Color over content?

The impact of Color Temperature on Brand Engagement in Instagram

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ABSTRACT

Title: "Color over content? The impact of Color Temperature on Brand Engagement in Instagram"

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When Social Media meets Marketing, endless possibilities become available for brands. Although the wide reach of these platforms provides a suitable channel for Marketing Managers to promote interaction with their customer base, little is known about the best practices for brands channeling their Marketing efforts to Social Media. Instagram is one of the fastest growing platforms and a highly potential one, with emphasis on visual content, known to perform better in terms of engagement. However, its usefulness for brands and the impact of image features, like color, on consumer engagement is not documented yet.

This dissertation analyzes the relationship between Color Temperature and Engagement Rate on Instagram to understand if color influences engagement and, if so, which color hues perform better. To this end, 450 Instagram posts were analyzed, from brands in 3 different product categories - Women's Fashion, Travel, and Food & Snacks.

Results showed Color Temperature directly impacts the engagement as Cool and Neutral colors overperform Warm colors regarding Engagement Rate. Additionally, a moderator effect for Product Category was found as the best performing colors differ with the category of the brand. These findings suggest that Marketing and Social Media Managers should contemplate the impact of color on their Digital Content strategy, by coordinating their content with the color temperature that drives the higher engagement for the respective product category.

Keywords: Social Media Marketing; Engagement Rate; Color Temperature; Instagram; Product Category; Brand Engagement.

SUMÁRIO

Título: "Cor sobre conteúdo? O impacto da Temperatura de Cor no Envolvimento com a Marca no Instagram."

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Quando as Redes Sociais e o Marketing se unem, surgem inúmeras possibilidades para as marcas. Embora o grande alcance destas plataformas garanta um canal apropriado para promover interações Marca-Consumidores, pouco se sabe sobre as melhores práticas nestes meios, para marcas que se focam nas Redes Sociais. O Instagram é uma das plataformas com maior crescimento e potencial, tendo como core um conteúdo visual à base de imagens, que gera um maior envolvimento. No entanto, a utilidade do Instagram para as marcas, e o impacto de detalhes visuais como a cor no Envolvimento do Consumidor, é pouco discutido.

Esta dissertação analisa a relação entre a Temperatura de Cor e a Taxa de Envolvimento no Instagram, com o fim de compreender se existe um impacto direto entre as duas variáveis, e, nesse caso, que cores geram um maior envolvimento. Com este fim, 450 publicações do Instagram, de marcas em 3 categorias diferentes – Moda de Mulher, Viagens e Bens Alimentares - foram analisadas.

Os resultados demonstraram que a Temperatura impacta diretamente a Taxa de Envolvimento: publicações com tons Frios e Neutros geram um maior envolvimento do que os tons Quentes, em termos gerais. Além disso, foi encontrado um efeito moderador ma Categoria de Produto, sendo que a cor com melhores resultados varia com a categoria. Estas conclusões sugerem que os gestores de Marketing e/ou Redes Sociais devem considerar o impacto da cor no planeamento das estratégias de conteúdo digital, tendo em atenção os tons que geram maior envolvimento na sua categoria.

Palavras-Chave: Marketing de Redes Sociais; Taxa de Envolvimento; Temperatura de Cor; Instagram; Categoria de Produto; Envolvimento de Marca.

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"The smallest act of kindness is worth more than the grandest intention."

- Oscar Wilde

To my dearest friends. To my boyfriend. To my parents. To my dissertation supervisor.

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CHAPTER 1: INTRODUCTION

1.1 Background & Problem Statement

Digital Technology and Marketing are two underwired concepts, evolving alongside for several years. The process usually starts with the emergence of new technology and its first use by the early adopters, followed by the popularity growth and eventual exploration by marketers, in search for new ways to interact with their target (Ryan & Jones, 2009). Coming together as Digital Marketing, this process has been changing the business landscape. According to Kotler et al (2009), Digital Marketing refers to the use of digital technology to interact and inform consumers, using internet-based channels.

One of the milestones of Digital Marketing was the emergence of Social Media. Defined by Kaplan & Haenlein (2010) as Internet-based applications that allow the exchange of User Generated Content (UGC) through the basis of Web 2.0, these platforms have caused a paradigm shift in the way companies to interact with their customers (Kohli, Suri, & Kapoor, 2015). Now, not only consumers can interact among themselves, but they also have the tools to start conversations with brands and are often in control of these (Kohli et al., 2015; Peters, Chen, Kaplan, Ognibeni, & Pauwels, 2013)

These changes were mainly determined by consumers' attitude towards brands and their products. If traditionally consumer path to purchase was defined by Lemon & Verhoef (2016) as a linear three-phased process, it's now more of a circular one (Kruh, 2017) as consumers are progressively turning to Social Media on each phase and using these channels to look for information or reviews to support their decision (Mangold & Faulds, 2009).

This adoption of Social Media by the consumers is clear when looking at worldwide usage data: according to Statista (2018), 71% of the global Internet users are now on social networks. This value rises to 90% when it comes to European and Northern American users (Chaffey, 2018). Additionally, the number of Social Media active users has grown by 13% since January 2017, as stated by Kemp (2018) in Hootsuite's Digital Yearbook. This means that, besides providing a richer communication channel and facilitating information exchange, Social Media is now a place where most worldwide consumers are.

Driven by these opportunities, brands are increasing its investment on Digital and Social Media Marketing and adopting it as a key Marketing channel – in 2018, American companies augmented their spending on Digital Marketing by 15,1% while cutting the investment on traditional Marketing by 1,7% (*The CMO Survey*, 2018).

One of the most popular Social Media platforms is Instagram – a free photo and video sharing mobile app, where users can share content in both these formats, with other users of their choice or all their followers (Instagram, 2018), and interact with this content. Instagram reached 1 billion monthly active users in June 2018, up from 800 million users as of September 2017 (Statista, 2018b). On average, 38% of the US citizens from 18 to 44 years old, use the app at least once a day (Statista, 2018a) and 80% of Instagram users follow a business (Instagram, 2017).

In 2016, the platform launched a dashboard of business tools, that brought several marketers into the platform: as of September 2017, there were 25 million active business profiles on Instagram (Ha, 2017), expanding its potential as a powerful Marketing tool. Accordingly, brands use the platform to share content that can engage their audience (Schmitt, 2012).

Therefore, Marketing and Social Media managers keep looking for the best-practices on Social Media, and for a deep understanding on how consumers use it and what makes them engage with this branded content (Hanna, Rohm, & Crittenden, 2011).

However, hardly any studies have focused on investigating how the visual elements of Instagram posts impact brand engagement on the platform, particularly color. It remains unclear what exactly makes users interact with an image shared by a brand on Instagram.

It's known that the psychology of color influences perceptions in several areas. Regarding Marketing, it is known to impact in-store purchases (Labrecque & Milne, 2012) and the perception of consumers towards the waiting time (Singh, 2006), so it does impact the Marketing efforts of brands overall. Can the dominant color of an Instagram post make a user interact with it too?

Further insight on this matter is becoming relevant as brands try to optimize their Social Media efforts.

1.2 Aim & Scope

The aim of this research is to study how the color of a Social Media post affects user engagement with this content. To asses this, throughout the dissertation two main research questions will be answered:

RQ1: Does the color of an image shared on Social Media impact consumers' engagement with it?

RQ2: Is the resulting impact moderated by the brands' product category?

The Social Media platform chosen for this study was Instagram. The platform's adoption all over the world has been noteworthy – as of January 2019, Instagram was the 6th Social Media platform with most users in the world (Statista, 2019). The 3rd, when only considering platforms that allow for brand profiles. Besides this, it's a highly visual platform, as the content shared can be either videos or photos, that are the highlight of each user's profile (Instagram, 2018). This makes photos and color much more relevant on Instagram, an image and video-only platform, than on Facebook, that allows a mix of images, videos, and text (Facebook, 2019).

For this dissertation, engagement is assessed through the total sum of interactions of an Instagram post, this is, the total amount of likes and comments on the given post. This data was selected as a metric since it's public to all the users and could be accessed for every brand studied.

Lastly, there is a need to restrict the brands in the analysis, and the profiles that would be used for this study. According to research on Yellow Pages advertising by Lohse, Rosen, & Hall (1999) color can function as a cue for the quality of a product or service – however, this effect depended on the product category. More recently, Bottomley & Doyle (2018) studied the effect the logo color has on brand perceptions. They concluded consumers find it more appropriate when colors are congruent with the product category. Both researches suggest the effect of color varies with the product category.

Building from these researches, and having color has a proven impactful variable, this dissertation will use the variable Product Category and study its moderator effect. Hence, the product categories in study will be Food & Snacks, and Women's Fashion and Travel. Instagram posts of brands in these categories will be analyzed and compared to understand if the product category is, in fact, a moderator for the impact of color on Social Media engagement.

1.3 Research Methods

To answer the research questions, secondary data was used. Quantitative data was analyzed, following an explanatory approach to study causal relationships between variables (Saunders, Lewis, & Thornhill, 2009).

Numbers of the total sum of interactions for 3 chosen posts and the follower count was collected from 150 business profiles on three different industries: Food & Snacks, Women's Fashion. And Travel These numbers were then used to derive the Engagement Rate of each post, a measure of Consumer Brand Engagement on Social Media.

Quantitative data on the dominant color of each post was collected using a color extraction tool[1]. This tool allowed the categorization of the posts in terms of Color Temperature.

The relationship of both variables was analyzed afterward, to understand how Color Temperature impacts the Engagement Rate on Instagram. Product category was introduced as a moderator of this impact.

1.4 Relevance

Providing guidelines and ideas on how to improve a brand's presence on Social Media, specifically on Instagram, is the ultimate intent of this dissertation. The results drawn will contribute to the knowledge about user behavior on Instagram, and topic researchers haven't focused much on until now.

As brands adopt Social Media as important channels, they also look for the best practices to share their content, whether it is on the impact of different message types (Peters, Chen, Kaplan, Ognibeni, & Pauwels, 2013), the impact of community (Naylor, Lamberton, & West, 2012) or even the best times to post (Kanuri, Chen, & Sridhar, 2018).

Having brand engagement as the goal for brands' Social Media presence (Phua & Ahn, 2016), a better understanding of how to increase it is meaningful for these brands.

[1] In https://labs.tineye.com/color/

The results of this dissertation will be useful for any Social Media Manager or others responsible for brand communication on these platforms. By knowing the characteristics of content users interact the most with, these professionals can plan their presence on the platform accordingly, considering not only brand identity but also these insights on how the users react to different colors. This dissertation will, therefore, provide marketers valuable and time-saving findings on this practice. Designers will also benefit these conclusions, when responsible for the digital content strategy.

Furthermore, when brands know and adopt the best practices to optimize engagement on Instagram, they can eventually impact brand performance positively, through brand loyalty and consumer satisfaction for instance (Barger, Peltier, Schultz, & Barger, 2016; Cummins, Peltier, Schibrowsky, & Nill, 2014; Dessart, 2017; Hollebeek, Glynn, & Brodie, 2014; Pansari & Kumar, 2017).

1.5 Dissertation Outline

The following chapter presents a literature overview and hypothesis development. It will dig deeper into Social Media, what's behind it and how it's an important tool for businesses. It will also go through the existent literature on brand engagement and the psychology of color. Chapter 3 presents in detail the methods used to collect and analyze the data. In Chapter 4, the main results of this dissertation will be presented and discussed, while Chapter 5 summarizes the conclusions drawn. The managerial implications, limitations of the study and suggestions for further research in the field are then detailed to close the dissertation.

CHAPTER 2: LITERATURE OVERVIEW & RESEARCH QUESTIONS

2.1 Digital Content Marketing

Social Media represents a good channel for brands to communicate with their target audience (Ashley & Tuten, 2013). Behind any kind of Social Media is the concept of digital content Marketing. Defined by the Content Marketing Institute (2013) as the "creation and distribution of valuable, relevant and consistent content to attract and retain a defined audience" content Marketing is now seen as a way to create and offer customer value (Rowley, 2010) and is a fundamental practice for brands on Social Media.

Similarly, Pulizzi (2012) defines it as "the creation of valuable, relevant and compelling content by the brand itself on a consistent basis, used to generate a positive behavior from a customer or prospect of the brand". In this case, besides attracting and retaining an audience, content Marketing should also focus on turning an audience into effective customers and generate positive behaviors.

On a different approach, Dan Blank, Marketing content specialist from *We Grow Media,* defines content Marketing as focusing on an idea instead of a product while engaging a community, trying to share valuable information first without expecting any return (Cohen, 2016). This definition, however, may appear to look at content as the opposite of advertising and is an example of how both should be considered. Content Marketing, in fact, includes both types: paid content (advertising) or nor paid (organic) (Kamerer, 2017). Regardless, the goal is to create something that should effortlessly attract your customers instead of pushing product information that they may not, be looking for, and this works for both organic and paid content (Opreana & Vinerean, 2015).

Although these definitions may partially or totally explain content Marketing through different lenses, it's understandable that this is still an evolving concept, in the fast-changing business environment (Kannan & Li, 2017).

Overall, all research on the concept agree on what are considered the main characteristics of digital content, for instance, it's contextual value, intangibility, reproducibility with no lost value (when it's shared for several users) and the accessibility through several devices (Koiso-Kanttila, 2004; Rowley, 2010).

When companies adopt a content Marketing strategy, they are trying to raise brand awareness, develop the relationships with their customers and eventually engage their audience with their brand or products (De Vries, Gensler, & Leeflang, 2012; Kumar, Bezawada, Rishika, Janakiraman, & Kannan, 2016).

However, as more and more brands are implementing these strategies it appears that more content is being produced than people can consume: according to a Smart Insights Infographic (Allen, 2017) the number of new posts on Facebook reaches the 3.3 million every 60 seconds and over 65 thousand on Instagram. At the same time, according to the same report, social shares are decreasing as 75% of the blog posts analyzed get 10 or fewer shares.

Data suggests there is a saturation that comes from the repeated consumption of similar content (Zhang & Sarvary, 2011), making it more difficult to create content that stands out and impact the audience. This is now the decisive task of digital and Social Media Marketing: produce content appealing and interesting enough to get noticed and foster the benefits Social Media can generate (Villarroel Ordenes et al., 2018).

To overcome this challenge brands should learn how to create valuable content that is significant to the customer (Malkin & Venkatesan, 2005) and how to do it through digital content, testing different Social Media posts, that may be images, video or text, depending on the social network in use (De Vries et al., 2012).

2.2 Consumer Brand Engagement

Brand engagement or consumer brand engagement (CBE) (Dessart, 2017) is now the factor every Social Media manager strives for (Leckie, Nyadzayo, & Johnson, 2016), as brands progressively go after emotional connections with their customers, rather than merely communicating sales messages (Pansari & Kumar, 2017).

Literature has been focusing on defining CBE, its drivers and consequences for several years now (Leckie et al., 2016) and researchers have shared distinct approaches on the topic.

Hollebeek (2011) defined CBE as “the level of a consumer’s motivational, brand-related and context-dependent state of mind characterized by specific levels of cognitive, emotional and behavioral activity in brand interactions", perceiving it as a multi-dimensional concept, alike other researchers' theories.

Mollen and Wilson (2010) focused specifically on online settings, describing CBE as "the cognitive and affective commitment to an active relationship with the brand as personified by the website or other computer-mediated entities designed to communicate brand value". In line with Hollebeek's study, the authors unfold this construct as a multi-dimensional concept as well, driven by cognitive, instrumental and experiential values.

While diverse, these theories explain CBE beyond consumer involvement, as a psychological condition triggered by consumer's emotional relationship with the brand (Brodie, Ilic, Juric, & Hollebeek, 2013; Dessart, 2017) and the experiences with it (Brodie et al., 2011). This means engagement is psychological and multidimensional as the authors describe – more than interactions, it is related to consumer needs, purposes and goals (Ashley & Tuten, 2013).

If consumers feel their needs are being answered by a brand or if their goals are supported, they will more easily engage (Ashley & Tuten, 2013). This should be maximized by creating strong brand associations, through valuable content, that can generate a sense of belonging and identity in the consumers, an emotional connection (Hollebeek et al., 2014).

In fact, theories like the Self-Expansion suggest that consumers engage with brands whose identities they identify themselves with, doing do so by attributing human character to a brand (Huang & Mitchell, 2014). If the consumer relates to this personality, it is easier to develop an engaging relationship.

This is a theory brand managers use to develop likable brands – create one that consumers can relate with (Reimann, Castaño, Zaichkowsky, & Bechara, 2012). This process is also known as Consumer-Brand Identification, driven by memorable brand experiences or associations and brand-self similarity (Stokburger-sauer, Ratneshwar, & Sen, 2012).

Social Media help by providing additional touch points, as every post or content shared will prompt certain emotions on consumers. These eventually helps developing associations with the brand, for instance associating a brand as a relatable entity that is, therefore, engaging and valuable (Ashley & Tuten, 2013).

Muntinga, Moorman, and Smit (2011) found out that there are two main motivations behind consumers interactions with brands on Social Media: entertainment or information. Informational content is any post that shares information about a company or product. Entertaining content is the one that appeals to the emotions. Both address different motivations and can be valuable depending on the consumers' needs. (De Vries et al., 2012)

Moreover, it's now known that interactive posts that call to a certain action like a click or answering a question, as well as multisensory – like videos with sound, that stimulates more than sight only - naturally get a higher number of interactions (De Vries et al., 2012). The same is proved to happen with posts that include photos (when compared to text-only posts) (Kim, Spiller, & Hettche, 2015).

By adopting the best content practices for engagement, brands can positively impact brand performance, through CBE. The direct outcomes remain unclear (Barger et al., 2016) but it's known that potential results from the consumer-brand relationships and increasing levels of CBE include a higher consumer satisfaction, sales growth, brand loyalty and customer lifetime value (Barger et al., 2016; Cummins et al., 2014; Dessart, 2017; Hollebeek et al., 2014; Pansari & Kumar, 2017).

Even if the addressed theories on CBE highlight the same emotional and psychological context of engagement, there seems to be doubt regarding an effective measure (Sashi, 2012). Hence, as Social Media are naturally interactive-based, brands often use relevant content to emotionally engage with consumers (Schmitt, 2012).

Engagement is subsequently assessed using social interaction metrics – such as likes, comments, and shares – that are then used to conclude about performance on Social Media (Barger et al., 2016; Sashi, 2012). Measuring the Engagement Rate from the interactions is now a regular procedure in most Social Media and a key metric recommended by several Marketing blogs (Buffer, 2018; Vaughan, 2011). It may vary with Social Media, but it's a feature included in the analytics reports of brand pages (Facebook, 2018), and is generally computed by dividing the Total Sum of Interactions of a post by the follower base of the brand on the platform.

2.3 Instagram as a Marketing Tool

Social Networking Sites are, according to Kaplan and Haenlein (2010) “applications that enable users to connect by creating personal information profiles, inviting friends and colleagues to have access to those profiles, and sending e-mails and instant messages between each other”.

On the top 10 of the most used SNS is Instagram, the 6th platform in terms of the number of active users (Statista, 2019). The SNS reached 1 billion monthly active users in June 2018, up from 800 million users as of September 2017 (Statista, 2018b).

Instagram is a free photo and video sharing mobile app, where users can share this content with other selected users or all their followers (Instagram, 2018). It works similarly to Facebook: each user as its own account where they can either get followed by the ones that are interested in their content or follow users they are interested in (Instagram, 2018).

After following a user, their content will start appearing regularly on the Instagram feed, based on an algorithm that tries to predict which content is more important or valued by the user (Loren, 2018). Users can then interact with the content through several actions, like ‘likes’, ‘comments’, ‘saves’ in a personal folder inside the app or ‘shares’ to other users.

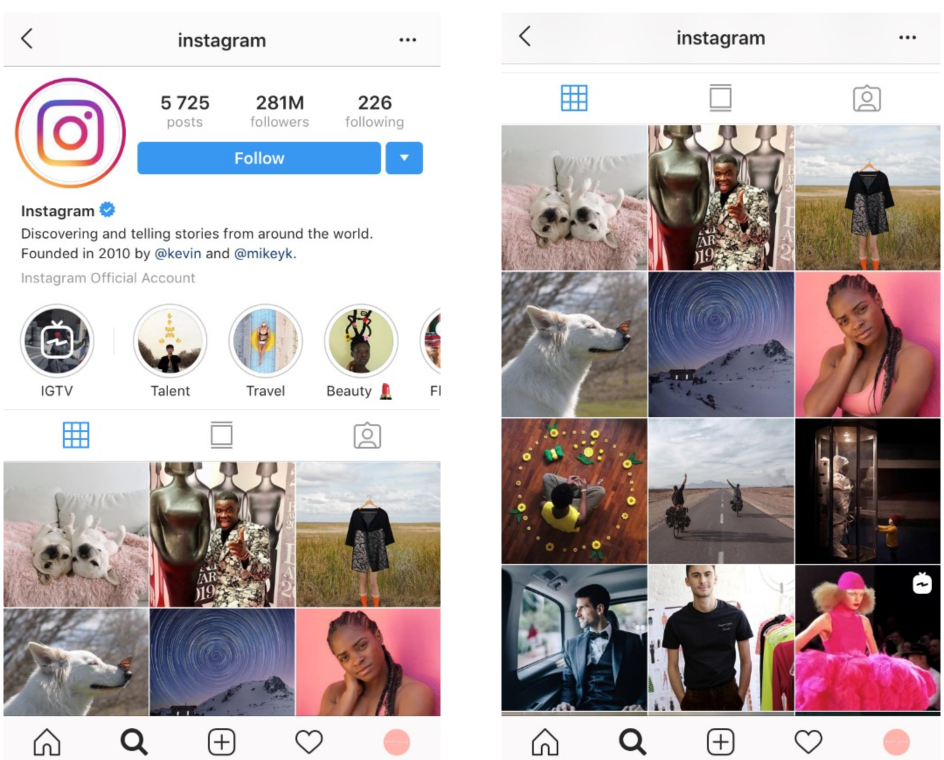


Figure 1 – Screenshots of an Instagram Feed

Instagram is a highly visual platform, as the users' profiles are composed by a grid of their lately shared photos or videos (Figure 1). As seen in the previous chapter, this content performs well in terms of engagement (Kim et al., 2015), meaning the app is also a powerful tool to interact with customers. On average, 38% of the US citizens from 18 to 44 years old, use Instagram at least once a day (Statista, 2018a) and 80% of Instagram users follow a business (Instagram, 2017), so Instagram is also a powerful Marketing tool.

The platform noticed this trend, and by May 2016 launched a set of tools for businesses, like the creation of business profiles linked to Facebook pages, a business analytics dashboard and the possibility of turning posts into paid ads for higher reach (Perez, 2016).

Using these tools, brands that create business profiles can access a set of information that was not tracked before. This includes not only data on the number of followers and unfollowers, but also detailed information about these followers/audience, their location, age range and gender (Figure *2*). This ends up having great utility for businesses trying to evaluate their efforts on Social Media.

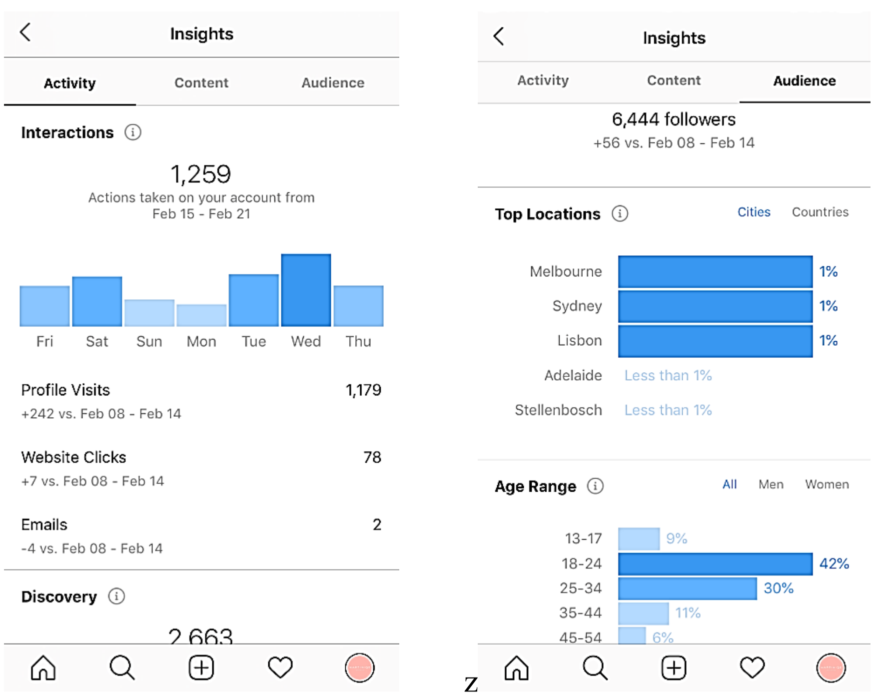


Figure 2 - Screenshots of an Instagram Analytics Dashboard

Regarding Brand Engagement, one of the most important Insights of this dashboard is content analysis. This allows businesses to analyze the engagement of their audience with each of their posts (Figure *3*).

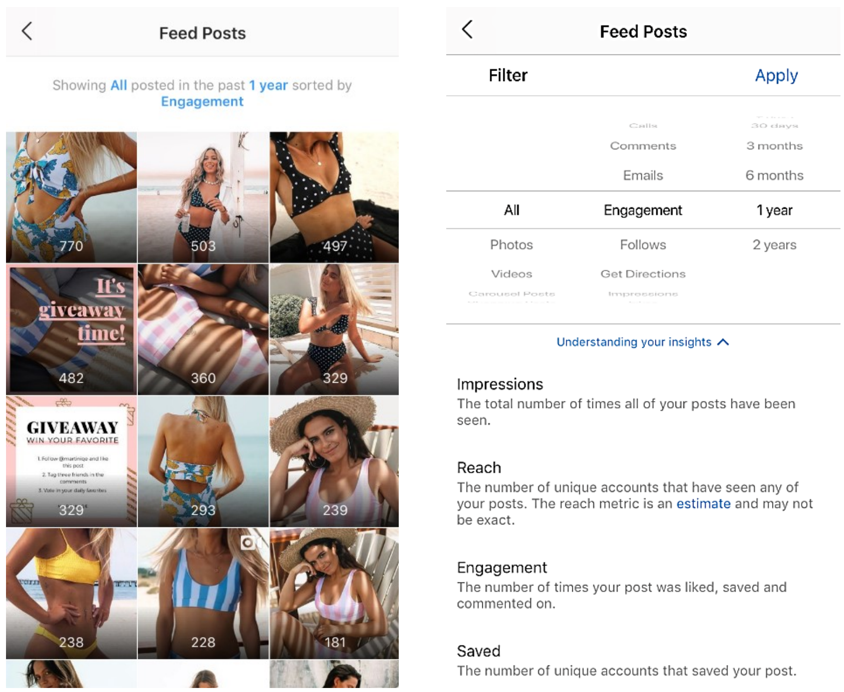


Figure 3 - Screenshots of an Instagram Content Analytics Dashboard

This metric, as seen in Figure 3, reflects "the number of times a post was liked, saved and commented on". However, only the brands' itself have access to the number of times a post was saved – this information is private and cannot be seen by a regular user. Therefore, for this dissertation, the engagement will be studied considered 'likes' and 'comments' only, this is, the total sum of interactions.

Overall, the success of Instagram goes in line with the Pew research by Rainie, Brenner, and Purcell (2012), that states photos and videos are now the "key social currencies online". Regardless of its popularity and growth, not many research has been focusing on Instagram, and information on best practices is still unanswered (Hu, Manikonda, & Kambhampati, 2014).

2.4 The Relevance of Color

With the adoption of Social Media and an increasing number of channels throughout which brands communicate, the ideal integration of all Marketing communications becomes relevant (Batra & Keller, 2016). The authors state that one of the main considerations regarding this integration is consistency, and how the same brand message should be delivered in different ways, to emphasize brand identity and associations.

One of the properties of visual consistency is the color scheme (McGrath, 2005) and possibly one of the most salient on Instagram, as other symbols such as the logo or typography are not so overly shared on the platform's profiles. This symbol, such as the name, carries strong associations intrinsically, that the consumers automatically translate to the personality of a brand (Abril, Olazábal, Cava, Keating, & Coltman, 2009). Moreover, research on Yellow Pages advertising (Lohse, Rosen, & Hall, 1999) showed color can influence the perception consumers have for the quality of a product or service.

Brand fans are attached to brands' colors and react to changes in the logo or in other visual elements (Labrecque & Milne, 2012), so it could be easy to hypothesize that these changes may also affect consumers reactions on Social Media. Thus, brands may often be tempted to follow a strict color scheme on all their communication efforts, for brand consistency purposes, but this may not be the best option to promote engagement, as colors have psychological meaning.

2.5 Psychology of Colors

Differences in color hues – red, blue, yellow and others - arose from the classic literature and the development of the first color wheel by Isaac Newton in 1666 (Soegaard, 2019). According to the author, hues are often divided by temperature to induce emotions and feelings, although they have different representations and meanings around the globe. The categories are warm colors including red, orange and yellow; cool colors, including green, blue and purple; neutral colors like white, black, gray and brown.

It's known that color affects our perceptions (Bagchi & Cheema, 2013) and even our purchase intentions (Belk, 1975; Kotler, 1974). As Bagchi and Cheema (2013) show, most research regarding the psychology of colors, focus on the differences of the colors red and blue, generally having red as a more arousing color, and blue as a relaxing one. (Elliot, Maier, Moller, Friedman, & Meinhardt, 2007; Labrecque & Milne, 2012).

From the classical to the contemporary research, this finding has not been contradicted. When applied to the digital background, blue is known to keep it's relaxing properties, shortening consumers' loading time perception on websites (Gorn, Chattopadhyay, Sengupta, & Tripathi, 2004). Also, Coursaris, Swierenga and Watrall (2008) found that consumers seem to have favorable perceptions of a website's design when it uses cooler colors like blue, as opposed to warmer colors like red.

In terms of shopping behavior, stores with blue environments are considered more pleasant, while red colors induce more negative behaviors, such as decreasing purchase intention and purchase postponement (Bellizzi & Hite, 1992).

Furthermore, in terms of digital content, these differences are also recognized. According to research by Jalali & Papatla (2016) on the impact of color on UGC, photos with higher proportions of green, a cooler color like blue, have a higher click-rate. The research focused on Instagram content and proved that color does impact the way an audience interacts with these posts, and therefore the engagement. Similarly, North & Ficorilli (2017) found that blue ads have higher rates than red ones.

On the other hand, the red hue is often linked to exciting and arousing features and usually concerned as a simulative color that promotes action (Clarke & Costall, 2008). According to Labrecque & Milne (2012), orange and yellow share similar properties of excitement, energy and live, although less than red.

2.6 Conclusion and Hypothesis

With the growth of Social Media and an increasing number of brands adopting it, it's getting more and more relevant to optimize digital content. The goal on platforms like Instagram is to drive users to interact with a brand's posts, make them feel engaged with valuable content. These interactions are often psychological: if users relate to a brand or post, they will more easily engage with it. Consequently, brands keep looking for ways to grab more attention towards this end – besides the content, a detail like the color is proved to impact users' actions.

As seen in the previous chapter, warmer colors are more stimulant (Clarke & Costall, 2008) and promote action. For this reason, it should be easy to hypothesize that these stimulating properties would make it easier for Instagram users to interact with posts where the dominant colors are warmer.

However, throughout the literature on the impact of colors, it's clear that blue is usually associated with more positive outcomes, as red is more related to negative ones (Labrecque & Milne, 2012). Regarding Marketing, blue is the color that provides better results in terms of purchase, perceptions and even click-through rates. Thus, we hypothesize:

RH1: Posts that have cooler predominant colors have higher Engagement Rates.

Warm hues share the same general characteristics according to research on the psychology of colors (Labrecque & Milne, 2012). Additionally, Color Temperature is linked to emotions, and will, therefore, be the color variable used for this study. Furthermore, most research on the subject is based on the comparison between red and blue hues (Bagchi & Cheema, 2013), so the use of Color Temperature including Neutral hues is already an extension on the topic, as it includes more than these two colors only.

Furthermore, knowing that the effect colors have on quality perception varies with the Product Category (Lohse, Rosen, & Hall, 1999), the same effect can be visible while assessing for Color Temperature. Therefore, we hypothesize.

RH2: The impact of Color Temperature in the Engagement Rates is moderated by the product category.

CHAPTER 3: METHODOLOGY

Chapter 3 presents and explains the methods used to study the research questions and hypothesis proposed in the last chapter, and how these are addressed.

The chapter goes over the research approach and its definition, followed by a presentation of the secondary data used for this study. Moreover, the data and analytical tools used to analyze it, are described.

3.1 Research Approach

The aim of this research is to study whether there is a significant relationship between the variables relating to post Color Temperature on Instagram and product category, and the variables reflecting brand engagement.

As seen through the literature review, past research has shown that these variables have been affecting brand attitude and brand performance (Abratt, 1989; Kotler, 1974) in offline environments, as well as on website perceptions (Gorn et al., 2004). This dissertation goal is understanding whether this link is also observable in the Social Media context and Instagram brand pages.

Having this, to study this causal relationship between variables, an explanatory approach was undertaken (Saunders et al., 2009). According to the authors, this approach is considered when studying causal relationships between variables and explaining them.

To proceed with this explanatory study, secondary data was used, by gathering quantitative data from past Instagram posts of brands on two different categories.

3.2 Research Design

To answer the research questions, data was compiled from 450 Instagram posts of 150 brands/Instagram pages in three different product categories. Data were collected concerning the three different variables in study:

Color Temperature:

Color Temperature is one of the independent variables in this dissertation. Quantittative data on the color of each post is obtained by extracting the dominant on the post and positioning it in terms of Color Temperature. The posts will be evaluated according to the following matrix:

Dominant Color	Color Temperature Level
Red, Orange, Yellow, Pink	Warm
Green, Blue, Purple, Violet	Cool
White, Black, Gray, Brown	Neutral

Table 1 – Color hue and temperature matrix

Product Category:

Product Category is the second independent variable and its influence as a moderator will be studied through the dissertation. The posts were labeled according to the product category as Food & Snacks, Women's Fashion on Travel, depending on the respective brand.

Engagement Rate:

Finally, the dependent variable in this dissertation is the Engagement Rate. This is a quantitative variable operationalized through the total sum of interactions and number of followers, as these are the metrics that express engagement on Social Media.

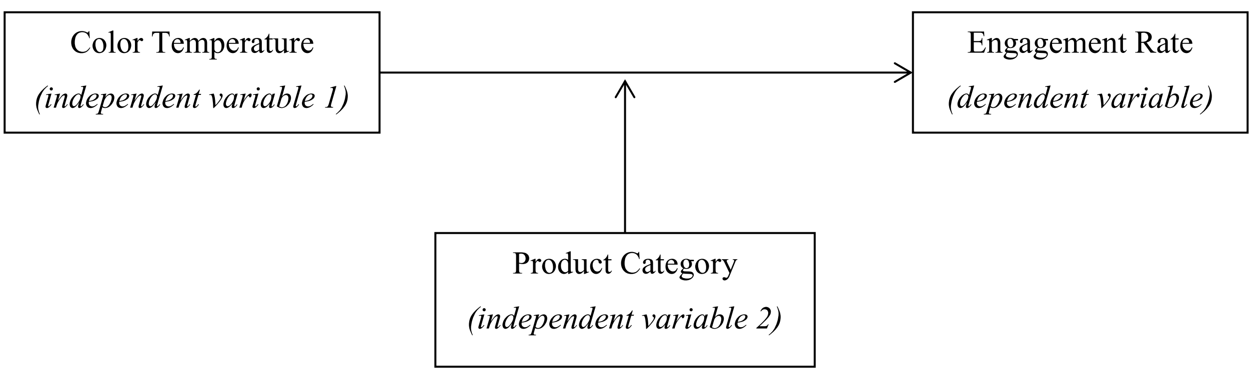
For this study, likes and comments will have the same relative weight on the total sum of interaction. However, it's easier for an Instagram user to like a post with one click only, that engaging enough to share their thoughts by writing a comment.

The brands in study were randomly selected, so differences in the follower base are notable: the database includes Zara with 31.1 million followers, and Califia Farms, with 207 thousand. When the follower base is this dissimilar, the total sum of interactions will be highly different too, as the post reaches much more users.

For this reason, Social Media Managers use the Engagement Rate to relativize the number of interactions, by dividing it by the total follower base. This way, engagement is analyzed as a percentual value, relative to the number of followers, and can be compared regardless of the audience size. Engagement Rate is therefore computed as:

$$Engagement\ Rate\ (\%) = \frac{Total\ Sum\ of\ Interactions\ of\ a\ Post\ (\#Likes + \#Comments)}{Number\ of\ Instagram\ followers}$$

Overall, having these three variables, we can operationalize the study through the following simplified model:



3.3 Population & Sample

The sample of this study consisted of 450 photos that brands shared on their own Instagram profile. The chosen posts were selected from the platform feed of 50 brands of each product category: 50 Food & Snacks brands, 50 Travel brands and 50 Fashion brands.

For each of these brands, 3 posts were selected. The images were selected randomly among the posts shared from the 1st December 2018 on, to ensure the current follower base is not that different from the base when the image was posted.

The brands chosen can be found in Appendix 1, with descriptive values on the number of posts with each Color Temperature that were analyzed.

3.4 Data Collection & Analysis

All the data in this analysis was collected to a data set including the brand, the URL of the Instagram post and the product category, for tracking and organization purposes.

The quantitative data collected from Instagram consisted of the brand's follower number and the total sum of interactions of the selected posts. This includes the total number of "likes" and "comments" on each post.

As there is no accessible tool to do this collection at the time of this dissertation, all the data was collected manually, by looking at each Instagram post individually. These values were then used to measure the Engagement Rate of each profile and post and introduced into the Excel database.

Moreover, quantitative data on the color of each post was collected. Even though the main Instagram platform is the mobile app, the desktop website was used for data collection, as it allows several add-ons that made the process easier and faster. On desktop, it's not possible for a user to click-right on an Instagram image to save it or copy its link thanks to certain platform restrictions over its content – it must be done over the page source, a time-consuming process. To accelerate this, a browser extension[2] was used to get the image URL and then insert it in a tool to extract the dominant color of an image.

TinEye Lab is an image search and recognition company ("TinEye - About Us," 2018) that allowed the assortment of data on Instagram posts' color. Using their color extraction tool[3], a picture is analyzed just by introducing its link. The page then displays a color palette with all the hues identified in an image, including the percentage of dominance (Figure *4*). The color that takes a higher percentual area in the image, will be considered the dominant color.

Using TinEye, besides the color code and area value, we can get a color approximation name. This makes the study objective, as we don't have to subjectively evaluate if the color is, for instance,

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[2] GetThatPic! Chrome extension was used to "Get url of instagram image easily and in well-known way". Extension can be found in: https://chrome.google.com/webstore/detail/getthatpic/fkdmnfbeaepmildaolaoicjbfkghpcco
[3] In https://labs.tineye.com/color/

green or blue, orange or red: the platform itself provides this information, and this one is always used with no space for perception bias.

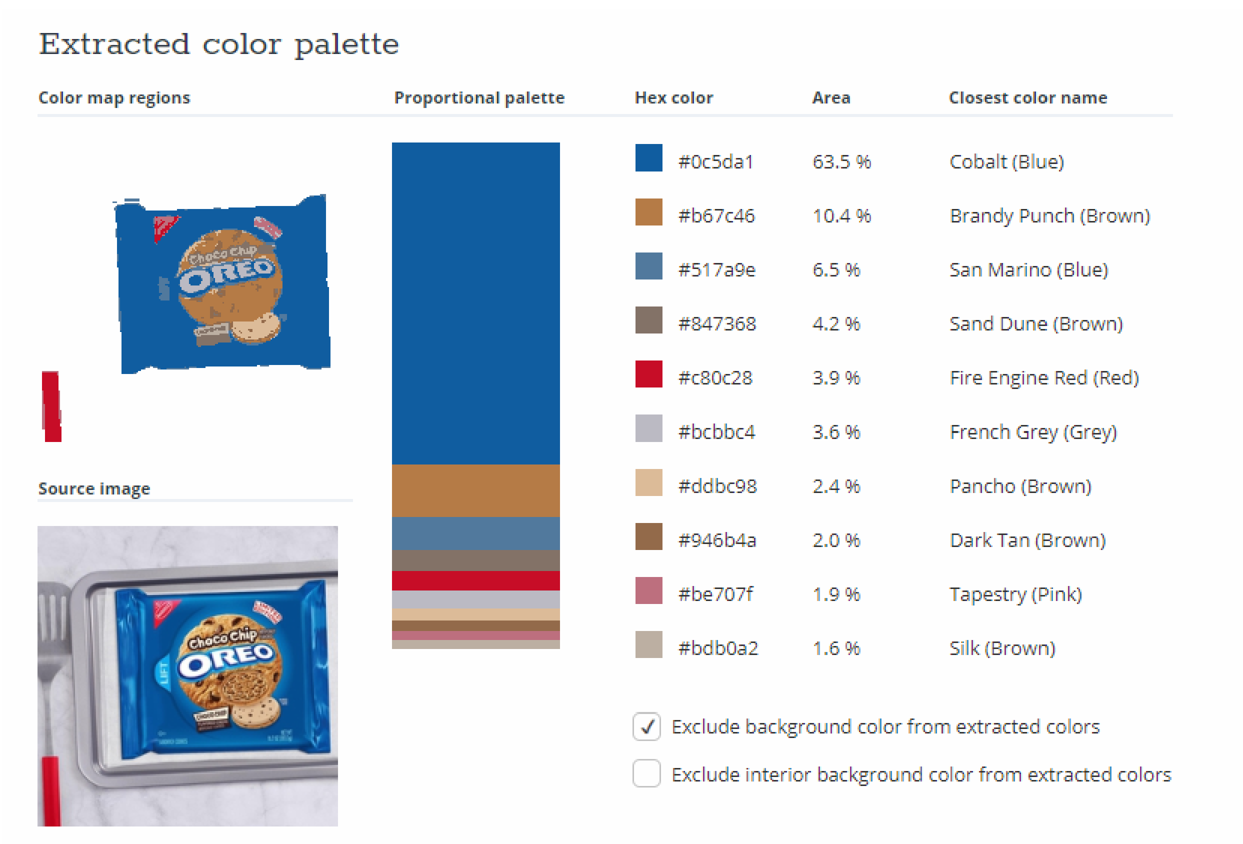

Figure 4 – Example of the dominant color extraction tool

Data was manually collected for each of the 450 posts, and introduced in the data set, one by one. Subsequently, based on each post’s dominant color, they were then categorized by Color Temperature, according to the division of hues above (Table *1*).

The collected data is afterward registered in a data set for precise presentation and examination. At the end of these stages, to answer RQ2, the database includes the three most relevant variables for the analysis: for each post, the Engagement Rate, product category, and Color Temperature. The database accounts for a total of 7 variables:

Product Category (string)	Category of the brand. Food & Snacks, Women Fashion or Travel
Likes (numeric)	Number of likes on each post
Comments (numeric)	Number of comments on each post
Sum of Interactions (numeric)	Total number of likes and comments on each post
Followers (numeric)	Number of followers of each brand's Instagram page
Engagement Rate (numeric)	Engagement Rate computed as (Sum of Interactions / Followers)
Color Temperature (string)	Color Temperature of each post. Warm, Neutral or Cool.

Table 2 - Database variables

No data cleaning was performed, and all the variables were compiled into an SPSS data set. When analyzing the frequencies of the dependent variable engagement and the ones that are used to operationalize it (Likes, Comments, Sum of Interactions and Followers), it was visible that they did not follow a normal distribution. This would hamper the following analysis as the assumptions for the parametrical tests could not be verified and these are usually more robust test (Rasch & Vienna, 2019). To verify the distribution, Shapiro-Wilk test and Kolmogorov-Smirnov test were then run. The results obtained are present in Table *3*.

	Kolmogorov-Smirnov[a]			**Shapiro-Wilk**		
	Statistic	**df**	**Sig.**	**Statistic**	**df**	**Sig.**
Engagement	,148	450	,000	,854	450	,000
Sum of Interaction	,338	450	,000	,424	450	,000
Comments	,302	450	,000	,521	450	,000
Likes	,338	450	,000	,422	450	,000
Followers	,343	450	,000	,403	450	,000

a. Lilliefors Significance Correction

Table 3 – Results of the Kolmogorov-Smirnov and Shapiro-Wilk normality tests

Having the highly significant p values, the null hypothesis is rejected for all the variables meaning that a normal distribution was not confirmed for any of them. Yet, these tests are known to lose robustness with the increase of the sample, and they may be limited to sample sizes between 3 to 50 (Royston, 1982), values way smaller than the 450 observation sample for this dissertation.

Therefore, to validate the results, the frequencies of the variables were run on SPSS through histograms with normality curves, present in Appendix 2. By analyzing them, it became clearer the variables did not follow a normal distribution.

Accordingly, and to continue the analysis, the variables were transformed through natural logarithms to linearize them. More precisely, the dependent variable for this study, Engagement, was transformed into Ln_Engagement. After this transformation, the variable seems to follow a normal distribution, perceptible in the Normality Curve and the Q-Q plots (Appendix 3). Moreover, the Skewness and Kurtosis values in Table 3 verify this normality ($-0.462 \in [-2;2]$).

N	Valid	450
	Missing	0
Skewness		-.462
Std. Error of Skewness		.115
Kurtosis		.429
Std. Error of Kurtosis		.230

Table 4 – Skewness and Kurtosis of the Depende Variable Ln_Engagement

Nonetheless, having the sample size of N = 450 no normality issues should be concerning, and this Ln transformed variable will be the one used in the following analysis.

To verify the assumption of Homogeneity of Variances, a Levene's Test of Equality of Variances was run Appendix 6. Having a significant p-value ($p=0{,}343 > 0{,}05$), the assumption of homogeneity of variance is met and parametric tests like One-Way ANOVA can be performed.

The normality of the independent variables was also assessed, this is, the Engagement distribution for each of the Product Category and Color Temperature groups. Following the same principles, and as the Shapiro Wilk test is not adequate for a 150-sample size, the Q-Q Plots were used to assess the normality of these interactions. To do so, the independent variables Product Category and Color Temperature were recoded into numeric values. Appendix 4 and Appendix 5 present these results and prove the normal distribution of these interactions.

CHAPTER 4: RESULTS AND DISCUSSION

This chapter presents the results of the analysis of the data collected from the 150 brand's Instagram profiles. It goes through the initial comparison of means between categories, followed by the analysis of Color Temperature impact on brand engagement. Lastly, the moderator effect of the product category is analyzed, and all the findings are discussed.

4.1 Mean Analysis

To start with, a comparison of means of the variables Followers, Sum of Interactions and Engagement was performed for each product category, to understand how different brands may impact the results.

Product Category		Followers	Sum of Interaction	Engagement
Fashion	**Mean**	2.844.104	12.513	0,71%
	Std. Deviation	5.589.407	255.178	0,75%
Food	**Mean**	1.133.552	9.882	1,16%
	Std. Deviation	2.744.573	25.319	0,91%
Travel	**Mean**	1.505.024	14.806	1,31%
	Std. Deviation	4.577.439	36.303	0,83%

Table 5 – Comparison of Means by Product Category

Table *5* illustrates the Means and Std. Deviations of the variables Followers, Sum of Interactions and Engagement, for each Product Category.

As to the follower base, Fashion is the category with a larger audience, followed by Travel ($M_{Travel\_Followers}$ = 1.505.024). Food is the category with the lowest follower mean, displaying less than half of the average followers of Fashion brands ($M_{Food\_Followers}$ = 1.133.552 against $M_{Fashion\_Followers}$ = 2.844.104).

It's observable by looking at the Food category that the Sum of Interactions decrease with the number of followers ($M_{Food\_Interactions}$ = 9.882). However, both Fashion and Travel contradict this rule of thumb: although it has the most followers, Fashion is not the category with the highest Sum of Interactions ($M_{Fashion\_Interactions}$ = 12.513). Travel brands, on the other hand, presented the highest values of interactions ($M_{Travel\_Interactions}$ = 14.806), even though the average of followers is less than half of the Fashion values.

Consequently, even with the lowest Follower and Sum of Interactions means, Food is not the category with the lowest Engagement Rate. In fact, the large audience of Fashion brands paired with the relatively low total Interactions, make this the product category with lowest engagement mean ($M_{Fashion\_Engagement}$ = 0,71%). Differently, both Food and Travel brands present high Engagement Rates ($M_{Food\_Engagement}$ = 1,16%; $M_{Travel\_Engagement}$ = 1,31%)

Though, all the results are widely disperse having standard deviations higher than the means in almost every scenario.

The same analysis was performed for the posts by Color Temperature, to run an initial study of how Color Temperature may impact the dependent variable, and the results are present in Table 6.

Color Temperature		Followers	Sum of Interaction	Engagement
Cool	**Mean**	1.766.680	13.618	1,21%
	Std. Deviation	4.467.530	32.717	0,96%
Neutral	**Mean**	2.041.444	14.882	1,1%
	Std. Deviation	4.898.147	34.616	0,87%
Warm	**Mean**	1.677.024	8.651	0,87%
	Std. Deviation	4.165.780	17.992	0,72%

Table 6 - Comparison of Means by Color Temperature

The posts that lead to better performance in terms of Engagement Rate are the ones with a cooler dominant color ($M_{Cool\_Engagement}$ = 1,21%) closely followed by the neutral colors ($M_{Neutral\_Engagement}$ = 1,1%). Warm posts perform worse ($M_{Warm\_Engagement}$ = 0,87%) than any others.

Although the neutral color posts come from brands with more Followers ($M_{Neutral\_Followers}$ = 2.041.444) the Sum of Interactions value is not high enough to make these the most engaging posts ($M_{Neutral\_Interactions}$ = 14.882). Warm posts are linked to lower values for all the variables ($M_{Warm\_Followers}$ = 1.677.024; $M_{Warm\_Interactions}$ = 8.651). The results regarding cool posts are relevant towards RH1, indicating that cool posts are associated with good engagement values.

Here too, standard deviation illustrates a high dispersion of values – though lower in the engagement, a good indicator for the significance of Color Temperature impact in the dependent variable.

4.2 Color Temperature

To go ahead with the study and develop the findings of Color Temperature a One-way ANOVA was run. This test analyzes if there any statistically significant differences between the means of Engagement Rate for each Color Temperature. With the normality and homogeneity of variances assumptions met, the test was performed (detailed in Appendix 6).

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1,511	2	,756	5,338	,005
Within Groups	63,277	447	,142		
Total	64,788	449			

Table 7 – ANOVA Table results

Table 7 presents the ANOVA analysis. Results show that the significance is below the 0,05 (F(2,447) = 5,338, p = 0,005)) and therefore there is a statistically significant difference in the mean Engagement Rate between different Color Temperatures.

To gain insights on which groups differ, a Tukey Post Hoc was conducted. The results are presented in Table 8.

Recoded_Temp	Recoded_Temp	Mean Difference	Std. Error	Sig.
Cool	**Neutral**	,0200700446	,0433092943	,888
	Warm	**,131944108***	**,0433092943**	**,007**
Neutral	**Cool**	-,020070045	,0433092943	,888
	Warm	**,111874064***	**,0437374032**	**,029**
Warm	**Cool**	**-,131944108***	**,0433092943**	**,007**
	Neutral	**-,111874064***	**,0437374032**	**,029**

Table 8 – Tukey Post-Hoc Test of the One-way ANOVA

From the results above, we can understand that there is a statistically significant difference in Engagement Rate between Cool and Warm posts (p = 0,007) and between Neutral and Warm posts as well (p = 0,029). However, no differences were found between Cool and Neutral colored posts (p = 0,888). Moreover, the Tukey post-hoc revealed that the Engagement Rate is statistically significantly higher for the Cooler (MD = 0,1319) and Neutral (MD = 0,1119) posts compared to the Warm ones.

4.3 Product Category

To answer RQ2 and understand if Product Category moderates the impact of Color Temperature on Engagement Rates, a Two-Way ANOVA was performed. The results of the test are shown in Table 9 – this is the Test of Between-Subjects Effects and analyzes if any of the independent variables or the interaction of both are statistically significant.

Tests of Between-Subjects Effects

Dependent Variable: Ln_Engagement

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	15,381[a]	8	1,923	17,161	,000
Intercept	2018,964	1	2018,964	18020,832	,000
Recoded_ProdCat	11,558	2	5,779	51,583	,000
Recoded_Temp	1,670	2	,835	7,451	,001
Recoded_ProdCat * Recoded_Temp	1,942	4	,486	4,334	,002
Error	49,407	441	,112		
Total	2090,293	450			
Corrected Total	64,788	449			

a. R Squared = ,237 (Adjusted R Squared = ,224)

Table 9 – Two-way ANOVA Results for the Color Temperature Product Category Interaction

These results suggest there is a statistically significant interaction between the effects of Product Category and Color Temperature on the Engagement Rate (F(4,441) = 4,334; p = 0,002). Both variables individually also show a statistically significant impact on the dependent variable

($p_{Temperature}$ = 0,001; $p_{Prod\_Category}$ = 0,000). Table 10 shows the impact of Product Category by itself on brand engagement and the Mean differences between categories.

(I) Product Category	(J) Product Category	Mean Difference (I-J)	Std. Error	Sig.
Fashion	Food	-,283418436621*	,0386497096	,000
	Travel	-,381352499359*	,0386497096	,000
Food	Fashion	,283418436621*	,0386497096	,000
	Travel	-,097934062738*	,0386497096	,031
Travel	Fashion	,381352499359*	,0386497096	,000
	Food	,0979340627384*	,0386497096	,031

Table 10 – Tukey Post Hoc Tests of the Two-Way ANOVA for Product Category

Results in Table 10 enlighten the statistically different Means of Engagement Rates by Product Category. Mean Differences are significant for all the categories: there is a statistically significant difference in Engagement Rate between Fashion and Food posts (p = 0,000), Food (p= 0,31) and Travel, and Travel and Fashion (p = 0,000).

Additionally, Travel is the Product Category with higher Engagement Rate means ($MD_{Travel-Fashion}$ = 0,3814; $MD_{Travel-Food}$ = 0,0979), results that are logically consistent with the initial Mean Comparison analysis but are now investigated in terms of statistical significance. Moreover, posts of Food brands perform better in terms of engagement than Fashion ones ($MD_{Food-Fashion}$ = 0,2834; p = 0,000).

Having a statistically significant interaction, it's vital to go deeper in the analysis and study the simple main effects. This will allow us to understand where the differences in the interaction lay, between groups. In this case, we will find where are the Mean Differences in Color Temperature for each product category. To analyze this interactions, a syntax change for the Two-Way ANOVA was performed, to run an Estimated Marginal Means analysis (Appendix 7).

Results of this test for the interaction Product Category * Color Temperature are presented in Table 11:

Product Category	(I) Recoded_Temp	(J) Recoded_Temp	Mean Difference (I-J)	Std. Error	Sig.[b]
Fashion	**Cool**	**Neutral**	-,141*	,066	,034
		Warm	,131*	,066	,050
	Neutral	**Cool**	,141*	,066	,034
		Warm	,272*	,069	,000
	Warm	**Cool**	-,131*	,066	,050
		Neutral	-,272*	,069	,000
Food	**Cool**	**Neutral**	,000	,068	,997
		Warm	,114	,068	,095
	Neutral	**Cool**	,000	,068	,997
		Warm	,113	,065	,084
	Warm	**Cool**	-,114	,068	,095
		Neutral	-,113	,065	,084
Travel	**Cool**	**Neutral**	,221*	,066	,001
		Warm	,178*	,066	,008
	Neutral	**Cool**	-,221*	,066	,001
		Warm	-,042	,068	,536
	Warm	**Cool**	-,178*	,066	,008
		Neutral	,042	,068	,536

Table 11 – Estimated Marginal Means of the Two-way ANOVA for the Interaction Product Category * Color Temperature

The significant differences in the interaction on Engagement Rates are here detailed. The Mean Differences of Color Temperature on Engagement Rates are presented by Product Category and will be analyzed as such.

First, or the Fashion Category posts, a statistically significant difference in Engagement Rate was found between all color temperatures, at different significance levels. The difference between Warm and Neutral posts is highly significant ($p = 0{,}000$) as the one between Neutral and Cool posts ($p = 0{,}034$). Cool and Warm posts still show a statistically significant difference, yet, with a p-value of 0,05. In this category, Neutral posts lead to higher Engagement Rates than both Cool and Warm ones ($MD_{Neutral\text{-}Cool} = 0{,}141$; $MD_{Neutral – Warm} = 0{,}272$). Cool posts have a better engagement than Warm posts too ($MD_{Cool\text{-}Warm} = 0{,}131$) making the warmer posts the ones with lowest means regarding the dependent variable.

Inversely, while analyzing the results of the Food Product Category, no statistically significant differences were found. The difference between Color Temperatures in this category is not statistically relevant, with p values between 0,084 and 0,997 for the interactions ($p > 0,05$).

Lastly, regarding the Travel Product Category, a third scenario is visible: only some of the Color Temperature comparisons are statistically significant. In this case, Cool posts have higher Engagement Rates than each of the other color temperatures: these perform better than both Neutral ($MD_{Cool\text{-}Neutral} = 0,221$, $p = 0,001$) and Warm posts ($MD_{Cool\text{-}Neutral} = 0,178$, $p = 0,008$). No statistically significant differences were found between Warm and Neutral posts in terms of Engagement Rate.

These significant mean differences on the Product Category * Color Temperature interactions are well represented on the Profile Plots in Appendix 7. As noticeable, the Product Category lines for Fashion and Travel are not parallel at all, which suggests an interaction effect. In this case, the plots show that the effect of Color Temperature is different for each Product Category.

Moreover, none of the lines is horizontal suggesting large differences on the Engagement Rates for each color, as analyzed above. Lastly, it's also visible in the plots how Neutral and Warm colors do not differ for the Travel category, as they lay in a close point on the vertical axis, referent to the Estimated Marginal Means of the dependent variable.

4.4 Discussion

According to the Mean Comparisons, Fashion is the product category with the highest Follower mean, not surprisingly, as it was one of the first industries to adopt Instagram with 98% of usage rate by March 2016 (Statista, 2016). Additionally, brands in this category are easily recalled.

Food is the least followed category, which may be explained by its low involvement characteristics and the fact that a user is not so easily inspired by food posts when comparing to the other categories. Its apparent low audience is also visible in the total sum of interactions: as seen, a smaller follower base often leads to less interactions, as the content audience is fewer.

The Food category certainly verifies this rule of thumb, nevertheless, it is contradicted by the other categories. In fact, although Fashion as the largest number of followers, Travel is the category with the highest sum of interactions. This means users interact more with Travel posts than Fashion ones, despite following the last ones more often. This ends up impacting the Engagement Rate. While being the category with a higher average of followers, Fashion is the one with the lowest Engagement Rate (0,7%) against the highly engaging Travel category (1,3%).

As noted above, the variables are highly dispersed. This is not a negative observation, however. As brands were randomly selected, no minimum or maximum values were defined, ending up with a vastly diverse sample of large and small brands.

The results of the Two-way ANOVA prove that engagement means are in fact influenced by Product Category. These findings and the detailed results are consistent with the first analysis of the Engagement Rate means.

After assuring that these differences were statistically significant, we can state that these results do not come entirely as a surprise. Instagram is a platform highly related to the Fashion industry. As seen, this was one of the first industries to adopt Social Media. Additionally, there is a larger concentration of Fashion bloggers (or influencers) that use their personal profiles to share Fashion looks, their daily outfit and lifestyle inspiration with their followers. For that reason, higher engagement values were expected, however, it's understandable that with this reputation, followers increase and consequently engagement rates decrease.

RH1: Posts that have cooler predominant colors have higher Engagement Rates.

Results indicate that Color Temperature has a significant impact on Engagement Rates means. Moreover, cooler posts are the ones that lead to higher Engagement Rates. The One-Way ANOVA results indicate that Color Temperature has a statistically significant impact on Engagement Rates. Research on the psychological effects of color and its implications to Marketing found that color influences purchase behavior (Belk, 1975; Kotler, 1974) and, in a Digital Marketing setting, loading time perception (Gorn et al., 2004). According to the results, in the Social Media environment, this is no different.

The general analysis performed with the ANOVA and the following Post Hoc tests show how Engagement Rates means are different for each temperature group. By running this comparison, regardless of Product Category, we find that Cool temperatures affect the Engagement Rate positively and are linked to higher rates than Warm posts. This means that, to promote Instagram Engagement, having a blue, green, purple or violet color palette is better than red, orange, yellow or pink posts.

Although it's proved that Cool posts perform better, the impact of this Color Temperature does not differ significantly from the impact of Neutral colors. This takes us to a different finding: in terms of main effects, cool colors are not necessarily the ones with higher Engagement Rates, as the Neutral ones can perform as good. However, it's certain that warm colors do perform worse and therefore, RH1 is validated, as cool colored posts do have higher engagement rates than warm ones.

These findings are consistent with the literature on the effect of colors in Marketing. Although warm colors are more arousing, in this case, the effect of blue colors as relaxing and confidence inducing (Labrecque & Milne, 2012) paired with its likable characteristic on website settings (Coursaris, Swierenga and Watrall, 2008) are more relevant. This may also be fostered by the negative associations of warm colors like red (Bellizzi & Hite, 1992).

These findings allow us to understand that the Psychology of Colors is applicable in Instagram too, and impacts the Engagement Rate on this platform. Color Temperature should, therefore, be considered when planning the Digital Content of brands on the platform.

RH2: The impact of Color Temperature in the Engagement Rates is moderated by Product Category.

Product Category was the second independent variable to study. In this case, not only its individual impact on Engagement Rate was analyzed but also its interaction with Color Temperature and consequent effect on the dependent variable. As seen, as an independent variable it significantly impacts Engagement Rates, showing the existence of a moderator effect and confirming RH2.

According to the results, the interaction between Product Category and Color Temperature is significant concerning the differences in engagement means. These findings show that Product Category impacts the effect of Color Temperature on Engagement Rates, and for each category this effect may be different. It proves the existence of a moderator effect.

In fact, the analysis performed showed that the three categories chosen were a suitable example of these differences, as for each Product Category the impact of temperature on the dependent variable radically changes:

By observing values for the Fashion brands' posts, it's visible that in this category all colors impact engagement rate differently. Each posts' color shows highly significant differences when comparing to any of the other colors. Fashion posts on Instagram are limitless and therefore content varies a lot. Consequently, details like color do apparently make a difference. For instance, in this category, Neutral posts are the ones that lead to higher engagement rates, as opposed to the warmer ones, that can harm brands' efforts on engagement.

On the other hand, regarding the Travel brands, results showed that differences arise only when comparing both Warm or Neutral to Cool. No difference was found between the Means of Warm and Neutral colors. This finding may be noticed by looking at random Travel profiles, that include several photos of nature that usually feature Blue (watery elements; sky) and Greenish tones (leaves; mountains; natural landscapes) and can justify the higher interaction in this category.

Finally, concerning the Food category, a third scenario is visible: Color Temperature showed no impact on Engagement Rates. This outcome shows the severe impact of Product Category on the relationship between the other two categories. The fact that this category has a weaker presence on Instagram may indicate that colors have a stronger impact on engagement for larger brands on the platform.

These findings validate RH2 and prove that Product Category act as a moderator on the impact of Color Temperature on Engagement Rates.

On a different approach, these findings suggest that Color Engagement has a higher impact on Engagement Rates for higher involvement products like Fashion and Travel are. This suggestion could be developed on further research.

CHAPTER 5: CONCLUSIONS AND LIMITATIONS

5.1 Main Findings & Conclusions

Social Media adoption has never been so clear, with over 90% of European and Northern America Internet users being active in these platforms (Chaffey, 2018). This offers a new channel for brands to interact with their worldwide consumers and one that is easily available 24 hours a day. Brands are therefore increasing their focus and investment on Social Media Marketing, on platforms like Instagram. This paradigm change is clearly an opportunity to build on consumer-brand relationships.

However, as business profiles and the content shared increase (Allen, 2017), digital content is getting saturated. Therefore, brands should find ways to innovate and stand out, with more valuable content (Villarroel Ordenes et al., 2018) and here, details like color can make a difference.

The goal should be to increase engagement on the platform, as this can lead to higher consumer satisfaction, sales growth, brand loyalty and customer lifetime value (Barger et al., 2016; Cummins et al., 2014; Dessart, 2017; Hollebeek et al., 2014; Pansari & Kumar, 2017).

Previous research showed the impact of color on purchase intention and brand attitudes behavior (Belk, 1975; Kotler, 1974). This dissertation was grounded on the same ideas, to understand how the color of an Instagram post affects user engagement with this content.

Results revealed that Color Temperature has a significant impact on Engagement Rate Means, and this effect is moderated by Product Category. Overall, Cool colors generate higher Engagement Rates than Warm colors, but no statistically significant difference was found between the first ones and Neutral colors.

Regarding Product Category, the one that drives the highest Engagement Rates is Travel, followed by Food, and only the Fashion. Besides, Product Category affects not only engagement but the impact of Color Temperature on this variable as well, revealing a moderator effect. Particularly, regarding Fashion, all color differences are significant, and the Neutral ones drove the highest Engagement Rates; while in the Travel category, the posts that lead to higher engagement are the Cooler ones. No differences were found in the Food category.

These results suggest that Marketing and Social Media managers should contemplate the impact of color temperature on their Digital Content strategy. This can be implemented by coordinating their content with the color that drives the higher engagement for the respective product category. In case there is no evidence yet on the best color for certain industries, managers should prefer and start with Neutral and Cooler colors, avoiding the Warmer tones that are proven to perform worst overall.

This dissertation was not meant to find a model that predicts the Engagement Rate, as more information would be needed. Nevertheless, it's proved that engagement on Instagram goes beyond content, beyond consistency with the brand, and that the psychological effects of color do matter and should be considered while planning the Marketing activities.

5.2 Managerial and Academic Implications

The findings on this dissertation provide valuable insights to professionals or students that work directly with Social Media platforms or are responsible for the Digital Content Strategy of a brand or personal profiles. With the goal of increasing Brand Engagement through Social Media, these professionals could benefit from these conclusions, to improve the Brand-Consumer relationship.

This information showed that discussion on the dominant color on a Social Media profile is relevant and should be considered in a Digital Content Marketing Strategy. Furthermore, findings are valuable for Social Media Managers working on the industries where Color Temperature did show a significant effect on the engagement, i.e. Fashion and Travel. In these industries, colors should be assessed and planned accordingly: for Fashion brands, the dominant color on Social Media posts should be Neutral, like gray or black. On the other hand, for brands on the Travel industry, Cooler posts where blue or green hues are dominant should be preferred.

This does not mean that warmer posts, like the ones with lower engagement rates, should be avoided at all costs. There are other variables that impact this decision, like the consistency with the brand or the brand's color palette. Nevertheless, these possibilities should be discussed, and color must be considered on the choices made.

Additionally, this dissertation extended the few research on Brand Engagement on Instagram and adds valuable insights to the topics regarding the effect of Color on Marketing efforts, particularly, Digital and Social Media Marketing. It adds to the existing research on the impact of color on a Digital context and brings new understandings on how consumers react to color.

This knowledge is relevant to the disciplines of Consumer Behavior and Marketing Psychology and will allow for the development of further research in the area.

5.3 Limitations and Further Research

Like any other study regarding color, color blindness is a relevant limitation. In this dissertation, it was assumed that all the Instagram users and the ones that interacted or followed the brand's posts and profiles, could see color. Color blindness affects on average 8% of the men and 0,4% of women worldwide (Birch, 2012). This means that in the entire world there are around 300 million people affected by this condition.

It's possible that a percentage of the users that interacted with the posts analyzed, could not differ colors, and were triggered to interact with it for several reasons other than color. In this case, color did not impact these interactions at all. There is no way to analyze this percentage however, so this condition should not be concerned for this dissertation.

When collecting Instagram data on the posts it was visible that posts on the same product category may vary a lot. This is, Fashion posts may be a photo of a piece of clothing or a photo of a person wearing it. Furthermore, Food posts can feature the product itself or a graphic image with a quote for instance. These content variations could be studied in the future. A way to analyze this would be to categorize different types of content for each Product Category and introduce a Content-Type variable in the database. In this case, not only would be relevant to study if the impact of color remains the same, as it could be pertinent to run a Linear Regression and understand the level at which each variable impact the engagement.

Another variable that can influence the results is the follower base of the profiles. For this dissertation, no distinction was made between large and small brands. The study would be highly biased if only large brands were analyzed as there's a necessary correlation between both variables that are visible through the Engagement Rate formula - the higher the followers, the lower the engagement. So, this could also be normalized on further research.

A different suggestion for further research would be to widen the Product Categories in study. Throughout this dissertation, three categories were used to analyze if this variable had a moderator effect, what was proved to happen. The same analysis could be developed in depth for any specific product category and it would be valuable for Social Media managers in each industry.

Lastly, further research could also focus on understanding if there is an impact on profile consistency on Engagement Rates, this is, if brands that consistently use one Color Temperature only, perform better than the ones that mix it up.

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APPENDICES

Appendix 1 - Selected brands by Product Category

Food & Snacks			
Brand	**Cool**	**Neutral**	**Warm**
Alpro	0	3	0
AlterEco	1	2	0
Banza	0	0	3
Barilla	2	0	1
Baskin Robbins	1	0	2
Ben&Jerrys	1	2	0
Burger King	1	2	0
Califia Farms	0	0	3
California Donuts	1	0	2
Cheetos	0	2	1
Chipotle	1	2	0
Chips Ahoy	2	0	1
Chobani	2	0	1
Doritos	1	0	2
Dunkin	0	1	2
Fomu	2	1	0
Frooti	3	0	0
General Mills	2	0	1
Green Giant	2	1	0
Halo Top Cramery	0	1	2
Heinz	0	2	1
Hersheys	2	1	0
Horizon Organic	1	2	0
Jamie Oliver	0	3	0
KitKat	1	2	0
Knorr	1	1	1
Kraft Recipes	0	1	2
Lays	0	1	2
Love Food	0	1	2
M&Ms	2	0	1
McDonalds	2	1	0
McVities	0	3	0

Women Fashion			
Brand	**Cool**	**Neutral**	**Warm**
Acne Studios	1	1	1
Aerie	1	1	1
American Apparel	1	0	2
Anthropologie	3	0	0
Asos	2	0	1
Bimba Y Lola	1	1	1
Brandy Melville	2	1	0
Brass Clothing	1	0	2
Bread & Butter	1	1	1
Desigual	1	1	1
Everlane	1	1	1
Faithful the Brand	1	0	2
Fame & Partners	0	2	1
Finders Keepers	1	1	1
For Love and Lemons	1	1	1
Ganni	2	0	1
H&M	1	1	1
Intimissimi	0	2	1
Intropia	1	2	0
J.Crew	1	0	2
Joie	0	3	0
Kate Spade	2	0	1
Lahana Swim	1	2	0
Loavies	0	2	1
Lucia Zolea	0	2	1
Madewell	2	0	1
Mango	0	2	1
Massimo Dutti	1	1	1
MaxMara	1	0	2
Missguided	2	0	1
Monrow Attire	1	1	1
NastyGal	1	1	1

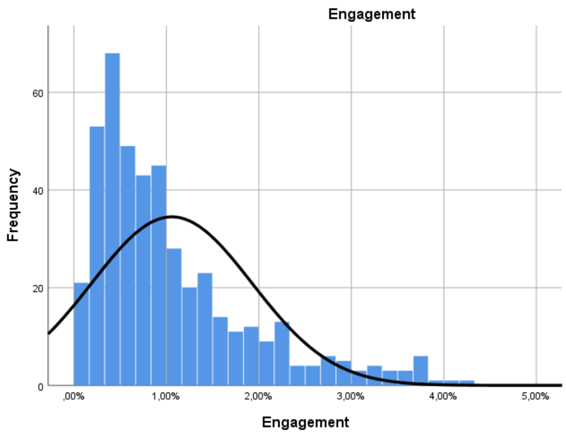
Mutti Pomodoro	0	2	1
Nestle	2	1	0
Nutella	0	2	1
Oreo	1	1	1
Oscar Mayer	1	0	2
Pacific Foods	0	1	2
Pillsbury	1	1	1
Plated	0	1	2
Postmates	1	1	1
Quaker	2	1	0
Siete Family Foods	1	1	1
Sprouts	1	0	2
Starbucks	0	2	1
Subway	1	1	1
Taco Bell	1	0	2
Tic Tac	1	0	2
Whole Foods	0	1	2
Yoplait	1	1	1
Total	45	52	53

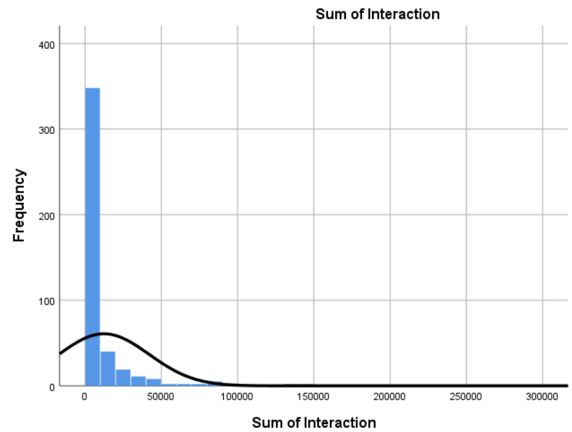
Net-à-Porter	2	0	1
Noah	1	2	0
Nordstorm	2	1	0
Oasis	1	0	2
Pepe Jeans	2	1	0
Reformation	1	1	1
Riffraff	1	1	1
Romwe	1	0	2
Springfield	1	1	1
Stateside	1	2	0
Topshop	1	1	1
Urban Outfitters	1	1	1
Uterque	1	2	0
Veja	1	2	0
Vogue	1	1	1
Wildfox	1	0	2
Zaful	1	2	0
Zara	1	0	2
Total	55	48	47

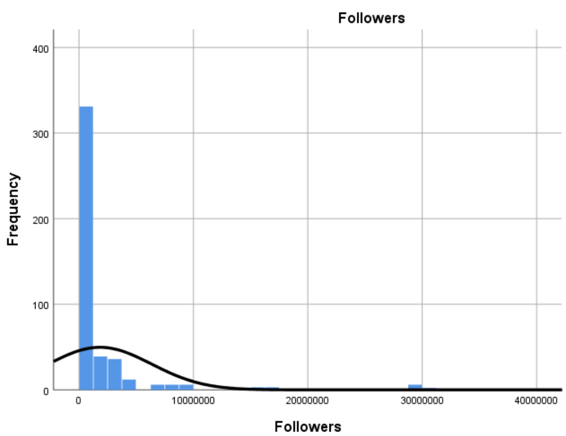
Travel			
Brand	**Cool**	**Neutral**	**Warm**
Australia	2	0	1
Two Nights In	1	2	0
Abercrombie & Kent	2	0	1
Adventure Culture	1	1	1
Airbnb	1	2	0
BBC Travel	1	2	0
Booking	1	2	0
CheapOAir	2	0	1
Conde Nast Traveler	1	1	1
Contiki	1	1	1
Destination British Columbia	2	1	0
Expedia	1	0	2
Explore Canada	2	1	0
FourSeasons	1	0	2
GoPro	1	1	1
Hilton Hotels	1	2	0
Iceland Travel	1	1	1
Interpid Travel	1	0	2
Kayak	1	0	2

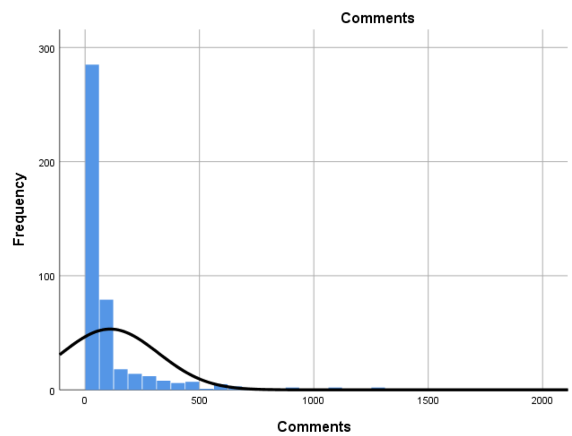
Kimpton	2	1	0
Visit California	1	2	0
Lonely Planet	0	1	2
Love Great Britains	1	1	1
Lufthansa	1	0	2
Margaret River Discovery	1	1	1
Marriott	1	1	1
Wilderness Safaris	0	1	2
Momondo	1	0	2
Nat Geo Travel	1	2	0
Norwegian Cruise Line	1	0	2
NY Times Travel	1	2	0
Orbitz	1	0	2
Aman	1	1	1
Royal Caribbean	1	2	0
Secret Escapes	1	1	1
Sky Scanner	2	1	0
Sheraton Hotels	1	1	1
Departures Mag	0	2	1
STA Travel	1	1	1
W Hotels Worldwide	2	1	0
Thomson Holidays	2	0	1
Travel + Leisure	1	1	1
Travel Alberta	1	2	0
Small Luxury Hotels	0	2	1
Travelocity	2	1	0
Tripadvisor	0	1	2
Travelling thorugh the Word	1	0	2
B Travel Brand	1	1	1
Travel Start	1	0	2
World Nomads	0	1	2
Total	54	48	48

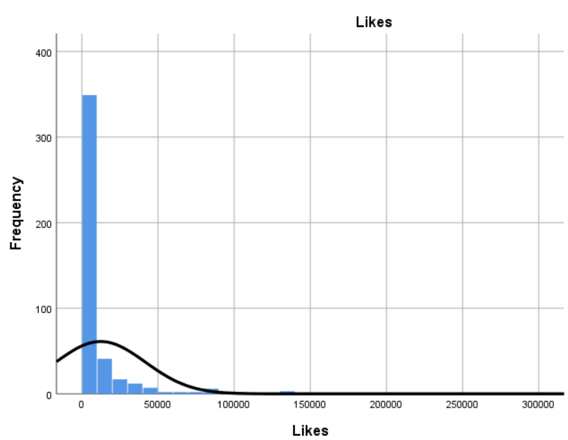
Appendix 2 – Histograms of the numeric variables with Normality Curves



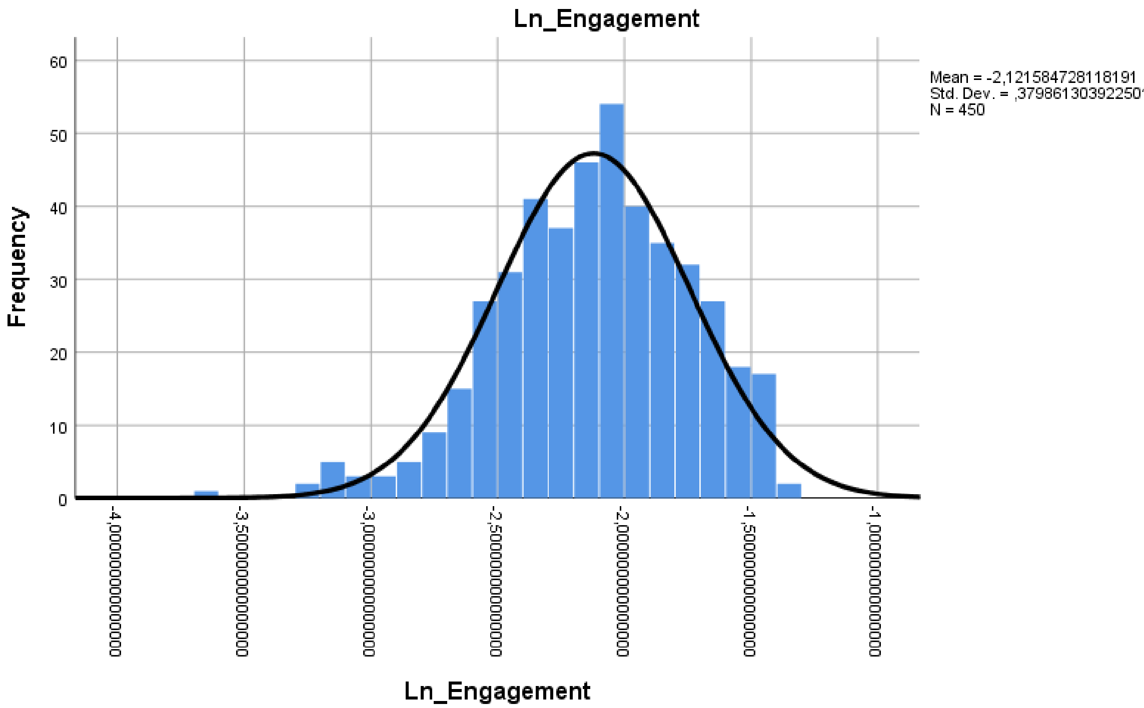


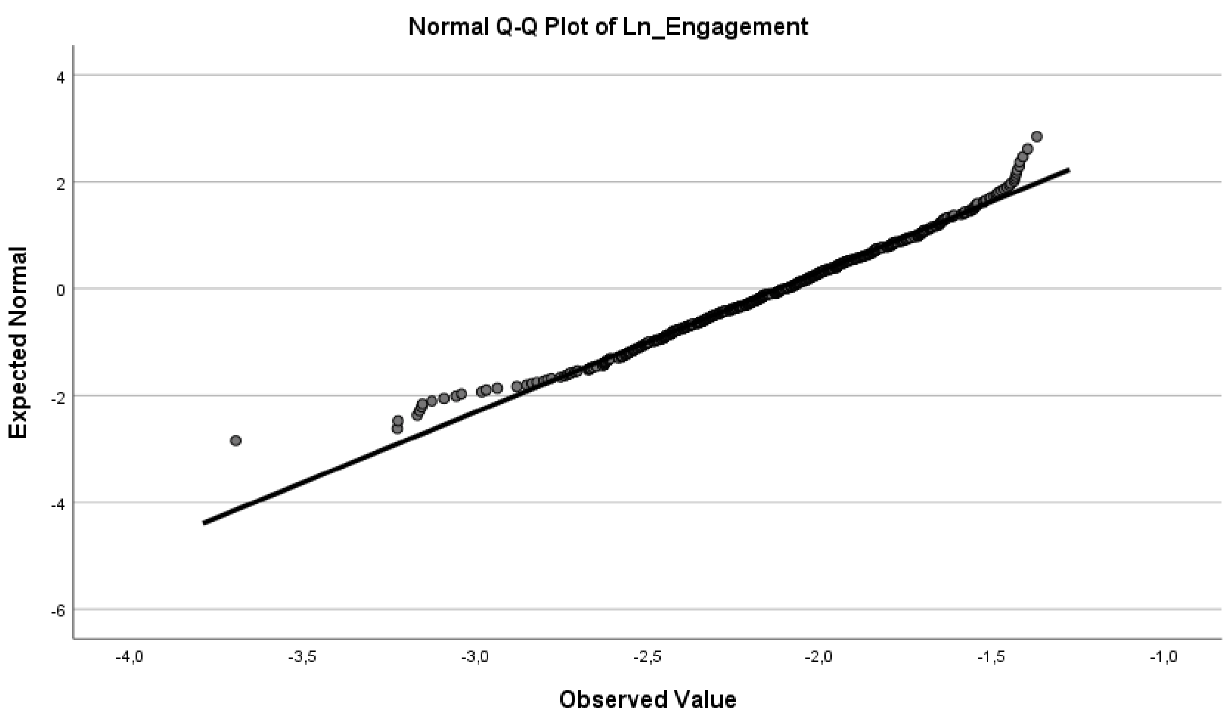






Appendix 3 – Normality Tests for the transformations of the dependent variable Engagement





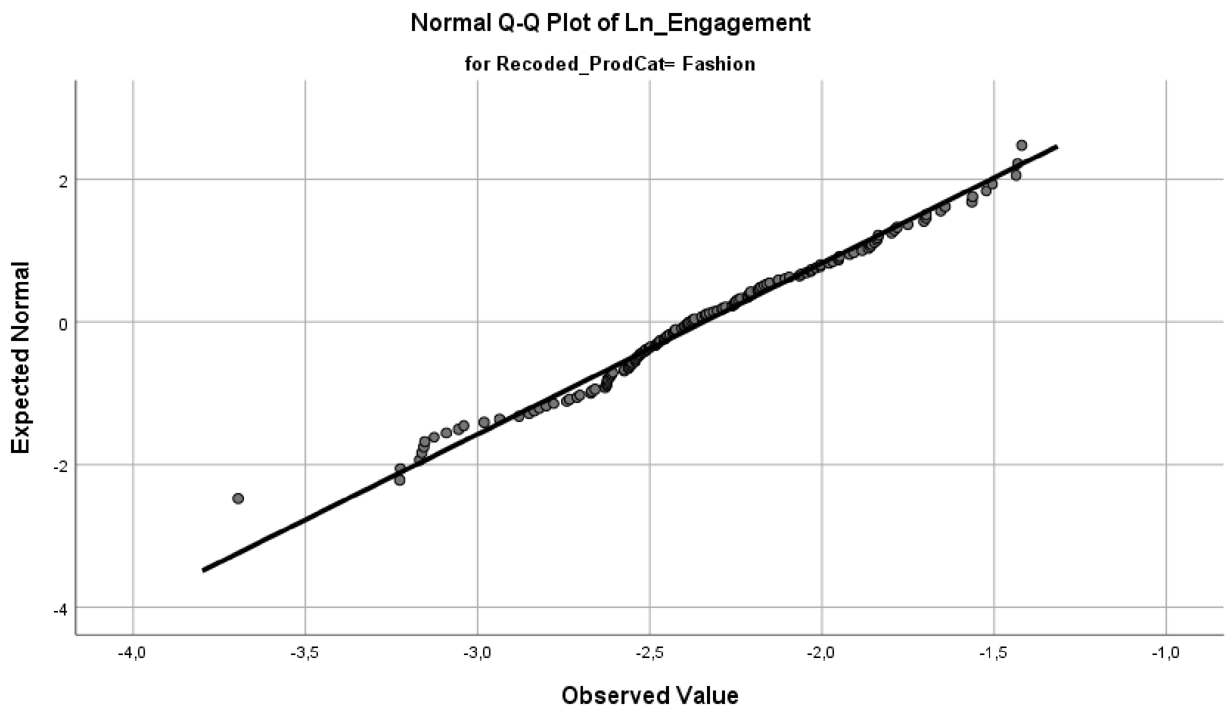
Appendix 4 – Test of Normality and Q-Q Plots for the Ln_Engagement and Product Category interaction

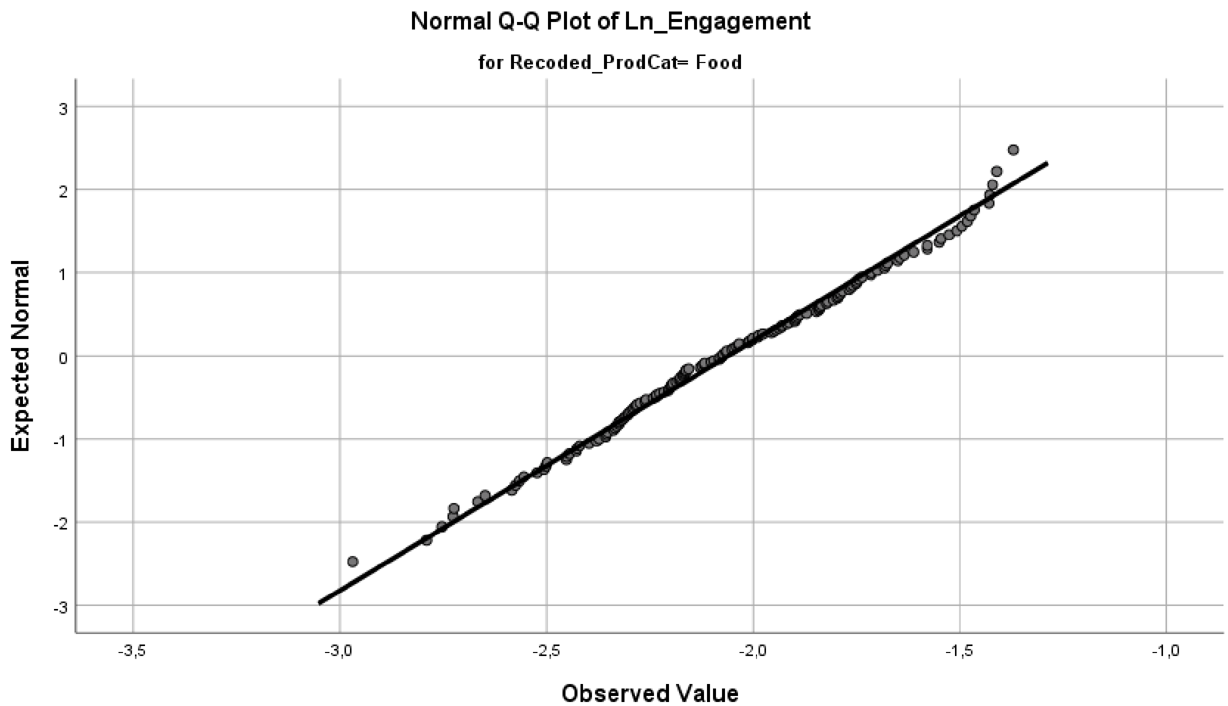
Tests of Normality

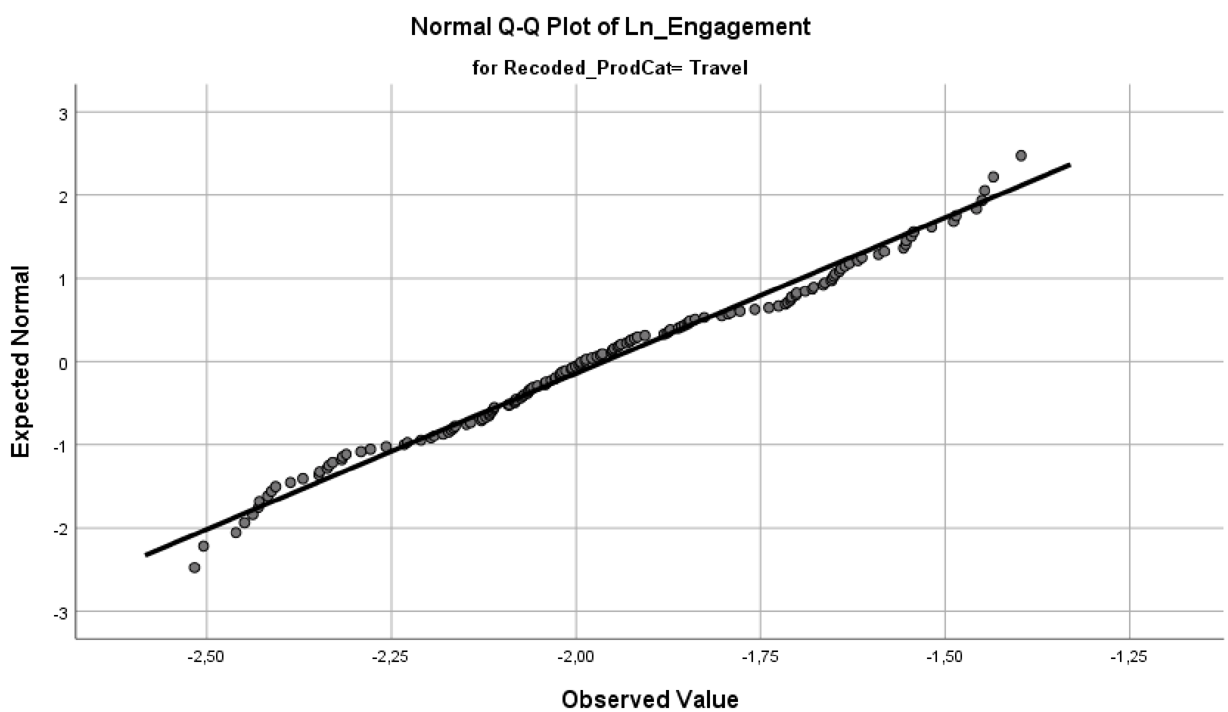
	Product Category	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
Ln_Engagement	**Fashion**	,072	150	,054	,987	150	,165
	Food	,055	150	,200*	,990	150	,406
	Travel	,068	150	,089	,981	150	,036

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction




Normal Q-Q Plot of Ln_Engagement
for Recoded_ProdCat= Food
Expected Normal
Observed Value
3
2
1
0
-1
-2
-3
-3,5
-3,0
-2,5
-2,0
-1,5
-1,0


Normal Q-Q Plot of Ln_Engagement
for Recoded_ProdCat= Travel
Expected Normal
Observed Value
3
2
1
0
-1
-2
-3
-2,50
-2,25
-2,00
-1,75
-1,50
-1,25

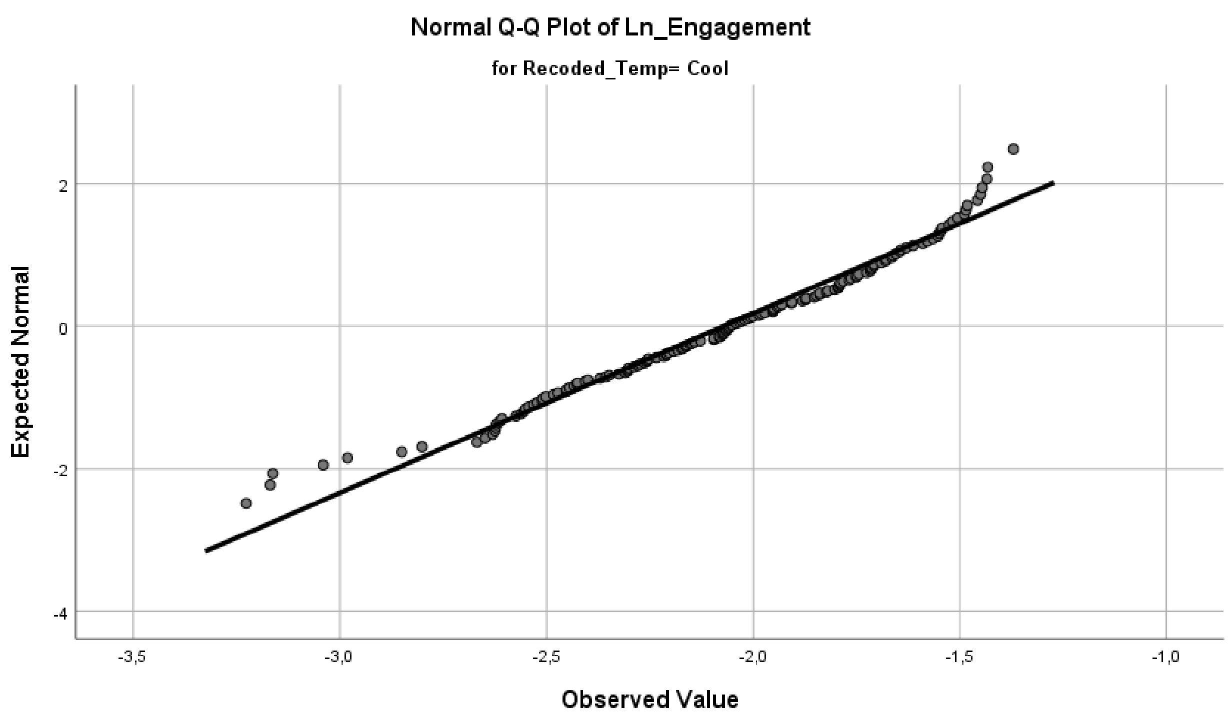
Appendix 5 - Test of Normality and Q-Q Plots for the Ln_Engagement and Color Temperature interaction

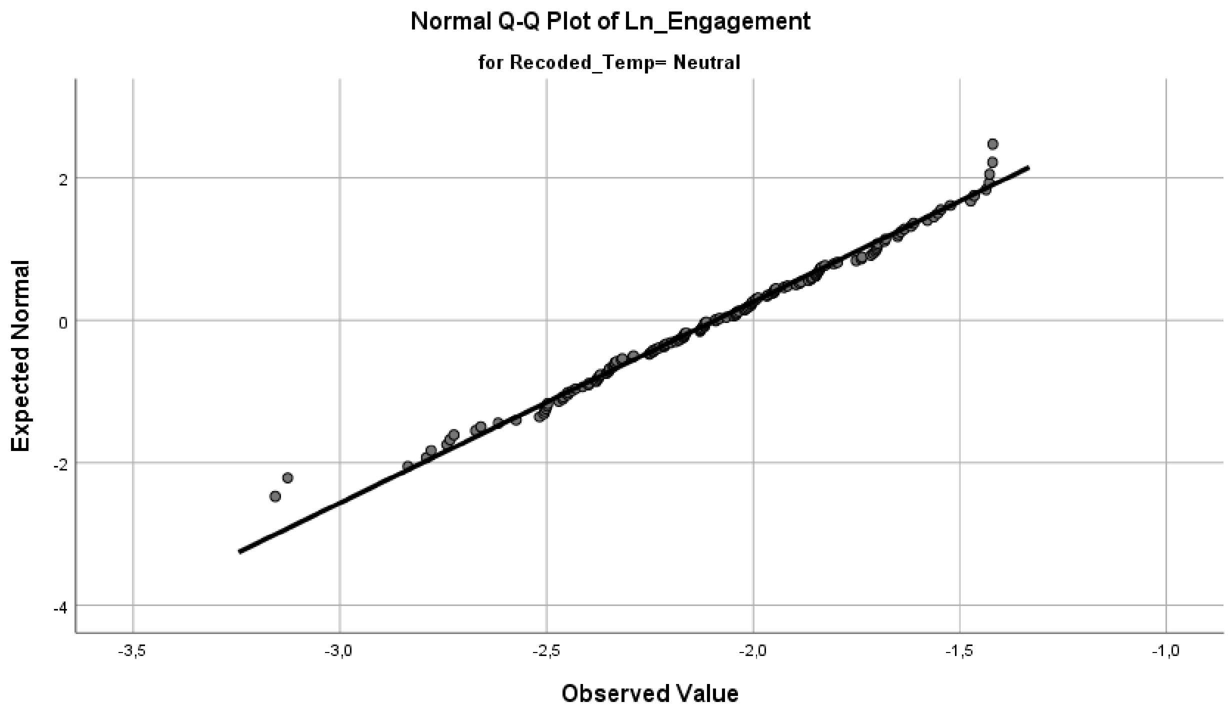
Tests of Normality

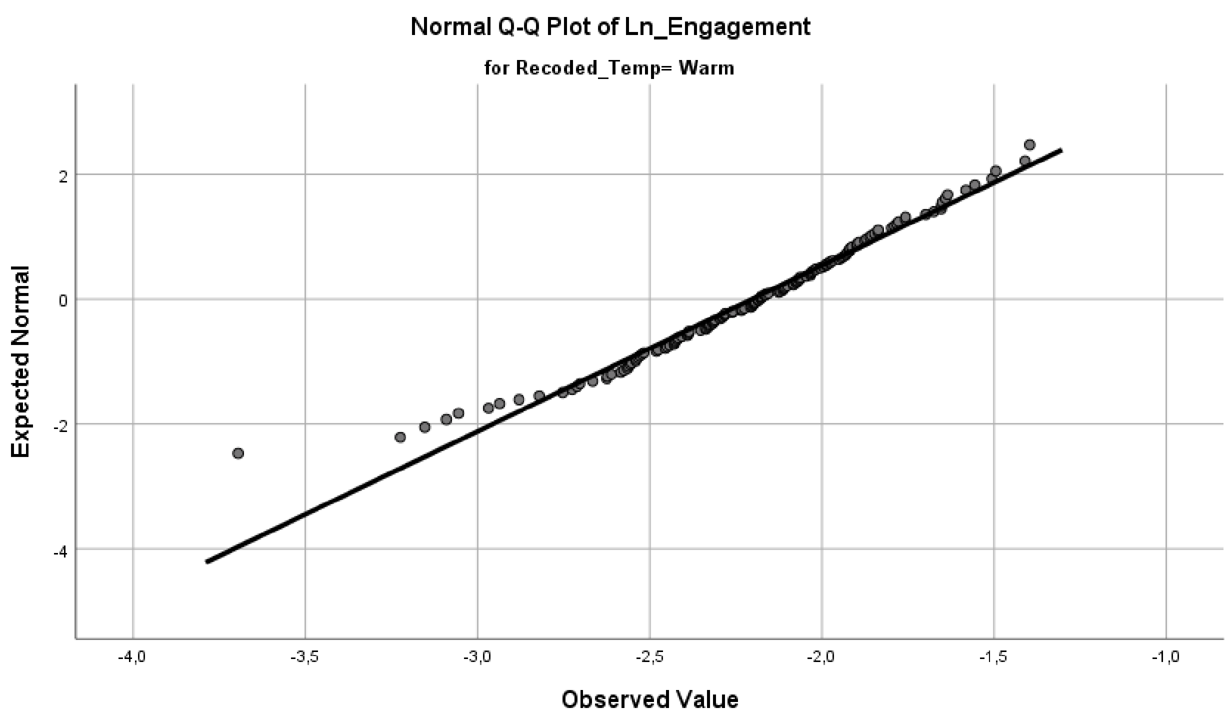
	Recoded_Temp	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
Ln_Engagement	**Cool**	,056	154	,200*	,972	154	,004
	Neutral	,039	148	,200*	,987	148	,165
	Warm	,050	148	,200*	,976	148	,010

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction




Normal Q-Q Plot of Ln_Engagement
for Recoded_Temp= Neutral
Expected Normal
2
0
-2
-4
-3,5
-3,0
-2,5
-2,0
-1,5
-1,0
Observed Value


Normal Q-Q Plot of Ln_Engagement
for Recoded_Temp= Warm
Expected Normal
2
0
-2
-4
-4,0
-3,5
-3,0
-2,5
-2,0
-1,5
-1,0
Observed Value

Appendix 6 – Results of the One-Way ANOVA comparing Engagement Rate means for each Color Temperature group

Descriptives

Ln_Engagement

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean Lower Bound	95% Confidence Interval for Mean Upper Bound	Minimum	Maximum
Cool	154	-2,07158896	,39672836	,031969283	-2,13474716	-2,00843075	-3,22647950	-1,37081346
Neutral	148	-2,09165900	,35400417	,029098963	-2,14916534	-2,03415266	-3,15626125	-1,42036295
Warm	148	-2,20353307	,375923619	,030900731	-2,26460012	-2,14246601	-3,69474511	-1,39703163
Total	450	-2,12158472	,379861303	,017906833	-2,15677633	-2,08639311	-3,69474511	-1,37081346

Test of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
Ln_Engagement	**Based on Mean**	1,073	2	447	,343
	Based on Median	1,041	2	447	,354
	Based on Median and with adjusted df	1,041	2	441,250	,354
	Based on trimmed mean	1,038	2	447	,355

ANOVA

Ln_Engagement

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1,511	2	,756	5,338	,005
Within Groups	63,277	447	,142		
Total	64,788	449			

Post Hoc Tests

Multiple Comparisons

Dependent Variable: Ln_Engagement

Tukey HSD

(I) Recoded_Temp	(J) Recoded_Temp	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Cool	**Neutral**	,02007004461	,04330929433	,888	-,0817737465	,12191383573
	Warm	,1319441083*	,04330929433	,007	,03010031714	,23378789940
Neutral	**Cool**	-,0200700446	,04330929433	,888	-,1219138357	,08177374651

	Warm	,1118740637*	,04373740320	,029	,00902355490	,21472457242
Warm	**Cool**	-,131944108*	,04330929433	,007	-,2337878994	-,0301003171
	Neutral	-,111874064*	,04373740320	,029	-,2147245724	-,0090235549

*. The mean difference is significant at the 0.05 level.

Appendix 7 - Results of the Two-Way ANOVA comparing Engagement Rate means for each Color Temperature and Product Category interactions

Univariate Analysis of Variance

Syntax	UNIANOVA Ln_Engagement BY Recoded_ProdCat Recoded_Temp /METHOD=SSTYPE(3) /INTERCEPT=INCLUDE /POSTHOC=Recoded_Temp(TUKEY) /PLOT=PROFILE(Recoded_Temp*Recoded_ProdCat) TYPE=LINE ERRORBAR=NO MEANREFERENCE=NO YAXIS=AUTO /EMMEANS=TABLES(Recoded_ProdCat*Recoded_Temp) COMPARE(Recoded_Temp) ADJ(LSD) /CRITERIA=ALPHA(0.05) /DESIGN=Recoded_ProdCat Recoded_Temp Recoded_ProdCat*Recoded_Temp.

Between-Subjects Factors

		Value Label	N
Product Category	1	Fashion	150
	2	Food	150
	3	Travel	150
Recoded_Temp	1	Cool	154
	2	Neutral	148
	3	Warm	148

Tests of Between-Subjects Effects

Dependent Variable: Ln_Engagement

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	15,381[a]	8	1,923	17,161	,000
Intercept	2018,964	1	2018,964	18020,832	,000
Recoded_ProdCat	11,558	2	5,779	51,583	,000
Recoded_Temp	1,670	2	,835	7,451	,001
Recoded_ProdCat * Recoded_Temp	1,942	4	,486	4,334	,002
Error	49,407	441	,112		
Total	2090,293	450			
Corrected Total	64,788	449			

a. R Squared = ,237 (Adjusted R Squared = ,224)

Post Hoc Tests

Product Category

Multiple Comparisons

Dependent Variable: Ln_Engagement

Tukey HSD

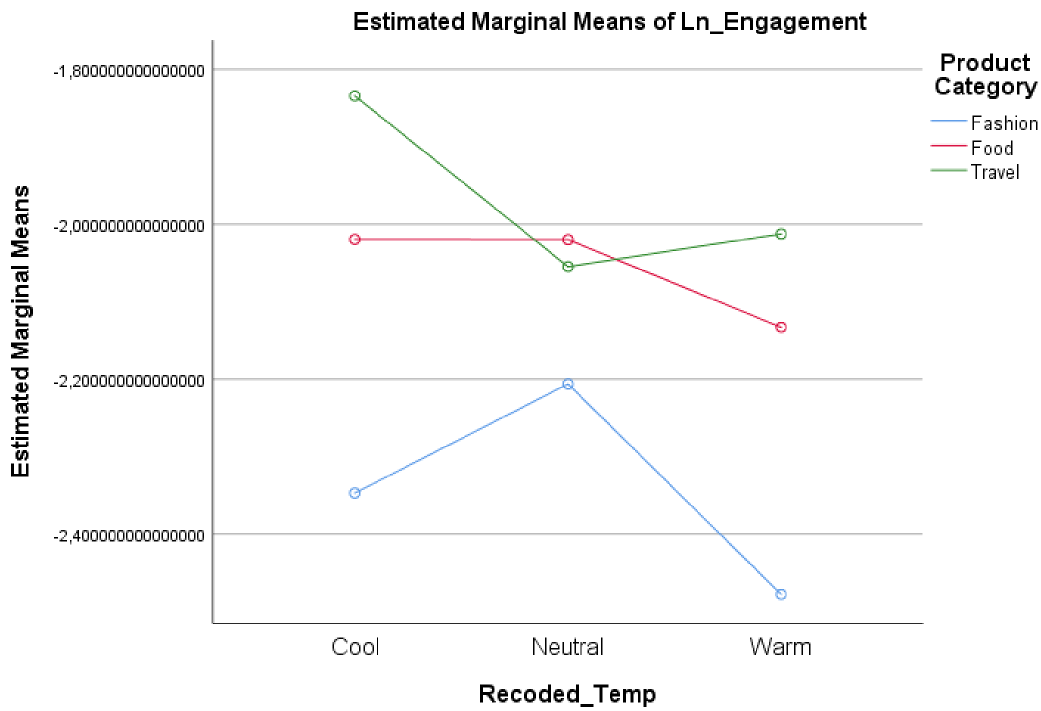
(I) Product Category	(J) Product Category	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Fashion	Food	-,283418436621*	,0386497096	,000	-,37430913793	-,19252773530
	Travel	-,381352499359*	,0386497096	,000	-,47224320067	-,29046179804
Food	Fashion	,283418436621*	,0386497096	,000	,192527735305	,374309137937
	Travel	-,097934062738*	,0386497096	,031	-,18882476405	-,00704336142
Travel	Fashion	,381352499359*	,0386497096	,000	,29046179804	,47224320067
	Food	,0979340627384*	,0386497096	,031	,007043361422	,18882476405

Based on observed means.

The error term is Mean Square(Error) = ,112.

*. The mean difference is significant at the ,05 level.

Profile Plots



Appendix 8 - Estimated Marginal Means on the Two-Way ANOVA for the interaction Product Category * Color Temperature

2. Product Category * Recoded_Temp

Estimates

Dependent Variable: Ln_Engagement

				95% Confidence Interval	
Product Category	**Recoded_Temp**	**Mean**	**Std. Error**	**Lower Bound**	**Upper Bound**
Fashion	**Cool**	-2,347	,045	-2,436	-2,259
	Neutral	-2,206	,048	-2,301	-2,111
	Warm	-2,478	,049	-2,574	-2,382
Food	**Cool**	-2,020	,050	-2,118	-1,921
	Neutral	-2,020	,046	-2,111	-1,929
	Warm	-2,133	,046	-2,223	-2,043

Travel	**Cool**	-1,834	,046	-1,924	-1,745
	Neutral	-2,055	,048	-2,150	-1,960
	Warm	-2,012	,048	-2,107	-1,917

Pairwise Comparisons

Dependent Variable: Ln_Engagement

Product Category	(I) Recoded_Temp	(J) Recoded_Temp	Mean Difference (I-J)	Std. Error	Sig.[b]	95% Confidence Interval for Difference[b] Lower Bound	Upper Bound
Fashion	**Cool**	**Neutral**	-,141*	,066	,034	-,271	-,011
		Warm	,131*	,066	,050	,000	,262
	Neutral	**Cool**	,141*	,066	,034	,011	,271
		Warm	,272*	,069	,000	,137	,407
	Warm	**Cool**	-,131*	,066	,050	-,262	,000
		Neutral	-,272*	,069	,000	-,407	-,137
Food	**Cool**	**Neutral**	,000	,068	,997	-,134	,134
		Warm	,114	,068	,095	-,020	,247
	Neutral	**Cool**	,000	,068	,997	-,134	,134
		Warm	,113	,065	,084	-,015	,242
	Warm	**Cool**	-,114	,068	,095	-,247	,020
		Neutral	-,113	,065	,084	-,242	,015
Travel	**Cool**	**Neutral**	,221*	,066	,001	,090	,351
		Warm	,178*	,066	,008	,048	,309
	Neutral	**Cool**	-,221*	,066	,001	-,351	-,090
		Warm	-,042	,068	,536	-,177	,092
	Warm	**Cool**	-,178*	,066	,008	-,309	-,048
		Neutral	,042	,068	,536	-,092	,177

Based on estimated marginal means

*. The mean difference is significant at the 0,05 level.

b. Adjustment for multiple comparisons: Least Significant Difference (equivalent to no adjustments).

Univariate Tests

Dependent Variable: Ln_Engagement

Product Category		Sum of Squares	df	Mean Square	F	Sig.
Fashion	**Contrast**	1,756	2	,878	7,836	,000
	Error	49,407	441	,112		
Food	**Contrast**	,440	2	,220	1,966	,141
	Error	49,407	441	,112		
Travel	**Contrast**	1,417	2	,709	6,325	,002
	Error	49,407	441	,112		

Each F tests the simple effects of Recoded_Temp within each level combination of the other effects shown. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.