the sample size may be limitation, since data used are collected from only seven fan pages during the 180 day period. Future research can examine a bigger sample observed over a longer period of time, which would further confirm results of this thesis and extent them beyond studied cases.

Secondly, manually coding the variables Content type, Hard-sell and Call-to-action is a limitation because of the human error and subjective perception which may have influenced the results. What is more, previous studies from similar fields state that deeper

text analysis like mood of the message or usage of common words which was lacking in the current research may bring new valuable insights.

During the analysis of the time related variables, a few limitations arise. First, the days should be evaluated separately, rather than grouped into “weekend” versus “workday”. Second, time of the day may be divided into smaller units than peak hour versus non-peak hour and different days can have different evaluations of posting time. Future research should concentrate into studying the timing of posts on social media deeper. Other factors also play a role in the limitations of this paper such as time of the year or presence of special events or news. Another limitation is the low number of occurrences of the highest vividness type Video. This could be done by studying a higher sample of brands during a longer period of time, because such research could capture more variety of the data.

Last but not least, the biggest limitation of such research is the subjective nature of the users’ perception of the post, which could not be quantified. However, this could be inspected by conducting a user survey or an experiment. Future research should incorporate a user survey in order to compare the results and correct for that limitation. The changing nature of social media can also bias the outcomes. The results of this thesis apply to the settings active during the research period, but those may change over time. It would be of a great interest to include more social media platforms, such as Instagram, Flickr, Google+, Pintrest or LinkedIn for future research.

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7. APPENDIX

Appendix 1 - Cross table of variables

		Correlations																			
		(log)Fans	Information	Entertainment	Remun	Vidness	Call to action	Question	Hard sell	Multiple	Weekend	(log)Length	Brand Name	HTTP	Emotcon	Fanpage	Time Night	Time Morning	Time Afternoon	Time Evening	
(log)Fans	Pearson Correlation	1	-.337**	.265*	.107	.248*	-.007	.033	-.189*	.090*	-.070	.001	-.234*	-.032	-.097*	.032	-.037	.104*	-.090		
	Sig. (2-tailed)		.000	.000	.042	.000	.820	.269	.000	.002	.019	.966	.275	.000	.276	.001	.278	.209	.000	.002	
	N	1128	364	364	364	1128	1128	1128	1128	1127	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	
Information	Pearson Correlation	-.337**	1	-.799**	-.182*	-.243*	.066	.069	.878**	-.054	-.013	.138*	-.040	.302**	-.036	-.095	.075	-.186*	.107		
	Sig. (2-tailed)			.000	.000	.000	.209	.186	.000	.304	.798	.009	.442	.000	.491	.000	.070	.155	.000	.041	
	N	364	364	364	364	364	364	364	364	363	364	364	364	364	364	364	364	364	364	364	
Entertainment	Pearson Correlation	.265**	-.799**	1	-.215*	.221**	-.115*	-.034	-.590**	.016	.056	-.052	.013	-.263**	.028	-.100	-.084	.222**	-.130*		
	Sig. (2-tailed)		.000	.000	.000	.000	.028	.524	.000	.759	.289	.320	.899	.000	.580	.000	.057	.072	.000	.013	
	N	364	364	364	364	364	364	364	363	364	364	364	364	364	364	364	364	364	364	364	
Remun	Pearson Correlation	.107	-.182*	-.215*	1	.013	.232*	-.007	-.120*	-.041	-.057	.134*	.025	-.014	-.037	-.046	-.037	-.009	.074		
	Sig. (2-tailed)		.042	.000	.000	.799	.000	.891	.015	.438	.277	.011	.641	.793	.483	.000	.383	.478	.864	.158	
	N	364	364	364	364	364	364	364	363	364	364	364	364	364	364	364	364	364	364	364	
Vidness	Pearson Correlation	.248**	-.243*	.221**	.013	1	.131**	.067	-.011	-.178*	.088*	-.052	.086*	.178**	.081*	-.312**	.182**	.031	.063	-.161*	
	Sig. (2-tailed)		.000	.000	.799	.000	.035	.706	.000	.022	.083	.054	.000	.042	.000	.000	.288	.030	.000	.000	
	N	1128	364	364	364	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	
Call to action	Pearson Correlation	-.007	.066	-.115*	.232*	.131**	1	.354**	.184**	-.091*	.025	.181**	.075	.323**	.053	-.163*	-.012	.016	-.026	.017	
	Sig. (2-tailed)		.209	.028	.000	.000	.000	.000	.002	.394	.000	.012	.000	.075	.000	.692	.580	.392	.559	.559	
	N	1128	364	364	364	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	
Question	Pearson Correlation	.033	.069	-.034	-.007	.067	.354**	1	.048	-.088*	-.010	-.002	-.006	.074	.004	-.070*	-.037	-.001	-.015	.030	
	Sig. (2-tailed)		.269	.186	.524	.000	.000	.000	.108	.003	.740	.905	.829	.013	.905	.018	.218	.978	.813	.315	
	N	1128	364	364	364	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	
Hard sell	Pearson Correlation	-.189**	.078*	-.590**	-.128*	-.011	.184**	.048	1	-.131**	.036	.150**	.021	.324**	.048	-.186*	.105*	-.003	-.042	.010	
	Sig. (2-tailed)		.000	.000	.015	.706	.000	.108	.000	.226	.000	.487	.000	.108	.000	.000	.000	.913	.162	.743	
	N	1128	364	364	364	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	
Multiple	Pearson Correlation	.090**	-.054	.016	-.041	-.176*	-.091*	-.088*	-.131**	1	-.050	.070	.000	-.225**	-.080*	.625**	-.006	.062	-.092*	.048	
	Sig. (2-tailed)		.002	.304	.759	.438	.000	.002	.003	.000	.395	.020	.998	.000	.007	.000	.839	.036	.002	.111	
	N	1127	363	363	363	1127	1127	1127	1127	1127	1127	1127	1127	1127	1127	1127	1127	1127	1127	1127	
Weekend	Pearson Correlation	-.070	-.013	.056	-.057	.068*	.025	-.010	.036	-.050	1	.010	.023	.043	-.044	.017	.003	-.076	.016	.047	
	Sig. (2-tailed)		.019	.798	.289	.277	.022	.384	.740	.226	.095	.739	.438	.152	.143	.561	.910	.011	.587	.118	
	N	1128	364	364	364	1128	1128	1128	1128	1127	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	
(log)Length	Pearson Correlation	.001	.138*	-.052	.134*	-.052	.181**	-.002	.150**	.070	.010	1	.060	.208**	.055	.065*	-.047	-.015	.045	-.019	
	Sig. (2-tailed)		.966	.009	.220	.011	.083	.000	.935	.000	.929	.739	.000	.044	.000	.067	.030	.118	.609	.129	
	N	1128	364	364	364	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	
Brand Name	Pearson Correlation	.033	-.040	.013	.025	.088*	.075	-.006	.021	.000	.023	.060	1	.134**	.210**	-.154**	.066*	-.028	.010	-.010	
	Sig. (2-tailed)		.275	.442	.809	.641	.004	.012	.829	.487	.998	.438	.044	.000	.000	.000	.028	.353	.748	.738	
	N	1128	364	364	364	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	
HTTP	Pearson Correlation	-.234**	.302**	-.263*	-.014	.178*	.323**	.074	.324**	-.225**	.843	.208**	.134**	1	.109	-.403**	.075	.035	-.041	-.013	
	Sig. (2-tailed)		.000	.000	.793	.000	.000	.013	.000	.000	.152	.000	.000	.000	.000	.000	.012	.247	.170	.674	
	N	1128	364	364	364	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	
Emotcon	Pearson Correlation	-.032	-.036	.028	-.037	.061*	.053	.004	.048	-.080*	-.044	.055	.210**	.109**	1	-.198**	.039	-.001	.044	-.060	
	Sig. (2-tailed)		.276	.491	.590	.483	.042	.075	.905	.108	.007	.143	.067	.000	.000	.000	.194	.967	.135	.043	
	N	1128	364	364	364	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	
Fanpage	Pearson Correlation	-.097**	*	*	*	-.312**	-.163*	-.070	-.186*	.625**	.017	.065	-.154**	-.403**	-.186**	1	-.076	-.014	-.138*	.187**	
	Sig. (2-tailed)		.001	.000	.000	.000	.000	.018	.000	.000	.561	.030	.000	.000	.000	.000	.010	.627	.000	.000	
	N	1128	364	364	364	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	
Time Night	Pearson Correlation	.032	.095	-.100	-.046	.182**	-.012	-.037	.105**	-.006	.003	-.047	.066*	.075*	.039	-.076*	1	-.085**	-.156**	-.117**	
	Sig. (2-tailed)		.278	.070	.057	.383	.000	.692	.218	.000	.839	.010	.118	.038	.012	.184	.010	.004	.000	.000	
	N	1128	364	364	364	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	
Time Morning	Pearson Correlation	-.037	.075	-.094	-.037	.031	.016	-.001	.003	.062*	-.078	-.015	-.028	.035	-.001	-.014	-.085**	1	-.454**	-.339**	
	Sig. (2-tailed)		.209	.155	.072	.478	.298	.580	.978	.913	.036	.011	.609	.353	.247	.967	.627	.004	.000	.000	
	N	1128	364	364	364	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	
Time Afternoon	Pearson Correlation	-.184**	-.169**	.223**	-.009	.065*	-.028	.015	.042	-.092*	.016	.045	.010	.041	.044	-.130**	-.156**	-.454**	1	-.625**	
	Sig. (2-tailed)		.000	.000	.864	.030	.392	.613	.162	.002	.587	.129	.748	.170	.135	.000	.000	.000	.000	.000	
	N	1128	364	364	364	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	1128	
Time Evening	Pearson Correlation	-.090**	.107	-.130*	.074	-.161*	.017	.030	.010	.048	.027	-.019	-.010	-.013	-.060	.187*	-.117**	-.339**	-.625**	1	
	Sig. (2-tailed)		.002	.041	.013	.158	.000	.559	.315	.743	.111	.118	.529	.738	.674	.043	.000	.000	.000	.000	
	N	1128	364	364	364	1128	1128	1128	1128	1128	1127	1128	1128	1128	1128	1128	1128	1128	1128	1128	

** Correlation is significant at the 0.01 level (2-tailed).
 * Correlation is significant at the 0.05 level (2-tailed).
 c. Cannot be computed because at least one of the variables is constant.

Appendix 2 – Regression analysis all brands

Engagement rate

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.433 ^a	.187	.176	.3638572845020

ANOVA^a

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	33,883	15	2,259	17,062	.000 ^b
Residual	147,088	1111	.132		

Coefficients^a

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
1 (Constant)	-,406	,131		-3,096	,002		
(log)Fans	-,195	,026	-,236	-7,646	,000	,769	1,300
Vividness	,154	,021	,219	7,174	,000	,786	1,272
Call to action	-,014	,028	-,016	-,508	,611	,756	1,323
Question	,047	,031	,045	1,543	,123	,861	1,161
Hard sell	-,092	,031	-,087	-2,945	,003	,842	1,187
Weekend	,058	,029	,055	2,011	,045	,970	1,030
(log)Lenght	-,130	,035	-,107	-3,709	,000	,876	1,142
Brand Name	-,005	,029	-,005	-,181	,856	,915	1,093
HTTP	-,015	,038	-,013	-,389	,698	,619	1,616
Emoticon	,024	,024	,029	1,032	,302	,919	1,088
Time Night	,517	,068	,214	7,588	,000	,917	1,091
Time Morning	,009	,030	,009	,319	,750	,849	1,178
Time Evening	,065	,026	,075	2,510	,012	,809	1,237
Fan page	-,144	,035	-,168	-4,077	,000	,430	2,327

a. Dependent Variable: (log)Engagement Rate

Like rate

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,234 ^a	,055	,042	,6543612008164

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	27,660	15	1,844	4,307	,000 ^b
	Residual	475,718	1111	,428		
	Total	503,378	1126			

Coefficients^a

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
1 (Constant)	-1,707	,236		-7,244	,000		

(log)Fans	-.092	,046	-.067	-2,013	,044	,769	1,300
Vividness	,055	,038	,047	1,430	,153	,786	1,272
Call to action	,025	,050	,017	,501	,616	,756	1,323
Question	-.029	,055	-.017	-,528	,598	,861	1,161
Hard sell	-.008	,056	-.005	-,145	,885	,842	1,187
Weekend	-.027	,051	-.015	-,518	,605	,970	1,030
(log)Length	,082	,063	,041	1,306	,192	,876	1,142
Brand Name	,319	,052	,188	6,167	,000	,915	1,093
HTTP	-,152	,069	-.082	-2,215	,027	,619	1,616
Emoticon	-.028	,042	-.020	-,671	,502	,919	1,088
Time Night	-.088	,123	-.022	-,716	,474	,917	1,091
Time Morning	,027	,053	,016	,506	,613	,849	1,178
Time Evening	,071	,047	,050	1,536	,125	,809	1,237
Fan page	-,200	,064	-,140	-3,143	,002	,430	2,327

a. Dependent Variable: (log)Like Rate

Comment rate

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,296 ^a	,087	,075	1,438288652132

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	220,341	15	14,689	7,101	,000 ^b
	Residual	2298,297	1111	2,069		
	Total	2518,638	1126			

Coefficients^a

Model	Unstandardized Coefficients		Standardized Coefficients		t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta				Tolerance	VIF
1 (Constant)	-1,181	,518			-2,279	,023		
(log)Fans	,036	,101	,012		,353	,724	,769	1,300
Vividness	-,090	,085	-,034		-1,059	,290	,786	1,272

Call to action	,077	,110	,023	,703	,482	,756	1,323
Question	,012	,121	,003	,101	,920	,861	1,161
Hard sell	-,023	,124	-,006	-,185	,853	,842	1,187
Weekend	,152	,113	,039	1,345	,179	,970	1,030
(log)Length	,043	,138	,010	,313	,754	,876	1,142
Brand Name	,177	,114	,047	1,553	,121	,915	1,093
HTTP	-,048	,151	-,011	-,315	,752	,619	1,616
Emoticon	-,875	,093	-,281	-,9404	,000	,919	1,088
Time Night	,431	,269	,048	1,598	,110	,917	1,091
Time Morning	,085	,117	,023	,725	,469	,849	1,178
Time Evening	,126	,102	,039	1,231	,218	,809	1,237
Fan page	-,042	,140	-,013	-,302	,763	,430	2,327

a. Dependent Variable: (log)Comment Rate

Share rate

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,292 ^a	,085	,073	1,459672204784

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	220,028	15	14,669	6,885	,000 ^b
	Residual	2367,144	1111	2,131		
	Total	2587,172	1126			

Coefficients^a

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
1 (Constant)	-1,148	,526		-2,183	,029		
(log)Fans	,139	,102	,045	1,363	,173	,769	1,300
Vividness	,029	,086	,011	,333	,739	,786	1,272
Call to action	-,044	,111	-,013	-,399	,690	,756	1,323
Question	-,327	,123	-,082	-2,658	,008	,861	1,161

Hard sell	,012	,125	,003	,093	,926	,842	1,187
Weekend	,070	,115	,018	,613	,540	,970	1,030
(log)Length	-,697	,140	-,152	-4,961	,000	,876	1,142
Brand Name	,093	,116	,024	,809	,419	,915	1,093
HTTP	,015	,153	,004	,098	,922	,619	1,616
Emoticon	,071	,094	,022	,746	,456	,919	1,088
Time Night	,119	,273	,013	,435	,664	,917	1,091
Time Morning	-,139	,119	-,036	-1,169	,243	,849	1,178
Time Evening	,095	,104	,029	,918	,359	,809	1,237
Fan page	,541	,142	,167	3,813	,000	,430	2,327

a. Dependent Variable: (log)Share Rate

Appendix 3 – Regression analysis Products and Services brands

Engagement rate

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
	Fan page = ,0 (Selected)			
1	,456 ^a	,208	,169	,4465382377394

ANOVA^{a,b}

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	18,020	17	1,060	5,316	,000 ^c
	Residual	68,792	345	,199		
	Total	86,812	362			

Coefficients^{a,b}

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
1 (Constant)	-,326	,249		-1,310	,191		
(log)Fans	-,220	,042	-,323	-5,267	,000	,609	1,642
Vividness	,146	,039	,208	3,738	,000	,745	1,342

Call to action	,105	,061	,105	1,725	,085	,622	1,607
Question	-,055	,064	-,046	-,860	,390	,804	1,244
Hard sell	,040	,077	,036	,518	,605	,470	2,129
Multiple	,093	,055	,087	1,709	,088	,893	1,120
Weekend	,085	,068	,066	1,258	,209	,841	1,189
(log)Length	-,116	,095	-,072	-1,221	,223	,655	1,526
Brand Name	-,006	,057	-,005	-,097	,922	,833	1,200
HTTP	-,148	,065	-,146	-2,281	,023	,562	1,779
Emoticon	,030	,050	,031	,599	,550	,866	1,155
Time Night	,511	,118	,221	4,337	,000	,886	1,128
Time Morning	-,016	,063	-,013	-,259	,796	,845	1,183
Time Evening	,204	,066	,165	3,088	,002	,806	1,240
Entertainmen t	-,007	,105	-,008	-,071	,943	,198	5,048
Remun	-,016	,165	-,007	-,100	,921	,508	1,969

a. Dependent Variable: (log)Engagement Rate

b. Selecting only cases for which Fan page = ,0

Like rate

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
	Fan page = ,0 (Selected)			
1	,339 ^a	,115	,071	,7000805764242

ANOVA^{a,b}

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	21,961	17	1,292	2,636	,000 ^c
	Residual	169,089	345	,490		
	Total	191,050	362			

Coefficients^{a,b}

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
1 (Constant)	-1,124	,390		-2,885	,004		
(log)Fans	-,070	,066	-,069	-1,068	,286	,609	1,642
Vividness	,059	,061	,056	,959	,338	,745	1,342
Call to action	-,034	,096	-,023	-,360	,719	,622	1,607
Question	-,018	,100	-,010	-,179	,858	,804	1,244
Hard sell	-,153	,120	-,094	-1,274	,203	,470	2,129
Multiple	,043	,086	,027	,496	,620	,893	1,120
Weekend	,039	,106	,020	,369	,713	,841	1,189
(log)Length	-,191	,149	-,080	-1,286	,199	,655	1,526
Brand Name	,413	,090	,255	4,593	,000	,833	1,200
HTTP	,009	,102	,006	,088	,930	,562	1,779
Emoticon	-,315	,079	-,217	-3,992	,000	,866	1,155
Time Night	,031	,185	,009	,169	,866	,886	1,128
Time Morning	,097	,099	,054	,980	,328	,845	1,183
Time Evening	,231	,104	,126	2,225	,027	,806	1,240
Entertainment	-,050	,165	-,034	-,302	,763	,198	5,048
Remun	-,248	,259	-,068	-,959	,338	,508	1,969

a. Dependent Variable: (log)Like Rate

b. Selecting only cases for which Fan page = ,0

Comment rate

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
	Fan page = ,0 (Selected)			
1	,278 ^a	,077	,032	1,427023988341

ANOVA^{a,b}

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	58,784	17	3,458	1,698	,041 ^c
	Residual	702,557	345	2,036		
	Total	761,342	362			

Coefficients^{a,b}

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
1 (Constant)	-2,571	,794		-3,237	,001		
(log)Fans	-,041	,134	-,020	-,308	,758	,609	1,642
Vividness	,036	,125	,017	,292	,770	,745	1,342
Call to action	-,147	,195	-,050	-,755	,451	,622	1,607
Question	,015	,203	,004	,075	,940	,804	1,244
Hard sell	,053	,245	,016	,217	,828	,470	2,129
Multiple	,146	,175	,046	,833	,405	,893	1,120
Weekend	,048	,217	,012	,219	,827	,841	1,189
(log)Length	,635	,303	,134	2,098	,037	,655	1,526
Brand Name	,025	,183	,008	,138	,890	,833	1,200
HTTP	-,081	,208	-,027	-,391	,696	,562	1,779
Emoticon	-,603	,161	-,208	-3,744	,000	,866	1,155
Time Night	,476	,377	,069	1,263	,207	,886	1,128
Time Morning	,256	,202	,071	1,265	,207	,845	1,183
Time Evening	,508	,211	,138	2,402	,017	,806	1,240
Entertainment	,214	,337	,074	,636	,525	,198	5,048
Remun	-,014	,528	-,002	-,026	,979	,508	1,969

a. Dependent Variable: (log)Comment Rate

b. Selecting only cases for which Fan page = ,0

Share rate

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
	Fan page = ,0 (Selected)			
1	,312 ^a	,097	,053	1,467341511792

ANOVA^{a,b}

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	79,839	17	4,696	2,181	,005 ^c
	Residual	742,816	345	2,153		
	Total	822,655	362			

Coefficients^{a,b}

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
1 (Constant)	-,641	,817		-,785	,433		
(log)Fans	-,060	,138	-,029	-,438	,661	,609	1,642
Vividness	,074	,128	,034	,574	,566	,745	1,342
Call to action	,050	,200	,016	,249	,804	,622	1,607
Question	-,496	,209	-,135	-2,372	,018	,804	1,244
Hard sell	-,045	,252	-,013	-,178	,859	,470	2,129
Multiple	,346	,180	,104	1,925	,055	,893	1,120
Weekend	,169	,223	,042	,759	,448	,841	1,189
(log)Length	-,528	,312	-,107	-1,695	,091	,655	1,526
Brand Name	-,014	,188	-,004	-,072	,943	,833	1,200
HTTP	-,166	,214	-,053	-,778	,437	,562	1,779
Emoticon	,102	,166	,034	,618	,537	,866	1,155
Time Night	,482	,387	,068	1,246	,214	,886	1,128
Time Morning	,455	,208	,122	2,186	,029	,845	1,183
Time Evening	-,119	,217	-,031	-,547	,584	,806	1,240
Information	-,257	,360	-,085	-,714	,475	,186	5,370
Entertainment	,004	,346	,001	,013	,990	,198	5,048
Remun	-,643	,543	-,085	-1,183	,237	,508	1,969

a. Dependent Variable: (log)Share Rate

b. Selecting only cases for which Fan page = ,0

Appendix 4 – Regression analysis Media and News brands

Engagement rate

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
	Fan page = 1,0 (Selected)			
1	,435 ^a	,189	,174	,3099766289800

ANOVA^{a,b}

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	16,776	14	1,198	12,471	,000 ^c
	Residual	71,968	749	,096		
	Total	88,744	763			

Coefficients^{a,b}

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
1 (Constant)	-,980	,181		-5,418	,000		
(log)Fans	-,068	,040	-,062	-1,713	,087	,814	1,229
Vividness	,168	,027	,222	6,272	,000	,865	1,156
Call to action	-,065	,030	-,080	-2,182	,029	,805	1,243
Question	,111	,033	,118	3,364	,001	,875	1,143
Hard sell	-,143	,036	-,139	-3,982	,000	,893	1,120
Multiple	-,044	,042	-,039	-1,053	,293	,797	1,254
Weekend	,022	,029	,026	,763	,446	,964	1,037
(log)Length	-,143	,035	-,144	-4,134	,000	,898	1,114
Brand Name	-,028	,032	-,030	-,887	,375	,970	1,031
HTTP	,082	,055	,054	1,490	,137	,822	1,217
Emoticon	,032	,025	,042	1,269	,205	,967	1,034
Time Night	,459	,085	,187	5,384	,000	,899	1,113
Time Morning	,025	,031	,029	,787	,431	,821	1,218

Time Evening	,008	,026	,012	,318	,750	,806	1,240
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a. Dependent Variable: (log)Engagement Rate

b. Selecting only cases for which Fan page = 1,0

Like rate

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
	Fan page = 1,0 (Selected)			
1	,244 ^a	,059	,042	,6203787258904

ANOVA^{a,b}

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	18,208	14	1,301	3,379	,000 ^c
	Residual	288,267	749	,385		
	Total	306,476	763			

Coefficients^{a,b}

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
1 (Constant)	-2,021	,362		-5,584	,000		
(log)Fans	-,118	,079	-,058	-1,487	,137	,814	1,229
Vividness	,067	,054	,048	1,249	,212	,865	1,156
Call to action	,056	,059	,037	,940	,348	,805	1,243
Question	-,019	,066	-,011	-,288	,774	,875	1,143
Hard sell	,042	,072	,022	,580	,562	,893	1,120
Multiple	,047	,084	,022	,555	,579	,797	1,254
Weekend	-,043	,059	-,026	-,734	,463	,964	1,037
(log)Length	,162	,069	,087	2,331	,020	,898	1,114
Brand Name	,306	,064	,173	4,805	,000	,970	1,031
HTTP	-,173	,110	-,062	-1,574	,116	,822	1,217
Emoticon	,117	,050	,084	2,337	,020	,967	1,034
Time Night	-,246	,171	-,054	-1,443	,150	,899	1,113
Time Morning	-,002	,063	-,001	-,034	,973	,821	1,218
Time Evening	,032	,052	,024	,612	,541	,806	1,240

- a. Dependent Variable: (log)Like Rate
- b. Selecting only cases for which Fan page = 1,0

Comment rate

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
	Fan page = 1,0 (Selected)			
1	,331 ^a	,110	,093	1,438564097761

ANOVA^{a,b}

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	191,309	14	13,665	6,603	,000 ^c
	Residual	1550,031	749	2,069		
	Total	1741,340	763			

Coefficients^{a,b}

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
1 (Constant)	-,973	,839		-1,159	,247		
(log)Fans	,172	,184	,036	,936	,349	,814	1,229
Vividness	-,177	,124	-,053	-1,428	,154	,865	1,156
Call to action	,143	,138	,040	1,035	,301	,805	1,243
Question	,011	,153	,003	,071	,943	,875	1,143
Hard sell	,103	,167	,022	,616	,538	,893	1,120
Multiple	,108	,195	,021	,556	,578	,797	1,254
Weekend	,081	,137	,021	,592	,554	,964	1,037
(log)Length	-,191	,161	-,043	-1,187	,236	,898	1,114
Brand Name	,224	,148	,053	1,513	,131	,970	1,031
HTTP	-,172	,255	-,026	-,675	,500	,822	1,217
Emoticon	-1,048	,116	-,318	-9,057	,000	,967	1,034
Time Night	,654	,396	,060	1,652	,099	,899	1,113
Time Morning	,010	,145	,003	,066	,947	,821	1,218

Time Evening	-.008	.120	-.003	-.068	.946	.806	1,240
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a. Dependent Variable: (log)Comment Rate

b. Selecting only cases for which Fan page = 1,0

Share rate

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
	Fan page = 1,0 (Selected)			
1	.240 ^a	.057	.040	1,442575132982

ANOVA^{a,b}

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	94,916	14	6,780	3,258	.000 ^c
	Residual	1558,686	749	2,081		
	Total	1653,602	763			

Coefficients^{a,b}

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
	1 (Constant)	-	,842				-
(log)Fans	,384	,185	,082	2,083	,038	,814	1,229
Vividness	-,027	,124	-,008	-,213	,831	,865	1,156
Call to action	-,060	,138	-,017	-,434	,664	,805	1,243
Question	-,265	,153	-,066	-1,72	,084	,875	1,143
Hard sell	,145	,167	,033	,867	,386	,893	1,120
Multiple	,019	,195	,004	,097	,923	,797	1,254
Weekend	,003	,137	,001	,019	,985	,964	1,037
(log)Length	-,762	,161	-,177	-4,72	,000	,898	1,114
Brand Name	,132	,148	,032	,890	,374	,970	1,031
HTTP	,254	,255	,039	,993	,321	,822	1,217
Emoticon	,041	,116	,013	,354	,724	,967	1,034
Time Night	-,231	,397	-,022	-,583	,560	,899	1,113
Time Morning	-,421	,146	-,113	-2,88	,004	,821	1,218
Time Evening	,076	,120	,025	,637	,524	,806	1,240

a. Dependent Variable: (log)Share Rate

b. Selecting only cases for which Fan page = 1,0