EXAMINING FACTORS THAT PREDICT USER ENGAGEMENT ON YOUTUBE

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Abstract

This research proposes a model to examine factors that predict user engagement with sports brand-related YouTube videos. This research also investigates which type of YouTube channels generate more user engagement. Prior research on social media engagement, YouTube, social influencers and sports marketing will be analyzed. Ten hypotheses are derived to carry out the research. The model concludes that factors such as the number of channel subscribers, channel age, video age, video duration and video definition have statistically significant relationship with YouTube engagement. Additionally, channel types: brand, private vlogger and news/updates also have a statistically significant relationship with YouTube engagement. Brands channels, having access to a larger network and the ability to feature sports celebrities, are likely to generate four times more engagement than other YouTube channels. This study contributes to the research on social media engagements in terms of examining the type of factors important in predicting user engagement on YouTube.

Keywords: Social Media, Social Media Engagement, YouTube, Social Influencers, Vloggers, Sports Marketing and Soccer.

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1. Introduction

The emergence of social media has broken many communication barriers, allowing individuals to connect and communicate among each other conveniently (Keegan and Rowley, 2017; Gerlitz, 2014; Voorveld, van Noort, Muntinga, and Bronner, 2018). Social media refers to the group of Internet based applications that allow users to connect, communicate, create and exchange content among their online groups and networks (Kaplan and Haenlein, 2010). Particularly, social media allows users to connect and communicate through the creation and exchange of user generated content (Kaplan and Haenlein, 2010). Online users mainly use social media to seek entertainment, interact among peers and spread or gain information (Saridakis, Baltas, Oghazi, and Hultman, 2016). Additionally, online users also find using social media as a form of personal identification and social empowerment (Saridakis, Baltas, Oghazi, and Hultman, 2016). Currently, the number of global active social media users is at 2.62 billion as of 2018, expecting to increase to 3 billion users by 2021 (Statista, 2019a). In Canada, the number of active social media users is at 22.2 million as of 2018, expecting to reach 24 million users by 2022 (Statista, 2019b).

User generated content refers to the content created by end-users (Smith, Fischer, and Yongjian, 2012). As social media applications are Internet based, user generated content is exchanged from around the world. This exchange of content has created topics, discussions, and online communities, based on users' interests (Muntinga, Moorman, and Smit, 2011). One of the most prevalent online communities includes brand communities, where online users connect and communicate around brands they find valuable (Arvidsson and Caliandro, 2016). Many brands also use and invest in social media to create their online brand communities (Klapdor, 2013; Tsimonis, 2014). According to the findings of Kozinets (2002), brands are interested in online brand communities on social media mainly due to two reasons: electronic word-of-mouth (eWOM) and consumer research. eWOM refers to online brand users sharing positive and negative brand experiences with other users (Balaji, Khong, and Chong, 2016). Social media facilitates the development of eWOM, allowing users to freely create and distribute brand-related knowledge and experience among their networks (Tsimonis, 2014). This creates an opportunity for brands and researchers to study online users' interactions in order to find new consumer insights and trends. New trends and insights help brands reshape themselves to provide a better brand experience to their consumers (Tsimonis, 2014). In addition, due to increasing market competition, cost reduction pressures and the growth and popularity of social media, many brands find social media as an innovative way to reach and connect with their consumers (Coursaris, 2016; Tsimonis, 2014).

Social media, despite providing new marketing opportunities, has also created some complexities for brands (Tsimonis, 2014; Voorveld et al., 2018). Brands face difficulties in achieving results for their social media marketing campaigns (Tsimonis, 2014; Voorveld et al., 2018). Particularly, brands struggle with generating high social media engagement (SME) for their online campaigns, one of the important social metrics to measure social media marketing results (Hoffman and Fodor, 2010; Lee, Hosanagar, and Nair, 2018). SME refers to the result of a process when community members interact with each other, or the brand on a repetitive basis (Martínez-López, 2017). Other authors also refer SME as engagement, user engagement, online brand community engagement and consumer engagement. SME is also refered to customer engagement, consumer brand engagement, online engagement, and online popularity (Sprott, Czellar, and Spangenberg, 2009; Phillips and McQuarrie, 2010; Brodie, Hollebeek, Juric, and Ilic, 2011; Martínez-López, 2017; Sarkar and Sreejesh, 2014; Gambetti, Graffigna, and Biraghi, 2012; Szabo and Huberman, 2008). SME helps brands measure the performance of creative and financial efforts used in social media strategies. As users can connect and communicate with a brand on a variety of social media applications, brands now require different social media strategies, with content that is relevent to the needs of users (Lee and Watkins, 2016). Therefore, it is important to study different factors affecting SME on individual social media applications.

With respect to individual social media applications, Facebook, Twitter, YouTube, and Instagram are the most common social media platforms used by a majority of brands and marketers worldwide (Statista, 2018a; Tuten and Solomon, 2015). Focusing this research on YouTube, the platform containing millions of content creators has become the preferred destination for sharing and viewing videos online. The YouTube Partner program allows content creators to monetize their videos (Hoiles, 2017). According to Alexa.com, a data analytics subsidiary website of Amazon.com, YouTube is ranked as the second most visited website globally, with over 4 million daily visitors (Alexa.com, 2019). Merrill Lynch, one of the world's largest wealth management company (Merrill Lynch, 2018), forecasted a gross digital advertising revenue for YouTube to be 20.4 billion USD for 2018, amounting to 38% of the total digital ad share (Statista, 2018).

YouTube allows users to create, view, post and share videos (Tsimonis, 2014). Users who create and upload content on YouTube are known as vloggers. Some vloggers become "YouTube celebrities" when they reach a considerate number of followers or subscribers (Lee and Watkins, 2016; Marwick, 2013). Creative vloggers can achieve a high reach due to a large following, with a few having more than 100 million subscribers (Lee, 2016). Vloggers establish a high online following due to their ability to develop and contribute novel information and influence the attitudes and behaviors of others (Liu et al., 2015). Vloggers have emerged to become important personalities as the online community has been found to correlate a high social trust, well-informed knowledge with such individuals (Liu et al., 2015). Considering the influence and importance of vloggers, there is little research around YouTube engagement studying which type of YouTube videos and channels (vlogger or brand) generate more engagement. To date, only the work by Kruitbosch and Nack (2008) and Checchinato, Disegna, and Gazzola (2015) provides some evidence that branded videos generate more engagement than the ones created by users.

YouTube contains videos from eighteen separate categories (Bärtl, 2018). Sports, one of the eighteen separate categories present on YouTube, is one of the most popular video categories and generates one of the highest number of views (Bärtl, 2018). In 2017, sports were the fourth most popular video category viewed on YouTube in the U.S (Statista Survey, 2017). Previous research on the use of online media for sports marketing is growing. Previous authors mainly study different factors affecting the relationship between sports teams and their supporters. Checchinato et al. (2015) concluded that soccer team supporters prefer content generated by the team's official YouTube channel more than the content generated by other supporters. Tsuji, Bennett, and Leigh (2009) concluded that sports teams can also be referred to as sports brands. Waters, Burke, Jackson, and Buning (2011) analyzed the impact of team sponsors on brand community engagement. Popp and Woratschek (2016) introduced the concept of branded communities created around a need or sport. Considering the prevalence and viewership of sports videos on YouTube, there is an opportunity to study sports videos and channels, created by different sports brands and vloggers, to develop an understanding of what factors generate engagement for such type of channels. As online interactions among brand community members differ from brand to brand (Habibi, Laroche, and Richard, 2014), it is also an opportunity to study factors affecting SME on content related to sports brands.

1.2 Research Objectives and Questions

The main research objective of this research is to examine factors that may help predict user engagement with sports brand-related YouTube videos and investigate which type of YouTube channels generate increased user engagement. This research aims to fill in the knowledge gap on how different factors, related to a YouTube video, can impact its user engagement generation. Thus, the overall research question is:

RQ: What factors predict user engagement with YouTube videos?

In order to answer the broad research question and narrow down the direction of research, additional research questions are investigated:

RQ1: Do channel properties predict user engagements?

Waters, Burke, Jackson, and Buning (2011) as well as Checchinato, Disegna, and Gazzola (2015) focused on the phenomena of online engagement between sports team and fans. However, a phenomenon of online engagement between sports brands and its fans, especially on YouTube, is unexplored. Kruitbosch and Nack (2008) concluded that professionally created videos generate more engagement in the form of video likes and comments, but due to the increasing use of YouTube, there is a need for another study. The number of videos on YouTube has drastically increased. As of 2016, the estimated number of videos on YouTube were four billion (Arthurs, Drakopoulou, and Gandini, 2018), compared to the estimate of 70 million uploads stated by Kruitbosch and Nack (2008). Khamis (2017) considers social media influencers or YouTube vloggers, in the case of this study, as individuals involved in developing a public image for commercial or cultural gain. According to Qian Tang (2012), vloggers consider the accumulation of the number of subscribers as a direct measure to their reputation and value the number of channel subscribers more than user engagement generated on their videos. Therefore, extending the work by Kruitbosch and Nack (2008) in analyzing which identity (brand or vlogger) generates more SME and using insights of Khamis (2017) and Qian Tang (2012) on vloggers, this research aims to explore the impact created by brands and vloggers on the success of the video in terms of SME generated. Thus, considering different channel properties, including channel type, age, and the number of channel subscribers, the first research question is derived.

RQ2: Do video properties predict user engagement?

Although longer video ad formats with personalized created content for social media platforms are increasingly common, marketers and advertisers still face some complexities in deciding the most effective video ad length (Chi, 2011; YuMe and IPG Media, 2016). According to a report of YuMe and IPG Media (2016), a digital media agency, a minimum of 15 seconds of content exposure is required to derive any persuasion metrics from the viewers. Similarly, the preferred optimal length for YouTube videos in Italy was found to be between two to five minutes (HR Solutions - Digital Coach, 2018). This study aims to analyze an optimal range of video length for sports brand-related content.

The second research question was derived based upon the insights of Dobrian et al. (2013) and Wu et al. (2017) on the positive impact of video quality on user engagement however, the video dataset used in the studies was very broad, questioning the validity of results for different video genres and categories. Using different video attributes including video length, quality, and age of activeness, and combining work of Tsuji, Bennett, and Leigh (2009) from the context of sports marketing, who investigates the impact of video properties on brand reach and awareness for sports brand, the second research question is derived.

2. Literature Review and Model Development

The review of literature starts with an overview of the importance of social media platforms in online marketing, describes the concept and theories of SME, and how SME can be measured from a marketing perspective. To focus this research on the YouTube platform, the review of literature provides an overview of the importance of the platforms and summarizes different studies reflected by other authors, particularly on measuring and stimulating online engagement. Narrowing this research on YouTube sports brand videos, the literature provides information on the importance of social media in sports, particularly soccer, as well as previous studies conducted on sports. The literature then informs about brand-related user generated content and how it aids brands with content marketing. Lastly, the literature informs about the importance of social influencers on social media and the concept of vloggers on YouTube. Hypotheses are derived section by section based on previous studies.

2.1 Online Marketing and Social Media

Using social media, brands and marketers can form relationships with current as well as new consumers to create a brand network that collaborates to recognize and solve consumer problems and queries (Habibi et al., 2014; Martínez-López, 2017; Tsimonis, 2014). Social media allows marketers and brands to implement key marketing tactics and promote product or service use without annoying consumers, therefore becoming an interpersonal communication channel (Wendt, Griesbaum, and Kölle, 2016). Online or digital marketing refers to the accomplishment of marketing objectives with the use of the Internet (Klapdor, 2013). According to Klapdor (2013), the main tools for marketing promotions are public relations and advertising. Despite the presence of vast social media channels, many brands are still struggling with leveraging the creative and analytical powers of social media (Kane, 2015). We live in a time where Gen-Yers tweet about their brand problems rather than dialing the 1-800 number (Kane, 2015). Such strategic issues provide a need for social media marketing research in terms of understanding how result-driven marketing campaigns can be created.

2.2 Social Media Engagement

Social media engagement (SME), also known as engagement, user engagement, online brand community engagement, consumer engagement, customer engagement, consumer brand engagement, online engagement and online popularity (Sprott et al., 2009; Phillips and McQuarrie, 2010; Brodie et al., 2011; Martínez-López, 2017; Sarkar and Sreejesh, 2014; Gambetti et al., 2012; Szabo and Huberman, 2008), is one of the important metrics marketers and brands derive from social media (Hoffman and Fodor, 2010). For this study, the term YouTube engagement is used in many sections of this research to further classify the social media platform studied in this research. Although many authors have posited different theories on measuring and stimulating engagement, it is still difficult to define and understand the term engagement in the space of social media. According to Achen, Lebel, and Clavio (2017) online users may also be engaged offline, beyond the traditional use of social media features such as likes, comments and shares. As a result, it is difficult to measure the many facets and interactions that comprise engagement.

Kahn (1990), an author of psychology, was the first researcher to study the concept of engagement in the field of organizational behavior. According to Kahn (1990), employees tend to have different versions of self-expressions in work roles. Employees who perceive work conditions to be motivating for their authentic self-expression are more likely to be engaged. Vivek, Beatty, and Morgan (2012) refer to the theoretical roots of consumer engagement as an expanded concept of relationship marketing. Vivek et al. (2012) suggest consumer engagement as a central concept within multiple marketing domains and systems. Based on this theoretical support, Brodie et al. (2011) define consumer engagement as an interactive psychological state that occurs through consumer co-creative experience with a focal object, where the object in most cases, is a brand. Martínez-López (2017) refers to SME as the result of a process when community members interact with each other, or the brand on a repetitive basis.

Social media behavior, defined by Muntinga, Moorman, and Smit (2011), falls into levels of consuming, contributing, and creating. Consuming refers to the users reading, watching or acknowledging content in the form of 'likes' on social media. Contributing, being the middle form, refers to users participating in the form of 'commenting' on content present on social media while creating, being the highest form of engagement, refers to users publishing content by the feature of 'share' present on social media (Kim and Yang, 2017). The use of engagement also reflects consumers intentions towards interaction, collaboration and participation in the community or network (Martínez-López, 2017). On the contrary, Dessart, Veloutsou, and Morgan-Thomas (2015) conceive consumer engagement in terms of three distinct categories: affective, cognitive and behavioral engagement. Affective engagement refers to the enthusiasm and enjoyment users gain from social media content. Cognitive engagement refers to users sustaining attention and detachment from other activities, when using social media. Behavioral engagement refers to users endorsing social media content through the use of like, comment and share features as well as seeking any information from the content (Dessart et al., 2015). Work by Dessart et al., (2015), Kim and Yang (2017), Martínez-López, (2017) and Muntinga et al. (2011) reflects how SME is generated and defines the importance of engagement in consumer behavior, reflecting the scope of this research.

SME, in many forms, has been a focus of study for many marketing practitioners for quite some time. Hollebeek (2011) works on creating a customer brand engagement model to show the conceptual difference between customer engagement and other marketing constructs like customer relationship quality and loyalty. Brodie, Hollebeek, Juric, and Ilic (2011) adds to the study of Hollebeek (2011) by proposing customer engagement on five themes. Brodie et al. (2011) conclude customer engagement different from other relational concepts like participation and involvement as customer engagement provides a more interactive user experience in contrast to the recent work by Martínez-López (2017), which includes participation as part of SME for online communities. Brodie, Ilic, Juric, and Hollebeek, (2013), and Gambetti, Graffigna, and Biraghi (2012), in context to brand communities, refer consumer engagement as complex and dynamic in nature. According to Brodie et al. (2013), the consumer engagement process includes multiple cognitive sub-processes which allows consumers to collaborate and co-create value among other members within online brand communities. Brands, if correctly recognize consumers cognitive sub-processes, including consumer needs and wants, can build stronger brand engagement with consumers (Gambetti et al. 2012).

One of the interesting insights highlighted in the study by Gambetti et al. (2012) is the appearance of consumer engagement as an overarching marketing concept that facilitates different consumer decision making processes with each other. Hollebeek (2013) studies the relationship between customer engagement and value for hedonic and utility brands. The author concludes that higher customer engagement leads to a higher customer value more for hedonic brands than utility brands. Kuo and Feng (2013) study the formation of 'oppositional brand loyalty' in online brand communities. According to Kuo and Feng (2013), community members, when engaging in online brand communities, provide each other with learning, social, personal and hedonic benefits. Such benefits affect the relationship or commitment of online users to a brand. If online users are more likely to be committed to a brand, they are more likely to form the feeling of hate for a rival brand (Kuo and Feng, 2013). The findings highlighted and concluded by other authors show the importance of SME in the field of marketing and its distinction from other marketing concepts. The findings also show the use of SME in online brand communities and its consequent effect on any brands' image and value.

Many researchers have also worked on predicting and quantifying SME. Sprott, Czellar, and Spangenberg (2009) propose an eight-item scale to measure brand engagement in order to predict consumers' brand recall and preference. Similarly, Phillips and McQuarrie (2010), and So, King, and Sparks (2014) studying traditional fashion and hospitality brand communities, and Habibi, Laroche, and Richard (2014) studying automobile brand communities, propose a five-item scale to quantify and predict user engagement. Many researchers also relate online popularity to social media engagement (Chatzopoulou, Sheng, and Faloutsos, 2010; Hassan Zadeh and Sharda, 2014; Szabo and Huberman, 2008; Trzciński and Rokita, 2017; Wu et al., 2017). However, the metrics and variables used to measure results remain to be similar. Szabo and Huberman (2008) use video views as a measure of online popularity for YouTube and Digg videos while Wu et al. (2017), defining YouTube video views as an engagement metrics, also use video views as a variable to predict video popularity. Similarly, Hassan Zadeh and Sharda (2014) and use engagement metrics, the number of tweets and retweets from Twitter, to measure brand post popularity.

Work by Brodie et al. (2011) and Hollebeek (2011) concludes that SME is interactive and dynamic in nature and differs from other marketing concepts. Online engagement, in the form of likes, comments, and shares, has a direct impact on online marketing initiatives taken by brands

(Hoffman and Fodor, 2010). While a high number of likes and positive comments add significance to any brand's image, negative comments can also affect a brand's popularity and perception (Wendt et al., 2016). Therefore, it is important to study SME to create and measure targeted marketing practices more effectively.

2.2.1 Measuring Social Media Engagement

Social media engagement, as demonstrated in the previous section, consists of multiple dynamic contracts (Brodie et al., 2011; Hollebeek, 2011). According to Tuten and Solomon (2018), marketers are encouraged to measure SME in ways that capture online users' intentional behavior, emotion and potential influence towards a brand. Tuten and Solomon (2018) classify interpretation of engagement into four constructs: involvement, interaction, intimacy, and influence. Involvement, being the lowest construct of engagement, measures the number of times online users are exposed to any information related to a brand on social media. The common metrics used to measure the involvement construct of engagement includes the frequency of brand page or profile views and brand content views (Tuten and Solomon 2018). The interaction construct measures the common actions online users take, or respond to, when exposed to any information related to a brand on social media. The common metrics used to measure the interaction construct of engagement includes the frequency of likes, shares, video views, comments and downloads on any brand-related content, page or profile (Tuten and Solomon 2018). The intimacy construct measures the affection or repulsion online users have towards a brand. The common metrics used to measure the intimacy construct of engagement includes: the number of positive and negative words associated with a brand, the frequency and quality of complaints and compliments posted on a brand's social media pages or profiles, the type of emotions online users associate with a brand and attitude of online users towards a brand on social media (Tuten and Solomon 2018). Influence, being the highest construct of engagement, measures the likelihood of online users recommending a brand to other people on social media. The common metrics used to measure the influence construct of engagement includes the quantity, frequency, and the score of brand reviews and ratings, the frequency of brand mentions on social media, and the frequency of brand referrals on social media (Tuten and Solomon 2018).

For this study, the interaction construct, which measures the actions online users take across social media platforms (Tuten and Solomon, 2018), is taken as the direct measure of engagement. Interaction construct mainly measures ways in which users can participate in a social media relationship with a brand. The most measurable common actions users take on social media involve the use of like, comment, and share features provided in most social media platforms. Similarly, the number of views (in the case of videos) and downloads can also be represented as actions taken by users on social media (Tuten and Solomon, 2018). According to Lee, Hosanagar, and Nair (2018), the cumulation of metrics number of likes, comments, shares, and views (in case of videos) are commonly used in the marketing and advertising industry as measures of SME. Engagement metrices for intimacy and influence constructs measure brand sentiment and loyalty (Tuten and Solomon 2018). The two constructs require a deeper knowledge of consumer behavior to interpret and are chosen as a segment of future study for this research. Therefore, following Lee et al. (2018) in using the cumulation of matrices including frequency of likes, comments, and shares as a measure of SME, this research also uses the cumulation of matrices. As defined by Tuten and Solomon (2018), the following interaction engagement metrics for YouTube videos are used:

Table 2.1: Summary of Engagement-Interaction Construct

Interaction Contract Matrices	**Definition**
Likes	The result of an online user liking social media content (Tuten and Solomon, 2018).
Comments	The result of an online user leaving a comment on the social media content.
Views	Mainly used for videos, the number of times online users watch a video. Any video, seen at least 30 seconds or over, is recorded as one video view (Google, 2018).
Cumulative Engagement:	To calculate the cumulative interaction engagement value, the total frequency of video views, likes, dislikes, and comments on a specific video are added together (Likes+Comments+Views) (Lee et al., 2018).

2.3 YouTube and Video Sharing

YouTube is the focal social media platform for this research. It offers users the ability to broadcast messages in the form of videos based on their interests, inspirations, and hobbies (Voorveld et al., 2018; Zhu and Chen, 2015). It is the world's largest video publishing and sharing website, with video sharing being the most common user activity on social media (Kousha, 2012; Penni, 2017). Additionally, YouTube also provides a few social interaction features, including liking, commenting and rating on videos, or giving comments about the remarks made by the other users (Siersdorfer, 2014). In terms of general demographics, YouTube is accessed by over one billion users and represents 60% of online video views (Hoiles, 2017). According to the report of Omnicore.com, a digital marketing agency, YouTube is viewed in over 80 countries in 76 different languages while 80% of the YouTube users reside outside the U.S (Omnicore.com, 2019). The fastest growing YouTube demographics are 35 and over (40%

growth in viewership), and 55 and over (80% growth in viewership) (MediaKix, 2017). Thirty-seven percent of users between 18 to 34 use YouTube for marathon-watching. Seventy-five percent of adults use YouTube to experience nostalgia rather than watching trending or tutorial videos. In addition to this, according to Omnicore.com, majority of female viewers use YouTube to watch beauty videos while majority of male viewers use to watch strategy games or soccer videos (Omnicore.com, 2019). In 2017, sports was the fourth most popular video category viewed on YouTube in the U.S (Statista Survey, 2017) while in 2016, the sports category on YouTube, containing 8.5 million sports-related videos, generated over 280 billion views (Gross, 2016). According to Chandra (2016), the top sports brands on YouTube based on number of YouTube subscribers in 2016 were Nike Football with over 2.5 million subscribers, Adidas Football with over 1 million subscribers, Nike with estimated 600,000 subscribers, i-D with estimated 500,000 subscribers, and Adidas with estimated 300,000 subscribers. For top sports teams on YouTube, in 2018, F.C Barcelona was the most followed team on YouTube with over 6.5 million subscribers, followed by Real Madrid C.F with over 4 million subscribers, and A.C. Milan with over 500,000 subscribers (StatSheep, 2018).

YouTube and YouTube engagement has been a focus of study for many researchers. Szabo and Huberman (2008) work on predicting the popularity of content for YouTube and Digg over a period of 30 days. According to Szabo and Huberman (2008), videos on YouTube remain popular for a longer period compared to videos on Digg. The results show a higher accuracy of prediction for videos that are viewed linearly over time. Qian Tang (2012) works on displaying the utility function for YouTube content creators. According to Qian Tang (2012), content providers seek video views as a short-term payoff in order to increase their ad revenue share, a monetary incentive provided by YouTube. On the long run, however, content providers seek an accumulative increase of a number of subscribers on their YouTube channel compared to accumulative video views as the content provider's media reputation is more influenced by an increase of new subscribers (Qian Tang, 2012). Yoganarasimhan (2012) studies the impact of the YouTube channel network's size and structure on the channel's content popularity. According to Yoganarasimhan (2012), the size and structure of a channel's network play the most significant role in the popularity of videos uploaded by the channel despite any characteristics present in the video. Dobrian et al. (2013) explore the impact of video quality on user engagement and how video quality can be optimized. Results conclude that the percentage of time spent on video buffering has the most significant impact on user engagement on all types of content. Abisheva, Garimella, Garcia, and Weber (2014) work on examining YouTube content's viewership and shareability. Results reveal that high Twitter shares lead to high final YouTube video views. Twitter activity metrics play a more important part in video popularity than the number of Twitter followers. According to Abisheva et al. (2014), content and category of the video plays an important role in effecting the response time to share videos for online users. Penni (2017) measures the impact of social connection on video virality on social media websites. Results uncover that video popularity is mainly because of the strength of interest in the video, as well as the duration of interested lasted for users (Penni, 2017).

With respect to recent studies, Hoiles (2017) examines the sensitivity of YouTube's metadata features on video views for YouTube videos. Results indicate that metadata level features including the number of channel subscribers, first day views; Google hits, the number of keywords/hashtags in the description, visibility of video thumbnail and title length of the video have a direct impact on video views. Gupta et al. (2017) work on establishing important factors used in successful YouTube advertisements. According to Gupta et al. (2017), factors including audio effects, visual effects, content story, and message appeals play an important role in generating video likes and views for YouTube advertisements. Rizoiu et al. (2017), using Hawkes intensity process (HIP), develop and validate a mathematical model to predict YouTube content popularity. Trzciński and Rokita (2017) work on predicting the impact of SME (video likes, comments and shares) and visual features of a video, on video views of Facebook and YouTube videos. The authors conclude that a higher prediction accuracy model can be established by studying the impact of visual features of a video on SME, combining video views, likes, comments and shares generated on the video, rather than studying video views alone. Wu et al. (2017) work on predicting and validating YouTube engagement in the form of video watch time by proposing a new metric, relative engagement, which is created using stable watched video time.

In terms of similar work related to this research on predicting YouTube engagement, most researchers focus on predicting video views only. Such a model could be inadequate as it may provide false positive results due to the changing user content consumption patterns as well as spam views (Wu, Rizoiu, and Xie, 2017). After studying the set of engagement metrics, including watch time, the percentage of video watched and relating the matrices to the total number of views and video properties such as length and content category, Wu, Rizoiu, and Xie (2017) propose a new engagement metric, relative engagement. “Relative engagement regulates over the length of a video, stable over time, and strongly is correlated with video quality” (Wu et al., 2017, p. 8). However, as claimed by the author, the user watch time and video views are taken as a measure of engagement. The study does not consider the effect of other engagement measures, including video likes and comments (Hoffman and Fodor, 2010) to predict YouTube engagement, compared Xu Cheng's (2014) findings which reflects a positive correlation between video views, likes, and comments. In addition, Hoiles (2017) insights on the impact of YouTube metadata features on video views can also be limited as it is difficult to measure which meta-level feature has the most impact on SME. Therefore, to measure any detailed short-term campaign or content result for any YouTube channel, the evaluation of factors influencing YouTube engagement is highly necessary to avoid any false positives.

Channel Properties are defined as the basic channel information that can be retrieved using YouTube API extraction tools (Abisheva, Garimella, Garcia, and Weber, 2014). Previous researchers have also studied different aspects of channel information or properties on YouTube. Channel subscribers have been mostly prioritized by many authors. Xie (2017) studies the impact of the number of channel subscribers on community engagement while Xu Cheng's (2014) study explores the uses of YouTube metadata, including channel subscribers, for better channel data analytics. Abisheva et al. (2014) on the other hand, explore the type of YouTube channels and videos viewed over Twitter. Based on the channel properties used by previous researchers, the following channel properties extracted from YouTube API are applied:

Table 2.2: Summary of Channel Properties Constructs (Abisheva et al., 2014; Hassan Zadeh and Sharda, 2014; Hoiles, 2017; Qian Tang, 2012; Xu Cheng, 2014)

Channel Properties	**Definition**
Channel Subscribers	Number of YouTube users subscribed to the YouTube channel
Channel Type	The type of identity operating the YouTube channel
Channel Age	The number of years the channel has been active on YouTube as of January 2018

The findings on channel subscribers reflected by previous authors include work by Hoiles (2017), who concludes that channel subscribers have a causal relationship with SME in the form of video views, especially for recently posted videos. Work by Hassan Zadeh and Sharda (2014) also suggests the number of channel subscribers, or followers of an online social network, is an integral dimension when creating predictive models for content popularity and SME. Qian Tang (2012) reflects interesting insight on channel subscribers as the author concludes that subscriber number does not only have a positive relationship with SME but also directly impacts a channel's reputation. Regarding channels age, although there has been no test conducted to determine the relationship between a channel's years of activeness and its subsequent SME, the dataset used in studies of Hoiles (2017) and Qian Tang (2012) include channels operating from the time YouTube went live. Hence, to evaluate the impact of channel subscribers and age on SME, in this case, YouTube engagement, the following hypotheses are derived:

H1: There is a statistically significant relationship between channel subscribers and YouTube engagement

H2: There is a statistically significant relationship between channel age and YouTube engagement

Video properties are defined as the basic video composition and production features, provided by the YouTube user when uploading content (Wu et al., 2017). Using YouTube API extraction tools, information on video properties, similar to channel properties, can be publicly accessed. Past studies have incorporated multiple aspects of video properties when researching YouTube. Dobrian et al. (2013) use the segment of video quality from video properties to measure its subsequent impact on engagement. Wu et al. (2017) incorporate variables video category and video quality while Szabo and Huberman (2008) integrate video age and video category as variables in predicting SME. Therefore, for this research, using similar techniques applied by previous authors, the following video properties extracted from YouTube API are applied:

Table 2.3: Summary of Video Properties Constructs (Dobrian et al., 2013; Szabo and Huberman, 2008; Trzciński and Rokita, 2017; Wu et al., 2017)

Video Properties	**Definition**	**Dimensions**
Video Duration	The overall duration of the video in minutes	
Video Definition	The definition in which the video is in when uploaded by the user	High-definition (HD) (720p or 1080p), standard-definition (SD) (480p, 360p, 240p or 144p)
Video Age	The number of years the video has been present on YouTube as of January 2018	

Following previous literature in exploring the relationship between video attributes and SME, for video length, studies revealed that videos were found to be engaging mainly because of users' strength of interest in the video, as well as the duration of interested lasted for users (Penni, 2017; Yoganarasimhan, 2012). Due to the complexity faced by marketers and advertisers with finding an optimal length for brand-related content (Chi, 2011; YuMe and IPG Media, 2016) makes this an ideal context to study the impact of video length on SME. According to the study conducted on YouTube statistics by Minimatters.com (2014), a video production company, videos below the length of 4 minutes are classified as short videos while videos, with the length above 20 minutes, are classified as long videos. According to ComScore, a media planning, transacting and evaluation company, in 2013, the average video length on YouTube was found to be 4 minutes and 20 seconds (Minimatters.com, 2014). A survey conducted on the optimal duration of YouTube videos by a private company in Italy concluded that almost half number of survey respondents preferred the optimal length of YouTube videos between two to five minutes

(HR Solutions - Digital Coach, 2018). Hence, to evaluate the impact of video length on SME, the following hypothesis is derived:

H3: There is a statistically significant relationship between short length videos and YouTube engagement

Findings from the study conducted by Dobrian et al. (2013) on understanding the impact of video quality on user engagement when viewing a video on demand, reflect a positive relationship between rendering quality and user engagement. Similarly, the work by Wu et al. (2017) also predicts high YouTube engagement for HD videos on YouTube. For video age, as previously described for channel age, although there has been no test conducted to determine the relationship between a video's timeframe of activeness and its subsequent SME, but the datasets used in studies of Hoiles (2017) and Qian Tang (2012) include videos from the time start YouTube started (2005). According to findings of Gill et al. (2007), online users do tend to enjoy watching videos that have been on YouTube for quite some time. Hence, to evaluate the impact of video definition and age on SME, the following hypothesis is derived:

H4: There is a statistically significant relationship between HD videos and YouTube engagement

H5: There is a statistically significant relationship between video age and YouTube engagement

2.4 Sports Marketing and Soccer

The strong prominence and activeness of sports brands and teams on social media, as well as the strong emotional connection among sports teams and their fans, (Richelieu, 2004; Vallerand et al., 2008), makes this subject an ideal context to study social media engagement (Parganas, Anagnostopoulos, and Chadwick, 2015). Indeed, sports brands and organizations at all levels have realized the brand-building benefits social media offers (Parganas et al., 2015). For this study, the sport soccer was chosen to study. In 2014, soccer was the most conversational topic on social media (McLaren, 2014), while soccer teams remained the most followed identities worldwide (Parganas et al., 2015). The soccer clubs from the first-tier league of England, the English Premier League, maintains one of the largest online following worldwide. In 2013-14, all clubs started to expand their social media presence from Facebook and Twitter to other mediums including Instagram and YouTube. Sports fans now expect ongoing communication, regarding team news and recent updates, from their favorite sports teams on social media (Ballouli & Hutchinson, 2010; Broughton, 2010; Parganas et al., 2015). In terms of statistics on sports viewership across all media platforms, soccer remains to be the most viewed sport with a viewership of 562 million annually, while in 2016, the soccer sports apparel and accessories market size for Europe alone was estimated to be 25.5 billion USD (Statista, 2017). Considering the prevalence of soccer teams on social media, soccer was chosen as the sport to study on YouTube.

Sports marketers and brands have always included celebrities in their marketing-mix, through successful endorsements and partnerships, to produce content that enhances the brand's image and personality (Khamis, 2017; Van-Tien Dao, 2014). Any success on an athlete's path creates a 'halo effect' which leads to a strong marketing pull (Khamis, 2017). Major and minor sports stars have now become priorities for many brands and advertisers allowing these celebrities to make more money through endorsements compared to any respective sports prize (Khamis, 2017; Rorsted, 2017). Many researchers have been targeting to find the impact of social media on brands belonging to different industries. Work by Kim and Ko (2012) shows the increase in customer equity due to their presence in social media for brands in the fashion sector.

Bruhn, (2012) shows the impact of social media on the brand image of companies operating in the pharmaceutical, telecommunication and tourism industry. Hutter, (2013) finds the impact of social media on brand awareness and association as increasing in the automobile world, while Schivinski and Dabrowski, (2015) explore the impact of social media on brand image increasing in the beverage, clothing and telecommunication industries. Work by Tsuji, Bennett, and Leigh (2009) comes a little closer to this research in describing factors affecting sports, alcohol, and automobile brands' awareness of virtual advertisements but the context of research remains mainly towards television media, rather than social media. With the rise of YouTube vloggers or celebrities, the impact of such online figures on SME, compared to traditional celebrities used in sports brand advertisements, remains to be seen. This study will compare results from both, a sports brand and vloggers, making content on the same brand, in order to examine the impact of video producer/creator on predicting engagement with YouTube videos.

With respect to research related to sports and social media, work by Checchinato et al. (2015) explored the type of content preferred by sports team supporters on YouTube. According Checchinato et al. (2015) sports team supporters prefer content created by sports brands over the content created by other team supporters on YouTube. However, Checchinato et al. (2015) identifies sports teams as sports brands and do not include commercial sports brands like Nike and Adidas in the study. Thompson, Martin, Gee, and Eagleman (2014) analyzed the development and maintenance of a social media strategy for a National Sport Organization. The authors concluded that online users interact with content that raised questions and they positively engaged with behind-the-scenes content of sporting events. Boehmer and Tandoc (2015) examined factors influencing users' intentions to share sports news on Twitter. They concluded that users are influenced to share news based on its informativeness, style and originality.

Additionally, users also considered their interest and relevance in the news topic, opinion similarity with the news, and the impact of news sharing on their Twitter followers before sharing the news message. Achen et al. (2017) examined how sports fans view and understand social media engagement and worked on discovering the types of social media content sports fans find engaging. According to Achen et al. (2017), sports fans not only consider using traditional methods of social media features such as liking, commenting, favoriting, retweeting and sharing as an idea of engagement but also consider reading social media content, sharing the content information with family and friends and discussing the content in different social setting offline as an idea of engagement as well. In terms of engaging content for sports fans, Achen et al. (2017) highlighted that sports fans find humorous, entertaining and personal content to be engaging. Additionally, sports fans also find content containing information that cannot be seen on other media such as behind-the-scenes and personal interest stories to be engaging. Alonso-Dos-Santos et al. (2018) explore the influence of virtual brand community of soccer team supporters on the brand's attitude towards sponsorship. According to Alonso-Dos-Santos et al. (2018), five causal factors, including attitude towards the -sponsor, the involvement of the sponsor, congruence with the sponsor brand, subjective norms and relationship quality of the brand quality directly impacts the engagement in a team's brand community. An interesting insight highlighted in the study by Alonso-Dos-Santos et al. (2018) is the process of image transfer, where team supporters identify sports team similar to the sponsor brand. This phenomenon directly affects the community members' attitude towards the sponsor brand. Team community members relate the attitude level of the sponsor brand to the same level as that of their sports team (Alonso-Dos-Santos et al., 2018). Study by Popp and Woratschek (2016) on the other hand, introduces the concept of branded communities as a replacement to traditional brand communities, which come together around an interest, need or a sport rather than a specific sports brand. According to Popp and Woratschek (2016), community members' identification and involvement with the sport as well as the quality of the community mainly determine their interest and loyalty towards the branded community. As highlighted in the study by Popp and Woratschek (2016), the research cover advantages of a branded community with regards to the loyalty towards a community sponsoring brand but loyalty towards the sports brand itself needs further exploration. The context of studies by Boehmer and Tandoc (2015), Checchinato et al. (2015), Thompson et al. (2014) and Alonso-Dos-Santos et al. (2018) mostly focused on various relationships between sports organizations and their supporters. However, research on the relationship between commercial sports brand and their supports, especially on YouTube, is limited. Therefore, considering Alonso-Dos-Santos et al.'s (2018) insight on the influence of sports team on its sponsor brand and limitation highlighted by Popp and Woratschek (2016), this study explores the relationship and impact of social media on commercial sports brands and their respective supporters, specifically on the platform YouTube.

With the rise of social media influencers and the change in user's preference to view brand-related content, choosing the medium for marketing purposes has become a hassle for marketers and advertisers (Khamis, 2017; Li, 2012; Liu et al., 2015). Although work by Checchinato et al. (2015) and Kruitbosch and Nack (2008) provides some evidence that branded videos generate more engagement than the videos created by online users, but based on the recent findings of Khamis (2017), who highlights social media influencers as self-brands, Liu et al. (2015) who classifies the type of social media influencers in the marketing world, and Rorsted (2017) who acknowledges how brands have started to shift towards social influencer marketing, the following hypothesis statements is depicted:

H6: There is no statistically significant relationship between brand uploaded videos and YouTube engagement.

2.5 Content Marketing and User Generated Content

Content marketing is defined as the "process for creating and distributing relevant and valuable content to attract, acquire, and engage a defined and understood target audience - with the objective of driving profitable customer action" (Charmaine, 2017, p. 2). However, the term content marketing has progressively extended over the years (Charmaine, 2017). Content marketing implements integrated marketing communication and relationship marketing theories to use marketing pull theories to engage consumers to brand content (Charmaine, 2017; Liu and Huang, 2015). Content marketing, unlike direct product promotion, is more of a branding tool that produces and dispenses related content to capture and involve the right targeted group. Marketers and advertisers publish and share brand stories online to create a familiar ground between the brand and the target audience (Charmaine, 2017).The evolution of social media has also lead to the creation of social media content communities that allows users to generate and share content on online communities like social media sites, blogs and photo/video sharing websites (Habibi et al., 2014; Muntinga et al., 2011; Tsimonis, 2014). This phenomenon arises from the consumer interest-driven participation theory (Charmaine, 2017). Hence, the term user generated content (UGC), a focal point of this research, arises and refers to the means through which online users communicate and express themselves with other users or the brand (Boyd and Ellison, 2010; Smith, Fischer, and Yongjian, 2012).

UGC is "what is produced in the moment of being social, as well as the object around which sociality occurs" (Smith et al., 2012, p. 2). UGC consists of different forms, based on the social media platform the content is generated. For example, status updates or shared video and image content on Facebook, self-produced images on Instagram, tweets on Twitter, and videos posted on YouTube. This may also include any consumer produced products or reviews (Dhar and Chang, 2009; Muñiz and Schau, 2011; Smith et al., 2012). Most importantly, for brands, UGC related to brands present across all social media platforms may have the ability to affect consumer brand perceptions (Smith et al., 2012; Tsimonis, 2014).

Consumers mainly view online brand-related content on their social media news feeds that allows them to engage with the content by using the like, share or comment features present on social media (Charmaine, 2017). This engagement becomes a form of electronic word-of-mouth (eWOM) when multiple consumers add their thoughts or responses to the content (Chen, Wang, and Xie, 2011; Chen and Xie, 2008). UGC is broader, but also overlaps with eWOM in the field of marketing sciences when UGC is related to a brand or product. eWOM is defined as "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, Gwinner, Walsh, and Gremler, 2004, p. 39). Brand posts that are constant, vivid and interactive generate the most engagement (Tafesse, 2015). Since content marketing is self-effacing in nature, non-promotional information and collaboration around a subject can easily float around social media, which features the brand as an idea pioneer, at the same time picking up insights about the intended target audience (Charmaine, 2017). Consequently, a gathering of brand promoters could build eWOM and consequently engagement. The content group additionally gives consumers and the brand an ideal chance to communicate a story (Charmaine, 2017). Content can be produced by a brand that acculturates its image and associates it with the intended target group by demonstrating an understanding of their needs and issues. At the same time, users can simultaneously create a story that reflects a great impression of the brand (Charmaine, 2017; Johnston, 2017).

Popular content communities include YouTube for videos, Instagram for photos, Pinterest for book marking, SlideShare for MS PowerPoint presentation and Soundcloud for audio, audiobooks, and podcasts. (Charmaine, 2017; Tsimonis, 2014). According to Chi (2011), users are more comfortable in accepting interactions on social media as it is less invasive, compared to traditional advertising. Social media has transformed communities by allowing users to interact with social content. Also, social media provides an opportunity for brands to become a part of such user interactions, through relevant and compelling content, without directly interfering with users (Chi, 2011). This phenomenon can also be used as an opportunity to study factors that can make brand-related content more engaging.

2.6 Social Influencers and YouTube Vloggers

Social influence is a course through which individuals change decisions based on their interactions with other users who share common mindfulness (Li, 2012). The process of decision making for online users is mainly affected by informative or normative aspects (Cheung, 2009; Li, 2012). The dynamic social impact theory uses such ideas, regarding social impact, to explain the dissemination of information through the social systems (Latané, 1996). The theory concludes that individuals are heavily influenced by the people close to them as well as the opinion of group members on different matters, fluctuate to find a possible correlation with other members (Li, 2012). Marwick (2013) indices social influencers or micro-celebrities as individuals having a celebrity status among a niche group, with their practices of self-representation as a form of entrepreneurial labor which requires them to form authenticity as a brand. Such practices of self-representation function within the growing cultural processes of ‘celebritization’ which in-turn allows the accumulation of social and economic capital growth for such individuals in fields like fashion, sports, politics, etc. depending on the media exposure (Arthurs et al., 2018). In the case of YouTube, individuals known as vloggers are users who create short videos stories on the goods they use or their personal life to generate traffic from subscribers and other viewers (Lee, 2016).

Khamis (2017) defines influencers as individuals that can change consumers’ views, thoughts, and action among various groups of people. According to Khamis (2017), the concept of influencers arises from the self-branding theory, also known as personal branding. It involves individuals emerging a unique public image for cultural and marketable gain (Khamis, 2017). Liu et al. (2015), on the other hand, classifies effective social media influencers into three different categories: emerging influencers, holding influencers, and vanishing influencers. According to Liu et al. (2015), effective influencers are those “who not only can maintain their high online status in a user trust network during a period but also have the ability to affect their followers’ acceptance of recommendations, product choices, and purchase decisions in specific domains” (Liu et al., 2015, p. 42). Therefore, using a combination of such ideas from marketing and social influence, a new field of ‘social influencing marketing’ is derived (Li, 2012).

Social influence marketing is a tool which adapts social influencers in social media to meet marketing and business goals (Li, 2012). Influencers are individuals that can change consumers’ views, thoughts, and action among various groups of people. Like commercially branded products, individuals also carry a unique selling proposition or characteristics that are compelling and responsive to the needs or interests of a specific group (Khamis, 2017). Research around finding the impact of social influence on consumer purchase behavior has been found in different areas including, blog networks and knowledge-sharing networks (Li, 2011). Vlogging, arising as an extension of the phenomena blogging which itself originates from the concept of personal diaries, is a result of user generated content prosumerism (where users produce and consume the same content) that has become a vital part of YouTube's core values (Arthurs et al., 2018).

Influential figures can act as a celebrity endorser as they become more profound within a social group or network, to carry out activities related to viral marketing (Li, 2012). Previous researchers infer that celebrity endorsers provide an incentive through the procedure of the transfer of importance (Amos, 2008; McCracken, 1989). Due to its capacity to draw consumer consideration and produce benefits, celebrity support has ended up being a profitable marketing promotion methodology (Amos, 2008; McCracken, 1989). In the case of YouTube, channel subscriptions, views, likes, and comments become an alternative for a channel's reputation which majority of vloggers leverage to additional gains, including ad revenues, sponsorship deals and other benefits in the world of traditional and digital media (Arthurs et al., 2018). In 2016, The Economist estimated YouTube influencers' earning to be double compared to the influencers working on Facebook and Instagram, with average earning ranging from USD 12,500 for about 500,000 followers and up to $300,000 for over 7 million followers (Arthurs et al., 2018). Looking in the landscape of YouTube and the type of vloggers active, there are multiple styles, preferences, and tastes adapted by vloggers. Vlogs generally revolve around on respective topics including games, beauty, fashion, politics, cooking, family, sports or other 'lifestyle' representing videos that are often produced in a more casual or domestic setting (Arthurs et al., 2018; Hillrichs, 2016).

Applying a suitable celebrity endorser to promote products, however, can be an expensive and troublesome strategy for brand if not correctly planned and executed. In a digital environment, where consumers seek advice and exchange information with others (Nambisan and Nambisan, 2008), influential support could be a good strategy for indirect marketing purposes due to its unique functionality. Therefore, to explore the relationship between the type of vloggers and the subsequent engagement generated, the following hypotheses are derived:

H7: There is a statistically significant relationship between private vlogger channel videos and YouTube engagement

H8: There is a statistically significant relationship between soccer news and updates channel videos and YouTube engagement

H9: There is a statistically significant relationship between soccer product reviewer videos and YouTube engagement

Additionally, the evolution of social media has also allowed traditional retail stores to find new ways to connect and communicate with their consumer in order to provide a better brand experience (Mahfouz, Joonas, Williams, Jia, and Arevalo, 2017). Big chain stores find social media as an opportunity to gain new audiences and customers. Mahfouz et al. (2017) discuss the examples of departmental retail stores which prioritize YouTube as a focal medium for their marketing communications. The author talks about the store J.C. Penney which does not only exists as a separate channel on YouTube but also partners with beauty and fashion vloggers to create customized content in order to attract new audiences as well as promote and sell the stores' merchandise. (Mahfouz et al., 2017). Therefore, in order to explore the phenomena used by retail chains and other online stores, the following hypotheses are established:

H10: There is a statistically significant relationship between soccer e-commerce store videos and YouTube engagement

2.7 Research Model

The theoretical model is presented in Figure 2.1. This study incorporates different theories comprising YouTube metadata and its consequent impact on social media engagement. As explained earlier, for channel properties variables, findings from work by Hassan Zadeh and Sharda (2014), Hoiles (2017) and Qian Tang (2012) are used to derive the hypotheses for the no. of channel subscribers and channel age. For channel type hypotheses, work by Arthurs et al. (2018), Hillrichs (2016), and Nambisan and Nambisan (2008) are used for hypotheses of private vlogger and news/updates YouTube channel. For product reviewer and e-commerce store YouTube channels hypotheses, insights from the work by Mahfouz et al. (2017) are used. For brand YouTube channel, insights from the work by Khamis (2017), Li (2012), Liu et al. (2015), Rorsted (2017), Checchinato et al., (2015) and Kruitbosch and Nack (2008) are used to derive the hypothesis. Similarly, for video properties variables, using findings and insights from work by Chi (2011), Penni (2017), Yoganarasimhan (2012) and YuMe and IPG Media (2016), the hypothesis of video duration is derived. For video definition and video age, insights and findings from work by Dobrian et al. (2013), Hoiles (2017) and Qian Tang (2012) are applied to derive the hypotheses. Table 2.4 provides a summary of all hypotheses guiding this study. Figure 2.1 describes the theoretical model used in the study.

Table 2.4: Summary of Research Hypotheses

Null Hypotheses
H01: There is a statistically significant relationship between channel subscribers and YouTube engagement
H02: There is a statistically significant relationship between channel age and YouTube engagement
H03: There is a statistically significant relationship between short length videos and YouTube engagement
H04: There is a statistically significant relationship between HD videos and YouTube engagement
H05: There is a statistically significant relationship between video age and YouTube engagement
H6: There is no statistically significant relationship between brand uploaded videos and YouTube engagement
H07: There is a statistically significant relationship between private vlogger channel videos and YouTube engagement
H08: There is a statistically significant relationship between soccer news and updates channel videos and YouTube engagement
H09: There is a statistically significant relationship between soccer product reviewer videos and YouTube engagement
H10: There is a statistically significant relationship between soccer e-commerce store videos and YouTube engagement

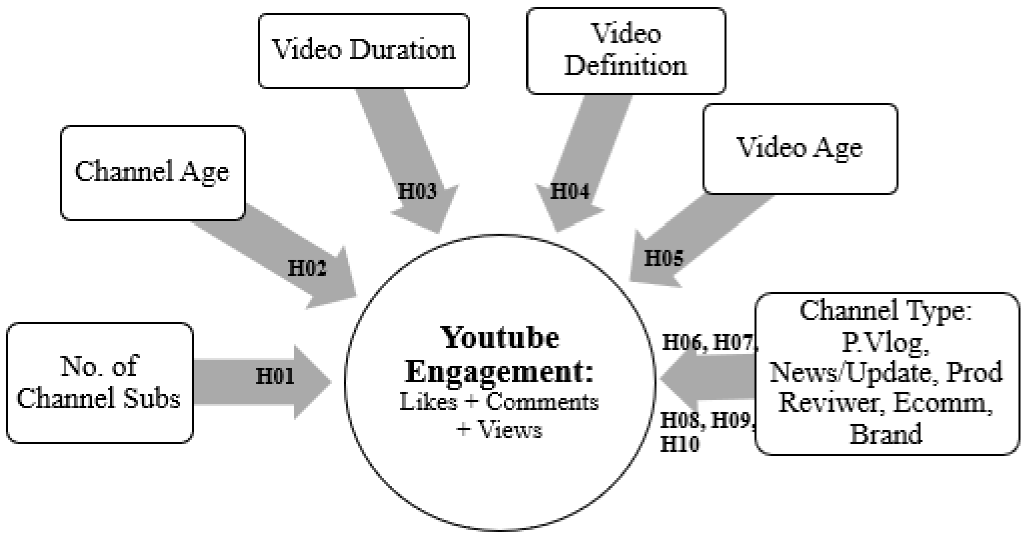

Figure 2.1: Theoretical Model for Factors Predicting YouTube Engagement.

3. Research Methodology

3.1 Data Collection and Sample

Data collection, as done in previous studies for YouTube as well as other social media platforms using API extraction tools, was followed. Arvidsson and Caliandro (2016) use the Twitter API extraction tool to retrieve data related to the fashion brand Louis Vitton from Twitter. Szabo and Huberman, (2008) use API tools to retrieve 'most recently uploaded videos' from YouTube and Digg. Wu et al. (2017) use different extraction tools including Twitter Streaming API tool to retrieve YouTube video links from Twitter. Xu Cheng (2014) uses a YouTube API extraction tool to retrieve videos of BroadbandTV's most popular channels from YouTube. Therefore, following previous work, we also relied on an API based tool to retrieve YouTube videos.

Using Netvizz, a cloud-based YouTube metadata extraction tool, we collected the dataset. Netvizz uses YouTube API v3 to retrieve information. We applied Netvizz's video list function, which created a script from a search query to retrieve a list of video metadata and information related to the query. After running the search query, a downloadable Microsoft (MS) Excel file containing video metadata was created by Netvizz (Netvizz, 2018). The search query involved a keyword search containing the terms 'Adidas Soccer' and 'Adidas Football.' We selected the two keywords to search videos only relevant to the brand Adidas and the sport, soccer. The first dataset, downloaded from Netvizz, contained a total of 616 video data records, created by 227 different YouTube channels. We used MS Excel to sort this dataset with respect to different types of channels, including video records for Adidas' official YouTube channels. As Netvizz limits the number of data records per dataset (Netvizz, 2018), data records retrieved for Adidas' YouTube channels were found to low (25 data records). To create a balanced dataset containing an equal number of brand and vlogger video records, we retrieved additional videos from Netvizz using its YouTube channel ID function. This function retrieves a list of video metadata and information based on the searched channel IDs (Netvizz, 2018). We obtained the channel IDs of Adidas' official YouTube channel from the initial dataset. After searching the channel IDs of Adidas' official YouTube channel on Netvizz, we retrieved a new dataset containing video metadata and information of videos uploaded on the Adidas' official YouTube channel. Results from this dataset were combined with the first dataset on MS Excel. We used the 'remove duplicate' function on MS Excel to delete any repetitive data records. This dataset included a total of 712 unique video entries, with 17% belonging to the Adidas YouTube channels and 83% belonging to other vlogger YouTube channels. To check for relevance, we opened each video on YouTube through the video ID link provided in the data sheet retrieved from Netvizz. A total of five irrelevant videos, not on Adidas or soccer, were found and removed from the dataset. The final total dataset was screened to 707 unique videos, created by 226 unique YouTube channels.

In order to find the types of channels producing and uploading soccer related videos, we selected a sample of 150 channels to study based on convenience. We studied each YouTube channel by visiting the about section as well as browsing other uploaded videos to categorize the domains on which these channels create their content related to soccer. We obtained the online link to the channel on YouTube as part of the information contained in the dataset retrieved from Netvizz. We highlighted channel descriptions and video titles and compared it with other channels to find the most common descriptions and titles describing the domains on which respective vlogger channels create soccer related videos. We were able to create a total five different channel categories on which sports brand-related YouTube channels create their soccer content. We cumulated the number of channels per classified channel type and then videos created per classified channel type to find the total number of channels and videos per channel type (see the appendix for the screen shot of MS Excel sheet used in this research). Table 3.1 provides the classification of channel types and their respective videos in the final dataset:

Table 3.1: Summary and Classification of Channel Types

Channel Type	Channels in Dataset	Description	Videos in Dataset
Brand	4	Channels belonging to the brand Adidas. All videos were created and uploaded by the brand	120
Private Vloggers	170	Channels posting videos related to tutorials on soccer	208
News and Update	14	Channels broadcasting happening news and updates on soccer	32
E-commerce	11	Online soccer related equipment stores with a direct URL to the website in the about section	66
Product Reviewers	27	Channels dedicated to reviewing, comparing and unboxing soccer related equipment	281

3.2 Multiple Linear Regression

This study uses multiple linear regression to predict the effects of channel and video properties on YouTube videos. Multiple linear regression is a statistical method used to model a relationship between a dependent variable and one or more independent variables (Rencher and Christensen, 2012). One of the most common applications of multiple linear regression includes building a predictive model using the observed data values of the dependent variable, also known as the response variable, and independent variables, also known as predictor variables (Rencher and Christensen, 2012). Initially, we ran different multiple linear regression analysis tests to determine the most appropriate measure of YouTube engagement. Separate multiple linear regressions models were established keeping the number of likes, number of video views and number of comments as dependent variables. The results achieved for models were similar to each other (see the appendix for details). We found the change in adjusted R^2 to range between 42% to 50%. According to Lee et al. (2018), the cumulation of engagement metrices (likes+ comments+ views) is a common measure of engagement in the industry. Therefore, following Lee et al. (2018), we decided to use the cumulation of engagement metrices as a measure of YouTube engagement for this research. Table 3.2 provides a summary of dependent and independent variables used in this research:

Table 3.2: Summary of dependent and independent variable

Dependent Variable	Independent Variables	
YouTube Engagement	**Channel Properties**	**Video Properties**
Video Views	Channel Subscribers	Video Duration
Video Likes	Channel Age	Video Definition
Video Comments	Channel Types:	Video Age
	Brand	
	Private Vloggers	
	News and Update	
	E-commerce	
	Product Reviewers	

Multiple linear regression method has been commonly used by different authors to predict and model different measures of engagement on multiple online channels including social media. Szabo and Huberman (2008) used linear regression method to create a model that predicts video views of YouTube and Digg videos for the next 30 days. The authors also measure the model's accuracy of predictions. The results show a higher accuracy of prediction for videos that are viewed linearly over time. Castillo et al., (2014) use linear regression to predict the number of website visits, generated from Facebook and Twitter posts related to the website. The authors conclude Facebook and Twitter posts that generate a high number of SME are more likely to increase the number of website visits. Trzciński and Rokita (2017) use three different regression methods (multivariate linear regression, multivariate radial basis function regression and univariate linear regression) to predict the impact of SME (video likes, comments and shares) and visual features of a video, on video views of Facebook and YouTube videos. The authors conclude that a higher prediction accuracy model can be established by studying the impact of visual features of a video on SME, combining video views, likes, comments and shares generated on the video, rather than studying video views alone. Lee, Moon, and Salamatian (2010), use the cox proportional hazard regression method to predict online engagement, in the form of comments, generated on content threads of Dpreview and Myspace online discussion forums overtime. The authors conclude that the number of comments generated on the content threads can be more accurately predicted by observing threads for five-six days, while the number of comments on the threads can be accurately predicted if the thread is observed for the first two-three days. Work by Castillo et al., (2014), Lee et al. (2010) Szabo and Huberman (2008) and Trzciński and Rokita (2017) provides support in using a linear regression for building predictive models. Therefore, Statistical Package for the Social Science (SPSS) software was used to process and analyze all data related to the research. Multiple linear regression analysis features were applied to determine the factors that may predict social media engagement generated on sports brand-related YouTube videos.

Based on ANOVA and descriptive statistics, we concluded that the data was not normally distributed. Logarithmic (Log) transformation is a common way to address normality of data (Field, 2018). Szabo and Huberman (2008) used logarithmic transformation on the dependent variable video views in order to address the issue of inherent distribution. Therefore, adapting the data transformation technique applied by Szabo and Huberman (2008), we also applied logarithmic transformation. The results from descriptive statistics showed that data after Log transformation was normally distributed. As described in Figure 3.1, the P-P plot for Log

(YouTube engagement) reveals a straight diagonal line which is an indicator of data normality. In addition to the P-P plot, the bell-shaped curve histogram in Figure 3.1 provides an indication of data being normally distributed. Additionally, the coefficient of variation which shows the ratio of standard deviation to the mean, was found to be low (24.5%). This reflects that the mean is a good fit for the data (Field, 2018).

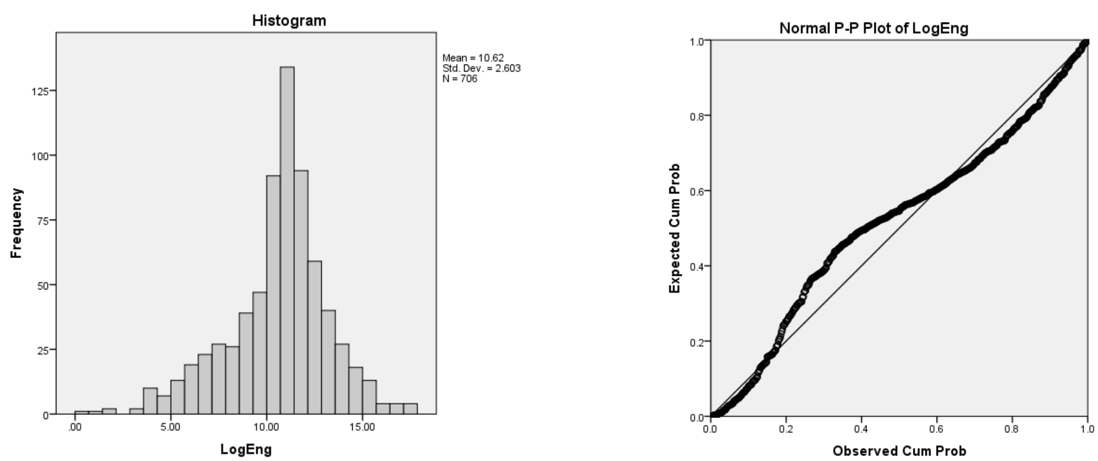

Figure 3.1: Histogram and Normal Distribution P-P plot for Log (YouTube engagement)

The histograms in Figure 3.2, 3.3, 3.4 and 3.5 show a reasonable match with normal distribution for the independent variables: the number of channel subscribers, channel age, video age, video definition and video duration. Although for variables the number of channel subscribers and video duration, the distribution curves are found to be right-skewed. This skewness represents channels with lower subscribers and videos with lower duration are overrepresented in the data, compared to channels with higher subscribers and videos with higher duration respectively. Since nature of the dataset used for this research was only specified to a video type (sports brand-related), videos in all lengths, created by channels with high and low number of channel subscribers were used to carry out this research. No other limitations or transformations were applied to the dataset. Szabo and Huberman (2008), when predicting SME, in the form of video views for YouTube and Digg videos, also use a similarly skewed dataset to carry out the research. Therefore, adapting Szabo and Huberman (2008) data analysis technique, independent variables without any data transformation were used to carry out the research.

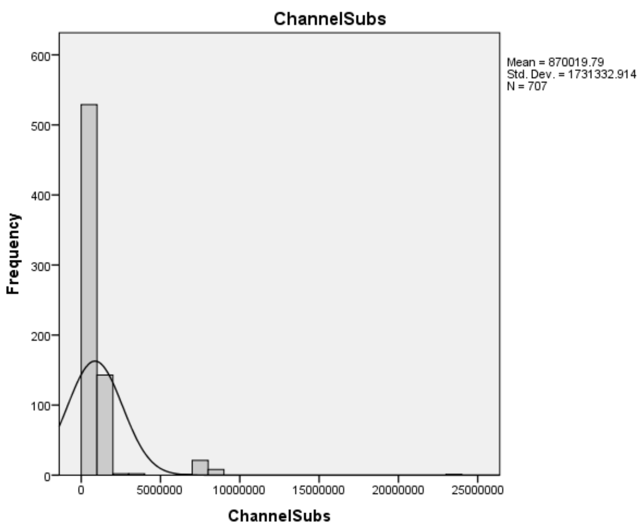

Figure 3.2: Histogram for variable “channel age”

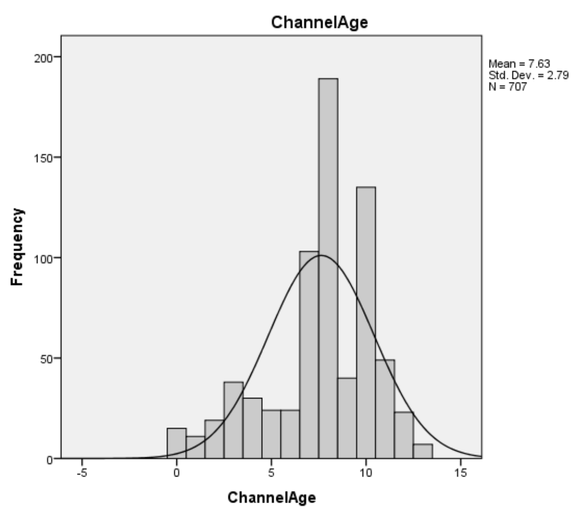

Figure 3.3: Histogram for variable “the number of channel subscribers”

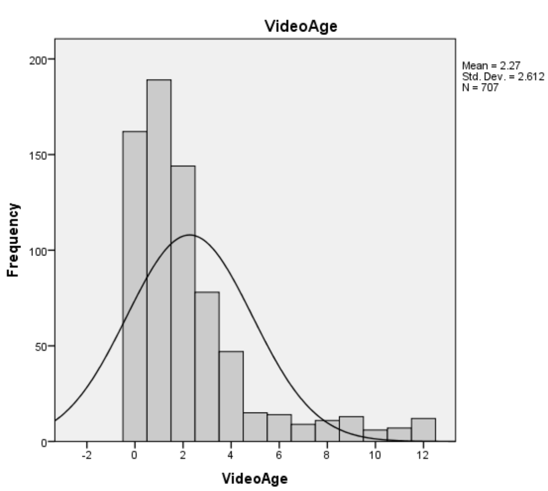

Figure 3.4: Histogram for variable “video age”

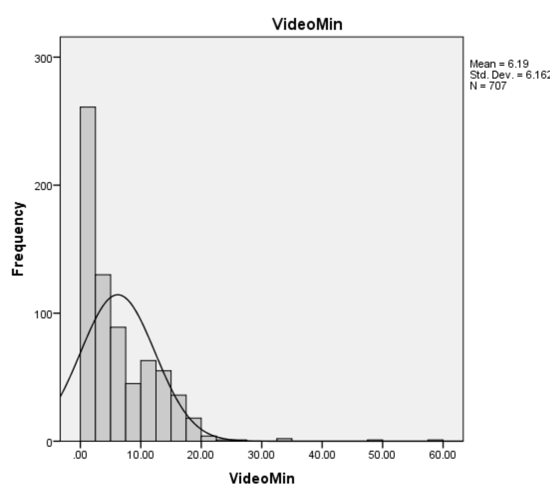

Figure 3.5: Histogram for variable “video duration”

3.2.1 Multicollinearity

Multicollinearity refers to the degree of redundancies among independent variables (Field, 2018). Tolerance and variance inflation factors (reciprocal of tolerance), being the most common measures of multicollinearity, refer to “the extent to which a given explanatory variable can be explained by all the other explanatory variables in the equation” (Studenmund, 2011, p. 259). In order to check for potential threats of multicollinearity, collinearity diagnostics, including tolerance and variance inflation factors (VIFs) were run. Generally, VIF’s way below of the value of 10 and tolerance above the value of 0.2, show no, or little, multicollinearity (Field, 2018). The VIF’s for all variables were found to be below 3 and in an acceptable range, while the tolerance value for all variables except product reviewer was found to be above 0.2. Therefore, the channel type, product reviewer, was automatically removed from the multiple linear regression analysis on SPSS as it showed perfect multicollinearity. Table 3.3 provides a summary of VIF and tolerance values for all independent variables.

Table 3.3: Multicollinearity Diagnostics - Independent Variables

	Independent Variables	**VIF**	**Tolerance**
Channel Properties	Brand	2.11	0.47
	Vlog	1.91	0.53
	E-commerce	1.33	0.76
	Prod Reviewer	*2.94*[13]	*0.00*
	News/Updates	1.27	0.79
	Channel Age	2.38	0.42
	Channel Subs	1.07	0.94
Video Properties	Video Duration	1.35	0.74
	Video Age	2.93	0.34
	Video Definition	2.17	0.46

4. Results

This chapter presents the data analysis of this research with respect to descriptive statistics and the multiple linear regression analysis results.

4.1 Descriptive Statistics

Table 4.1 presents the summary of the main descriptive statistics of the dependent and independent variables. For Log (YouTube engagement), the mean score (M=10.6; standard-definition (SD)=2.69) is in the upper middle range of possible Log (YouTube engagement), reflecting that sports brand-related videos generate almost average possible engagement on an exponential scale. The mean YouTube engagement for the dataset, after removing logarithm transformation, is 40,134.8 ($e^{10.6}$). The mean score reflects only a few videos in the dataset are found to be generating a high number of YouTube engagement than the majority. Channel type, being a binary variable, contains "product reviewer" videos in a majority with 281 videos in the dataset, followed by "private vlogger" with 208 videos, "brand" with 120 videos, "e-commerce" with 66 videos and "news and update" with 32 videos in the dataset. This indicates that the dataset for sports brand-related videos, in the majority, contains "product reviewer" videos.

For the variable "number of subscribers", the mean score (M=870019.8; SD=1731332.9) is in the lower range of a possible number of subscribers, reflecting that the number of subscribers for channels of sports brand-related videos is relatively low. For the variable "channel age", the mean score (M=7.63; SD=2.79) is in the middle range of possible channel age, indicating that the age of channels, uploading sports brand-related videos, is almost eight years on average. For the variable "video age", the means score (M=2.27; SD=2.61) is in the lower range of possible video age, reflecting that the age of sports brand-related videos is just over two years. For the variable “video duration” the mean score (M=6.19; SD=6.16) in the lower range of possible video duration, indicating that the duration of sports brand-related videos is just over six minutes on average. For the variable “video definition”, high-definition (HD) videos were in a majority with 635 videos in the dataset while standard-definition videos (SD) with 72 in the dataset. This indicates that sports brand-related videos are mainly created in HD.

Table 4.1: Descriptive Statistics for dependent and independent variables (N=707)

Variables	Min	Max	Mean	Std. Deviation
Log YouTube Engagement	0	17.63	10.62	2.60
Channel Age	0	13	7.63	2.79
Channel Subs	0	23791251	870019.8	1731332.9
Video Duration	0	57.7	6.19	6.170
Video Age	0	12	2.27	2.612

Variables	Frequency
Channel Type	
Brand	120
Vlog	208
E-commerce	66
Prod Reviewer	281
News/Updates	32
Video Definition	
HD	635
SD	72

4.2 Regression Results

This study analyzed ten hypotheses of which, seven were represented by channel properties, and three were represented by video properties, in order to expose variables that are statistically significant in predicting YouTube engagement. Multiple linear regression analysis was applied using SPSS. Table 5.3 provides the summary of descriptive statistics and Table 5.4 provides the summary of the overall fit of the regression model. F-value and Adjusted R-squared (R^2), is the most common statistics to determine the overall fit of a regression model (Field, 2018), were applied. The Adjusted R-squared is the proportion of variance explained by the regression model when accounting for the independent variables and the sample size in the study (Field, 2018). The Adjusted R^2 value of 0.419 indicated in Table 4.1, reflects that the variables used in the study explain 42% of the variation in YouTube engagement for sports brand-related YouTube videos.

The F-value reflects whether the regression model is statistically significant to predict the outcome of values better than the mean. The F-value looks whether the variance explained by the model is significantly greater than the error within the model by taking degrees of freedom in the account (Field, 2018). The greater the F-value, the greater of the total variance is accounted for by the model (Zikmund, 1999). The F-value of 55.85 indicated in Table 4.2 reflects statistical significance, indicating that the regression model supports in understanding the relationship between dependent and independent variables, providing a validation that the model can be used for prediction purposes.

Table 4.2: Overall Fit of the Model

Dependent variable	**R**	**R^2**	**Adjusted R^2**	**Std. error of Estimate**	**F value**	**Sig. F change**
Log YouTube Engagement	0.647	0.419	0.411	2.019	55.85	0.00

After establishing the goodness of fit for the overall model, the results of significant effects of respective independent variables on the dependent variable (Log YouTube engagement), at a 95% confidence interval level, were evaluated. Table 5.6 shows the summary of the regression results for all the independent variables used in the study. Variables for channel properties, including brand channel type, vlog channel type, news and updates channel type, channel age, and the number of channel subscriber were found to statistically significant with a p-value less than equal to 0.05 ($p<=0.05$). Only channel type e-commerce and channel type product reviewer showed no statistically significant relationship ($p>0.05$). Since the variable channel type product reviewer showed perfect multicollinearity, the variable was automatically removed from the multiple linear regression analysis. All variables for video properties, including video age, video duration, and video definition were found to statistically significant with p-value less than equal to 0.05 ($p<=0.05$).

The estimated unstandardized coefficient beta (B) represents the change in Log YouTube engagement with every 1 unit change in the independent variable, assuming all other independent variables remain constant (Field, 2018). A positive sign for the beta indicates a positive relationship with Log (YouTube engagement) while a negative sign for the beta represents a negative relationship with Log (YouTube engagement). According to the regression results of channel properties variables, brand channel type was found to have a positive relationship with Log (YouTube engagement), indicating that for every brand video in the dataset, Log engagement will increase by 1.52 units. Similarly, for every vlog and news/updates channel type video in the dataset, Log engagement will decrease by 0.91 and 1.02 units respectively. Since channel type product reviewer and e-commerce were found to be statistically insignificant ($p>0.05$), no relationship with Log (YouTube engagement) for both channel types was concluded. For channel age, every 1 unit increase in the channel's age will increase Log (YouTube engagement) by 0.17 units. For channel subscribers, every 1 unit increase in channel subscribers, Log (YouTube engagement) will increase very minimally, by 5.10^{-7} units. For video properties variables, video age and video duration were found to have a positive relation with Log (YouTube engagement). For video duration, every 1-minute increase in the video's duration, Log (YouTube engagement) will increase by 0.17 units. For video age, every 1 unit increase in the video's age will increase Log (YouTube engagement) by 0.09 units. The video properties variable, video definition, was found to have a negative relationship with Log (YouTube engagement). For every standard-definition (SD) video in the dataset, Log (YouTube engagement) will decrease by 1.38 units. Table 4.3 provides a summary of regression results for all independent variables included in the model.

Table 4.3: Summary of Regression Analysis for Independent Variables

Dependent Variable:	Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Significant P-value	Effect on Log (YouTube Engagement)
(Constant)	8.18	0.311	0.00	
Channel Properties				
Brand	1.52	0.30	0.00**	For every brand video in the dataset, Log (YouTube engagement) will increase by 1.52 units
Vlog	-0.91	0.23	0.00**	For every vlog video in the dataset, Log (YouTube engagement) will decrease by 0.91 units
E-commerce	*-0.46*	*0.30*	*0.13*	
News/Updates	-1.02	0.40	0.01*	For every news/updates video in the dataset, Log (YouTube engagement) will decrease by 1.02 units
Channel Age	0.17	0.04	0.00**	For every 1-year increase in the channel's age, Log (YouTube engagement) will increase by 0.17 units
Channel Subscribers	5.10^{-7}	0.00	0.00**	For every 1 unit increase in channel subscribers, Log (YouTube engagement) will increase by 5.10^{-07} units
Video Properties				
Video Duration	0.09	0.01	0.00**	For every 1-minute increase in a video's duration, Log (YouTube engagement) will increase by 0.09 units
Video Age	0.17	0.05	0.00**	For every 1-year increase in the video's age, Log (YouTube engagement) will increase by 0.17 units
Video Definition	-1.38	0.37	0.00**	For every SD video in the dataset, Log (YouTube engagement) will decrease by 1.38 units
*p<0.05 **p<0.001				

According to regression analysis results, independent variables for channel properties, including channel type brand, private vlogger and news, and updates were found to be statistically significant at a 95% confidence interval. Similarly, the number of channel subscribers and channel age were also found to be statistically significant. For video properties, all variables, including video duration, video age, and video definition were found to be statistically significant at a 95% confidence interval level. The summary of hypotheses results are as follows:

H01 (there is a statistically significant relationship between channel subscribers and YouTube engagement) – as expected, was **accepted** with significant result (p=0.00). The number of channel subscribers increases the likelihood for a video to reach more online users, therefore, increasing the likelihood for the video to generate more engagement.

H02 (there is a statistically significant relationship between channel age and YouTube engagement) – as expected, was **accepted** with significant result (p=0.00). The longer a channel is active on YouTube, the more likely it is for the channel to be viewed by more online users.

H03 (there is a statistically significant relationship between short length videos and YouTube engagement) – was **accepted** due to significant result (p=0.00). Although there is a significant relationship between short length videos and YouTube engagement, according to regression results, longer durational videos tend to generate more engagement. This can be due to the strength of interest sports brand videos establish for the online user. Since online users willingly watch longer videos, the likelihood of sports brand videos generating more engagement increases due to a longer user watch time.

H04 (there is a statistically significant relationship between HD videos and YouTube engagement) – as expected, was **accepted** with significant result (p=0.00). Majority of brands and vloggers tend to record videos in HD quality in order to provide the best display of their content which can increases the likelihood for their videos to generate more engagement.

H05 (there is a statistically significant relationship between video age and YouTube engagement) – as expected, was **accepted** with significant result (p=0.00). As described for channel age, new subscribers are more likely to engage in older videos of the YouTube channel. This can increase the overall engagement of the channel. Older videos present on the YouTube channel gives users more content to view which can increase the likelihood of generating engagement.

H06 (there is a no statistically significant relationship between brand uploaded videos and YouTube engagement) – unexpectedly, was **rejected** due to significant result (p=0.00). Branded videos feature soccer celebrities like Messi and Pogba. Since brands and celebrities have a large audience, the likelihood of branded videos reaching more users increases. As brand videos can reach more users, the likelihood of brand videos to receive more recommendations and engagement increases.

H07 (there is a statistically significant relationship between private vlogger channel videos and YouTube engagement) – as expected, was **accepted** with significant result (p=-0.00). Private vloggers create videos on teaching and promoting the tips and tricks of the sport soccer. This allows them to attract groups or networks interested in new videos on soccer, therefore increasing the likelihood of generating YouTube engagement on their videos.

H08 (there is a statistically significant relationship between soccer news and updates channel videos and YouTube engagement) – as expected, was **accepted** with significant result (p=0.01). Vloggers creating videos around the latest news and updates in the world of soccer including videos on the latest soccer apparel and footwear accessories, can attract groups or networks interested in soccer. This increases the likelihood for the videos to generate more YouTube engagement.

H09 (there is a statistically significant relationship between soccer product reviewer videos and YouTube engagement) – unexpectedly, was **rejected** due to lack of significance (p=1.00). Based on the regression results, soccer product reviewer videos, contains a high multicollinearity, stating that the variable is redundant and can be possibly explained by other variables.

H10 (there is a statistically significant relationship between soccer e-commerce store videos and YouTube engagement) – unexpectedly, was **rejected** due to lack of significance (p=0.13). E-commerce store channels, promoting similar products to brand channels in their videos, were not able to attract groups or networks interested in soccer. This is because brand channels' videos, having a larger network and the ability to feature soccer celebrities, might have created more interested in their videos for online users.

5. Discussion

5.1 Interpretation of Results

This section provides the interpretations of all hypotheses on channel and video properties proposed to predict YouTube engagement. To evaluate the direct effect of all independent variable on YouTube engagement, the following equation was used to represent Log function with dependent and independent variable:

Eq. (1) - Log (YouTube engagement) = bx

Where *b* represents the value of unstandardized coefficient beta (B) of the independent variable *x*.

After removing the removing the Log function, the following equation was derived to interpret results for YouTube engagement:

Eq. (2) - YouTube engagement = e^{bx}

Where *b* represents the value of unstandardized coefficient beta (B) of the independent variable *x* and *e* represents the value of exponential function (inverse of Log function).

Starting with channel properties, the first hypothesis, which proposes a positive significant relationship between the number of channel subscribers and YouTube engagement, was accepted. Based on the unstandardized coefficient beta (b), the results show a very minimal impact on YouTube engagement for every unit increase in channel subscribers ($b=5.10^{-7}$), the relationship however, is positively statistically significant. For every unit increase in number of channel subscribers, YouTube engagement is likely to increase by 1 unit. This also means, for every new subscriber, YouTube engagement is likely to increase for the channel. The hypothesis was derived based on the findings achieved different authors. According to Qian Tang (2012), YouTube content creators or celebrities, when making decisions to produce or create content, consider not only the potential revenue that may be obtained through the YouTube's partner revenue sharing program but also other benefits, including funding, collaborations and project opportunities that can be brought through enhanced reputation. Accumulation of the number of subscribers, being a direct measure to the reputation of content creators or celebrities, is given more importance than engagement by the majority of top YouTube influencers (Qian Tang, 2012). Furthermore, Xu Cheng (2014) adds to the conclusion of Qian Tang (2012) that the number of channel subscribers not only enhance the reputation of YouTube influencers but also become the source of engagement for their YouTube channels. The audience which subscribes the YouTube influencers' channels, is more likely to engage in other videos of respective influencers, therefore increasing the overall engagement of the channel. This phenomenon also becomes a motivation for YouTube influencers to create and upload videos of similar interest to their followings (Xu Cheng, 2014). Similarly, study by Hoiles (2017) establishes a causal relationship between YouTube engagement, in the form of video views, and number of channel subscribers. According to Hoiles (2017), who tests the impact of YouTube engagement on the number of channel subscribers for a YouTube channel, -inverse of what this study tested in the first hypothesis – YouTube engagement has a direct positive statistically significant impact on the number of channel subscribers but only for the first few days of video or content upload. Hoiles (2017) also concludes that "increasing the number of subscribers will also increase the view count of videos that are uploaded by the channel owners" (Hoiles, 2017, p. 1433). Therefore, work by Xu Cheng (2014), Qian Tang (2012) and Hoiles (2017) helps justify the conclusion of the first hypothesis that the number of channel subscribers has a statistically significant impact YouTube engagement for sports brand-related YouTube videos.

The second hypothesis, stating a statistically significant relationship between channel age and YouTube engagement, was confirmed by the model. The results show that for every one-year increase in a channel's age, YouTube engagement is likely to increase by 1.18 units. Although there were no direct tests conducted to find the relationship between YouTube channels' age and its subsequent impact on YouTube engagement, the dataset used by Qian Tang (2012), in displaying the utility function for YouTube content creators, and Hoiles (2017), in examining the impact of YouTube metadata on engagement, use dataset of YouTube channels from 2005. According to Xu Cheng (2014) and Qian Tang (2012) consideration on the number of channel subscribers and YouTube engagement, the audience which subscribes the YouTube influencers' channels, is more likely to engage in other videos of respective influencers also applies for channel age. The more a channel uploads videos, the more new subscribers are likely to be attracted by the channel (Xu Cheng, 2014). A high number of new subscribers are more likely to engage in older videos of the channel, therefore increasing the overall engagement of the channel on all videos. Hence, if channels continue to upload new videos, they are more likely to increase the engagement for the channel as it ages. Therefore, conclusions of Xu Cheng (2014) and Qian Tang (2012) also help justify the results achieved for the second hypothesis that channel age has a statistically significant impact on YouTube engagement for sports brand-related YouTube videos.

For video properties variables, the third hypothesis, which shows a statistically significant relation between video duration and YouTube engagement, was accepted based on significance. Although the hypothesis statement for video duration, asserting a significant relationship between short length video and YouTube engagement was accepted, the relationship however, was found to be inverse. Based on the regression results, for every one-minute increase in video duration, YouTube engagement is likely to increase by 1.10 units. The results show that longer videos are likely to generate more engagement, opposite to what was hypothesized. The hypothesis was derived based on the conclusions of Penni (2017), who explores the future of online social networks, and Yoganarasimhan (2012), who studies the impact of online social network structure on online content circulation. According to Penni (2017) and Yoganarasimhan (2012), user engagement have a direct relationship with online users' strength of interest in the video as well as how long the interest lasts in the video. For sports brand-related videos, it can be seen through the regression results that the strength of interest for such videos is higher for longer durational videos based on the YouTube engagement generated on them. Since online users spend more time watching a long video, they are more likely to be encouraged to not only view the video but also like or share the same video (Dean, 2017). Additionally, based on the video length classification provided by Minimatters.com, a video production company, videos of length 4 minutes or below are classified as short videos while videos of length 20 minutes or above are classified as long videos (Minimatters.com, 2014). Therefore, using findings of Penni (2017) and Yoganarasimhan (2012), the results for the third hypothesis can be justified that longer durational videos can generate more YouTube engagement due to the strength of interest sports brand videos may establish for the online user, which may in-turn, increase the likelihood of generating more engagement due to a longer user watch time.

The fourth hypothesis, which states a statistically significant relationship between HD quality videos and YouTube engagement, was confirmed by the model. The results show that for every SD quality video, YouTube engagement is likely to increase by 0.2 units only while for every HD quality video, YouTube engagement is likely to increase by 1 unit. The hypothesis was derived using similar research conducted by Dobrian et al. (2013), who study the impact of video quality on user engagement when viewing videos on demand, and Wu et al. (2017), who work on predicting YouTube engagement in the form of video watch time. Results for both studies conclude a positive correlation between HD quality videos and user engagement for both, YouTube and VoD videos. According to Dean (2017), firstly, majority of vloggers tend to record videos in HD quality in order to provide the best display of their content. Secondly, the platform YouTube tends to have an inherent preference for HD videos. The search query on Netvizz to create the dataset of this study also provided majority of videos in HD quality, validating that majority of sports brand-related channels also prefer HD quality when creating and uploading videos. HD videos also tend to lead the YouTube's first page of search results. 63% of videos on the first page of YouTube's video search are found to be in HD quality (Dean, 2017). Therefore, findings from the work by Dobrian et al. (2013), Wu et al. (2017) and Dean (2017) helps justify the results achieved for the fourth hypothesis that HD quality videos have a statistically significant impact on YouTube engagement for sports brand-related YouTube videos.

The fifth hypothesis, proposing that there is a statistically significant relationship between video age and YouTube engagement, was confirmed by the model. According to the regression results, for every one-year increase in the video's age, YouTube engagement will increase by 1.18 units. As previously described for the variable channel age, the hypothesis was derived using datasets used in studies of Hoiles (2017) and Qian Tang (2012). Although there are no direct tests conducted by previous authors to determine the relationship between video age and YouTube engagement, work by Gill et al. (2007), which explores viewership patterns of YouTube videos, concludes that online users do tend to enjoy watching videos that have been on

YouTube for quite some time. According to Gill et al. (2007), since the platform YouTube, running on the foundation of Web 2.0 allows the publishing of new videos to the platform, there is always new and old content for online users to view. Furthermore, Qian Tang (2012) conclusion on YouTube vloggers prioritizing the number of subscribers more than YouTube engagement also helps in justifying results for the fifth hypothesis. As described for channel age, new subscribers are more likely to engage in older videos of the YouTube channel, therefore, increasing the overall engagement of the channel. Older videos present on the YouTube channel gives users more content to view which can increase the likelihood for the channel to generate engagement.

The sixth hypothesis, which asserts that there is no statistical relationship between brand channel videos and YouTube engagement, was rejected due to significant results. Based on the regression results, brand channel videos have a statistically significant relationship with YouTube engagement (p=0.00). Additionally, based on the value of unstandardized coefficient beta (b), for every brand channel video in the dataset, YouTube engagement is likely to increase by 4.6 units. The hypothesis was derived based on findings and conclusions drawn by other authors. According to the findings of Khamis (2017), Li (2012) and Liu et al. (2015), the prevalence of social media influencers and change in online users' preference to view brand-related content has created problems for brands and advertisers in choosing the correct media for marketing purposes, but this does not seem to apply for Adidas. Based on the regression results, channels of Adidas soccer generate more engagement on YouTube than other vlogger channels promoting or mentioning the brand Adidas. The phenomena can be explained by the type of videos uploaded by the channel. The brand Adidas does not only upload and promote the brand's advertisement but also uploads other types of longer videos. According to Christina (2018), who studies video views on YouTube, the recommendation system on YouTube draws its data from two main sources. The first source includes content data, such as metadata like video titles and descriptions. The second source includes user activity data including video ratings, favorites, and video view time. Since brand names usually appear more in the title of videos, they are more likely to get more recommendation through the recommender systems than other non-branded videos only because the brand name appears in the title. This phenomenon creates an algorithm bias where the algorithm of the recommender system is likely to be biased to branded videos by including more branded videos in the recommended video section. Branded videos, hence, appear more in users' YouTube feeds, becoming more likely to receive more engagement (Christina, 2018). There are also other factors for which branded videos get more recommendations. For example, the amount of time users spends watching these videos and the number of views on the videos. In addition, majority of Adidas soccer videos include international soccer celebrities like Paul Pogba and Lionel Messi. Brands use celebrities to not only promote the brand, but to also enhance the brand's image and personality (Khamis, 2017; Van-Tien Dao, 2014). According to Khamis (2017), when a celebrity endorses a brand, any success on the celebrities' side creates a 'halo effect' on the brand, leading to a stronger marketing pull and brand recall. Since brands and celebrities have a large audience, the collective view time of branded videos becomes large. This automatically increases the likelihood for branded videos to receive more recommendations and engagement (Christina, 2018). Hence, using findings from Christina (2018), Van-Tien Dao (2014) and Khamis (2017), the results achieved for the sixth hypothesis can be justified on why brand channel videos and YouTube engagement have a statistically significant relationship.

The seventh hypothesis, which stated a statistically significant relationship between private vlogger channel videos and YouTube engagement, was confirmed by the model. Based on the regression results, for every vlogger video in the dataset, YouTube engagement is likely to increase by 0.4 units. Similarly, the eighth hypothesis, stating a statistically significant relationship between soccer news and updates channel videos and YouTube engagement, was also confirmed by the model. Based on the regression results, for every soccer news/updates video in the dataset, YouTube engagement is likely to increase by 0.36 units. The hypotheses were derived after considering different theories and conclusions drawn by authors studying, engagement, social influencers and user generated content (UGC). Kahn (1990), the first author to study engagement, concludes employees tend to be more engaged if motivated to self-express in the work place. Based on the regression results, private vloggers videos are found to the most engaging among all vloggers. This reflects private vloggers being engaged with brand and the sport soccer that motivates them to create such videos. Arthurs et al. (2018) define the concept of 'vlogging' as an extension of the phenomena blogging, which itself originates from the concept of personal diaries. Since YouTube allow users to create and upload content that represents their lifestyle, the YouTube channel, where user created content is uploaded, becomes an extension of their personal diary for such online users (Arthurs et al. 2018). For this research, private vlogger channels are defined as YouTube channels posting videos related to teaching and promoting tips and tricks on soccer while news/updates channels are defined as YouTube channels promoting happening news and updates on soccer. According to Khamis (2017), vloggers and social media influencers arise from the self-branding theory which states that individuals carrying a unique public image for cultural and marketable gain, emerge as a personal brand. Like commercial brands, self-branded individuals also carry unique selling characteristics that compel and respond to the needs or interests of a specific group (Khamis 2017). Such personal brands can also act as celebrity endorsers due to their influence within a social group or network (Li 2012). In the case of this research, private vloggers represented in the study are portrayed as online soccer celebrities who specialize in teaching and promoting the tips and tricks of the sport soccer that allows them to attract groups or networks interested in soccer, therefore increasing the likelihood of generating YouTube engagement on their videos. Additionally, according to Smith et al. (2012), UGC is something that is produced around sociality occurring objects and topics. Charmaine (2017), from the context of consumer interest-driven participation theory, adds that UGC, when combined with marketing and promotional tools, allows brands to be the center of sociality without disturbing the consumers. Topics and interests like soccer allows users to create and upload content around the sport's sociality, including different soccer brands as part of the content. Such an example can be seen for the dataset used in this research where vloggers, creating videos on soccer, feature the brand Adidas as part of the content.

The ninth hypothesis, asserting a statistically significant relationship between soccer product reviewer videos and YouTube engagement, was reject by the model. The hypothesis was rejected due lack of significance (p=1.00) as well as high multicollinearity. Based on the multicollinearity diagnostics results for the product reviewer channel type, values of tolerance (0.00) and VIFs (2.94^{13}) were found to be insignificant. The results represent that the independent variable, product reviewer channel type was found to be redundant and can be explained by other variables in the model (Field, 2018). Similarly, for the tenth hypothesis, asserting a statistical relationship between e-commerce store videos and YouTube engagement, was also rejected by the model due to lack of significance (p=0.13). The hypotheses were derived based on findings of Mahfouz et al., (2017) and Rorsted (2017) who highlight how retail chain stores give importance to YouTube and social media influencers. According to Mahfouz et al. (2017), retail chain stores not only exist as a separate channel on YouTube, but also partner with social media influencers and vloggers, from time to time, in order to create customized content to promote the stores' merchandise and attract new audiences. Based on the multicollinearity results for the fifth hypothesis, the channel type variable, soccer product reviewer videos, contains a high multicollinearity, stating that the variable is redundant and can be possibly explained by other variables. For this research, product reviewer channels are defined as channels dedicated to reviewing, comparing and unboxing soccer related equipment. It can be possible that other channel type variables including private vlogger channels, brand channels and e-commerce channels also explain the effects of channel type variable product reviewer on YouTube engagement. E-commerce channels, for this research, are defined as online soccer related equipment stores with a direct URL to the website in the about section. With brand channels promoting similar products to e-commerce channels in their respective videos, e-commerce stores were not able to attract that many groups or networks interested in soccer. With soccer celebrities featured in brand channel videos, online users might be more interested in videos created by the brand channels compared to videos created by e-commerce channels, promoting similar products.

5.2 Theoretical Implication

This research was designed based on previous studies conducted on social media engagement, YouTube, social influencers and sports marketing. This research contributes to the theory of engagement with respect to how different types of YouTube metadata, including different channel and video properties, impact user engagement generated on YouTube videos.

Based on the regression results, channel and video properties such as channel age, video age and video duration have statistically significant relationship with YouTube engagement. If YouTube channels continue to stay active, they are more likely to generate more engagement for the channel as it ages. Similarly, older videos are also likely to generate more engagement as users enjoy watching content that has been on YouTube for some time (Gill et al,. 2007).

The research also contributes to the literature on sports with respect to how various types of YouTube sports channels, creating videos on similar sports brands, have different effects on YouTube engagement. The research confirms conclusions drawn by Khamis (2017) on the prevalence of YouTube vloggers, and Li (2012) on YouTube vloggers potential to act as celebrity endorsers due to their influence within a social group or network. The research adds to the literature on sports in that sports brands on YouTube have the highest effect on YouTube engagement. Through the analysis, it was discovered that sports brand channels have the highest effect on YouTube engagement, followed by private vloggers and news and updates channels. Sports brand channels have access to a larger network and the ability to feature sports celebrities. This allows sports brand channels to attract more viewers which increases the likelihood for their videos to generate more engagement. Similarly, private vlogger and news and updates channels carry characteristics that compel and respond to the needs or interests of groups interested in soccer. This allows private vlogger and news and updates channels to attract more viewers and subscribers which increases the likelihood for their videos to generate engagement.

The research also concludes a theoretical model for other researchers to follow when predicting user engagement on YouTube for different types of brands. Although it is difficult to define and understand the term engagement in the space of social media (Achen et al., 2017), the value of adjusted R^2 in this research (0.411) indicated a large effect size according to the (Cohen, 1992).

5.3 Implications for Practice

In practice, this research helps marketing practioners in understanding the phenomena of YouTube engagement generation. The research provides additional important variables for brands and advertisers to consider when establishing a channel on YouTube. Based on the analysis, it can be concluded that longer videos are likely to generate more YouTube engagement. This allows brands not to only focus on producing and uploading brand promotional videos but also produce more non-promotional videos that are relevant to the users in their everyday life. This can help brands establish a stronger social media and YouTube presence, therefore a stronger brand identity and awareness, as online users would have additional stimuli of brands to remember. Additionally, for new YouTube channels, based on the analysis of the number of subscribers, new YouTube channels should focus on building a high subscriber following as it has a direct impact on YouTube engagement. Instead of focusing only on content, new YouTube channels can work on collaborating with other similar YouTube channels to have more relevant content outreach. This will give a push start to new YouTube channels in attracting new subscribers, therefore, increasing the likelihood of generating more engagement.

The research also provides new variables for marketers and advertisers to consider when creating a YouTube strategy. As YouTube engagement is one of the important metrics to measure social media marketing return on investment (Hoffman and Fodor, 2010), the set variables used in the study can help marketers and advertisers make relevant decisions when creating and implementing media plans to amplify YouTube engagement. By looking through the important channel and video properties for YouTube channels involved in any campaign, marketers and advertisers can have a better understanding of which type of videos are likely to generate more videos. The model can help marketers and advertisers save additional costs as it provides more information to consider when making promotional budget decisions for any YouTube campaign.

5.4 Research Limitations

After considering and analyzing as many variables as possible for predicting user engagement, there were still a few factors this research design could not control for. The variables used in the study were extracted based on convenience using YouTube API. The research design could not control for other variables that may impact user engagement, including the content of the video, online user and preference behavior, offline advertising of the brand and vloggers, and any media amplification done by any YouTube channel used in the study. Since the measurement and extraction of other mentioned variables required additional tools and information, variables collected based on convenience were used in the study.

The research was also limited as it did not account for all constructs of social media engagement. As concluded by Achen et al. (2017), it is still difficult to define and understand the term engagement in the space of social media. According to Achen et al. (2017), online users not only considered using traditional methods of social media features such as liking, commenting, favoriting, retweeting and sharing as an idea of engagement but also considered reading social media content, sharing the content information with family and friends and discussing the content in different social setting offline as engagement as well. For this study, the metrices of interaction construct of engagement were taken as a measure of YouTube engagement (Tuten and Solomon, 2018). Although this is a limitation, several past studies have used fewer metrices of interaction construct of engagement such as the number of video views, to predict user engagement (Figueiredo, Almeida, Gonçalves, and Benevenuto, 2016; Rizoiu et al., 2017; Szabo and Huberman, 2008; Trzciński and Rokita, 2017; Wu et al., 2017; Xu Cheng, 2014). The research could not account for other engagement constructs and metrices highlighted by Tuten and Solomon (2018), Achen et al. (2017) and Hoffman and Fodor (2010) such as positive and negative sentiments of video comments, channel views, influencer network size, average video watch time and social media engagement beyond online measures in the study.

5.5 Recommendation for Future Research

Video content is one of the main characteristics which separates different YouTube channels from one another (Chen, 2008; Smith et al., 2012). By carrying out a content analysis of the videos used in the dataset, additional variables can be drawn. These variables can be further used to predict YouTube engagement for sports brand-related video on a broader level. The content analysis would provide different content themes used by brand channels and vlogger channels. Content themes, along with channel and video properties, can be further used as independent variables to predict YouTube engagement for brand and vlogger channels. Multiple regression can be used to build an expanded model. It would be interesting to see the different types of content themes used by respective brand and vlogger channels as well as the how much the content differs for respective channels. The resulting model from this research will not only help brands and advertisers in strategic planning but also provide creative professionals a set of guidelines to follow when producing or directing YouTube videos.

Interaction terms can be included in the regression analysis to expand the relationship among the current variables used in the study. Looking into the example of the hypothesis for video duration, which stated a significant relationship between short videos and YouTube engagement can be further explored by adding interaction term to see if there is another value interfering (confounding) with this variable. The result (coefficient) for video duration was found that longer videos have a positive relationship with YouTube engagement. This is highly likely due to the content in the video. For example, a long video could be about the personal story of a vlogger or an athlete that would interest more users to watch than a short video advertisement. If this is the case, then the content of the video (personal story vs. ad) would be a confounding factor with the length of the video and can be controlled by including this as an interaction term in the regression model. Interaction terms would be created by forming a new variable for the content and coding it based on the type of content. The length of the video and the content variable can be included as the main effect, the interaction of both can be added. In order to include the interaction term in a model, the main effects should also be included (the original variables of the interaction). Sometimes a factor on its own does not create an effect, but when combined with another they both do. This method is useful for studying models where factors interact to affect the dependent variable (Cortina, 1993).

Engagement constructs including intimacy and influence, can also be used as a measure of SME to carry out a similar research. Metrices of intimacy construct including the number of positive and negative words associated with a brand and the frequency and quality of complaints and compliments posted on a brand's social media pages, can be used as dependent variables to study the impact channel and video properties have on these variables. Similarly, metrices of influence including the quantity, frequency and score of brand reviews, ratings and frequency of brand mentions on social media, and frequency of brand referrals on social media or profiles, can also be used as dependent variables to study the impact channel and video properties have on these variables. A mix of sentiment, content and network analysis could be used to quantify the mentioned variables to examine which factors help predict SME in the form of intimacy and influence.

5.6 Conclusion

This study contributes to research on social media engagements in terms of, examining the type of factors important in predicting user engagement on YouTube. The most highlighting contribution added to the literature by this study is the identification of the brand channel type as the mostly likely channel to generate higher YouTube engagement among other channel types. According to the results, brand channel videos are likely to generate four times more engagement than other YouTube channels due their ability to feature of sports celebrities in the video. Additionally, brand channel videos have a higher probability to be included in the recommended videos section on YouTube. The research also specified other channel types, including private vlogger and news/updates channels to have a statistically significant relationship with YouTube engagement, while channel types e-commerce and product reviewers having no statistically significant relationship with YouTube engagement.

Another important contribution added by this study was highlighting the impact and relationship of different channel and video properties on YouTube engagement. According to the results, channel properties, including the number of channel subscribers and channel age have a statistically significant relationship with YouTube engagement. Additionally, video properties all video properties, including video age, definition and duration have a statistically significant relationship with YouTube engagement. The most interesting insight provided by video properties results was that longer videos tend to generate more YouTube engagement. This is due to the strength of interest sports brand videos may establish for the online user, which may in-turn, increase the likelihood of generating more engagement due to a longer user watch time.

In summary, this research used a linear regression method to examine factors predicting user engagement on YouTube. The linear regression model accounted for 43% of variance. At 95% confidence level, the results showed that channel types brand, private vlogger and news/updates have a statistically significant relationship with YouTube engagement. Additionally, number of channel subscribers, channel age, video age, video duration and video definition have a statistically significant relationship with YouTube engagement. The research provides a pathway for marketing and advertising practioners as well as social media researchers to consider when investigating YouTube engagement.

Appendices

A1 MS Excel Data Sheet

Channel Id	Video Id	Channel Title	Video Title	Channel Type	Channel Age	Channel Subs	Vid Age	Vid Dur	Vid Def	Views	Likes	Comments
UC_i37oIK2jj	sixWBvGV	LucasFootball	Adidas Blue	Vlog	3	1377	1	0.68	hd	607	14	4
UC_i37oIK2jj	D0bxtmgp	LucasFootball	New Adidas	Vlog	3	1377	2	0.48	hd	17620	156	27
UC_RkluqFB	pD4EXVrG	Brad Hall	adidas Yeez	Vlog	3	274640	2	2.22	hd	47470	1372	124
UC_xJPr8tMy	c8iOiv5EW	JackBreureTV	Adidas X 16.	Vlog	3	1245	2	2.15	hd	47089	354	60
UC0L76yZFkT	4BVWM8X	NLP	TOP 10 Adid	Product Reviewer	7	36323	1	4.03	hd	44852	347	36
UC0L76yZFkT	f7Xgdy0Fi	NLP	Top 10 Adid	Product Reviewer	7	36323	3	4.90	hd	245380	1408	124
UC0L76yZFkT	FKujsytw-E	NLP	Top 10 Adid	Product Reviewer	7	36323	2	5.95	hd	88088	672	90
UC0L76yZFkT	Fk21epona	NLP	Top 10 Adid	Product Reviewer	7	36323	3	5.10	hd	347649	1806	167
UC0L76yZFkT	MIceoLjclC	NLP	Top 10 Adid	Product Reviewer	7	36323	2	4.80	hd	203719	1099	113
UC0PRCNt52	wR6bfZEsF	calsky	adidas socce	Vlog	12	6	12	2.32	sd	48186	158	16
UC0smKJrJXC	dYfg4utEx	soccerloco	adidas Worl	E-Com	8	1677	0	1.02	hd	938	8	4
UC0X9flnKqC	gsJ_3Vy7O	WaÃ¨l Sawan	Adidas socce	Vlog	12	2	6	0.02	sd	170	2	0
UC10_3YEKZ	INF8ga94R	chongsiu2000	Adidas Socc	Vlog	10	86	9	5.02	sd	595	4	0
UC10_3YEKZ	qdf4ludEE	chongsiu2000	Adidas Socc	Vlog	10	86	9	5.02	sd	541	3	0
UCaQHxlbPA	pxlLaRlyJq	adidas Footba	Introducing	Brand	10	1361755	0	0.52	hd	1071737	987	38
UCaQHxlbPA	0IA24J0FN	adidas Footba	David Beckh	Brand	10	1361755	1	15.17	hd	251682	4868	197
UCaQHxlbPA	AGyVUrYg	adidas Footba	Don't Play G	Brand	10	1361755	1	9.72	hd	1280627	5935	202
UC10_3YEKZ	Qg_LFRGjk	chongsiu2000	Adidas Socc	Vlog	10	86	9	5.02	sd	786	0	0
UC1jMVbdM	WMSqbqv	The Fake Play	Adidas Yeez	Product Reviewer	7	2613	2	2.15	hd	8017	46	10
UC1jYJ15FzF	Szq5s_BJI9	MrMarioespi7	Giveaway -	Vlog	7	352	5	2.03	sd	2532	255	320

A2 Linear Regression Analysis for Dependent Variables: Log (Likes), Log (Views) and Log (Comments)

	Log (Likes)	Log (Views)	Log (Comments)
Independent Variables	Standardized Coefficients Beta β		
Video Age	-0.02	0.17	-0.04
Video Definition	-0.20**	-0.16**	-0.19**
Video Duration	0.23**	0.20**	0.26**
Brand	0.22**	0.35**	0.07
Vlog	0.00	0.00	0.00
E-commerce	0.03	0.05	0.01
Prod Reviewer	0.18*	0.17**	0.24**
News/Updates	-0.02	-0.01	-0.04
Channel Age	0.16**	0.18**	0.16**
Channel Subscribers	0.40**	0.33**	0.31**
N	707	707	707
R^2	0.51	0.42	0.45
Adjusted R^2	**0.50****	**0.42****	**0.44****
*p<0.05 **p<0.001			

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