Does the use of Real Time Marketing (RTM) as brand content strategy on Instagram have an impact on social media engagement? An analysis for Portugal

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Abstract

This dissertation studies the impact that the use of Real Time Marketing (RTM), specifically on Instagram, has over social media engagement, focusing on the Portuguese context.

Previous research are not unanimous regarding the effects of RTM. Thus, the current dissertation aims to further investigate this topic and explore new facets to the problem, by means of analyzing other components that might influence Real Time Marketing performance such as the presence of brand promotional appeal and the effects on sentiment of comments from followers.

A total of 537 posts from Portuguese Instagram accounts of brands listed in Forbes' Most Valuable Brands were collected. In total, 10 brands were considered.

The findings reveal that Real Time Marketing has a comparable performance to Non-Real Time Marketing on engagement and on sentiment of comments. Besides, the presence of brand promotional appeal on RTM posts does not influence the effects on engagement.

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Sumário

A presente dissertação estuda o impacto que a utilização do Real Time Marketing (RTM), especificamente no Instagram, tem sobre o engagement nas redes sociais, focando-se no contexto português.

Os estudos anteriores não são unânimes quanto aos efeitos do RTM, pelo que esta dissertação pretende aprofundar esta temática e explorar novas facetas do problema, através da análise de outras componentes que podem influenciar o desempenho do Real Time Marketing, como a presença da marca nos posts e os efeitos no sentimento dos comentários dos seguidores.

A pesquisa realizada envolveu a recolha de 537 posts de contas de Instagram portuguesas de marcas listadas na lista da "Forbes' Most Valuable Brands in the world". No total, foram consideradas 10 marcas.

Os resultados revelam que o Real Time Marketing tem um desempenho semelhante ao N-Real Time Marketing no que respeita ao engagement e ao sentimento dos comentários. Para além disso, a presença de marca nos posts de RTM não influência o engagement.

Título: O uso do Real Time Marketing (RTM) como uma estratégia de conteúdo de marca no Instagram tem impacto no engagement nas redes sociais? Uma análise para Portugal

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Palavras-Chave: Real Time Marketing; Instagram; Engagement

List of Contents

List of Figures

List of Tables

1. Introduction

1.1. Topic Presentation

In recent years, social media has become increasingly important, with consumers using and depending on social networks more and more every day. People spend hours on these platforms every day, abandoning other means of communication that were more efficient in the past, such as television, newspapers and magazines (Durante, 2021).

With this natural evolution caused by the advances in technology and the globalization of the Internet, brands that a few years ago invested mainly in traditional means of communication had to start diversifying the platforms they used in order to be more successful in spreading their messages and promoting their products. In this way, communicating in social media became a challenge for brands, because although it is an easy way to be close to consumers, it is a challenge to create content that really interests them, relates to them and creates engagement (Ha, Huang & Park, 2019).

To better engage with consumers, brands are, for example, using content formats such as Real Time Marketing (RTM). However, while Real Time Marketing is thought to increase engagement, previous findings are not unanimous. Previous studies have found mixed results, with a positive effect over engagement on Twitter (Willemsen et al., 2018 and Santini et al., 2020), but no significant effect on Instagram (Mazerant et al., 2020).

Since there is not more literature on this subject regarding Real Time Marketing specifically on Instagram, it would be interesting to test the effects of this content format in the specific context of Portugal, taking into account additional facets of the problem, namely the presence of brand promotional appeal and the level of sentiment of comments written by brand followers.

1.2. Problem Statement

The purpose of this research is to understand Real Time Marketing impact on engagement on Instagram. The following Research Questions are proposed:

RQ1: Do Real Time Marketing posts on Instagram perform better on generating engagement (number of likes and comments) than Non Real Time Marketing?

RQ2: Do Real Time Marketing posts on Instagram perform better on generating a positive sentiment on followers' comments than Non Real Time Marketing?

RQ3: Does the presence of brand promotional appeal impact performance of Real Time Marketing posts on engagement (number of likes and comments)?

1.3. Scope of Analysis

Since Real Time Marketing messages can be understood differently from country to country depending on how much a country is aware of the moment or situation a certain post is referring to, this study will focus on Portugal, using only brands that have Portuguese Instagram accounts, disregarding global brand accounts.

1.4. Academic and Managerial Relevance

This research will provide marketeers a second analysis on Real Time Marketing effects on engagement, strengthening the previous study or, on the other way around, giving a different perspective, if the results show a different outcome. Besides, it will add the output about the effects that the use of product on RTM posts might have. This kind of conclusions can be very useful for marketeers so brands can work their communications on Instagram on the more effective way, impacting their targets more and leading to better performances to the respective companies.

In an academic way, this study will provide a deeper analysis on RTM in regard to the brand promotional appeal on Instagram posts and the weekday of the post, but it will also be an addition to the previous study already done about RTM results on engagement on Instagram (vs non-RTM).

1.5. Dissertation Outline

This dissertation starts with the introduction to the subject of the research on section 1. Then on section 2 presents the readers with results from other articles and papers useful for this study and then enters on section 3 where the methodology of the research is explained. On section 4 the results and findings of this dissertation are shown and finally on the last section

the conclusions are developed, as well as limitations and recommendations for future studies about engagement on social media.

2. Literature Review and Proposition of Hypothesis

2.1. Social Media

According to Hermida et al. (2012), people use social media to be updated of other people's lives and about the world. Social media users are mostly motivated by the need to keep up with social events, news and obtaining first-hand information about important events. Another author, Voorveld (2016), as cited by Willemsen et al. (2018) also studied that people use social media specially to interact with others and keep informed about current events.

According to Fournier and Avery (2011) and Kaplan and Haenlein (2010) as cited by Willemsen et al. (2018), social media platforms have a great potential for brands to reach large publics, since brands can pass their messages through consumer communities in an easier and cheaper way than in other platforms. This is facilitated by the sharing behavior observed in these platforms between social media users, who organize themselves as fans communities around brands profiles.

Given the fact that peers are the most trusted source of influence (Nielsen, 2015), brands "can create a halo effect of trust for their messages" (Willemsen et al., 2018, p. 3) when social media users share brand messages between each other and on their timelines. This way, it is important for brands to post messages that potentiate sharing to gain visibility for their messages and be more persuasive (Willemsen et al., 2018).

2.2. Engagement

According to a survey done to over 800 executives, customer engagement on the digital was the biggest priority for companies (McKinsey & Company 2014), which can be explained by the thought that social media engagement has several positive outcomes, such as an increase in sales, brand loyalty or brand equity (Syrdal & Briggs, 2018).

Despite this, there is no consensus on how to measure engagement. Some measure it by the size of the brand's fan base while others measure it according to people's behavior online, such as likes, comments or shares (Syrdal & Briggs, 2018).

However, based on interviews to online brand community members made by Dessart, Veloutsou and Morgan-Thomas (2015), they conclude that even though there are different interpretations of consumer engagement, it involves affective, cognitive and behavioral dimensions, including enjoyment and enthusiasm for the affective dimension, attention and

absorption for cognitive dimension and learning, endorsing and sharing for the behavioral dimension.

Based on the study made by Syrdal & Briggs (2018) where they interview marketing practitioners who use social media in their marketing strategies, they conclude that engagement can be demonstrated by likes, comments and shares, but a person that reads or just views the social media content is also engaging with the brand. In this way, they refer to the first type of engagement as an active engagement, while they categorize the second as passive engagement. Besides, they also agree that engagement can be viewed as a continuum, where viewing and reading represent less engagement, shares and comments indicate greater engagement and liking is in the middle. At the same time, they also observe that sometimes liking, sharing or commenting does not always means engagement, since these actions sometimes can be observed due to some personal connection with the person who developed the social media content, when we are talking about smaller brands that are managed by a single person (Syrdal & Briggs, 2018).

An important note to do is that depending on the social media platform, consumers may differ their behaviors towards content. For example, according to another study done by Syrdal & Briggs (2018), while on Facebook people feel there are more people who can see what they are interacting with (family, coworkers, etc), on Instagram, for example, they feel more free to like and share content because their interactions are more private (even if it is the same content from Facebook). Additionally, there are also people who consider they engage with the content because they look and read it, however they don't like, comment or share because they don't want to be associated with the owner of the content or they don't want other people to know they have engaged with that type of content (especially if it is political or religious) (Syrdal & Briggs, 2018). This shows that consumers have a different vision from marketers over engagement, the first group sees it more as a state of mind where they feel enjoyment and involvement, while the second group measures it by likes, comments and shares. Following this rational, when consumers experience this state of mind, they might either choose to interact with the content or not, making a conscious decision rather than having a behavior led by the level of engagement they are feeling.

Another study about customer engagement on social media has concluded that positive emotions contribute directly to increase customer engagement and also, trust strengthens customer engagement trough satisfaction (Santini et al., 2020)

Santini et al. (2020) found that Customer Engagement is very valuable for companies, since it directly impacts firm performance, behavioral intention and word-of-mouth, however while behavioral intention contributes to firms' performance, word-of-mouth does not.

Another conclusion taken from Santini et al. (2020) meta-analysis is that a high involvement with the brand's product contributes to customer engagement effects on firm performance when compared to low product involvement.

2.3. Viral Content

A dimension that may also influence social media engagement is the degree to which a content goes viral.

According to Allsop, Bryce & James (2007), 59% of people frequently share online content with others, whether it's Youtube videos, newspaper articles or restaurant reviews. However not all content goes viral, even though social transmission is frequent and important (Berger & Milkman, 2011).

Berger & Milkman study (2011) shows that positive and negative content go more viral than normal content that don't evoke any of these emotions, however positive content is more viral than negative content. Nonetheless, while content that induces positive emotions is more viral than content that induces negative emotions, it is important to warn that high-arousal negative emotions are also positively associated with virality (such as, for example, awe, anger and anxiety). This happens because negative emotions characterized by arousal are linked with virality, while negative emotions characterized by deactivation (such as sadness) are negatively linked to virality. Another important conclusion from Berger & Milkman study (2011) is that external drivers of attention such as the promotion of the content by its owner (featuring or paying), has the same importance in making the content viral as content characteristics. A further conclusion of this study is that more practically useful, interesting and surprising content also becomes more viral.

2.4. Real Time Marketing

Real Time Marketing is a content format that associates its messages with public and temporary events such as news, trending or popular topics or even holidays (Willemsen et al., 2018).

This content format was already used in traditional media messages and even 16 years ago authors like Kumar, Jacob, and Sriskandarajah (2006), as cited by Willemsen et al. (2018), already talked about the importance of timing in advertising to increase revenue. An example of Real Time Marketing used before social media was the Christmas ad from J&B Whisky in 1990, where a billboard stated "ingle ells, ingle ells—The holidays aren't the same without JB" (Willemsen et al., 2018).

These days, Real Time Marketing has gained a new interest for marketers, since social media is formed by networks that share content and updates on a real time nature (Willemsen et al., 2018). According to Kerns (2014) and Scott (2011), as cited by Willemsen et al. (2018), brands increasingly link their messages with widely discussed events and join conversations to gain momentum. This way, brands believe they can gain the attention that these events are receiving, become part of the conversation and gain a much bigger visibility that they wouldn't accomplish in any other way and also as Mazerant et al. (2020) say, they are also able to shorten the distance they have from consumers, since they start talking about the same subjects consumers are talking at the moment.

Social media has brought new opportunities for brands to connect with current events, however it is necessary to understand which associations are more relevant to do. There is the possibility to share content associated with predictable moments (such as holidays and sports events, that can be foreseen or happen on a regular basis) or share messages associated with unpredictable moments (for example a surprisingly cold summer or an unexpected dance move done by a popular person that becomes a topic of conversation) (Willemsen et al., 2018).

Real Time Marketing success must also be analyzed considering the creativity used on the messages. According to Willemsen et al. (2018), creativity is determined by originality and meaningfulness and according to Mazerant et al. (2020) it is also determined by craftmanship. Originality regards to how unexpected the message is, how much it deviates from the norm (Ang and Low, 2000) and how unique and innovative it is (White, Shen and Smith, 2002). Meaningfulness, on a consumer perspective, is how relevant it is to the audience, how much it makes sense and how logical it is (White, Shen and Smith, 2002 and Lehnert, Till & Ospina, 2014). Craftmanship refers to ads pleasing to the eye and well-executed messages in terms of

aesthetics (for example due to the use of attractive colors and shapes) (Koslow, Sasser and Riordan, 2006 and Smith, Chen and Yang, 2008).

The study from Willemsen et al. (2018) that was based on Twitter shows that RTM can be an effective strategy to increase sharing behavior on this social network and that it has even more potential when it is linked with unpredictable moments or moment-driven visuals. Moment-driven visuals, meaning, content that makes a visual connection to a current event, lead to an increase of shares when compared to visuals in general. Additionally, meaningfulness and originality on RTM posts are the dimensions that increase shares on Twitter. Nevertheless, these two dimensions of creativity affect shares in opposite directions when in presence of unpredictable events. Even though unpredictable RTM was still positive for sharing behavior on Twitter, originality was negatively affected by time constraints for content creation, while on the other hand, meaningfulness was enhanced in these posts and therefore, was the dimension that allowed shares the most (Willemsen et al., 2018).

On the other hand, Mazerant et al. (2020) found that on Instagram, RTM messages yield less consumer responses than non-RTM messages. Real Time Marketing messages on Instagram are meaningful at the expense of originality and craftmanship (meaningfulness is where they score higher) and since from these three dimensions of creativity only craftmanship increases consumer responses on Instagram, that is the reason why RTM on Instagram enables less consumer responses (Mazerant et al., 2020). On the opposite direction, non-RTM messages on Instagram are well crafted at the expense of being original, which makes then score higher on craftmanship (Mazerant et al., 2020).

Even though Real Time Marketing on Instagram does not increase consumer responses when compared to non-RTM messages, between RTM messages, originality induces positive attitude towards the message and the brand. On the other hand, a higher level of meaningfulness does not positively induce consumer responses. And finally, RTM messages with a higher level of craftmanship evoke a more positive attitude towards the brand and the message than RTM messages with a lower level of craftmanship (Mazerant et al., 2020).

This difference observed on the success of Real Time Marketing on Twitter vs on Instagram is explained by the different goals of each of these social media platforms. According to Papetti et al. (2018) and Zhu & Chen (2015), as cited by Mazerant et al. (2020), Instagram is used by its members to get inspired by visually attractive content while on the other hand, Twitter is useful to keep its members updated about relevant moments.

2.5. Promotional Brand messages on Social Media

According to Ashley & Tuten (2015), branded social media activities can contribute to increase awareness, brand linking and engagement with the brand, among other effects such as word-of-mouth and loyalty. For example, branded social media content can also be useful as an advertising tool that can influence consumer attitudes (Ashley & Tuten, 2015). However, this may depend on the purpose of the post, as explored by Vargo (2016) & Schultz (2017).

Although Vargo (2016) & Schultz (2017) both conclude that the purpose of the post can influence engagement, their findings are opposite.

Vargo (2016) conducted his study on Twitter and concluded that promotional messages (posts that promoted the brand or the product) negatively influenced engagement, resulting in fewer shares (retweets) and likes. However, the author also concludes that brand posts promoting giveaways have a positive impact on engagement, resulting in more shares and likes. The difference between the second and the first observation may be due to consumers' skeptical view of product information coming from the brand itself (as suggested by Vargo, 2016).

On the other hand, Schultz (2017) conducted his study on Facebook and concluded that the majority of content types lead to fewer interactions when compared to product posts. The author also observed that this happens because the other content types only appeal to a portion of the audience. In addition, posts with product promotions also positively influenced commenting and sharing, although they negatively affected likes.

2.6. Sentiment Analysis on Social Media

Sentiment analysis is a data mining method that has emerged in recent years but has already been used in several studies on social media (Öztürk & Ayvaz, 2018). Öztürk & Ayvaz (2018) research captures numerous examples where this analysis has been used, such as a sentiment analysis of political tweets during the 2012 United States presidential election, or an analysis of the public health perspective on the spread of infectious diseases. Apart from the studies enumerated by these authors, others such as Smith & Cipolli (2021) also use this method to understand the sentiments triggered by the Instagram/Facebook prohibition of graphic images of self-harm.

Sentiment analysis is a technique that uses Natural Language Processing (NLP) methods to identify opinions, behaviors and feelings present on data displayed in text. This tool is also considered a model for identifying the polarity of data, as it classifies text into a set of predefined sentiment groups, acting as a dictionary that gives the correspondence of words to specific sentiment punctuation (Öztürk & Ayvaz, 2018).

From the literature researched, all authors use R software, although some use R own sentiment package to get a sentiment score to its data (Öztürk & Ayvaz, 2018) and other lexicon packages such as tm package (Feinerer, Hornik & Meyer, 2008) and NRC (Smith & Cipolli, 2021).

The relevance of using this method is justified by the significant casual effects of sentiment on sales, as studied by Hu, Koh, & Reddy (2014). The authors used a text mining method as well to study the impact that the sentiment present on online reviews had on product sales and they concluded that sentiments had a direct significant influence on sales (Hu, Koh, & Reddy, 2014).

2.7. Proposition of Hypothesis

According to the literature, Real Time Marketing does not have an impact on engagement on Instagram, however there is only one study that analysis this social media platform on this subject and, on the other hand, other studies conclude that on Twitter, for example, Real Time Marketing positively impacts engagement.

Since previous authors also state that engagement is measured by likes, comments and shares on social media, it would be interesting to do a second study on the impact of Real Time Marketing on Instagram, having these measures in mind and also applying other variables to the study.

This way, the following hypothesis were formulated:

RQ1: Do Real Time Marketing posts on Instagram perform better on generating engagement (number of likes and comments) than Non Real Time Marketing (N-RTM)?

H1: The use of Real Time Marketing has a positive effect over the number of likes when compared to N-RTM posts.

H2: The use of Real Time Marketing has a positive effect over the number of comments when compared to N-RTM posts.

RQ2: Do Real Time Marketing posts on Instagram perform better on generating a positive sentiment on followers' comments than Non Real Time Marketing?

H3: The use of Real Time Marketing has a positive effect over the sentiment of the comments when compared to N-RTM posts.

RQ3: Does the presence of brand promotional appeal impact performance of Real Time Marketing posts on engagement (number of likes and comments)?

H4: The Real Time Marketing posts without brand promotional appeal generate more likes than RTM posts with promotional appeal.

H5: The Real Time Marketing posts without brand promotional appeal generate more comments than RTM posts with promotional appeal.

Based on the suggested research, Figure 1 represents the structure of the above hypothesis:

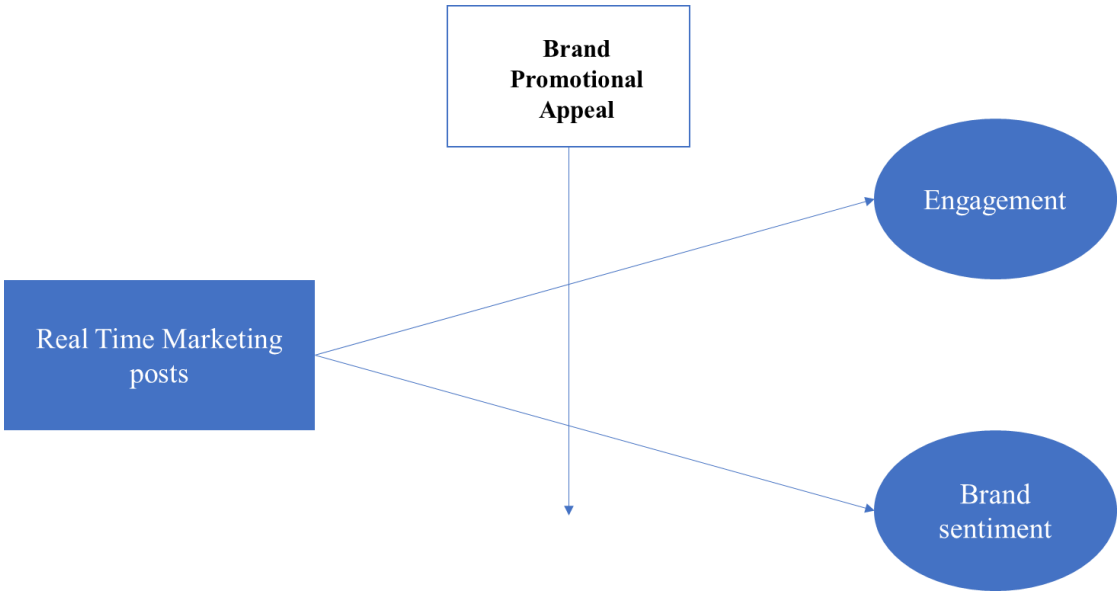

Figure 1 – Conceptual Framework

3. Methodology and Data Collection

After gathering various articles about the topics related to this investigation, it was conducted an analysis to several brands' Instagram posts that were collected, in order to conclude about engagement, according to the research questions defined on the beginning.

The brands chosen to be part of this post extraction were all part of the Forbes' Most Valuable Brands in the world (Forbes Media LLC, 2023) and were chosen, by order, from the most to the least valuable. From this list, they were only selected brands that had a Portuguese Instagram account. It was used a sample of 10 brands, since they guaranteed a significative sample of posts (Table 1)

Brands	Instagram Followers	Facebook Followers	# Posts per Week on Instagram
Coca-Cola Portugal	34 200	109 541 325	1
Disney Portugal	26 300	52 926 370	5
Samsung Portugal	168 000	162 500 545	3
McDonald's Portugal	148 000	82 474 969	3
Toyota Portugal	30 100	147 800	5
Mercedes-Benz Portugal	82 400	501 200	6
Netflix Portugal	659 000	88 072 790	12
BMW Portugal	77 800	75 000	3
Honda Portugal - Automóveis	41 000	134 000	2
L'Oréal Portugal	86 000	2 791 807	1

Table 1 – sample of brands collected and its characteristics

The collection of posts was made considering a period of 3 months and all posts were collected to the exception of videos, since they don't gather the same conditions to analyze performance and engagement.

While collecting each post, it was also manually collected the following information: date of the post and day of the week, number of likes and comments and first comment of each post. It was selected only the first comment in order to see what the most genuine and immediate reaction to each post was.

In order to guarantee that the collected data was comparable, the number of likes and comments of each post was normalized based on the number of followers each brand had.

After this collection, it was also made a categorization of which posts used RTM and which didn't. This classification was made according to Willemsen et al. (2018) definition of this content format: Real Time Marketing is when the messages of the posts are associated with

public and temporary events (such as holidays, news or other trending or popular topics). Posts that were contests were classified as “other activities”, not entering neither on the RTM nor non-RTM classification.

Another classification made was regarding the use of Unpredictable Real Time Marketing, according to to Willemsen et al. (2018) definition that states that Unpredictable RTM happens when the messages of the posts are associated with events that were unpredictable to happen.

It was also made a classification whether the posts had presence of brand promotional appeal, which was captured by only means of the presence of the product itself, excluding the presence of brand elements as a criteria.

Finally, to analyze whether the comments collected represented a positive, negative or neutral brand sentiment, it was used the Excel text mining add in “Meaning Cloud”. This tool categorized the content of the comments in a 5 points scale: N+ (negative +), N (negative), NEU (neutral), P (positive) and P+ (positive +). On the cases this tool couldn’t identify the sentiment associated and labeled the comment with “None” or “Error”, the classification was made manually.

In the end, all classifications were validated with two independent contributors.

All de data was codified and submitted on SPSS for analysis.

4. Results and Findings

4.1. Data collection and data cleaning

The collection of posts according to the criteria above led to a total of 537 posts, however only 77 of them used Real Time Marketing (table 22, Appendix 1), so in order to have a balanced sample of RTM posts and non-RTM posts, SPSS was used to randomly choose from the 449 posts that did not use RTM, a second sample of 80 posts.

It was also excluded from the analysis all the posts that didn't fit neither on the Real Time Marketing definition nor on the non-RTM. This included mainly situations such as contests.

The database obtained from this collection is available on the link displayed on Appendix 3.

4.2. Sample Description

As mentioned above, it was collected a total of 537 posts from 10 brands. The primary data collection was composed of 1% of posts from Coca-Cola Portugal, 13% from Disney Portugal, 8% from Samsung Portugal, 7% from McDonald's Portugal, 11% from Toyota Portugal, 15% from Mercedes-Benz Portugal, 28% from Netflix Portugal, 8% from BMW Portugal, 5% from Honda Portugal - Automóveis and 3% from L'Oréal Portugal (Table 2).

Brands	**% of Posts**
Coca-Cola Portugal	1%
Disney Portugal	13%
Samsung Portugal	8%
McDonald's Portugal	7%
Toyota Portugal	11%
Mercedes-Benz Portugal	15%
Netflix Portugal	28%
BMW Portugal	8%
Honda Portugal - Automoveis	5%
L'Oréal Portugal	3%

Table 2 – Sample composition

From these posts, 84% (449) were non-RTM posts, 14% were RTM posts and 2% were other activities such as contests that didn't fit on the two previous definitions. (Table 22, Appendix 1).

From the 77 RTM posts, 94% (72) were linked with predictable moments and only 6% were associated with unpredictable moments. (Table 23, Appendix 1).

Considering all the posts, the day when the majority of the posts were published was on a Friday, with 16% of posts (85 from 537 posts) being published on that day of the week. (Table 24, Appendix 1).

Regarding the presence of product, 70% of posts had the presence of the brand's product, meaning almost 375 from the 537 posts. (Table 25, Appendix 1).

In terms of likes and comments, on average these posts had 2 904 likes, with a median of 503 likes. The average amount of comments per post was 14, with a median of 4 comments. From the total of 537 posts, there were 16% (87) of posts that didn't have any comment. (Table 26 and 27, Appendix 1).

Finally in terms of the brand sentiment analyzed trough comments, from the 450 posts that had comments, the most common reaction detected on the first comment of each post was a positive one (P), with 51% of posts gathering that feeling. The second most detected reaction post was positive plus (P+), with 22%. There were only 1% of posts that created a more negative sentiment (N+) and 10% with a negative sentiment (N). (Table 28, Appendix 1).

Since to the analysis that follows it was only used the reduced sample that SPSS randomly chose, it is also important do characterize this reduced sample.

On the reduced sample, they were analyzed a total of 157 posts from the 10 brands. This sample was composed of 2% of posts from from Coca-Cola Portugal, 17% from Disney Portugal, 10% from Samsung Portugal, 12% from McDonald's Portugal, 10% from Toyota Portugal, 6% from Mercedes-Benz Portugal, 24% from Netflix Portugal, 9% from BMW Portugal, 8% from Honda Portugal - Automoveis and 3% from L'Oréal Portugal (table 3).

Brands	% of Posts Reduced Sample
Coca-Cola Portugal	2%
Disney Portugal	17%
Samsung Portugal	10%
McDonald's Portugal	12%
Toyota Portugal	10%
Mercedes-Benz Portugal	6%
Netflix Portugal	24%
BMW Portugal	9%
Honda Portugal - Automoveis	8%
L'Oréal Portugal	3%

Table 3 – Reduced sample composition

From these posts, 51% (80) were non-RTM posts and 49% (77) were RTM posts. (Table 29, Appendix 2).

From the 77 RTM posts, 94% were linked with predictable moments and only 6% were associated with unpredictable moments. (Table 30, Appendix 2).

Considering this reduced sample, the day when the majority of the posts were published was on a Tuesday, with 18% of posts being published on that day of the week. (Table 31, Appendix 2).

Regarding the presence of product, 60% of posts had the presence of the brand's product, meaning 94 from the 157 posts. (Table 32, Appendix 2).

In terms of likes and comments, on average these posts had 2 586 likes, with a median of 527 likes. The average amount of comments per post was 14, with a median of 5 comments. From the total of 157 posts, there were 13% of posts that didn't have any comment. (Table 33 and 34, Appendix 2).

Finally in terms of the brand sentiment analyzed trough comments, from the 137 posts that had comments, the most common reaction detected on the first comment of each post was a positive one (P), with 49% of posts gathering that feeling. The second most detected reaction post was positive plus (P+), with 23%. There were only 2% of posts that created a more negative sentiment (N+) and 9% with a negative sentiment (N). (Table 4).

Polarity

		Frequência	Porcentagem	Porcentagem válida	Porcentagem acumulativa
Válido	N+	2	1,3	1,5	1,5
	N	12	7,6	8,8	10,2
	NEU	24	15,3	17,5	27,7
	P	67	42,7	48,9	76,6
	P+	32	20,4	23,4	100,0
	Total	137	87,3	100,0	
Omisso	Sistema	20	12,7		
Total		157	100,0		

Table 4 – Frequencies from the reduced sample: Polarity of comments

Since on the study below done with SPSS, the data that was used to get the conclusions was the normalized data of likes and comments, meaning the ratio of likes and comments each post had considering the number of followers each brand had on their Instagram accounts, it is also important to characterize these indicators. On average, only 1,1% of followers left a like on these brands' posts and regarding comments, this percentage was even lower, with only 0,01% of followers commenting these posts. (Table 5).

Estatísticas

		Likes rate	Comments rate
N	Válido	157	157
	Omisso	0	0
Média		,0112	,0001
Mediana		,0067	,0000
Modo		,00	,00
Erro Desvio		,01316	,00015
Mínimo		,00	,00
Máximo		,07	,00

Table 5 – Statistics from the reduced sample: Likes rate and Comments rate

4.3. Hypothesis Analysis

In order to study the research questions proposed on the beginning of this dissertation, there will be developed several Hypothesis to test on SPSS.

Hypothesis 1: The use of Real Time Marketing has a positive effect over the number of likes when compared to N-RTM posts.

To test this hypothesis, we are going to use two variables: the independent variable is going to be RTM and the dependent variable is going to be the likes ratio.

Null Hypothesis = The use of Real Time Marketing has no effect over the number of likes when compared to N-RTM posts.

A Simple Linear Regression was made, considering the sample has more than 20 observations and all the observations are independent between each other.

Observing the results, first we can see that there is a very small relation between the use of RTM and the number of likes (0,027 – table 6).

Correlações			
		Likes ratio	RTM
Correlação de Pearson	Likes ratio	1,000	,027
	RTM	,027	1,000
Sig. (1 extremidade)	Likes ratio	.	,370
	RTM	,370	.
N	Likes ratio	157	157
	RTM	157	157

Table 6 - Simple Linear Regression – Correlations Table

Later on the Model Summary, we can observe that R Square is also low: 0,001 (Table 7), meaning that only 0,1% of the variance on likes is explained by the use of Real Time Marketing.

Resumo do modelo[b]

Modelo	R	R quadrado	R quadrado ajustado	Erro padrão da estimativa	Estatísticas de mudança					Durbin-Watson
					Mudança de R quadrado	Mudança F	df1	df2	Sig. Mudança F	
1	,027[a]	,001	-,006	,01319	,001	,111	1	155	,739	1,595

a. Preditores: (Constante), RTM

b. Variável Dependente: Likes rate

Table 7 – Simple Linear Regression – Model Summary

At last, when we observe the p-value on the Table 8, we can see that it assumes the value 0,739. Since this value is bigger than 0,05, it means that for a confidence interval of 95%, we cannot reject the Null Hypothesis that the use of Real Time Marketing has no effect over the number of likes.

This way, the use of Real Time Marketing does not impact the number of likes of the posts that use this content format when compared to posts that do not use RTM. H1 is rejected.

ANOVA[a]						
Modelo		Soma dos Quadrados	df	Quadrado Médio	Z	Sig.
1	Regressão	,000	1	,000	,111	,739[b]
	Resíduo	,027	155	,000		
	Total	,027	156			

a. Variável Dependente: Likes ratio
b. Preditores: (Constante), RTM

Table 8 – Simple Linear Regression – ANOVA table

Since the result from H1 was that Real Time Marketing does not impact the number of likes, it would be interesting to check if depending on the day of the week that the post is published this result changes: for example, it would be interesting to understand if publishing a RTM post at the end of the week has a positive effect over the number of likes when compared to Non-Real Time Marketing posts. To study this, it will be done an ANCOVA where the covariate is going to be the weekday of the post.

First, to do an ANCOVA it is necessary to test two prerequisites:

The first one is that the independent variable RTM as no effect over the covariate weekday of the post. To test this, it is going to be done a One-Way ANOVA.

Testes de efeitos entre sujeitos					
Variável dependente: Weekday of the Post					
Origem	Tipo III Soma dos Quadrados	df	Quadrado Médio	Z	Sig.
Modelo corrigido	5,837[a]	1	5,837	1,365	,244
Intercepto	2629,022	1	2629,022	614,708	<,001
RTM	5,837	1	5,837	1,365	,244
Padrão	662,914	155	4,277		
Total	3294,000	157			
Total corrigido	668,752	156			

a. R Quadrado = ,009 (R Quadrado Ajustado = ,002)

Table 9 – One-Way ANOVA – test of between-subjects effects

According to the p-value given on this test (0,244 – table 9), since it is bigger than 0,05, there is no effect of RTM over the weekday of the post. The null hypothesis that the use of Real

Time Marketing has no effect over the weekday of the post is not rejected for a confidence interval of 95%.

Next it is necessary to test the second prerequisite which is the homogeneity of regression parameters.

Testes de efeitos entre sujeitos					
Variável dependente: Likes rate					
Origem	Tipo III Soma dos Quadrados	df	Quadrado Médio	Z	Sig.
Modelo corrigido	,001[a]	3	,000	1,154	,330
Intercepto	,006	1	,006	33,538	<,001
RTM	,000	1	,000	2,239	,137
dia_semana	,000	1	,000	1,055	,306
RTM * dia_semana	,000	1	,000	2,119	,148
Padrão	,026	153	,000		
Total	,047	157			
Total corrigido	,027	156			

a. R Quadrado = ,022 (R Quadrado Ajustado = ,003)

Table 10 – ANCOVA – test of between-subjects effects

According to the table 10, the p-value of the interaction between RTM and the weekday of the post is bigger than 0,05 (0,148), so for a confidence interval of 95%, we cannot reject the null hypothesis that there is homogeneity of the regression parameters.

Assured the two prerequisites for the ANCOVA, is it possible to continue the study. Defining the null hypothesis:

Null Hypothesis = The use of Real Time Marketing on posts has no effect over the number of likes, considering the weekday of the post.

Observing the results on table 11, the p-value for the weekday of the post is bigger than 0,05 (0,271), so for a confidence interval of 95%, the Null Hypothesis cannot be rejected.

So we conclude that Real Time Marketing posts published at the end of the week do not generate more likes when compared to Non-Real Time Marketing posts.

Testes de efeitos entre sujeitos					
Variável dependente: Likes rate					
Origem	Tipo III Soma dos Quadrados	df	Quadrado Médio	Z	Sig.
Modelo corrigido	,000[a]	2	,000	,666	,515
Intercepto	,006	1	,006	33,417	<,001
dia_semana	,000	1	,000	1,221	,271
RTM	3,295E-5	1	3,295E-5	,190	,664
Padrão	,027	154	,000		
Total	,047	157			
Total corrigido	,027	156			

a. R Quadrado = ,009 (R Quadrado Ajustado = -,004)

Table 11 – ANCOVA – test of between-subjects effects

Hypothesis 2: The use of Real Time Marketing has a positive effect over the number of comments when compared to N-RTM posts.

To test this hypothesis, we are going to use two variables: the independent variable is going to be RTM and the dependent variable is going to be the comments ratio.

Null Hypothesis = The use of Real Time Marketing has no effect over the number of comments when compared to N-RTM posts.

A Simple Linear Regression was used, considering the sample has more than 20 observations and all the observations are independent between each other.

Observing the results, there is a very small relation between the use of RTM and the number of comments (0,039 – table 12).

Correlações			
		Comments ratio	RTM
Correlação de Pearson	Comments ratio	1,000	,039
	RTM	,039	1,000
Sig. (1 extremidade)	Comments ratio	.	,312
	RTM	,312	.
N	Comments ratio	157	157
	RTM	157	157

Table 12 – Simple Linear Regression – Correlations Table

When we observe the p-value on the Table 13, we can see that it assumes the value 0,624. Since this value is bigger than 0,05, it means that for a confidence interval of 95%, we cannot reject the Null Hypothesis that the use of Real Time Marketing has no effect over the number of comments.

Just as the conclusion for likes, the use of Real Time Marketing does not impact the number of comments on the posts that use this content format when compared to posts that do not use RTM. H2 is rejected.

ANOVA[a]						
Modelo		Soma dos Quadrados	df	Quadrado Médio	Z	Sig.
1	Regressão	,000	1	,000	,241	,624[b]
	Resíduo	,000	155	,000		
	Total	,000	156			

a. Variável Dependente: Comments ratio
b. Preditores: (Constante), RTM

Table 13 – Simple Linear Regression – ANOVA table

Since the result from H2 was rejected, it is also going to be done a study to understand if publishing a RTM post at the end of the week has a positive effect over the number of comments when compared to Non-Real Time Marketing posts. To study this, it will also be done an ANCOVA where the covariate is going to be the weekday of the post.

Similarly to the test done after Hypothesis 2, to do an ANCOVA it is necessary to test two prerequisites:

The first one is that the independent variable RTM as no effect over the covariate weekday of the post, and this prerequisite was already assured before (table 9).

And the second prerequisite regarding the homogeneity of regression parameters was assured was well (table 10).

Assured the two prerequisites for the ANCOVA, is it possible to continue the study. Defining the null hypothesis:

Null Hypothesis = The use of Real Time Marketing on posts has no effect over the number of comments, considering the weekday of the post.

Observing the results on table 14, the p-value for the weekday of the post is bigger than 0,05 (0,287), so for a confidence interval of 95%, the Null Hypothesis cannot be rejected.

So we conclude that Real Time Marketing posts published at the end of the week do not generate more comments.

Testes de efeitos entre sujeitos					
Variável dependente: Comments rate					
Origem	Tipo III Soma dos Quadrados	df	Quadrado Médio	Z	Sig.
Modelo corrigido	3,161E-8[a]	2	1,581E-8	,690	,503
Intercepto	3,344E-7	1	3,344E-7	14,604	<,001
dia_semana	2,609E-8	1	2,609E-8	1,139	,287
RTM	7,938E-9	1	7,938E-9	,347	,557
Padrão	3,526E-6	154	2,290E-8		
Total	4,490E-6	157			
Total corrigido	3,557E-6	156			

a. R Quadrado = ,009 (R Quadrado Ajustado = -,004)

Table 14 – ANCOVA – test of between-subjects effects

Hypothesis 3: The use of Real Time Marketing has a positive effect over the sentiment of the comments when compared to N-RTM posts.

To test this hypothesis, we are going to use two variables: the independent variable is going to be RTM and the dependent variable is going to be the polarity of comments.

Null Hypothesis = The use of Real Time Marketing has no effect over the polarity of comments when compared to N-RTM posts.

A Simple Linear Regression was used again, considering the sample has more than 20 observations and all the observations are independent between each other.

Observing the results, there is a very small relation between the use of RTM and the polarity of comments (-0,001 – table 15).

Correlações			
		Polarity	RTM
Correlação de Pearson	Polarity	1,000	-,001
	RTM	-,001	1,000
Sig. (1 extremidade)	Polarity	.	,494
	RTM	,494	.
N	Polarity	137	137
	RTM	137	137

Table 15 – Simple Linear Regression – Correlations Table

When we observe the p-value on the Table 16, we can see that it assumes the value 0,988. Since this value is bigger than 0,05, it means that for a confidence interval of 95%, we cannot reject the Null Hypothesis that the use of Real Time Marketing has no effect over the polarity of comments.

Again, the use of Real Time Marketing does not impact the positivity of comments on the posts that use this content format, it does not impact sentiment. H3 is rejected.

ANOVA[a]						
Modelo		Soma dos Quadrados	df	Quadrado Médio	Z	Sig.
1	Regressão	,000	1	,000	,000	,988[b]
	Resíduo	118,467	135	,878		
	Total	118,467	136			

a. Variável Dependente: Polarity
b. Preditores: (Constante), RTM

Table 16 – Simple Linear Regression – ANOVA table

Hypothesis 4: The Real Time Marketing posts without brand promotional appeal generate more likes than RTM posts with promotional appeal.

To test this hypothesis, we are going to use only the sample of Real Time Marketing posts and we will use two variables: the independent variable is going to be the presence of product and the dependent variable is going to be likes ratio.

Null Hypothesis = The lack of product on Real Time Marketing posts has no effect over the number of likes when compared to RTM posts that have presence of product.

A Simple Linear Regression was used again, considering the sample has more than 20 observations and all the observations are independent between each other.

Observing the results, there is a very small relation between the presence of product on RTM posts and the number of likes (0,049 – table 17).

Correlações			
		Likes ratio	Product Presence
Correlação de Pearson	Likes ratio	1,000	,049
	Product Presence	,049	1,000
Sig. (1 extremidade)	Likes ratio	.	,336
	Product Presence	,336	.
N	Likes ratio	77	77
	Product Presence	77	77

Table 17 – Simple Linear Regression – Correlations Table

When we observe the p-value on the Table 18, we can see that it assumes the value 0,671. Since this value is bigger than 0,05, it means that for a confidence interval of 95%, we cannot reject the Null Hypothesis that the lack of product on Real Time Marketing posts has no effect over the number of likes.

So we also conclude that a RTM post that does not have product in it does not have more likes when compared to a RTM post that have the presence of product. H4 is rejected.

ANOVA[a]						
Modelo		Soma dos Quadrados	df	Quadrado Médio	Z	Sig.
1	Regressão	,000	1	,000	,182	,671[b]
	Resíduo	,017	75	,000		
	Total	,017	76			

a. Variável Dependente: Likes ratio
b. Preditores: (Constante), Product Presence

Table 18 – Simple Linear Regression – ANOVA table

Hypothesis 5: The Real Time Marketing posts without brand promotional appeal generate more comments than RTM posts with promotional appeal.

Just like it was done to test the influence on likes, to test this hypothesis, we are going to use only the sample of Real Time Marketing posts and we will use two variables: the independent variable is going to be the presence of product and the dependent variable is going to be comments ratio.

Null Hypothesis = The lack of product on Real Time Marketing posts has no effect over the number of comments when compared to RTM posts that have presence of product.

A Simple Linear Regression was used again, considering the sample has more than 20 observations and all the observations are independent between each other.

Observing the results, there is a very small relation between the presence of product on RTM posts and the number of comments (0,085 – table 19).

Correlações			
		Comments ratio	Product Presence
Correlação de Pearson	Comments ratio	1,000	,085
	Product Presence	,085	1,000
Sig. (1 extremidade)	Comments ratio	.	,231
	Product Presence	,231	.
N	Comments ratio	77	77
	Product Presence	77	77

Table 19 – Simple Linear Regression – Correlations Table

When we observe the p-value on the Table 20, we can see that it assumes the value 0,461. Since this value is bigger than 0,05, it means that for a confidence interval of 95%, we

cannot reject the Null Hypothesis that the lack of product on Real Time Marketing posts has no effect over the number of comments.

So we also conclude that a RTM post that does not have product in it does not have more comments when compared to a RTM post that have the presence of product. H5 is rejected.

ANOVA[a]						
Modelo		Soma dos Quadrados	df	Quadrado Médio	Z	Sig.
1	Regressão	,000	1	,000	,548	,461[b]
	Resíduo	,000	75	,000		
	Total	,000	76			

a. Variável Dependente: Comments ratio
b. Preditores: (Constante), Product Presence

Table 20 – Simple Linear Regression – ANOVA table

Hypothesis	**Results**
H1: The use of Real Time Marketing has a positive effect over the number of likes when compared to N-RTM posts.	Not Accepted
H2: The use of Real Time Marketing has a positive effect over the number of comments when compared to N-RTM posts.	Not Accepted
H3: The use of Real Time Marketing has a positive effect over the sentiment of the comments when compared to N-RTM posts.	Not Accepted
H4: The Real Time Marketing posts without brand promotional appeal generate more likes than RTM posts with promotional appeal.	Not Accepted
H5: The Real Time Marketing posts without brand promotional appeal generate more comments than RTM posts with promotional appeal.	Not Accepted

Table 21 – Findings' Summary

5. Discussions and Conclusions

5.1. Main Conclusions

The goal of this dissertation was to understand if specifically on Instagram the use of Real Time Marketing by brands had an impact on engagement and sentiment. To study these effects, three Research Questions were formulated. By the reviewing of literature and the collection of data from Instagram posts, both descriptive and exploratory research approaches were adopted.

Engagement on social media can be expressed in various ways and more than that, people can engage with content and yet not manifest themselves through any reaction. However, according to Syrdal & Briggs (2018), active engagement happens when people like, comment or share content, so having that in mind and since it is not possible to collect information about the number of shares an Instagram post had, this study was centered on likes and comments.

Following this reasoning, the first Research Question aimed to understand if the use of Real Time Marketing by brands influenced positively the number of likes and comments of RTM posts vs non-RTM posts. The results, however, indicated that we could not reject neither of the null hypothesis that stated that Real Time Marketing had no effect over likes and that it had no effect over comments. Therefore, contrary to what was hypothesized, the use of RTM does not contribute differently from N-RTM for engagement. This conclusion goes according to the conclusions presented by Mazerant et al. (2020) when doing an analysis to Instagram posts as well, so it reinforces these insights, even though its curious that on a different social media platform such as Twitter the results are very different, and the conclusion is that Real Time Marketing can positively influence shares (Willemsen et al., 2018).

Although the results regarding the effect of Real Time Marketing on likes and comments were not positive for the use of this content format, maybe they could behave differently if the post was published on a specific day of the week. To test this, it was added the covariate "day of the week the post is published" to understand if it would have any effect on likes and comments. However the results showed that the day of the week that a RTM post is published does not influence the engagement of RTM posts.

Nevertheless, even though RTM does not influence the number of likes and comments on Instagram when compared to N-RTM, it could have a positive effect over followers' comments on brands' posts. So it was developed a second Research Question that aimed to

analyze the positivity of comments on RTM post vs non-RTM posts. However, again, after analyzing the first comment of each post, the null hypothesis that RTM had no effect over comments polarity wasn't rejected, so it means that the use of RTM does not contribute to increase the positivity of comments when compared to N-RTM.

Finally, since the results below showed that Real Time Marketing could not influence the positivity of comments when compared to N-RTM either, a further research question was formulated to analyze whether the presence of product on Real Time Marketing posts influenced the performance in terms of likes and comments when compared with RTM posts where the product appeal is not present. The results of these analysis, however, did not reject the two null hypotheses that RTM posts without product appeal have no effect over the number of likes or comments. This means that the absence of the product on Real Time Marketing posts will not help those posts get more likes and comments versus RTM posts with brand promotional appeal.

In conclusion, Real Time Marketing as a content format on Instagram is not superior to Non-RTM, but it performs well as an alternative for diversifying the content calendar. Furthermore, we can also conclude that the removal of the product from these posts does not contribute to an increase in engagement in terms of likes or comments, and that choosing a specific day of the week to publish a RTM post does not influence engagement either.

These findings do not corroborate Mazerant et al. (2020) study, that founds that on Instagram specifically, the well-crafted posts in terms of visual appearance are the ones that increase engagement, and since RTM posts on Instagram are less well-crafted at the expense of being more creative and meaningful, RTM posts end up having less engagement than non-RTM posts. However the difference observed on both results might be due to the proportion of Unpredictable RTM posts analyzed on the sample that both studies had (for example this study only gathered 6% of unpredictable RTM posts vs 94% of predictable RTM posts). The weight of unpredictable RTM posts can be the reason for the different conclusions because as posts that react to unpredictable moments are less well-crafted (Mazerant et al., 2020), they create less engagement on Instagram and therefore a sample that is composed mostly of unpredictable RTM posts is going to lead to the conclusion that RTM posts create less engagement than Non-RTM posts.

5.2. Theoretical and Managerial Implications

The previous literature that studies the impact of Real Time Marketing on social media engagement are ambiguous and reflect non-consistent results, specially between different social media networks. Therefore, this study supports the vision that RTM does not performs better than N-RTM, but that it can be an alternative for a more diverse content on social media posts.

The conclusions of this dissertation should provide managers with useful insights for their strategic communication plans on social media. Nowadays, the main goal of marketers when posting online on brands' social media is to create engagement and get closer to their target, so they need to focus on the right formats that easily achieve this goal. Since Real Time Marketing is a content format that performs as well as Non Real Time Marketing in terms of engagement, I suggest that brands continue using RTM as a way of diversifying their content. Moreover, and building on the findings of Mazerant et al. (2020), we would also suggest that when using Instagram, Marketers should invest above all in well-crafted visuals, more than any other dimension of creativity. Given the characteristics of Instagram, this should be their main concern if they want to engage with social media users.

5.3. Limitations and Future Research

This dissertation corroborated the prior study about the same subject, however there are some limitations to its results.

The main limitation observed is that due to the criteria defined to select the brands subject to this study, the author ended up using brands that do not give much use to Real Time Marketing as a content format on Instagram and that are not very skilled at it, so it resulted in a sample that had very few RTM posts, especially compared to the amount of non-RTM posts.

On the other hand, the selection criteria did not allow to study other brands that are very well-known for the Portuguese audience for posting very interesting posts (either making use of RTM or not). This way brands such as, for example, Control, Licor Beirão or Super Bock could not be part of this sample.

Another limitation was the number of brands defined to collect posts. Perhaps if the selection included much more than 10 brands, it would have been possible to have a more balanced sample of RTM and non-RTM posts, sparing the need to create a reduced sample of

non-RTM posts. It would have been also possible to expand the number of posts that used unpredictable RTM.

Apart from these limitations, future research can study the impact on engagement that RTM posts that score high on craftmanship can have versus non-RTM posts. This way, it might be possible to understand if Real Time Marketing is really a content format that will never create more engagement versus non-RTM or if under these circumstances, it is actually more effective than non-RTM posts.

Another suggestion for future research would be to understand what are other social media communication methods that can increase engagement on Instagram. For example, is the use of influencers by brands a more efficient way to engage with consumers when compared to a simple post done by the brands' Instagram account? Several ramifications could come out of this main study.

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Appendices

Appendix 1 – Categorization of the primary sample

RTM

		Frequência	Porcentagem	Porcentagem válida	Porcentagem acumulativa
Válido	NON-RTM	449	83,6	83,6	83,6
	RTM	77	14,3	14,3	98,0
	Others	11	2,0	2,0	100,0
	Total	537	100,0	100,0	

Table 22 – Frequencies from the primary sample: RTM

Unpredictable RTM

		Frequência	Porcentagem	Porcentagem válida	Porcentagem acumulativa
Válido	Predictable RTM	72	13,4	93,5	93,5
	Unpredictable RTM	5	,9	6,5	100,0
	Total	77	14,3	100,0	
Omisso	Sistema	460	85,7		
Total		537	100,0		

Table 23 – Frequencies from the primary sample: Unpredictable RTM

Weekday of the Post

		Frequência	Porcentagem	Porcentagem válida	Porcentagem acumulativa
Válido	2ªf	70	13,0	13,0	13,0
	3ªf	79	14,7	14,7	27,7
	4ªf	79	14,7	14,7	42,5
	5ªf	76	14,2	14,2	56,6
	6ªf	85	15,8	15,8	72,4
	Sábado	75	14,0	14,0	86,4
	Domingo	73	13,6	13,6	100,0
	Total	537	100,0	100,0	

Table 24 – Frequencies from the primary sample: Weekday of the post

Product Presence

		Frequência	Porcentagem	Porcentagem válida	Porcentagem acumulativa
Válido	Não	162	30,2	30,2	30,2
	Sim	375	69,8	69,8	100,0
	Total	537	100,0	100,0	

Table 25 – Frequencies from the primary sample: Product Presence

Estatísticas

		Likes	Comments
N	Válido	537	537
	Omisso	0	0
Média		2903,81	13,72
Mediana		503,00	4,00
Modo		217	0
Erro Desvio		5335,470	41,845
Mínimo		22	0
Máximo		48900	546
Soma		1559347	7367
Percentis	25	196,00	1,00
	50	503,00	4,00
	75	3296,00	11,00

Table 26 – Likes and comments statistics from the primary sample

Comments

		Frequência	Porcentagem	Porcentagem válida	Porcentagem acumulativa
Válido	0	87	16,2	16,2	16,2
	1	60	11,2	11,2	27,4
	2	50	9,3	9,3	36,7
	3	29	5,4	5,4	42,1
	4	49	9,1	9,1	51,2
	5	28	5,2	5,2	56,4
	6	26	4,8	4,8	61,3
	7	23	4,3	4,3	65,5
	8	8	1,5	1,5	67,0
	9	16	3,0	3,0	70,0
	10	12	2,2	2,2	72,3
	11	16	3,0	3,0	75,2
	12	8	1,5	1,5	76,7
	13	12	2,2	2,2	79,0
	14	12	2,2	2,2	81,2
	15	6	1,1	1,1	82,3
	16	6	1,1	1,1	83,4
	17	7	1,3	1,3	84,7
	18	4	,7	,7	85,5
	19	8	1,5	1,5	87,0
	20	1	,2	,2	87,2
	21	2	,4	,4	87,5
	22	2	,4	,4	87,9
	23	3	,6	,6	88,5
	25	5	,9	,9	89,4
	26	4	,7	,7	90,1
	28	3	,6	,6	90,7
	29	3	,6	,6	91,2
	30	1	,2	,2	91,4
	31	2	,4	,4	91,8
	32	2	,4	,4	92,2
	34	2	,4	,4	92,6
	35	1	,2	,2	92,7
	36	3	,6	,6	93,3
	41	1	,2	,2	93,5
	44	1	,2	,2	93,7
	45	1	,2	,2	93,9
	47	1	,2	,2	94,0
	48	1	,2	,2	94,2
	49	1	,2	,2	94,4
	50	1	,2	,2	94,6
	52	2	,4	,4	95,0
	53	2	,4	,4	95,3
	55	1	,2	,2	95,5
	56	2	,4	,4	95,9
	57	1	,2	,2	96,1
	61	1	,2	,2	96,3
	66	1	,2	,2	96,5
	69	1	,2	,2	96,6
	72	1	,2	,2	96,8
	74	1	,2	,2	97,0
	87	2	,4	,4	97,4
	89	1	,2	,2	97,6
	90	1	,2	,2	97,8
	95	2	,4	,4	98,1
	96	1	,2	,2	98,3
	99	1	,2	,2	98,5
	105	1	,2	,2	98,7
	114	1	,2	,2	98,9
	118	1	,2	,2	99,1
	180	1	,2	,2	99,3
	242	1	,2	,2	99,4
	454	1	,2	,2	99,6
	475	1	,2	,2	99,8
	546	1	,2	,2	100,0
	Total	537	100,0	100,0	

Table 27 – Frequencies from the primary sample: Comments

Polarity

		Frequência	Porcentagem	Porcentagem válida	Porcentagem acumulativa
Válido	N+	5	,9	1,1	1,1
	N	44	8,2	9,8	10,9
	NEU	70	13,0	15,6	26,4
	P	230	42,8	51,1	77,6
	P+	101	18,8	22,4	100,0
	Total	450	83,8	100,0	
Omisso	Sistema	87	16,2		
Total		537	100,0		

Table 28 – Frequencies from the primary sample: Polarity of comments

Appendix 2 – Categorization of the reduced sample

RTM

		Frequência	Porcentagem	Porcentagem válida	Porcentagem acumulativa
Válido	NON-RTM	80	51,0	51,0	51,0
	RTM	77	49,0	49,0	100,0
	Total	157	100,0	100,0	

Table 29 – Frequencies from the reduced sample: RTM

Unpredictable RTM

		Frequência	Porcentagem	Porcentagem válida	Porcentagem acumulativa
Válido	Predictable RTM	72	45,9	93,5	93,5
	Unpredictable RTM	5	3,2	6,5	100,0
	Total	77	49,0	100,0	
Omisso	Sistema	80	51,0		
Total		157	100,0		

Table 30 – Frequencies from the reduced sample: Unpredictable RTM

Weekday of the Post

		Frequência	Porcentagem	Porcentagem válida	Porcentagem acumulativa
Válido	2ªf	21	13,4	13,4	13,4
	3ªf	28	17,8	17,8	31,2
	4ªf	16	10,2	10,2	41,4
	5ªf	18	11,5	11,5	52,9
	6ªf	26	16,6	16,6	69,4
	Sábado	21	13,4	13,4	82,8
	Domingo	27	17,2	17,2	100,0
	Total	157	100,0	100,0	

Table 31 – Frequencies from the reduced sample: Weekday of the post

Product Presence

		Frequência	Porcentagem	Porcentagem válida	Porcentagem acumulativa
Válido	Não	63	40,1	40,1	40,1
	Sim	94	59,9	59,9	100,0
	Total	157	100,0	100,0	

Table 32 – Frequencies from the reduced sample: Product Presence

Estatísticas

		Likes	Comments
N	Válido	157	157
	Omisso	0	0
Média		2585,85	14,06
Mediana		527,00	5,00
Modo		239	0
Erro Desvio		4768,051	46,003
Mínimo		23	0
Máximo		31100	546
Soma		405979	2208
Percentis	25	204,50	1,50
	50	527,00	5,00
	75	2496,50	12,50

Table 33 – Statistics from the reduced sample: Likes and Comments

Comments

		Frequência	Porcentagem	Porcentagem válida	Porcentagem acumulativa
Válido	0	20	12,7	12,7	12,7
	1	19	12,1	12,1	24,8
	2	18	11,5	11,5	36,3
	3	6	3,8	3,8	40,1
	4	13	8,3	8,3	48,4
	5	6	3,8	3,8	52,2
	6	7	4,5	4,5	56,7
	7	7	4,5	4,5	61,1
	8	2	1,3	1,3	62,4
	9	5	3,2	3,2	65,6
	10	5	3,2	3,2	68,8
	11	7	4,5	4,5	73,2
	12	3	1,9	1,9	75,2
	13	5	3,2	3,2	78,3
	14	3	1,9	1,9	80,3
	15	1	,6	,6	80,9
	16	1	,6	,6	81,5
	17	1	,6	,6	82,2
	18	3	1,9	1,9	84,1
	19	2	1,3	1,3	85,4
	21	1	,6	,6	86,0
	22	1	,6	,6	86,6
	23	1	,6	,6	87,3
	25	4	2,5	2,5	89,8
	26	3	1,9	1,9	91,7
	28	1	,6	,6	92,4
	29	1	,6	,6	93,0
	31	1	,6	,6	93,6
	34	1	,6	,6	94,3
	36	1	,6	,6	94,9
	53	1	,6	,6	95,5
	56	1	,6	,6	96,2
	66	1	,6	,6	96,8
	72	1	,6	,6	97,5
	95	1	,6	,6	98,1
	96	1	,6	,6	98,7
	105	1	,6	,6	99,4
	546	1	,6	,6	100,0
	Total	157	100,0	100,0	

Table 34 – Frequencies from the reduced sample: Comments

Appendix 3 – Document containing the collected posts

Accessible through the following link: Posts Collection.xlsx