MASTER'S DISSERTATION

"ONLINE CUSTOMER ENGAGEMENT ON INSTAGRAM: AN ANALYSIS OF SUBSCRIPTION VIDEO-ON-DEMAND SERVICES' POSTS"

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PORTO'S SCHOOL, JUNE 2022

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Dissertation presented to IPAM, to fulfill the requirements needed to obtain the Master's Degree in Marketing, developed under the scientific supervision of Professor Miriam Taís Salomão, Ph.D.

ACKNOWLEDGEMENTS

To my advisor, Prof.ª Dr.ª Miriam Taís Salomão, I would like to express my sincere gratitude for all the help and expertise in the development of this thesis. The constant availability and dedication were crucial, but most importantly the trust put in me and the patience to deal with my constant doubts.

To Professor Bruno Carvalho da Silva, I would like to offer a special thanks for all the specific knowledge and guidance given which helped my thesis go further than I thought it could.

To my parents and my sister, I extend my gratitude as their faith in me has kept my motivation high during this journey.

To Zé, I want to show my deep appreciation for all the emotional support and for always believing in me.

ABSTRACT

Social media has become one of the most influential and important virtual platforms, both for users and businesses. Thus, there has been a growing necessity for insight into what works for each industry. That leads to this study's main goal, which is to investigate the influence of social media posting of subscription video-on-demand services (Netflix Portugal, Disney Plus Portugal and HBO Portugal) on Portuguese customer engagement.

Therefore, a literature review was conducted about customer engagement, social media post characteristics, eWOM comment valence and the relationship between SVoD services and social media. As a netnography, posts from Netflix Portugal, Disney Plus Portugal and HBO Portugal were collected, over the period of one month, for a total of 142 posts. Also, 3402 comments were analysed using VADER lexicon and sentiment analysis tool.

The statistical analyses allowed to conclude that an image and emotional appeal increases the number of likes, the use of a carousel increases the number of likes and comments, while interactivity decreases the number of likes and comments. It is also possible to do a reliable prediction for the number of likes based on the use of a carousel, the interactivity and the post appeal, as well as for the number of comments based on the use of a carousel and interactivity. There was no statistically significant relation between the post characteristics and eWOM comment valence. Managers of SVoD brands can be guided by this research with regard to deciding which characteristics they should use when posting.

Keywords: Online Customer Engagement; eWOM comment valence; Sentiment Analysis; Instagram; SVoD services.

RESUMO

As redes socias tornaram-se numa das plataformas virtuais mais influentes e importantes, tanto para os utilizadores como para as empresas. Assim, tem havido uma crescente necessidade de entender o que funciona para cada indústria. Isso leva ao objetivo principal deste estudo, que é investigar a influência das publicações das redes sociais dos *subscription video-on-demand services'* (Netflix Portugal, Disney Plus Portugal and HBO Portugal) no *customer engagement* português.

Logo, foi realizada uma revisão de literatura sobre *customer engagement*, as características das publicações das redes sociais, *eWOM comment valence* e a relação entre *SVoD services* e as redes sociais. Como uma netnografia, foram recolhidas publicações da Netflix Portugal, Disney Plus Portugal e HBO Portugal, durante o período de um mês, num total de 142 publicações. Além disso, foram analisados 3402 comentários usando o léxico e a ferramenta de análise sentimental VADER.

A análise estatística permitiu concluir que uma imagem e o apelo emocional aumentam o número de *likes*, o uso do carrossel aumenta o número de *likes* e de comentários, enquanto a interatividade diminui ambos. De igual modo, é possível fazer uma previsão confiável para o número de *likes* com base no uso do carrossel, na interatividade e no apelo, tal como para o número de comentários com base no uso do carrossel e na interatividade. Não houve relação estatisticamente significativa entre as características das publicações e a *eWOM comment valence*. Os responsáveis pelas marcas dos *SVoD services*

podem ser guiados por esta pesquisa no que diz respeito a decidir quais as características que devem usar nas suas publicações.

Palavras-chave: *Online Customer Engagement; eWOM comment valence*; Análise Sentimental; Instagram; *SVoD services*.

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SVoD – Subscription video-on-demand

WOM – Word-of-mouth

eWOM – Electronic word-of-mouth

US – United States

ANOVA – Analysis of Variance

INTRODUCTION

Over the course of the last decade, social media has emerged as a force with 4.55 billion users worldwide, in October 2021, equating to 57.6 per cent of the total global population (Kemp, 2022). New platforms utilizing Web 2.0 technologies offer interaction and communication opportunities between brands and consumers making social media a viable and critical marketing tool (Aydin, 2020). Customers, by liking, commenting or sharing on brand posts, offer direct feedback about their perceptions of the branded content and disseminate it throughout their social network reaching new audiences (Demmers et al., 2020). Because customers are spending more time on their mobile devices, marketers must create strategies to develop their presence and effectively engage with customers (Mathews & Lee, 2018).

Despite this, brands face challenges in converting social media investments into meaningful customer engagement (Santini et al., 2020). Since an average of 43.2 per cent of the global population uses social media to do brand research (Kemp, 2022), brands need to understand how they should interact with their online customers and which factors influence customer engagement (Tavares & Nogueira, 2021). Engaged customers have been seen to contribute to sales increases, improved positive word-of-mouth, and enhanced organizational performance (Bijmolt et al., 2010), which justifies its strategic importance. The online share of opinions and comments amongst customers, known as the electronic Word-of-Mouth (eWOM), has become so powerful that it can affect how customers perceive brands. Hence the importance of brand knowledge to positively influence what is being discussed online among customers (Chemela, 2019).

Among the world's most used social media platforms are Facebook, YouTube, WhatsApp and Instagram (Statista, 2021c). Instagram, a mobile-based application, has been incessantly growing and appealing to more customers since its creation in 2010 (Brunner & Diemer, 2019). Instagram is the fourth most popular social media platform, reaching a billion active users (Statista, 2021c). The platform can be used by both private and corporate users and offers editing and posting features (e.g., posts in the main feed, Stories, Reels, and IGTV) and communication tools (e.g., direct messages and video calls). With the creation of Instagram Business in 2016, brands started to use Instagram as a way to raise brand awareness, build a brand community and get real-time statistics about followers and interaction metrics (Chemela, 2019). According to Instagram, there are more than 200 million business accounts globally that users visit every day and 90% of Instagram users follow at least one business (Instagram Business Team, 2020) which is a big opportunity for brands.

In recent years, subscription video-on-demand (SVoD) services have become relevant players within the video market (Wayne, 2018). According to Valuates Reports (2020), the SVoD market size, in 2019, was 24.9 billion dollars and it is expected to reach 32.3 billion dollars by 2025 at a 4.5% compound annual growth rate. SVoD services offer their subscribers a customized catalogue of video content accessible 24/7 at a fixed monthly rate which creates flexibility in when to watch content and on which devices to watch it (Taeyoung Kim, 2022; Noh, 2021; Pérez, 2020; Wayne, 2018). The first movers in this market were Netflix and Amazon Prime, followed by Hulu and HBO and, more recently, by Disney Plus, Apple TV and Peacock (Taeyoung Kim, 2022). According to the European Audiovisual Observatory, in 2019, the three most relevant SVoD services in the Portuguese market were Netflix (47%), AppleTV (21%) and Amazon Prime (13%) with 22 out of every 100 Portuguese households having at least one SVoD service. This is above the European average of 18 out of 100 (Grece, 2021).

All these services are competing for attention and, more importantly, for subscribers, and they are doing it through the quality of their content but also through brand perception (Rahe et al., 2021). According to Conviva (2021), content streamed for the first time was discovered in four ways: word-of-mouth, advertising, social media and streaming service recommendations, which emphasizes the importance of social media for this market.

SVoD not only dodged the damaging effects of the COVID-19 pandemic but indirectly prospered because of it. With people being forbidden to leave their homes due to lockdowns, and having limited forms of entertainment, SVoD gained a massive boost with an increase in the number of hours spent watching and, also, in the number of subscribers (Hooson, 2021; Rajan, 2020). In 2020, it was expected that the number of global subscribers of SVoD would be 900 million but it reached 949 million mostly due to the pandemic (Statista, 2021a).

In the past decade, numerous studies have investigated what drives consumer engagement with brand-generated content on social media platforms. However, there is a lack of a cohesive basis for researching customer engagement in social media and, also, very few studies provide data in the Instagram context given that Instagram is relatively new to the customer engagement scene (Bilro & Loureiro, 2020; Castillo et al., 2021; Paruthi & Kaur, 2017; Santini et al., 2020).

Considering this, the main research goal of this study is to investigate the influence of social media posting of subscription video-on-demand services (Netflix Portugal, Disney Plus Portugal and HBO Portugal) on Portuguese customer engagement. To achieve it, the specific goals are:

- To analyse how each social media post characteristic (post type, use of a carousel, time frame, interactivity and post appeal) impacts the online customer engagement (number of likes, number of comments and eWOM comment valence) on Instagram.
- To evaluate how the combination of social media post characteristics (post type, use of a carousel, time frame, interactivity and post appeal)

can predict online customer engagement (number of likes, number of comments and eWOM comment valence) on Instagram.

The present chapter serves as an introduction to the problem background and the research's main goal and specific goals. In the next chapter, the literature review will establish the theoretical bases through prior research. Then, the study will proceed with the definition of the methodological approach and the choice of data collection and analysis tools to be used. This research will end with the analysis and discussion of the results, which will respond to the initially established research goals.

1. Literature Review

In this literature review chapter, the concept of customer engagement will be investigated, and then the social media post characteristics enumerated and analysed. After this, the definition of eWOM comment valence and its influence on customer engagement will be explored and the relationship between SVoD services and social media reviewed.

1.1. Customer Engagement

The term engagement started to be explored in the context of employees' behaviour and it began to be studied from a marketing perspective at the beginning of the current century (Bowden, 2009; Vivek et al., 2012). The array of 'engagement'-based concepts clarifies the increasing and developing importance of this concept for marketing research (Hollebeek et al., 2014). One of these concepts is customer engagement with the brand. Even though this term is not a novelty, its operationalization is still evolving, which means that there is not a universally accepted definition (Addo et al., 2021; Obilo et al., 2021). One of the most well-known definitions belongs to Bowden (2009, p.65) under a service brand context, which characterizes engagement as a "psychological process that models the underlying mechanisms by which customer loyalty forms for new customers of a service brand as well as the mechanisms by which loyalty may be maintained for repeat purchase customers”. So, here, engagement is seen as a mixture of calculative commitment, trust, participation and, ultimately, emotional commitment (Bowden, 2009). Hollebeek et al. (2014, p.6) defined customer engagement as a “consumer's positively valenced brand-related cognitive, emotional and behavioural activity during or related to focal consumer/brand interactions”. In this definition, the widely defended notion of customer engagement as a multidimensional concept is present. Cognitive refers to the thought processing and rationality present in brand interaction; while emotional refers to the degree of affection in that same interaction; finally, the behavioural refers to the level of effort, energy and time spent on that interaction (Hollebeek et al., 2014) with an emphasis on the active role of the customer (Javornik & Mandelli, 2012). So, customer engagement is more focused on the aspects that influence the decision-making process of purchasing a product/service and goes beyond the act of purchase itself (Vivek et al., 2012). This increases the complexity of the concept and demands researchers to look at it through different lenses to fully understand it (Pansari & Kumar, 2017). As a result, the present study adopts a behavioural and emotional conceptualization of customer engagement in social media.

Customer engagement behaviours have become an ever-growing important topic since it has been proven that it has business results such as sales growth, cost reductions, greater profitability, brand referrals and customer loyalty (Bowden, 2009; Hollebeek et al., 2014). An engaged customer has an emotional intimacy with a brand that results in repeat purchases and retention and, also, positive word-of-mouth (WOM) and user-generated content (Sashi, 2012) which, in consequence, helps create the previously mentioned results. So, these behaviours are seen as the "mechanics" that create value for a business (Pansari & Kumar, 2017) since customers have become more active and engaged participants in the creation and consumption of brands' activities (Obilo et al., 2021). This happens since engaged customers join in behaviours such as "recommending, referring and discussing the brand on social media as well as providing feedback to the company" (Chiang et al., 2017; Pansari & Kumar, 2017). This reveals the importance of understanding how customers can be better engaged to maximize businesses' success and of devoting the necessary resources to build customer engagement past business–customer transactions (Pansari & Kumar, 2017). It is also important to measure customer engagement and many scales were created in order to quantify this phenomenon (Bowden, 2009; Hollebeek et al., 2014; Vivek et al., 2012). However, all these scales are self-assessed measurements whose data is collected through surveys with consumers (and, therefore, measure the declared engagement). No scale was found in the literature for the measurement of real online engagement behaviour that captures consumers' reactions as likes and comments on posts.

The interest in customer engagement was boosted with the arrival of social media (Hudson & Thal, 2013) since it offers the opportunity to engage with customers and achieve greater reach. This happens due to the nature of social media that allows brands to improve their relationship with existing customers and communicate with new ones (N. J. De Vries & Carlson, 2014). Just as the definition of customer engagement, social media also does not have a consensual definition agreed by all, but the importance of these platforms for managers is undeniable (Weller, 2015). Stephen and Bart (2015) considered three forms of information flow that are simplified by social media: first, the brand-to-customer information flow in the form of brand posts and social media advertising (Hewett et al., 2016); second, the customer-to-brand information flow in the form of likes, comments and customer-generated content (Gensler et al., 2013); and third, the customer-to-customer interactions, which can take the form of WOM (Verhoef et al., 2010) and brand communities (Dessart et al., 2016). All these forms of information flow interact with each other since characteristics of a brand post drive online customer engagement behaviour, such as liking, commenting and sharing (Schultz, 2017). Vivek et al. (2012) defend that engaged and satisfied customers are more likely to provide positive WOM and act as an advocate of the brand. However, if there is no satisfaction, the customer may warn others of the experience by engaging in negative WOM which can damage the brand image (Van Doorn et al., 2010). This means that brands have to manage their online customer engagement on social media carefully to avoid negative WOM (Hollebeek et al., 2014). Hence, brands should take advantage of the interactive nature of social media to create brand-related conversations to emotionally connect and have a closer relationship with customers resulting in higher levels of online customer engagement (Wang & Kim, 2017).

To conclude, value, trust, emotional commitment, WOM, loyalty and brand community are outcomes of customer engagement (Vivek et al., 2012). Therefore, to benefit from these outcomes, brands should have a steady flow of quality posts on social media to positively drive online customer engagement (Grover & Kar, 2020). The characteristics of these posts will be discussed, according to the literature, in the next sub-chapter.

1.2. SOCIAL MEDIA POST CHARACTERISTICS

As it was previously aforementioned, brands need to understand which post characteristics promote engagement and, for this, they have to recognize which ones exist and their differences. Brands have initial control over the content they post, so they should take advantage of that by making good decisions on the characteristics of the post (Lei et al., 2017). This means that a brand's customer engagement activities in social media should be managed from the combined perspective of the customer and the brand to benefit both parties (Larivière et al., 2013). Besides this, social media makes behavioural metrics such as likes, comments and shares quickly available for analysis (Barger et al., 2016).

Social media platforms, most specifically Instagram but also others, have an internal algorithm that analyses each post to, then, decide which ones to present to a specific user. This algorithm is continuously changing, but one of the key criteria is the amount of user interaction, which is determined by the number of likes, comments and shares of a post. User interaction determines post distribution and, ultimately, post effectiveness. Considering this, increasing user interaction should be a brand's central goal (Wagner et al., 2017). However, as C. Kim & Yang (2017) have studied, different behaviours have different amounts of intensity and levels. Likes, which are on the lower level, demand less commitment and cognitive effort since it is only a click. Comments, which belong to the intermediate level, require extra commitment and cognitive effort given that it demands the customer to express itself through written words or emojis. Finally, shares occupy the highest level with the highest demand of commitment and cognitive effort, because the shared post is part of the customer's self-presentation since it appears on its own page visible to its friends and family (C. Kim & Yang, 2017).

There is also an important distinction, according to Sabate et al. (2014), between soft and hard criteria that help categorize content attributes of social media platforms. The soft criteria are qualitative and focus on the semantics and interpretation behind a post which requires a subjective content analysis of texts, images or videos. The hard criteria are more objective and allow to be quantified without subjective interpretation (Sabate et al., 2014). Different studies have had different focuses. For instance, some studies focused solely on soft criteria such as post category (Coelho et al., 2016) or post appeal (Wagner et al., 2017). Other studies focused only on hard criteria by looking, for example, into the richness of a post (image, video or link) and its time frame (Sabate et al., 2014). Other studies went further and researched a mix of both soft and hard criteria. C. Kim and Yang (2017) studied both the format of a post (text, photo, audio, video) and message interactivity. Schreiner et al. (2019) used classifications such as topic, component, length, interactivity, shared or original content, timing and position. Both studies, Balio and Casais (2021) and Tavares and Nogueira (2021), suggested four determinants for influencing customer engagement: post type, time frame, interactivity and post appeal.

In the next five sections, each driver will be thoroughly explored considering the existing literature about them.

1.2.1.Post Type

The first characteristic addressed is post type, a hard criterion. Post type has been present in a variety of studies which shows its significance since the majority demonstrate that this characteristic is a relevant predictor of online customer engagement. However, different authors have achieved distinct conclusions, mostly due to the differences in industries, countries and social media platforms (Balio & Casais, 2021).

L. De Vries et al. (2012) analysed the vividness of a post by looking into three different levels. The low level of vividness was defined as a photo or image, the medium level was an event, and the highest level was a video. For L. De Vries et al. (2012), the degree of vividness varied according to the way each format stimulated different senses. A video is considered more vivid than a picture because it stimulates both sight and hearing. A multisensory post with a higher vividness degree seems to have a positive effect on the number of likes, but not on the number of comments (L. De Vries et al., 2012). Cvijikj and Michahelles (2013) concluded the same by defending that videos enhanced like and share behaviour, but it did not have any significant effect on the commenting behaviour, while photos enhanced both like and comment behaviour.

Sabate et al. (2014) chose a different way of differentiating content types (images, videos and links) to reduce the subjectivity of how richness can be perceived. Despite the difference in categorization, the conclusion was the same since they supported that image creates more customer engagement than videos since videos only had a significant effect in terms of likes. However, C. Kim and Yang (2017) and Schultz (2017) defended the opposite of L. De Vries et al. (2012), Cvijikj and Michahelles (2013) and Sabate et al. (2014) since they concluded that photos have a negative impact on the number of comments.

More recently, Moran et al. (2020) found that both photos and videos have a positive effect on likes and comments within the media sector. Balio and Casais (2021) concluded that, on Facebook, video has a more positive effect on likes, reactions, comments and shares while images only were significantly related to likes, reactions and comments. On Instagram, videos had a negative effect on likes, so the authors concluded that the preferred type is image due to the specifications of the social media platform (Balio & Casais, 2021). Tavares and Nogueira (2021) determined that, on Facebook, images generated more likes and comments, while videos generated more shares. On Instagram, the authors concluded that the post type did not have any effect on the likes and comments (Tavares & Nogueira, 2021). Finally, Shahbaznezhad et al., (2021) concluded that photos encouraged likes while videos encouraged comments.

Despite the variances in the conclusions, as it is possible to see in Table 1, there seems to be a consensus that the use of either images or videos in social media can, overall, impact positively customer engagement (Balio & Casais, 2021; L. De Vries et al., 2012; C. Kim & Yang, 2017; Moran et al., 2019; Cvijikj & Michahelles, 2013; Sabate et al., 2014; Schultz, 2017; Shahbaznezhad et al., 2021; Tavares & Nogueira, 2021).

Argument(s)	Authors supporting the argument(s)
Video provided the highest level of vividness, but this only translated in the number of likes and shares and not in the number of comments. Photo/image generated both likes and comments.	Cvijikj & Michahelles, 2013; L. De Vries et al., 2012; Sabate et al., 2014
Photo/image had a negative impact on the number of comments.	C. Kim & Yang, 2017; Schultz, 2017
Photo encouraged likes while video encouraged comments.	Shahbaznezhad et al., 2021
Both photo and video had a positive effect on likes and comments.	Moran et al., 2020
On Facebook, video generated more engagement than image. On Instagram, image was the preferred type.	Balio & Casais, 2021
On Facebook, image generated more engagement than video. On Instagram, the post type was irrelevant.	Tavares & Nogueira, 2021

Table 1 – Post Type's Literature Summary
Source: Own Elaboration

1.2.2.Use of a carousel

The second characteristic under analysis is the use of a carousel, another hard criterion. In 2017, Instagram added a new feature called carousel which allows users to upload up to 10 images or videos or a combination of both in one large post, forming a slideshow (Jones & Lee, 2021). Users can swipe right or left to look at a carousel post (Wahid & Gunarto, 2021) which increases potential post-interaction (Jones & Lee, 2021). With this feature, a message can be given in a single image/video or divided into several. Besides aesthetic decisions, this option can help focus the user's attention on specific and shorter messages, while if the content is concentrated in one single image/video, the user receives all the stimuli at once (Oltra et al., 2021). Mixed multimedia features like carousels are slightly more vivid than images, demanding followers to interact longer with the post to see all the images (Jones & Lee, 2021).

This is a very recent subject, and somehow neglected, in social media studies (Wahid & Gunarto, 2022) and only two authors studied the effects of using this feature on customer engagement. Oltra et al. (2021) found that when a call to action is introduced in a carousel it creates greater stimulation to act and intention to participate in eWOM. Wahid and Gunarto (2021) concluded that the use of the carousel format significantly enhanced likes, but it had an insignificant effect on comments.

Thus, this study updated prior studies by focusing on a neglected feature in academia that has been evermore used in social media. In table 2 is possible to find a summary of the literature reviewed.

Argument(s)	Authors supporting the argument(s)
The use of a carousel creates greater stimulation to act and intention to participate in eWOM.	Oltra et al., 2021
The use of the carousel significantly enhanced likes, but it had an insignificant effect on comments	Wahid & Gunarto, 2021

Table 2 – Use of a carousel's Literature Summary
Source: Own Elaboration

1.2.3.Time Frame

The third characteristic reviewed is time frame, also a hard criterion. Researchers have been recognizing the importance of knowing when to publish a post on social media since the so-called 'walls' have been overloaded with content and it is possible for the post to lose its spotlight without being seen due to bad timing (Cvijikj & Michahelles, 2013; Sabate et al., 2014).

In the different studies, time has been framed through three different perspectives: the first one and most frequent is the weekday vs weekend approach; the second one is the influence of the time of publication (hours); and the third one refers to the seasonality of posts (months) (Balio & Casais, 2021).

Cvijikj and Michahelles (2013) found that posting during the weekday affected positively the commenting behaviour, while the behaviour of the likes saw only a small negative effect. Wagner (2017) also concluded that posting on the weekend (Saturday and Sunday) receives fewer comments than weekday posts. L. De Vries et al. (2012) and Coelho et al. (2016) did not find any significance statistically regarding days of the week as a control variable. Tavares and Nogueira (2021) also concluded that time frame was not significantly related to none of Facebook and Instagram metrics. Thus, more research has to be developed to understand the effect of time frame.

Regarding time of publication, Cvijikj and Michahelles (2013) distinguished between low (from 4 am to 3 pm) and peak hours (from 4 pm to 3 am) defined considering the volume of posts and determined that peak hours negatively affect engagement in terms of likes and shares, while commenting was not influenced. Differently, Sabate et al. (2014) differentiated between business (from 10 am to 4 pm) and non-business hours and found that posting during business hours has a positive effect only on the number of comments. As it is possible to see, there is some dispute over the exact definition of the most effective time period (Sabate et al., 2014) that might explain the differences in the conclusions. This distinction might not work for brands that work globally due to time zones which are also important to consider (Schultz, 2017).

Finally, concerning seasonality, Coelho et al. (2016) used the months from January to August to prove that customer engagement is influenced by the month a post is published. On Facebook, months such as March, April, May and June had the biggest increases in terms of likes and February, March, April and July had rises in the number of comments. On Instagram, the impact, although not equal every month, was all positive. Some of the positive variances could be explained by the existence of national holidays and vacation period in the country surveyed (Coelho et al., 2016). Balio and Casais (2021) also analyse the impact of months on customer engagement. On Facebook, December was negatively related with likes and comments, August with reactions and October with the number of reactions and comments. On Instagram, no conclusion was achieved since no month had a significant variable.

Thus, despite the controversy on the exact 'when', there is a recognized importance for brands to know when to post on social media (Balio & Casais, 2021; Coelho et al., 2016; Cvijikj & Michahelles, 2013; L. De Vries et al., 2012; Sabate et al., 2014; Tavares & Nogueira, 2021; Wagner et al., 2017). In Table 3, it is possible to see a summary of the aforementioned arguments.

Argument(s)	Authors supporting the argument(s)
Posting during the weekday had better customer engagement than posting on the weekend.	Cvijikj & Michahelles, 2013; Wagner et al., 2017
Posting on a weekday vs weekend showed no statistical relevance for engagement.	Coelho et al., 2016; L. De Vries et al., 2012; Tavares & Nogueira, 2021
Posting during peak/business hours negatively affected likes and shares.	Cvijikj & Michahelles, 2013; Sabate et al., 2014
On Facebook, February, March, April, May, June and July had increases in engagement, while on Instagram it was all positive.	Coelho et al., 2016
On Facebook, August, October and December negatively affected engagement, while it had no significance on Instagram.	Balio & Casais, 2021

Table 3 – Time Frame's Literature Summary
Source: Own Elaboration

1.2.4. Interactivity

The fourth characteristic is interactivity, a soft criterion. Interactivity in the online context has been defined as "the extent to which the communicator and the audience respond to each other's communication needs" (Ha et al., 1998). In this case, the communicator is the brand and the audience is the customer, which engage in two-way communication (Aydin, 2020; Demmers et al., 2020). The communication promoted by interactivity is key in social media since it supports the development of relationships (Lei et al., 2017).

Different studies have achieved distinct conclusions on whether interactivity increases engagement (Aydin, 2020; Balio & Casais, 2021; Bozkurt et al., 2020; Cvijikj & Michahelles, 2013; L. De Vries et al., 2012; Demmers et al., 2020; C. Kim & Yang, 2017; Lei et al., 2016; Luarn et al., 2015; Sabate et al., 2014; Tavares & Nogueira, 2021) and what is the optimal level of interactivity. Demmers et al. (2020) defend that the optimal level depends on the match between the effort needed to interact and the customers' willingness to exercise that effort. Interactivity has different levels depending on the content and the amount of effort required rises with the increase of the interactivity (Demmers et al., 2020). There are four levels: no interactivity, where there is no interactive content; low interactivity, which is a link to a website or a hashtag; medium interactivity, which is contests, quizzes or polls; and high interactivity, which is an open question (L. De Vries et al., 2012; Demmers et al., 2020).

L. De Vries et al. (2012) concluded that posting a question has a negative effect on the number of likes since it cannot be answered through likes, but also interactive brand characteristics do not have an effect on the number of comments and website links have a negative effect on the number of comments. Similar conclusions were achieved by Cvijikj and Michahelles (2013) and Sabate et al. (2014) that pointed out a negative effect of interactivity on engagement since it requires a longer engagement time which does not conform with social media usage patterns. Tafesse (2015) also found a negative effect given that the more interactive content a post had, the probability of being liked or shared declined. Considering this, the author defended that a way to increase likeability is to keep interactivity to a minimum.

Other studies concluded partially the positive effect of interactivity. Lei et al. (2016) found that a contest and a call to action had a positive effect on engagement while asking a question or using links did not. C. Kim and Yang (2017) also found that response-inviting posts positively affected comments, but not likes and shares. Demmers et al. (2020) concluded that medium-level interaction attracted more engagement than high-level interaction and, also, that a low level of interaction did not generate more engagement than no interaction. Balio and Casais (2021) also concluded that response-inviting posts, on Facebook, are positively related to likes, reactions and comments, while on Instagram there was no influence on the metrics. Tavares and Nogueira (2021) only found a positive effect between interactivity (questions or action verbs) and Facebook comments, while none was found on other metrics or Instagram.

Another group of studies did find a strong positive relation between interactivity and customer engagement. Suh et al. (2010) found that a hashtag and a link increased a brand's retweetability. Luarn et al. (2015) concluded that a high level of interactivity may entice the customer to engage with brand content. Schultz (2017) has verified that hashtags have significant and positive effects on likes and comments, as well as calls to action, contests and polls.

Aydin (2019) determined that the likelihood of achieving higher engagement due to interactive content was 1.37 times greater than for non-interactive content. Bozkurt et al. (2020) found that perceived social media interactivity positively affects customer engagement behaviours since customers are more willing to buy products/services and offer suggestions/referring when they perceive the brand to be highly interactive irrespective of the type of social media platform. Moran et al. (2020) concluded that both open questions and calls to action had positive effects on both likes and comments.

To conclude, given the interactive nature of social media, customers expect more interaction to happen (Bozkurt et al., 2021) which helps brands to improve their relationship with customers, causing higher engagement (X. Liu et al., 2021). All these arguments are summarized in Table 4.

Argument(s)	Authors supporting the argument(s)
Interactivity has a negative effect on engagement with questions leading to a decline in likes and website links leading to a reduction in comments and, also, shares being affected by the interactivity levels.	Cvijikj & Michahelles, 2013; L. De Vries et al., 2012; Sabate et al., 2014; Tafesse, 2015
A contest and call to action increase engagement, while asking a question or using links did not.	Lei et al., 2016
Response-inviting posts increased comments, but not likes and shares.	C. Kim & Yang, 2017
Medium-level interaction attracted more engagement than high-level interaction.	Demmers et al., 2020
Interactivity generates engagement on Facebook, but not on Instagram.	Balio & Casais, 2021; Tavares & Nogueira, 2021
Interactive content motivates customers to engage more than non-interactive content.	Aydin, 2020; Bozkurt et al., 2020; Luarn et al., 2015; Moran et al., 2020; Schultz, 2017; Suh et al., 2010

Table 4 – Interactivity's Literature Summary
Source: Own Elaboration

1.2.5. Post Appeal

The fifth characteristic explored is post appeal, also a soft criterion. Customers have been increasingly feeling the need to be involved and connected with a brand in a unique experience which emphasizes the importance of having an appealing post and overall brand to generate the conversation that drives customer engagement (Balio & Casais, 2021; Wagner et al., 2017).

Considering this, content marketing is crucial since it is a process that involves the creation and distribution of relevant and valuable content to attract, acquire and interact with customers (Content Marketing Institute, 2012). So, having valuable and relevant content helps drive engagement, but engaged customers also help to increase the effectiveness of content marketing which explains the importance of post appeal (Balio & Casais, 2021).

The majority of categorizations can be simplified into rational and emotional appeals. Rational appeals are information focused motivated by the functional goal to gather the information that is pertinent to the purchase decision and consumption experience, while emotional appeals are more emotion-focused that can arouse positive (e.g., love, warmth, happiness, humour) or negative (e.g., fear, shame, guilt) feelings (Demmers et al., 2020; J. Liu et al., 2017).

Bagozzi et al. (1999) was the first study to research the effect of emotional and rational appeal on consumer persuasion. The authors concluded that consumers adjust their behaviour according to the emotions caused/associated with the brand, whether they are positive or negative.

L. De Vries et al. (2012) distinguished between informative and entertainment posts but neither shown to have an impact on post popularity. Demmers et al. (2020) also used this categorization and found that the engagement driven by the content is contingent on the stage of the customer journey. In the pre-consumption stage, informative posts generated more engagement, while the opposite happened during the consumption stage and, in the post-consumption stage, there was no difference between the two types.

Cvijikj and Michahelles (2013) added another category (the remuneration posts) to the ones mentioned above and concluded that entertaining content increased engagement in terms of likes, comments and shares, while information content just did not create engagement in terms of shares and remuneration only had a positive effect over the comments. Tafesse (2014), instead of remuneration, added transactional content and discovered that entertainment content is more likely to receive likes, but the number of shares is not significantly different from the informational and transactional posts. Luarn et al. (2015) categorized the content type in information, entertainment, remuneration and social and found different results on engagement from low to high: likes (social, entertainment, information, remuneration), comments (remuneration, information, entertainment, social) and shares (social, remuneration, information, entertainment). Shahbaznezhad et al. (2021) concluded that a rational appeal gets more likes than comments, while an emotional appeal has a significant negative effect on both, and a transactional appeal leads to an increase of likes but a decrease in comments.

Swani et al. (2013) categorized in terms of functional and emotional appeal and discovered that customers, more specifically in service brands, were more prone to engage with posts that were not excessively commercial and that contained emotional feelings. Wagner et al. (2017) concluded that when a post has the appeal that the customer seeks, they are more likely to engage with the brand. This means that one appeal is not better than the other, what is important is that brands adapt their posting strategy and use the post appeals that are more 'popular' with their customers. Taemin Kim et al. (2018) found that both informational and emotional post appeals help drive customers' word-of-mouth behaviour. J. Liu et al. (2017) and Tavares and Nogueira (2021) concluded that emotional post appeals drive more engagement than functional appeals. Dolan et al. (2019) found that rational appeals have a superior effect compared to emotional appeals in terms of facilitating active and passive engagement. However, both had a positive effect on likes and none on comments.

Thus, it is possible to conclude that the branded content with which customers engage influences the extent to which consumers do engage (Barger et al., 2016). Table 5 outlines the content of this subchapter.

Argument(s)	Authors supporting the argument(s)
Informative and entertainment appeals have no impact on engagement.	L. De Vries et al., 2012; Demmers et al., 2020
Entertainment content generated more engagement than the informative or remuneration/transactional content.	Cvijikj & Michahelles, 2013; Tafesse, 2015
Remuneration appeal generates likes, while social appeal generates comments, and the entertainment appeal drives shares.	Luarn et al., 2015
Rational appeal gets more likes than comments, while an emotional appeal has a significant negative effect on both, and a transactional appeal leads to an increase of likes but a decrease in comments.	Shahbaznezhad et al., 2021
Emotional appeals drive more engagement than functional appeals.	Bagozzi et al., 1999; J. Liu et al., 2017; Swani et al., 2013; Tavares & Nogueira, 2021
Both functional and emotional appeals drive customer engagement.	Dolan et al., 2019; T. Kim et al., 2018; Wagner et al., 2017

Table 5 – Post Appeal's Literature Summary
Source: Own Elaboration

1.3. eWOM Comment Valence

With the advent of social media, marketers have lost the control they had in traditional settings regarding advertising information and negative reactions since there was a shift in control over marketing information from the marketer to the consumer. This means that consumers nowadays can say what they want online, which can be positive or negative, and impact a product/event/brand's image (Hayes et al., 2018). But this social media presence has also created engagement and collaboration opportunities where brands can gain valuable and unmediated customer insights (Hudson et al., 2015). Since human behaviour is heavily influenced by emotion and not only reason, the customer-brand relationship is equally emotional (Pawle & Cooper, 2006) which is why brands and marketers need to analyse customer emotional valence.

Customers can interact with brands on social media through direct mechanisms (posting a comment) or indirect opinion expression (liking a post) which diversifies the format of eWOM (Lee et al., 2020). eWOM refers to "any positive or negative statement made by potential, actual, or former customers about a product or company, which is made available to a multitude of people and institutions via the internet" (Hennig-Thurau et al., 2004, p.39). In this definition of eWOM, the idea of valence is present since it refers to an audience's subjective evaluation that can be conceptualized in a bipolar attitude between positive and negative feelings at two extremes, and a neutral evaluation in the middle (Kaplan, 1972). Positive emotion is a "state of high energy, full concentration, and pleasurable engagement" and negative emotion is a state of "distress and unpleasurable engagement that subsumes a variety of aversive mood states, including anger, contempt, disgust, guilt, fear, and nervousness" (Watson et al., 1988, p.1063). So, customers' comments can either be positive, neutral or negative (L. De Vries et al., 2012).

eWOM is a powerful phenomenon since customers use it as a source of product information and share the content with their friends and the general public (Choi et al., 2017). The four main reasons why customers engage in eWOM are: to pursue social interaction, care for other customers, enhance their own self-worth or respond to economic incentives (Hennig-Thurau et al., 2004). Customers' comments are deemed more credible and trustworthy, since they are considered harder to manipulate, than the brand's self-created content, so customers adjust their behaviours and attitudes appropriately (Chen et al., 2017).

Positive eWOM can enhance the effectiveness of the post (Chen et al., 2017), the sharing motivation and positively impacts product sales (Hayes et al., 2018) while improving the value of the brand and creating empathy among customers (L. De Vries et al., 2012). By leaving positive comments on a brand's post, customers are investing cognitive and emotional efforts that improve the visibility of a post (Taemin Kim et al., 2019). Despite this, positive content and eWOM might have the negative effect of attracting customers who do not fit with the brand's image or target audience (Harmeling et al., 2017).

Negative eWOM produces a negative emotion that might lead to a decrease in the attractiveness of the post which leads to a reduction of likes and shares and, even, there is peer pressure to not engage with a post where other customers commented negatively (L. De Vries et al., 2012). When a consumer is disappointed, there is a tendency to engage in negative eWOM to vent, seek retaliation and/or warn other customers (De Matos & Rossi, 2008; Van Doorn et al., 2010). Customers gained a new outlet to complain more directly, conveniently, and effectively which demands a quick answer from the brand before it goes viral (Balaji et al., 2015). The damage of negative eWOM tends to go beyond the products reviewed to impact the overall brand image (Daugherty & Hoffman, 2014). There seems to be a consensus that negative comments evoke stronger negative emotions while positive comments lead to less strong positive emotions (Chen et al., 2017; Daugherty & Hoffman, 2014; Hayes et al., 2018).

Commenting, more than liking and sharing, is considered a stronger digital engagement indicator since it enables the customer to communicate directly with the brand, offering feedback, as it would happen in an offline situation (Yoon et al., 2018). In addition to text, emojis have been commonly used in social media to reflect the emotional state of the users/customers. The term "emoji" means "e" (picture) and "moji" (letter/character) and is defined as a "graphic symbol, ideogram that represents not only facial expressions, but also concepts and ideas, such as celebration, weather, vehicles and buildings, food and drink, animals and plants, or emotions, feelings, and activities." (Moussa, 2019; Novak et al., 2015, p.2). These characters are images that have been standardized across the Internet by Unicode Consortium (Mathews & Lee, 2018). According to Unicode Consortium, 92% of the online population use emojis and the 10 most-used emojis worldwide in 2021 were: 😂, ❤️, 🤣, 👍,

😭, 🙏, 😘, 🥰, 😍 and 😊 (Daniel, 2021). Emojis can interact with text in six ways: replace a word/phrase, repeat a word/phrase for emphasis, express the speaker's emotion, emphasize an emotion, modify the meaning of the text (e.g. sarcasm) and be used for politeness (Tian et al., 2017). Emojis are also universally interpreted between cultures and they add tones and moods to a message (Mathews & Lee, 2018). Furthermore, there is a tendency to use emojis that express positive emotions more frequently than emojis that express negative emotions (Novak et al., 2015; Tian et al., 2017). Tian et al. (2017) classified emojis into emotions, while Novak et al. (2015) created an emoji sentiment lexicon which allows to give sentiment scores to emojis, and Moussa (2019) developed an emoji-based metric to monitor customer's emotions on social media.

Considering this, it is possible to conclude that customers' comments can help understand if there is consistency (positive eWOM) or discrepancy (negative eWOM) between what the brand claims to be and what consumers actually think (Chen et al., 2017). With social media, brands have a significant opportunity to leverage their content to influence the sentiment of digital engagement (Meire et al., 2019). However, it is important to highlight that no literature has been found that presents valence of eWOM comments as a consequence of one or more social media post characteristics, which will be further discussed in this study.

1.4. SVoD Services and Social Media

Subscription video-on-demand services have become increasingly relevant within the video market (Rahe et al., 2021; Wayne, 2018). The shift from traditional cable services to online paid subscriptions lead to changes in the way the content itself is promoted, with social media as the most adopted mean. Social media platforms present the chance to introduce, for example, a new TV show to many followers and boost audience engagement (Fernández-Gómez & Martín-Quevedo, 2018a). Through social media marketing, SVoD services are strengthening their brands by creating viral campaigns that advertise their services and encourage social exchanges between subscribers and the brand and between the subscribers themselves (Martín-Quevedo et al., 2019).

Considering this, a few studies have been developed to understand and analyse the social media strategies used by different SVoD services and their results. In 2018, Fernández-Gómez and Martín-Quevedo developed two studies to understand Netflix Spain's Twitter strategy. The authors found that the majority of tweets are original promotional content with a focus on specific series and movies, while some focused on the brand itself or the binge-watching model. The tweets used a lot of humour or intrigue, asked questions and they relied on hashtags, emojis and gifs which all helped in increasing engagement (Fernández-Gómez & Martín-Quevedo, 2018a, 2018b).

In 2019, Martín-Quevedo et al. did a comparative analysis of the Spanish and American Instagram accounts of HBO and Netflix. The results were that the two Spanish accounts posted more informational messages than the American ones, but both emphasized the self-produced content which generated more engagement. The American accounts also used more links to celebrities' profiles with HBO America publishing this content the most. The use of images and videos was more coherent between the two Netflix accounts than the two HBO accounts with HBO Spain using mainly screenshots taken from TV shows. Both Netflix and HBO expressed emotions and had a positive tone, but Netflix did it more often using more humour which was linked to higher engagement. With this, the author found that, although HBO posted more, Netflix attracted more users.

In 2020, Pérez also compared Netflix Spain and Netflix United States (US) and observed that both accounts post mostly promotional content focused on the brand with a strong focus on the company's own-produced content. The US account was more informative with premiere dates, while the Spanish was more humorous and used more call-to-actions. While Netflix US tends to embrace user-generated content more often, Netflix Spain makes a stronger effort to consider the specific cultural context when engaging with users.

Also in 2020, Ortega Fernández and Santos Herrero developed a study to understand how Netflix, HBO and Movistar+ engage with their followers on Instagram. They concluded that each SVoD service has a differentiated strategy and that there is no key approach for success. This is why Netflix is more humorously informal focusing on images and memes. HBO is more formal and uses pictures accompanied by text. Movistar+ is more commercial and uses more videos. Each must invest in creating their own unique style and strategy that works best for their target followers.

More recently, in 2021, Martínez-Sánchez et al. did a case study of Spanish Netflix, HBO, Amazon Prime and Disney Plus's social media strategy. Amazon Prime was found to be the most active on social media and HBO the least active. On Facebook, Amazon Prime had a balanced strategy with 42 images and 30 videos; Netflix focused its efforts on videos using very few images; Disney Plus used the reverse strategy of Netflix giving greater weight to images; and HBO replicated Disney Plus' strategy of using more images. On Instagram, Amazon Prime used the same strategy with very few carousels; Netflix used the opposite of its Facebook strategy now focusing more on images and using a lot of carousels; Disney Plus published more videos than images, although it is balanced, as well as carousels; and HBO keeps its strategy of focusing on images but with fewer carousels than Netflix and Disney Plus.

Moreover, Derin, in 2021, developed a thesis on the role of social media in increasing customer loyalty within the SVoD industry. There is an indication of a strong positive relationship between social media and customer loyalty in streaming services. Netflix's social media showed a stronger influence on customer loyalty than Disney Plus, although its followers were also loyal.

Finally, also in 2021, Rahman did a comparative analysis between Amazon Prime and Disney Plus on Instagram. The authors found that, although Amazon Prime posted more frequently than Disney Plus, Disney Plus had a superior engagement in likes and comments. Amazon Prime posts were mainly third-party content with a focus on movies and with a lack of hashtags and emojis. Videos were preferred over images, more specifically behind-the-scenes and teasers/trailers. The same happens with Disney Plus since they used no image, but it had more original content focused on TV shows and a balanced mix of hashtags and links. Finally, Disney Plus leaned toward entertaining content without any sort of negativity, while Amazon Prime embodied a broad range of emotions (humour, fear, anger, sadness, etc).

Considering the findings of this literature, it is possible to conclude that, in this context, video creates more engagement than image, hashtags are associated with increased post discoverability and humour is very well received by the target audience and so is the promotion of self-produced original content. More literature has to be developed related to this subject.

2. CONCEPTUAL MODEL AND HYPOTHESES SUMMARY

As a way to schematize the analysis of this study, a conceptual model was developed (Figure 1). A conceptual model is a guiding scheme that organizes in a logical and integrative way the numerous concepts and dynamics under study, representing the complexity of the relationships that are established between the parts that make up the answer to the problem (Oliveira & Ferreira, 2014).

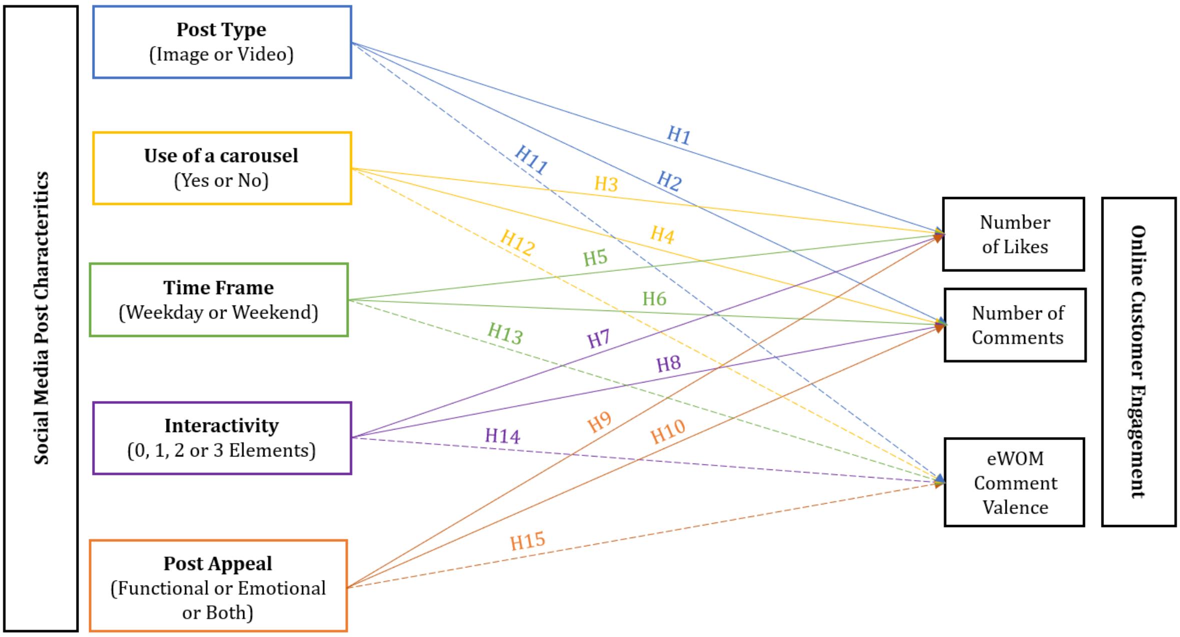

Figure 1 – Conceptual Model
Source: Own Elaboration

The hypotheses of this study are presented in this model. Each arrow identifies a relationship between one independent and one dependent variable. The independent variables refer to the post characteristics of this study, namely the post type, use of a carousel, time frame, interactivity and post appeal. The dependent variables are the ones that represent the online consumer engagement: number of likes, number of comments and eWOM comment valence. As mentioned in chapter 1.1, the online engagement scales found in the literature were developed based on the declared engagement, assessed through surveys. However, no online engagement scale was found in the literature that combines secondary data to its measurement. Therefore, in this study, the three dependent variables (number of likes, number of comments and eWOM comment valence) will be used as a proxy for online customer engagement. The relationship between variables will help understand the impact of these social media post characteristics on online customer engagement on Instagram.

In Figure 1, there are two types of arrows: the straight lines and the dotted lines. The ten straight-line arrows represent the hypotheses developed from the literature (H1-H10). The five dotted-line arrows represent hypotheses brought by the researcher (H11-H15) since the eWOM comment valence may translate the online customer engagement differently from the number of likes and the number of comments as the comments themselves may express emotions. As said previously, consumers can now say what they want online, which can be positive or negative, and impact a product/event/brand's image (Hayes et al., 2018), thus being eWOM comment valence a complementary way of measuring online customer engagement. Considering this, the five additional hypotheses developed follow the logic of the previous hypotheses since a post with a high number of likes and/or comments will likely get a more positive eWOM comment valence. Table 6 summarizes the proposed hypotheses.

Hypotheses		Literature supporting the hypotheses
H1	Image post type generates more likes than video post type.	Balio & Casais, 2021; Cvijikj & Michahelles, 2013; L. De Vries et al., 2012; Sabate et al., 2014; Shahbaznezhad et al., 2021; Tavares & Nogueira, 2021
H2	Image post type generates more comments than video post type.	Balio & Casais, 2021; Cvijikj & Michahelles, 2013; L. De Vries et al., 2012; Sabate et al., 2014; Tavares & Nogueira, 2021
H3	The use of a carousel generates more likes than not using a carousel.	Martínez-Sánchez et al., 2021; Oltra et al., 2021; Wahid & Gunarto, 2021
H4	The use of a carousel generates more comments than not using a carousel.	Martínez-Sánchez et al., 2021; Oltra et al., 2021; Wahid & Gunarto, 2021
H5	Posting on weekdays generates more likes than posting on weekends.	Cvijikj & Michahelles, 2013; Wagner et al., 2017
H6	Posting on weekdays generates more comments than posting on weekends.	Cvijikj & Michahelles, 2013; Wagner et al., 2017
H7	There is a positive relationship between the number of interactive elements and the number of likes.	Aydin, 2020; Bozkurt et al., 2020; Fernández-Gómez & Martín-Quevedo, 2018; Luarn et al., 2015; Moran et al., 2020; Rahman, 2021; Schultz, 2017; Suh et al., 2010
H8	There is a positive relationship between the number of interactive elements and the number of comments.	Aydin, 2020; Bozkurt et al., 2020; Fernández-Gómez & Martín-Quevedo, 2018; Luarn et al., 2015; Moran et al., 2020; Rahman, 2021; Schultz, 2017; Suh et al., 2010
H9	Content with an emotional appeal generates more likes than content with a functional or both appeal.	Bagozzi et al., 1999; Fernández-Gómez & Martín-Quevedo, 2018; J. Liu et al., 2017; Martín-Quevedo et al., 2019; Ortega Fernández & Santos Herrero, 2020; Pérez, 2020; Rahman, 2021; Swani et al., 2013; Tavares & Nogueira, 2021
H10	Content with an emotional appeal generates more comments than content with a functional or both appeal.	Bagozzi et al., 1999; Fernández-Gómez & Martín-Quevedo, 2018; J. Liu et al., 2017; Martín-Quevedo et al., 2019; Ortega Fernández & Santos Herrero, 2020; Pérez, 2020; Rahman, 2021; Swani et al., 2013; Tavares & Nogueira, 2021
H11	Image post type generates more positive eWOM comment valence than video post type.	-

H12	The use of a carousel generates more positive eWOM comment valence than not using a carousel.	-
H13	Posting on weekdays generates more positive eWOM comment valence than posting on weekends.	-
H14	There is a positive relationship between the number of interactive elements and the eWOM comment valence.	-
H15	Content with an emotional appeal generates more positive eWOM comment valence than content with a functional or both appeal.	-

Table 6 – Summary of the hypotheses under investigation
Source: Own Elaboration

3. METHODOLOGY

Recalling the research's main objective, which is to investigate the influence of social media posting of subscription video-on-demand services (Netflix Portugal, Disney Plus Portugal and HBO Portugal) on Portuguese customer engagement, this thesis follows a positivist research philosophy. This means that there only exists one reality and it will be observed objectively and independently of its observer (Ryan, 2018). Also, this study was conducted under a quantitative approach. Although there are some subjective elements in this study, they were quantified in order to make them integrated into the chosen perspective, as detailed in sections 3.4.1 and 3.4.2. Finally, this study brings a combination of both deductive and inductive approaches. On the one hand, this study follows an organized framework whose hypotheses (H1 to H10) were based on existing literature, thus showing the deductive approach. And, on the other hand, the inductive approach is reflected in the five hypotheses (H11 to H15) that were drawn both from the researcher's experience and from studies in analogous (albeit different) contexts.

3.1. SCOPE AND DATA SOURCE

Regarding the scope of this study, the present study investigated the subscription video-on-demand industry. SVoD services try to be at the centre of the social discussion that takes place on social media, while customers try to share their viewing habits, their thoughts about the content, create or consume humorous content, or engage with the production and obtain more information (Pérez, 2020). The numerous roles of social media within the SVoD industry are developing and improving the brand; increasing customer loyalty to increase retention and reduce churn rates; acquiring more customers through virality; nurturing customer engagement; and developing online brand communities, an informal place for brands to interact with their customers (Derin, 2021). The focus of this study will be on the role of nurturing online customer engagement.

The data source of this study was Instagram. The choice was a result of the intersection between the age of SVoD services' target audience and social media preferences by age. According to Morning Consult & Hollywood Reporter (2021), millennials (ages between 26 and 41 years) dominate the subscription of SVoD services with 33% subscribing to Netflix, 40% subscribing to HBO Max and 42% subscribing to Disney Plus (Shevenock, 2021). This target audience is strongly present on Instagram with 47.1% of the users being aged between 25 and 44 years, in October 2021 (Statista, 2021b). Also, Instagram has a high average engagement rate for all post types of 1.94%, while for example Facebook only has 0.07% (Kemp, 2022), which was relevant for this study since the subject under analysis was online customer engagement.

Thus, this study had its focus on SVoD services' Portuguese Instagram accounts, more specifically Netflix Portugal, Disney Plus Portugal and HBO

Portugal. Other SVoD services' Instagram accounts were left out since they do not have a Portuguese account, only other nationalities.

3.2. Population and Sample

Since the goal of this study is to investigate the influence of social media posting of subscription video-on-demand services (Netflix Portugal, Disney Plus Portugal and HBO Portugal) on Portuguese customer engagement, the population of this study is all posts posted on Instagram by Netflix Portugal, Disney Plus Portugal and HBO Portugal.

The posts published on Instagram between January 1st and January 31st, 2022, constituted the sample. This sample was collected one month later (beginning on January 31st until March 2nd, 2022) since, according to Sabate et al. (2014) and Wagner et al. (2017), a post is not expected to receive new engagement after one month. So, whenever a post achieved one month of being posted, its information was collected. This investigation supported that one month is a sufficient interval between the time of posting and the time of collecting the data. Considering this, the present study was cross-sectional since all data was collected at one point in time.

A total of 142 posts were retrieved during the month of January of 2022: 64 from Netflix Portugal, 53 from Disney Plus Portugal and 25 from HBO Portugal.

Screenshots were taken to all posts, and, in each post, it is possible to observe the post characteristics. HBO Portugal only has 25 posts because, in the middle of January, they changed the account to HBO Max Portugal and deleted all posts previous to February 1st, 2022. So, it was only possible to gather posts until January 18th and the majority was removed from analysis due to the inability to access the post link to see the video or the carousel. This restriction, although inconvenient, did not generate bias in the sample since the aim of the study is not to compare posts between SVoD services, but rather to analyse the posts in a grouped manner. Also, a post was excluded from the analysis because it did not fit into any of the post type categories. Besides this, all user comments from the 142 posts, a total of 3402 comments, were retrieved. Comments made by the brands were removed and not considered in this analysis.

3.3. Data and Method of Collection

Considering that the data source was Instagram, this study is a netnography due to the fact it utilized public information available online to understand the online customer engagement within this social media. This research method was used in other similar studies (Aydin, 2020; Balio & Casais, 2021; Coelho et al., 2016; Cvijikj & Michahelles, 2013; N. J. De Vries & Carlson, 2014; Demmers et al., 2020; Dolan et al., 2019; Jones & Lee, 2022; C. Kim & Yang, 2017; Lei et al., 2017; Luarn et al., 2015; Moran et al., 2019; Sabate et al., 2014; Schultz, 2017; Shahbaznezhad et al., 2021; Suh et al., 2010; Swani et al., 2017; Tafesse, 2015;

Tavares & Nogueira, 2021; Wagner et al., 2017; Wahid & Gunarto, 2022). Besides this, its increased popularity in marketing research, which is a reflection of the intensification of customers' online activity and its importance to brands (Heinonen & Medberg, 2018), also justified this option. Therefore, the data collected for this study was secondary data obtained on Instagram accounts.

This research presents an adaptation of the four drivers contained in the studies of both Balio and Casais (2021) and Tavares and Nogueira (2021), namely post type, timeframe, interactivity and post appeal, with the addition of the use of a carousel as a new driver. As some of the data is qualitative in nature, for the purposes of analysis, it was necessary to categorize this non-numerical data into groups and attribute numerical codes to these groups. Table 7 shows the different variables present in this dissertation and their respective definitions and codes:

Variable	Definition	Code
Post Type	On Instagram, it is possible to use the following types of posts: images or videos.	0: "Video" 1: "Image"
Use of a carousel	On Instagram, it is possible to upload up to 10 images and/or videos in one large post. A post is considered a carousel when it has more than 1 image/video.	0: "No" 1: "Yes"
Time Frame	Time frame in social media refers to posts published during the weekdays (between Monday and Friday) or weekend (Saturday and Sunday).	0: "Weekend" 1: "Weekdays"
Interactivity	Any post that encourages an answer directly from the public is considered interactive. Response-inviting posts are those that use hashtags and/or verbs of action and/or open questions. A post can have zero or one or two or all of these elements of interactivity.	0: "0 elements of interactivity" 1: "1 element of interactivity" 2: "2 elements of interactivity" 3: "3 elements of interactivity"
Post Appeal	Functional appeals are information-focused and pertinent to the purchase decision and consumption experience, while emotional appeals are more emotion-focused that can arouse positive or negative feelings. A post can also have the presence of both elements.	1: "Functional" 2: "Emotional" 3: "Both"
Likes	The number of likes by users a post receives.	Numerical ≥ 0
Comments	The number of comments by users a post receives.	Numerical ≥ 0
eWOM comment valence	eWOM comment valence refers to the user's subjective evaluation that occurs in the comment section of a post. It can be conceptualized as a bipolar attitude between positive and negative feelings, and a neutral evaluation in the middle.	Positive: >= 0.05 Neutral: > -0.05 and < 0.05 Negative: <= -0.05

Table 7 – Coding criteria
Source: Own Elaboration

For every post, the collected data through print screen encompassed the visual content, the date, the caption, the number of likes and the number of comments. In Figures 1, 2 and 3, it is possible to see examples of the posts retrieved for this study. Also, every user comment written in the comment section of the post was retrieved through a browser extension (IG Comment

Exporter) and systematized in Excel. With all these steps, it was possible to retrieve the necessary information about the eight variables under analysis.

Figure 2 – Post Example Netflix Portugal
Source: Netflix Portugal's Instagram

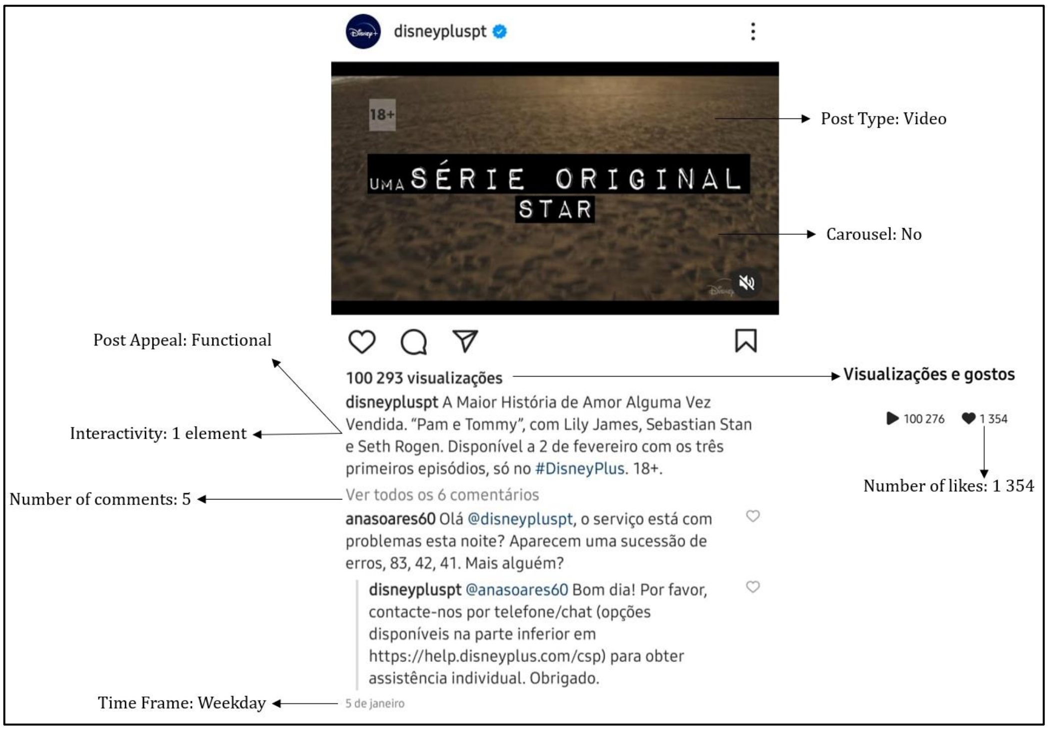

Figure 3 – Post Example Disney Plus Portugal
Source: Disney Plus Portugal's Instagram

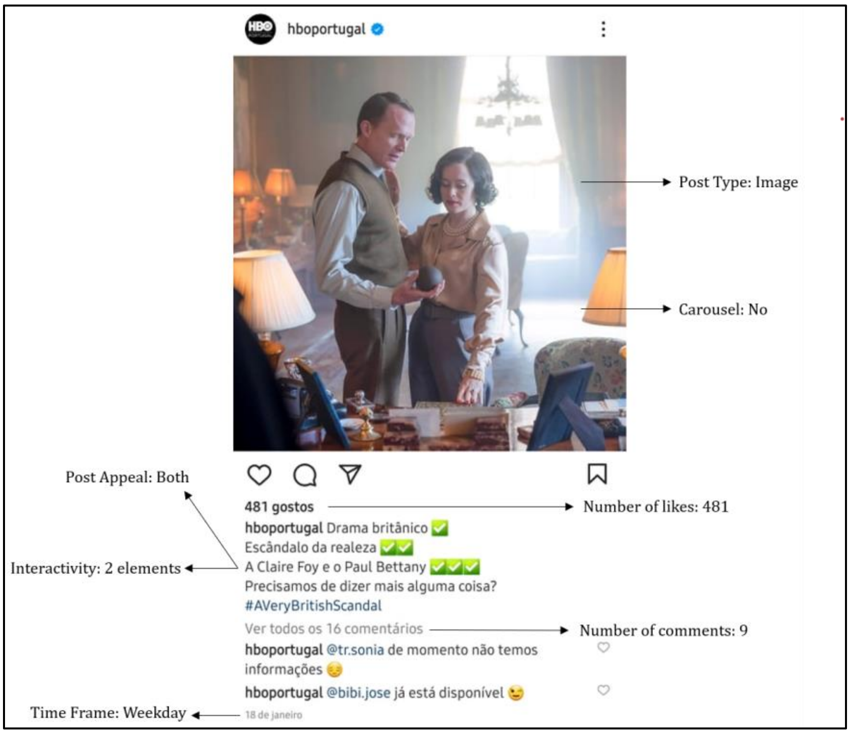

Figure 4 – Post Example HBO Portugal
Source: HBO Portugal's Instagram

3.4. Data Treatment

Two of the variables under analysis required particular treatment before being submitted to the hypothesis testing processes, namely post appeal and eWOM comment valence.

3.4.1. Post Appeal Treatment

Due to the subjective nature of the post appeal, it was necessary to adopt a data analysis technique that offered an opportunity to attribute meaning to the content within the context of SVoD services' communication strategy. In order to analyse the appeal of each post (whether functional, emotional or both), coders and reliable research were used to minimize subjectivity. When there is a convergence between raters about how to code a piece of content, this works as an indicator of the reliability of the data. Considering this, the technique chosen to measure this interrater agreement was Kappa Fleiss since it allows to determine the level of agreement between two or more raters when assigning categorical ratings to several items (Laerd Statistics, n.d.-b). For this study, besides the researcher, two more people (a content specialist and an Instagram heavy-user) were inquired to independently classify all the posts considering the following appeals: functional, emotional or both. After this evaluation, all answers were systematized in Excel. Kappa Fleiss compares the observed agreement with the expected agreement, so this Kappa was measured to discover the kappa value, its statistical significance and its 95% confidence interval.

3.4.2.eWOM Comment Valence Treatment

The data analysis technique used to read the eWOM comment valence was fine-grained sentiment analysis, also known as opinion mining, an approach that "analyses people's opinions, sentiments, evaluations, appraisals, attitudes, and emotions towards entities such as products, services, organizations, individuals, issues, events, topics, and their attributes" (B. Liu, 2012, p.7). The sentences are broken into pieces of texts and classified statistically according to their sentiment level, based on a predefined set of words' sentiment scores, the sentiment lexicons. The alternance from very negative to very positive derives not only the overall sentiment about content but also its polarity density (Kirci & Gulbak, 2020; Novak et al., 2015). This study adopted VADER (Valence Aware Dictionary for Sentiment Reasoning) lexicon, a rule-based sentiment analysis tool since it performs well in the social media domain (Hutto & Gilbert, 2014), this study's focus. It indicates both sentiment polarity (positive/negative) and sentiment intensity (emotion strength) in which the words are scored with a sentiment valence. Also, it evaluates punctuation, capitalization, degree modifiers, the contrastive conjunction "but" negation, slang, emojis, acronyms, and initialisms. This analysis also used emojis since they convey emotions and, subsequently, are particularly relevant cues for sentiment analysis (Guibon et al., 2017). It contributed to a better understanding of whether the customer engagement generated, by the characteristics under this study, was good or bad for the brands. Furthermore, the inclusion of grammatical and lexical features and syntactical considerations allows VADER to perform better than other highly regarded sentiment analysis tools, due to its more robust lexicon dictionary composed of 7520 lines of validated/scored features (Hutto & Gilbert, 2014). Thus, 3402 users' comments were retrieved and systematized in a .csv file document to start the preprocessing phase, to clean and prepare the data. This study carried out unsupervised machine learning techniques to:

1. Translate all comments into English since VADER's algorithm demonstrates better results in this language.
2. Apply the VADER algorithm using the VADER's library for R Studio to have a first impression of the dataset studied. Thereafter, the results of this first part were screened to identify:
   – Features with mismatched meanings and scores, for instance, the Portuguese slang "vc" instead of "você" (in English "yu" instead of "you") and the variations of "kkk" that refers to "risos" (in English "hahaha" referring to "laugh out loud").
   – Emojis with asymmetric evaluations, for instance, there were three of them whose scores were not fitting to the context meaning: The emojis Fire (🔥), Tears of Joy (😂), and Red Heart (❤️) that showed different scores due to their rational neutral/negative connotation; however, in the proposed context their subjective meanings are correspondently hot/attractive or lit/exciting, hysterical laughter, and lovely affectionate feelings.

From the above findings, a bag of features with their new meanings was created and accessed through a semi-supervised algorithm to replace the words with inaccurate compounds. The new set of terms was inductively updated according to Emojipedia (https://emojipedia.org/) their subjective meaning to achieve high precision during the analysis. This action improved VADER's dictionary/lexicon with new features, such as emojis updated with their contextual and contemporary meanings by their hexagonal codes (The

Unicode Consortium, 2021) using these inputs to the machine reading and replacement. After completing the preprocessing steps, the dataset was ready for applying VADER's sentiment analysis to classify the comments as positive, negative, neutral, and compound.

Having established the methodological approach and the tools for collecting and preparing the data, the following section develops the analysis of the results obtained.

4. Data Analysis

In this chapter, the results of the 142 collected posts are analysed using the statistical analysis tool SPSS Statistics. Data analysis techniques should be chosen according to the nature of the data collected. Firstly, the post appeal treatment was carried out using the Kappa Fleiss interrater agreement test in order to identify the type of appeal present in the posts. Also, the VADER lexicon and rule-based sentiment analysis tool prepared the eWOM comment valence for the statistical tests. Then, using descriptive statistics, the post characteristics employed by the brands were analysed. Subsequently, ANOVA and respective confidence intervals were performed to analyse in isolation the effects of the post type, use of a carousel, time frame, interactivity and post appeal on the number of likes and comments and the eWOM comment valence. Finally, multiple linear regressions were developed to understand the joint effect of the independent variables on the dependent variables.

4.1. Treatment and Validation of the Collection Process

As aforementioned in subchapter 3.4, it was necessary to treat two of the variables before being submitted to the hypothesis testing processes, namely, post appeal with the Kappa Fleiss' test and eWOM comments valence with the VADER lexicon and rule-based sentiment analysis tool.

The Kappa Fleiss' test showed that there is a good strength of agreement between the three raters (k=0.775 [CI 95%: 0.704-0.845]; p<0.001). This strength of agreement is determined considering Altman's (1990) guidelines that define that a value of k between 0.61 and 0.80 is good. Also, one can be 95% confident that the populational value of Fleiss' kappa is between 0.704 and 0.845. To make this analysis more thorough, the individual kappas were also analysed. These kappas are calculated for each of the categories of the response variable separately against all other categories combined. With this, we could conclude that the three raters have a very good strength of agreement when rating a 'functional' appeal (k=0.848) or an 'emotional' one (k=0.822). However, the 'both' appeal was the one with the smallest kappa (k=0.570) which means that the strength of agreement was only moderate, considering Altman's (1990) guidelines. Considering these results, it was possible to use the researcher's appeal evaluation as the necessary categorization of the 142 posts since the good strength of agreements works as an indicator of the reliability of the data.

With the VADER lexicon and sentiment analysis tool, it was possible to classify the emotional valence of the 3402 comments under analysis. This tool works with word, sentiment and compound scores. The emotional valence was calculated through the sum of the sentiment score of each word according to their sentiment intensity on a scale from -4 to +4. It resulted in a compound score, normalized between -1 (most extreme negative) and +1 (most extreme positive). To gather the overall sentiment a post generated, the average of all compound scores of the comments retrieved from that post was used. This study adopted these averages as a single unidimensional measure in the analysis. The typical threshold values used and adopted in this study were positive if >= 0.05; neutral if between > -0.05 and < 0.05; and negative if <= -0.05 (Hutto & Gilbert, 2014). In table 8, it is possible to see examples of the scores resulting from VADER's sentiment analysis of comments present in this study.

Comment	Compound Score	Positive	Neutral	Negative	But Count
Eu triste por terem tirado prison break 😢 😢 😢 😢	-0.957	0	0.324	0.676	0
Eu quero saber da próxima temporada de Black Mirror dona Netflix!!!!	-0.354	0.086	0,73	0.184	0
Com legendas, nada de séries ou filmes dobrados, por favor	0.026	0.219	0.571	0.21	0
@fortheloveofmadden Exatamente, ela passou uma visão diferente para os filmes do gênero, mas as pessoas não devem ter percebido, o que é bem triste!	0.236	0.291	0.661	0.137	1
Amo 😍 ❤️	0.943	0.75	0.25	0	0

Table 8 – Example of VADER's sentiment analysis
Source: Own Elaboration

4.2. Descriptive Analysis

Descriptive statistical analysis was carried out in order to describe and obtain a general understanding of the use of SVoD's Instagram pages, in particular regarding the social media post characteristics. This analysis helped to summarize the data and to find possible patterns in post characteristics within the SVoD Instagram context.

Table 9 presents a frequency distribution of the independent variables present in this study.

Variables		Frequency	Percentage
Post Type	**Image**	118	83.1%
	Video	24	16.9%
Use of a carousel	**Yes**	53	37.3%
	No	89	62.7%
Time Frame	**Weekend**	46	32.4%
	Weekday	96	67.6%
Interactivity	**0 elements**	59	41.5%
	1 element	52	36.6%
	2 elements	29	20.4%
	3 elements	2	1.4%
Post Appeal	**Functional**	61	43.0%
	Emotional	52	36.6%
	Both	29	20.4%

Table 9 – Descriptive statistics of the independent variables for n=142
Source: Own Elaboration

Considering that the category "3 elements" only has a frequency of 2, a new category was created named "2 or more elements" that merges the "2 elements" and the "3 elements" together reaching a frequency of 31 and a percentage of 21.8% for an n=142.

Table 10 presents a descriptive summary of the dependent variables. There are four missing values in the eWOM comment valence due to the fact that there are four posts with zero comments.

	Missing Values	Average	Standard Deviation	Median	Minimum	Maximum
Number of Likes	0	5708.65	6341.79	2220.50	161.00	24320.00
Number of Comments	0	23.94	33.47	12.50	0.00	195.00
eWOM Comment Valence	4	0.38	0.23	0.40	-0.72	0.93

Table 10 – Descriptive statistics of the dependent variables for n=142
Source: Own Elaboration

In order to assess the normality of the dependent variables, skewness and kurtosis tests were performed as presented in Table 11. The data is considered normal if skewness is between -2 to +2 and kurtosis is between -7 to +7 (Hair et al., 2010), thus one can conclude that the number of likes and eWOM comment valence pass both tests while the number of comments does not.

	Skewness		Kurtosis	
	Statistics	Standard Error	Statistics	Standard Error
Number of Likes	1.16	0.20	0.29	0.40
Number of Comments	2.89	0.20	9.32	0.40
eWOM Comment Valence	-0.87	0.21	3.57	0.41

Table 11 – Skewness and kurtosis tests' results for n=142
Source: Own Elaboration

To resolve this issue, the outliers in the number of comments were removed in an attempt to reduce the skewness and kurtosis levels. A value was considered an outlier if it is three standard deviations apart from the mean. So, all posts with more than 82 comments were removed from the analysis. 8 posts were eliminated from the full dataset which lead to a sample size of n=134. As it is possible to see in Table 12, the number of comments is now considered normal, passing both tests.

	Skewness		Kurtosis	
	Statistics	Standard Error	Statistics	Standard Error
Number of Likes	1.40	0.21	1.22	0.42
Number of Comments	1.79	0.21	3.04	0.42
eWOM Comment Valence	-0.92	0.21	3.67	0.42

Table 12 – Skewness and kurtosis tests' results for n=134
Source: Own Elaboration

Now, the descriptive analysis done previously will be repeated for this new 'n'. Through the analysis of Table 13, it can be seen that, on Instagram, the format most used by these brands is image with 82.8% of total of the posts under analysis. More than the majority of posts does not use a carousel with only 36.6% using this feature. Also, two-thirds of the posts were published during the week. It is possible to observe that the number of posts made on Instagram that do not contain interactive features (38.8%) or just one element (38.1%) is higher than those that have two or more (23.1%). Finally, it is also possible to verify that the functional appeal (42.5%) is more used than the emotional appeal (35.8%) or both (21.6%), although the difference between functional and emotional is not very large.

Variables		Frequency	Percentage
Post Type	**Image**	111	82.8%
	Video	23	17.2%
Use of a carousel	**Yes**	49	36.6%
	No	85	63.4%
Time Frame	**Weekend**	43	32.1%
	Weekday	91	67.9%
Interactivity	**0 elements**	52	38.8%
	1 element	51	38.1%
	2 or more elements	31	23.1%
Post Appeal	**Functional**	57	42.5%
	Emotional	48	35.8%
	Both	29	21.6%

Table 13 – Descriptive statistics of the independent variables for n=134
Source: Own Elaboration

Considering the dependent variables, Table 14 presents a descriptive summary. On average, a post has 5067 likes with a standard deviation of 5878 likes, varying from 161 to more than 24 thousand likes. Analogously, a post has, on average, 17 comments with a standard deviation of 18 comments, varying from 0 to 81. The data appear to be skewed to the right, which explains why the average is greater than the median. This indicates that the majority of posts present a smaller number of likes and comments. This does not happen in eWOM comment valence since it presents a symmetry with a low standard deviation. A post has, on average, a score of 0.4 varying from -0.7 to 0.9.

	Missing Values	Average	Standard Deviation	Median	Minimum	Maximum
Number of Likes	0	5066.48	5877.93	2017.00	161.00	24320.00
Number of Comments	0	17.19	17.47	12.00	0.00	81.00
eWOM comment valence	4	0.38	0.23	0.40	-0.72	0.93

Table 14 – Descriptive statistics of the dependent variables for n=134
Source: Own Elaboration

4.3. Hypotheses Tests

In this section, several ANOVAs were performed to assess the relationship between independent and dependent variables. After running the ANOVAs, multiple linear regressions were carried out for additional analysis.

4.3.1. Analysis of Variance (ANOVA)

To test the fifteen hypotheses of this research, the ANOVA was used as the primary statistical analysis. The one-way analysis of variance is used to establish whether the mean of a dependent variable is the same in two or more unrelated, independent groups. The choice of this analysis is derived from the fact that the independent variables are categorical while the dependent variables are continuous (Laerd Statistics, n.d.-d). Since each post is not connected with any other post, the independence of observations' assumption was met. Also, a test for skewness and kurtosis ensured that are no significant outliers. A Levene test was performed on all hypotheses data in order to assess the homogeneity of variances (Laerd Statistics, n.d.-d). The data that passed the variance homogeneity test (H2, H4, H6, H8, H10, H11, H13, H14, H15) were analysed with a one-way ANOVA and a Bonferroni post-hoc test. The data that did not pass the variance homogeneity test (H1, H3, H5, H7, H9, H12) were analysed with a Welch ANOVA and a Games-Howell post-hoc test which do not assume homogeneity of variances. The null hypothesis defines that the averages of the dependent variable are equal for the group if $p > 0.05$. This alpha level was used for all analyses.

The first independent variable to be analysed is the post type. This variable is composed of two groups: video type (n=23) and image type (n=111). In terms of the number of likes, there was a statistically significant difference between groups as determined by welch ANOVA ($F(1, 132) = 5.202$; $p= <0.001$). With this, H1 is supported since image type, 95% CI [4413.64; 6757.37], has a higher average of number of likes than video type, 95% CI [1426.59; 3696.63]. Regarding the number of comments, there was no statistically significant difference between groups as determined by one-way ANOVA ($F(1, 132) = 0.373$; $p = 0.542$). Considering this, there is a lack of evidence of an effect, and it is not possible to support H2. Concerning the eWOM comment valence, there was no statistically significant difference between groups as determined by one-way ANOVA ($F(1, 128) = 3.332$; $p =$

0.070). So, there is a lack of evidence of an effect, and it is not possible to support H11.

The next independent variable to be analysed is the use of a carousel. This variable is composed of two groups: yes (n=49) and no (n=85). On the subject of the number of likes, there was a statistically significant difference between groups as determined by welch ANOVA ($F(1, 132) = 19.010$; $p<0.001$). So, H3 is supported since using a carousel, 95% CI [5949.61; 9656.43], has a higher average of number of likes than not using a carousel, 95% CI [2431.69; 4546.19]. In terms of the number of comments, there was a statistically significant difference between groups as determined by one-way ANOVA ($F(1, 132) = 5.607$; $p=0.019$). So, H4 is also supported since using a carousel, 95% CI [16.09; 27.46], has a higher average of number of comments than not using a carousel, 95% CI [11.17; 17.82]. Regarding the eWOM comment valence, there was no statistically significant difference between groups as determined by welch ANOVA ($F(1, 128) = 0.123$; $p = 0.727$). So, there is a lack of evidence of an effect, and it is not possible to support H12.

The third independent variable is the timeframe composed of two groups: weekend (n=43) and weekday (n=91). Concerning the number of likes, there was no statistically significant difference between groups as determined by welch ANOVA ($F(1, 132) = 2.047$; $p = 0.197$). So, there is a lack of evidence of an effect, and it is not possible to support H5. With regard to the number of comments, there was also no statistically significant difference between groups as determined by one-way ANOVA ($F(1, 132) = 0.037$; $p = 0.847$). So, there is a lack of evidence of an effect, and it is not possible to support H6. Pertaining to the eWOM comment valence, there was no statistically significant difference between groups as determined by one-way ANOVA ($F(1, 128) = 0.839$; $p = 0.361$). So, there is a lack of evidence of an effect, and it is not possible to support H13.

The following independent variables in the interactivity which is divided into three groups: 0 elements (n=52), 1 elements (n=51) and 2 and more elements (n=31). In terms of number of likes, there was a statistically significant difference between groups as determined by welch ANOVA ($F(2, 131) = 21.366$; $p<0.001$). A Games-Howell post-hoc test revealed that for '0 elements' the number of likes was statistically significantly different from '1 element' and '2 or more elements' ($p<0.001$). For '1 element' and '2 or more elements', the number of likes was also statistically significantly different from each other ($p=0.016$). Thus, since for '0 elements' the number of likes was statistically significantly higher than the other two groups, H7 is rejected. Relating to the number of comments, there was also a statistically significant difference between groups as determined by one-way ANOVA ($F(2, 131) = 3.927$; $p=0.022$). A Bonferroni post-hoc test revealed that for '0 elements' the number of likes was statistically significantly different from '2 or more elements' ($p=0.018$), but not statistically different from '1 element' ($p=0.484$). Also, '1 element' and '2 or more elements' were not statistically significantly different from each other (p=0.360). Similarly to H7, '0 element' was statistically significantly higher than the other two groups, so H8 is rejected. Regarding the eWOM comment valence, there was no statistically significant difference between groups as determined by one-way ANOVA (F(2, 127) = 0.033; p = 0.968). So, there is a lack of evidence of an effect, and it is not possible to support H14.

Finally, the last independent variable under analysis is the post appeal. This variable is composed by three groups: functional (n=57), emotional (n=48) and both (n=29). Concerning the number of likes, there was a statistically significant difference between groups as determined by welch ANOVA (F(2, 131) = 24.631; p<0.001). A Games-Howell post-hoc test revealed that for the emotional appeal the number of likes was statistically significantly different from the functional and both appeals (p<0.001), but the functional and both appeals were not statistically significantly different from each other (p=0.507). Hence, since the emotional appeal was statistically significantly higher than the other two appeals, H9 is supported. Pertaining to the number of comments, there was no statistically significant difference between groups as determined by one-way ANOVA (F(2, 131) = 1.947; p = 0.147). So, there is a lack of evidence of an effect, and it is not possible to support H10. Finally, in regard to the eWOM comment valence, there was no statistically significant difference between groups as determined by one-way ANOVA (F(2, 127) = 0.410; p =

0.665). So, there is a lack of evidence of an effect, and it is not possible to support H15.

Table 15 summarizes the results of all ANOVA tests.

	Ind. Var.	Dep. Var.	F statistic	p-value	CI (95%)	Conclusion
H1	post type	number of likes	F(1, 132)=5.202	<0.001	Video: [1426.6; 3696.6] Image: [4413.6; 6757.4]	Supported
H2	post type	number of comments	F(1, 132)= 0.373	0.542	Video: [7.17; 23.09] Image: [14.33; 20.83]	Not Supported
H11	post type	eWOM comment valence	F(1, 128)= 3.332	0.070	Video: [0.34784; 0.57460] Image: [0.32386; 0.40791]	Not Supported
H3	use of a carousel	number of likes	F(1, 132)=19.010	<0.001	No: [2431.69; 4546.19] Yes: [5949.61; 9656.43]	Supported
H4	use of a carousel	number of comments	F(1, 132)= 5.607	0.019	No: [11.17; 17.82] Yes: [16.09; 27.46]	Supported
H12	use of a carousel	eWOM comment valence	F(1, 128) 0.123	0.727	No: [0.33053; 0.44561] Yes: [0.32838; 0.41834]	Not Supported
H5	time frame	number of likes	F(1, 132)= 2.047	0.197	Weekend: [3994.60; 8243.68] Weekday: [3466.31; 5671.82]	Not Supported
H6	time frame	number of comments	F(1, 132)= 0.037	0.847	Weekend: [12.37; 22.80] Weekday: [13.26; 20.65]	Not Supported
H13	time frame	eWOM comment valence	F(1, 128)= 0.839	0.361	Weekend: [0.34080; 0.47805] Weekday: [0.32053; 0.41952]	Not Supported
H7	interactivity	number of likes	F(2, 131)= 21.366	<0.001	0 elements: [6785.62; 10282.96] 1 element: [2349.20; 5178.02] 2 or more elements: [473.86; 2312.01]	Not Supported
H8	interactivity	number of comments	F(2, 131)= 3.927	0.022	0 elements: [15.94; 26.99] 1 element: [11.96; 21.49] 2 or more elements: [6.56; 14.73]	Not Supported
H14	interactivity	eWOM comment valence	F(2, 127)= 0.033	0.968	0 elements: [0.31933; 0.44615] 1 element (n=51): [0.30987; 0.44545] 2 or more elements (n=31): [3049; 0.47758]	Not Supported
H9	post appeal	number of likes	F(2, 131)= 24.631	<0.001	Functional: [1643.68; 3242.14] Emotional: [7124.74; 11133.21] Both: [1749.82; 5248.18]	Supported
H10	post appeal	number of comments	F(2, 131)= 1.947	0.147	Functional: [10.43; 18.43] Emotional: [15.50; 26.62] Both: [9.19; 22.33]	Not Supported
H15	post appeal	eWOM comment valence	F(2, 127)= 0.410	0.665	Functional: [0.33622; 0.46291] Emotional: [0.30817; 0.45496] Both: [0.28259; 0.41867]	Not Supported

Table 15 – ANOVA Results
Source: Own Elaboration

4.3.2.Multiple Linear Regressions

As can be identified in different studies (Balio & Casais, 2021; Tavares & Nogueira, 2021), several multiple linear regressions were carried out in order to identify the predictors of the dependent variables. Multiple regression also allows to determine the overall fit (variance explained) of the model and the relative contribution of each of the predictors to the total variance explained. The stepwise method was chosen as it allows to examine iteratively the statistical significance of each independent variable until it arrives at the best fit line equation (Laerd Statistics, n.d.-c). This type of model requires that the independent variables are either scalar or binary; considering that all of the independent variables under analysis are categorical, but two of them (interactivity and post appeal) are not binary, it was necessary to apply the dummy coding technique to these variables. It was necessary to create one less dummy variable than the number of categories in the categorical independent variable (Laerd Statistics, n.d.-a). Thus, for the interactivity variable, it was created two dummies: int1 and int2 (baseline is 0 elements, hence int1=0 and int2=0; for 1 element, int1=1 and int2=0; and for 2 or more elements, int1=0 and int2=1). For the post appeal variable, it was also created two dummies: appeal1 and appeal2 (baseline is functional, thus appeal1=0 and appeal2=0; for emotional, appeal1=1 and appeal2=0; and for both, appeal1=0 and appeal2=1).

In order to ensure the assumptions for carrying out the multiple linear regression were respected, tests for independence, normality, homoscedasticity and multicollinearity were performed and considered acceptable.

A multiple regression was run to predict the number of likes from all the post characteristics, namely post type, use of a carousel, time frame, interactivity and post appeal. The analysis resulted in a model statistically significant [$F(4, 129) = 23.535$, $p < 0.001$, $R^2 = 0.422$]. The predictors variables statistically significant for the number of likes are: the appeal1 ($\beta = 0.398$; $t = 5.300$; $p < 0.001$); the use of a carousel ($\beta = 0.268$; $t = 3.822$; $p < 0.001$); the int2 ($\beta = -0.259$; $t = -3.063$; $p = 0.003$) and the int1 ($\beta = -0.179$; $t = -2.186$; $p = 0.031$). The equation that predicts the number of likes is:

*Number of likes = 8646.819 + 4860.385 * appeal1 + 3262.717 * use of a carousel – 3600.602 * int2 – 2157.396 * int1*

Subsequently, another multiple regression was run to predict the number of comments from all the post characteristics, namely post type, use of a carousel, time frame, interactivity and post appeal. The analysis resulted in a model statistically significant [$F(2, 131) = 5.053$, $p = 0.008$, $R^2 = 0.072$]. The predictors variables statistically significant for the number of comments are: the int2 ($\beta = -0.178$; $t = -2.087$; $p = 0.039$) and the use of a carousel ($\beta = 0.174$; $t = 2.035$; $p = 0.044$). The equation that predicts the number of comments is:

*Number of comments = 16.564 – 7.333 * int2 + 6.259 * use of a carousel*

Finally, a last multiple regression was run to predict the eWOM comment valence from all the post characteristics, namely post type, use of a carousel, time frame, interactivity and post appeal. The analysis resulted in a model that was not statistically significant, which corresponds to the result of ANOVA, so no predictors were shown.

Table 16 summarizes the results of the multiple linear regressions.

Models	Predictors	Beta	p-value
Model of Likes	Appeal 1	0.398	<0.001
	Use of a carousel	0.268	<0.001
	Int2	-0.259	0.003
	Int1	-0.179	0.031
Model of Comments	Int2	-0.178	0.39
	Use of a carousel	0.174	0.44
Model of eWOM comment valence	-	-	-

Table 16 - Multiple Linear Regression Results
Source: Own Elaboration

5.RESULTS DISCUSSION

In this chapter, the findings presented and described in the results chapter will be explained in order to understand their meaning concerning this study's research goals, as well as how they fit into the existing literature. The potential reasons for these results will also be discussed.

The main goal of this study is to investigate the influence of social media posting of subscription video-on-demand services (Netflix Portugal, Disney Plus Portugal and HBO Portugal) on Portuguese customer engagement. In order to respond to the main and specific goals of this study, secondary data was collected on Instagram. Posts made by Netflix Portugal, Disney Plus Portugal and HBO Portugal on this social media during the month of January were gathered. After collecting a total of 142 posts and 3402 comments, all information was systematized and analysed in SPSS Statistics.

For the first specific goal, each social media post characteristic was analysed in order to understand the impact on the online customer engagement on Instagram. The first social media post characteristic was the post appeal. The findings obtained in this study reveal that when a post is an image, it receives a higher number of likes, but not a higher number of comments or more positive eWOM comment valence. A video post does not receive a higher online customer engagement in either of its three forms. These results corroborate the findings of C. Kim and Yang (2017) and Schultz (2017) that discovered that photo/image had a negative impact on the number of comments, which also happened in this study. The results are also in line with Balio and Casais (2021) since image was also the preferred type on Instagram which is correlated to its core function. However, the results contradict part of the claims of Cvijikj and Michahelles (2013), L. De Vries et al. (2012), Moran et al. (2020), Sabate et al. (2014) and Shahbaznezhad et al. (2021) since video did not positively impact the number of likes or comments. This study also achieved a different conclusion from Tavares and Nogueira (2021) that determined that the post type was irrelevant on Instagram and Rahman (2021) that concluded that, in the SVoD context, video was preferred over image. One possible reason is that watching videos demands more time and attention and customers normally do not have that availability when consuming content from Instagram. This availability could be also considered to explain why images are not associated with a higher number of comments since commenting requires an extra effort in comparison with liking. Another possible explanation is that the majority of videos tend to be teasers or trailers and some people do not like to watch those due to possible spoilers and this could explain the fewer success within this specific context.

Concerning the use of a carousel, the results of this study point toward the importance of using it due to the existence of a positive correlation between the use of a carousel and the number of likes and comments. This analysis supports the study of Oltra et al. (2021) that the use of a carousel stimulates the act of commenting and, also, partially supports Wahid and Gunarto (2021) conclusions since there was a significant effect on likes, but also on comments. These results are probably explained by the crescent use of this feature that allows for more content to be shown. The fragmentation allows for the user's attention to be distributed among different stimuli making it easier to consume the content. However, the eWOM comment valence was not statistically related to the use of a carousel.

The third post characteristic under analysis was the time frame. The data suggests that no relation exists between time frame and the number of likes, number of comments and eWOM comment valence. This contradicts the findings of Cvijikj and Michahelles (2013) and Wagner et al. (2017). These results build on existing evidence from Coelho et al. (2016), L. De Vries et al. (2012) and Tavares and Nogueira (2021) who also concluded that weekday vs weekend had no statistical relevance for engagement. This is probably due to the fact that people now spend most of their time on their phones and social media, so there is no difference between weekdays and a weekend in terms of social media presence and online customer engagement.

In terms of the fourth post characteristics, although it was expected from previous literature that interactivity generated engagement and contrary to the hypothesized association, the findings obtained actually revealed that 0 elements of interactivity generated a greater number of likes and comments than 1 element or 2 or more elements. These are in line with the conclusions achieved by Balio and Casais (2021), Cvijikj and Michahelles (2013), L. De Vries et al. (2012), Sabate et al. (2014), Tafesse (2015) and Tavares and Nogueira (2021). A possible explanation for this occurrence is that an interactive post requires a longer engagement time which would contradict the usage patterns of Instagram since people spend less time consuming each post due to the overload of content. Nevertheless, these results contradict the claims made by Fernández-Gómez and Martín-Quevedo (2018) and Rahman (2021) within the SVoD context that determine that interactive elements, such as hashtags and open questions, were related to higher engagement. However, eWOM comment valence was not statistically related to the interactivity.

Lastly, in terms of post appeal, this study demonstrates a correlation between emotional appeal and the number of likes. Nonetheless, there was no evidence of a positive relationship between the appeal and the number of comments or the eWOM comment valence. These results were partially in accordance with the ones achieved by Bagozzi et al. (1999), J. Liu et al. (2017), Swani et al. (2013) and Tavares and Nogueira (2021). Only partially because they concluded that emotional appeals drive more engagement than functional appeals, however, in this study the emotional appeal only drove the number of likes. The results do not fit with the conclusions of Dolan et al. (2019), Taemin Kim et al. (2018) and Wagner et al. (2017) since the functional appeal did not drive engagement. Also, the findings of Shahbaznezhad et al. (2021) were not in accordance with the ones in this study as the functional appeal did not generate likes and the emotional appeal had no significant negative effect on the number of likes. This is probably explained by the fact that the SVoD industry is an entertainment industry, which tends to have happier interactions between customers and brands. There is an emotional attachment between fans and their programs, so whenever the content is related to their programs, there is an appeal to a happy emotion which creates a higher probability of engagement. Even so, this emotion was only translated into likes and not into comments/valence most likely because of the usage patterns of Instagram and people's lack of time to invest in commenting. So, customers are probably happy to signal approval through like, but less inclined to engage in commenting. Also, whenever a functional element is present in a post that seems to drive away engagement may be because of two reasons. The first is because it may signal a persuasion effort which is unequal to customers' motivations to follow SVoD services' brands. The other reason is that these posts do not reduce uncertainty due to the fact that customers are already highly knowledgeable, so the information is not relevant.

The lack of a statistically significant relationship between the eWOM comment valence and the five post characteristics is probably explained by the fact that further investigation is needed on the sentiment analysis algorithm and on the issues faced when transforming sentiments into metrics. This is a new and modern method that still needs improvement in order to achieve accurate results in sentiment detection and solve problems such as disambiguation, use of sarcasm or metaphors, etc (Palomino et al., 2020). This possible incorrect sentiment scoring could have had an impact on the results of this study and explain why no relationship was found. Another possible explanation is that the absence of literature on eWOM comment valence as part of online customer engagement is a reflection of the absence of a proven relationship thus this study was built upon no scientific agreement thus far.

For the second specific goal, the social media post characteristics were analysed in a grouped manner through a multiple linear regression to evaluate how they drive online customer engagement. The model hereby proposed supports that 42.2% of the variation in the number of likes is explained by the variation in the post appeal, use of a carousel, and the number of interactivity elements. The analysis of this model indicates that, on average, a post has around 8600 likes. When an emotional appeal is added to the post, it gains, on average, around 4900 likes (an increase of more than 50%). The same happens with the use of a carousel since it leads to an average increase of around 3300 likes (an increase of almost 40%). However, when any element of interactivity is added to the post, there is a loss of, on average, between 2200 and 3600 likes (more than a quarter). No other characteristics were predictors of the number of likes. So, for example, if a post has an emotional appeal, uses a carousel and has 0 elements of interactivity, then the predicted number of likes is around 16770. If a post has a functional appeal, does not use a carousel and has 2 elements of interactivity, then the predicted number of likes is around 5046.

The model herewith proposed supports that 7.2% of the variation in the number of comments is explained by the variation in the use of a carousel and the number of interactivity elements. The analysis of this model suggests that, on average, a post has around 17 comments. The use of the carousel is still the only characteristic that generates an increase of about 6 comments, on average. When 2 or more elements of interactivity are added, a post loses, on average, around 7 comments. No other characteristics were predictors of the number of comments. So, for instance, if a post uses a carousel and has 2 elements of interactivity, then the predicted number of comments is around 16.

Finally, the model for the eWOM comment valence was not valid, which makes it impossible to analyse the respective effect of the characteristics. All these results were in accordance with the ANOVA results which proves robustness.

To summarize, according to the data collected in the present thesis, it becomes possible to understand the post characteristics which drive Portuguese online customer engagement on Instagram within the SVoD services industry. It confirmed the importance of characteristics such as the post type, the use of a carousel, the interactivity and the post appeal on the analysed metrics. However, the importance of time frame on the analysed metrics could not be proven.

6. CONCLUSION

This chapter will conclude this thesis by summarizing the key research findings in relation to the research goals. It will also explicit the theoretical contributions and practical recommendations therefrom.

This present study was designed to investigate the influence of social media posting of subscription video-on-demand services (Netflix Portugal, Disney Plus Portugal and HBO Portugal) on Portuguese customer engagement. To this end, the thesis adopted a quantitative approach using ANOVA tests and multiple linear regressions. The results indicate that, on Instagram, an image increases the number of likes, the use of a carousel increases the number of likes and comments, the presence of elements of interactivity decreases the number of likes and comments and the emotional appeal increases the number of likes. Furthermore, it is possible to have a reliable prediction for the number of likes based on the use of a carousel, the interactivity and the post appeal; also, one can predict the number of comments based on the use of a carousel and interactivity. Additional findings show that none of the five post characteristics has a statistically significant effect on eWOM comment valence.

Based on the limitations and suggestions given by Tavares and Nogueira (2021), it is intended that this thesis provides a deeper insight into the rapidly expanding field of customer engagement in social media. One of the main theoretical contributions of this study consists of presenting eWOM comment valence as a consequence of one or more social media post characteristics using sentiment analysis as the method of analysis. Whilst this study did not confirm a relationship between the characteristics and the valence, it did substantiate the importance of this metric for online customer engagement. Another theoretical contribution lies in the fact that this study added a new post characteristic, the use of a carousel, to the ones used previously in analogous studies. Thus, it was possible to broaden the analysis by growing the number of variables under analysis and achieving more up-to-date results. This research also contributed to expand VADER lexicon's dictionary with a new bag of words and the addition of emojis. This was done in order to enhance the algorithm to give more accurate results within the social media context. Furthermore, the majority of studies within social media uses primary survey data. This study supplemented this field by exhibiting how social media content, as secondary data, can be extracted and analysed to establish relationships. Lastly, this dissertation strengthens the existing literature, more specifically within the SVoD Services and Social Media literature and the Portuguese context. It provides specific knowledge on the different kinds of content published on the SVoD services' Instagram accounts and the engagement generated in customers by it.

On the other hand, this work contributes to a better understanding of posting on Instagram within the SVoD services industry. The number of likes and comments on brand content is a signal of brand popularity and thus an important metric for managers to measure (Swani et al., 2017). The insights gained from this study may be of assistance to SVoD brand managers in order for them to know what to post since each post requires resources to be developed. Concerning the type of post, it was discovered that the type affects only the number of likes, with the image format showing a better performance than the video format. This is an important finding since developing an image post and a video post requires a different amount of time and resources. Therefore, it is recommended that SVoD brands invest in the image format in their posts. Regarding the use of a carousel, it was found that its use has an effect on both the number of likes and the number of comments. It is therefore recommended that brands take advantage of this feature to increase their online customer engagement on Instagram. In terms of interactivity, it was discovered that the absence of elements of interactivity generated both likes and comments. So, it is advised that SVoD brands should be careful in the use of hashtags, calls to action or open questions in their copy. In this study, 43% of the posts were functional and 20.4% had a presence of a functional appeal in both compared to the 36.6% that were emotional. Considering that the emotional appeal generates a greater number of likes than the presence of a functional appeal, brands have an opportunity to improve their content by increasing the number of posts that incorporate emotional appeals into their content. Even when a post is emotional, if it has a functional part, the positive effect of an emotional appeal is lost. Although this study focuses on SVoD services, the findings may well have a bearing on other entertainment industries.

To conclude, this thesis acknowledges the growing importance of Instagram as a branding tool and its influence on consumers' life. This could potentially inspire brands to develop a strategy that brings monetary gains while building a strong and loyal brand community. With these results, SVoD brands are able to establish a more specific strategy for their post which will in turn generate higher, and better, online customer engagement. It also contributes to the growth of academic literature in an under-research social media and industry segment.

7. LIMITATIONS AND FUTURE RESEARCH

The present thesis has its limitations, which can provide abundant suggestions for future research. First and foremost, the time constraint did not allow to collect more data which would, in turn, make the analysis more robust. Ergo, one future research suggestion would be to collect data for a longer period of time (longer than one month) gathering a larger sample of posts to achieve deeper insights and understand if the results suffered changes in comparison to the ones achieved in this study. This larger sample could also help better accommodate other players' in the SVoD industry which could, in turn, help with the possible dominance of Netflix within this market and the potential overshadowing of this brand when analyzing the data.

An additional uncontrolled factor and limitation was the elimination by HBO Portugal of posts prior to February 2022. This led, as explained previously in subchapter 3.2, to the removal of the majority of posts due to the inability to access the post to watch the video or the use of a carousel. Regardless, this did not generate bias in the sample since the aim of the study was to analyse the posts in a grouped manner and not compare the SVoD brands. However, a consideration for future research would be to replicate this study with the main goal of comparing posts between SVoD services.

The scope of this study was limited in terms of the variables under study, more specifically the interactivity and the post appeal. Both variables could have involved more categories which would, in turn, make the analysis more thorough. A future research possibility would be to analyse a possible relationship between the interactive content and calls to action that drive action to the SVoD platform. Another future research suggestion would be to broaden the appeals in order to be more specific than functional vs emotional. Also, it would be interesting to deepen the post type variable by including Gifs as one type of post, something that could not be done in this study since there were not enough gifs to create a meaningful sample. Additionally, another suggestion would be to analyse the different duration of videos to understand if a smaller video and a longer video have the same kind of impact on online customer engagement.

One source of weakness in this study that may have affected the eWOM comment valence was the translation of the comments and possible incorrect sentiment scoring by the algorithm. Since this is a recent method of analysis, more research needs to be performed to determine the reliability of the VADER sentiment analysis and ways of improving the lexicon and tool. However, as it is a trending topic presently in academia, there is a belief that, in the next years, important discoveries will be made within the sentiment analysis literature and, thus, this study should be repeated. Besides this, another suggestion would be to develop the study of eWOM comment valence between different social media and compare them since the overall emotion behind social media might affect the way customers engage in it.

In terms of additional future research suggestions, the first one would be to replicate this study for other industries. Each industry has its own specificities, so it is only beneficial to understand what works, or not, for an industry in particular. More specifically, as SVoD is an entertainment industry, replicate it in industries that are not so inherently happy and, traditionally, do not generate such positive emotions. Also, another suggestion would be to replicate this study in other countries to see if there are possible cultural differences. Here, the focus was on the Portuguese market with only Portuguese accounts of SVoD services. Another replication would be to use this same study for other social media, for example, Facebook or Twitter, or other SVoD services, for example, Amazon Prime or Hulu. Finally, to gather further insights on SVoD services' online activity on Instagram, both brand managers and customers could be interviewed in order to obtain new perspectives. This would introduce a qualitative viewpoint to this quantitative study which would, in turn, bring more depth to the analysis.

In conclusion, this research elucidates which post characteristics influence online customer engagement (number of likes, number of comments and eWOM comment valence) on SVoD services' Instagram within the Portuguese market. This thesis responds to calls for research on customer engagement in social media and, more specifically, within the Instagram context. In this process, it was identified differences in the popularity of post characteristics in this segment that can advise managerial practice and future academic efforts in this area.

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