Paid to post: The relationships between sponsorship characteristics and user engagement indicators of beauty-related videos on Dutch YouTube channels. A quantitative content analysis

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PAID TO POST: THE RELATIONSHIPS BETWEEN SPONSORSHIP CHARACTERISTICS AND USER ENGAGEMENT INDICATORS OF BEAUTY-RELATED VIDEOS ON DUTCH YOUTUBE CHANNELS. A QUANTITATIVE CONTENT ANALYSIS

ABSTRACT

Online influencer marketing in the form of sponsored content is becoming increasingly prevalent on YouTube. However, there are multiple issues associated with sponsored content, such as inconsistencies among creators when it comes to when and where to provide a disclosure, as well as the visibility of these disclosures. As a result, viewers are oftentimes unaware that they are being exposed to an advertisement, which leads to discussion among academics and media practitioners whether or not this type of marketing strategy can be considered ethical. Despite the efforts of establishing clear guidelines, rules regarding sponsored content are often not abided by due to confusion and/or lack of consequences. While the effects of sponsored content on viewers have been researched extensively, little to no research focuses on how viewers actually experience the use of this advertising strategy on YouTube and subsequently, react upon it. Therefore, in this study the relationships between sponsorship characteristics and nine indicators of user engagement were analyzed, to see if relationships between these concepts exist. The corresponding research question that belonged to this research goal was: 'What are the relationships between sponsorship characteristics of, and indicators of user engagement around, beauty-related videos on Dutch YouTube channels?'.

The research method that was used was a quantitative content analysis. The data set consisted of 300 Dutch videos, sampled from 15 different YouTube channels, in which beauty products were evaluated. The channels themselves were expert sampled. For each video, multiple sponsorship characteristics were coded (e.g. how the YouTuber got the product, if and how this is disclosed, the YouTuber's valence regarding the product, and the presence of a giveaway), as well as several indicators of user engagement (such as the amount of likes, dislikes, comments, shares, etc.). The main findings were that all indicators of user engagement (except for amount of subscriptions driven) could be predicted by the sponsorship characteristics in this study. The YouTuber's valence was the most prevalent predictor, as it predicted six out of nine user engagement variables. A visual representation of the resulting model, which highlights the significant relations between the predictors and indicators of user engagement, was provided as well. The findings of this study have theoretical implications on multiple theories, such as the uses and gratifications framework, the ACE typology, and persuasion knowledge theory. In terms of practical implications, these findings help media practitioners (such as marketeers, advertisers, and YouTube influencers) optimize their marketing and engagement strategies. Based on the results, detailed recommendations for these media practitioners were provided as well.

<u>KEYWORDS:</u> *Marketing, YouTube, Sponsored Content, User Engagement, Social Media*

Preface

I would like to start by thanking my thesis supervisor Ruud Jacobs for his detailed feedback and guidance throughout this graduation phase. I would also like to thank my boyfriend, Jan Hubers, for his help and support when writing this report. Another special thanks goes to dr. Jay Lee, for his advice and suggestions regarding the program SentiStrength. Finally, I would like to express my gratitude towards Simone van der Zee and Renske Pin, who were so kind to meet me during my Christmas holiday in Curaçao (!) to brainstorm about my thesis and help me solve the problems I was facing at that time.

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1. Introduction

As online media are undeniably becoming a substantial part of our everyday lives, advertisers are increasingly using digital marketing techniques to reach their target groups (Smith, 2011). The prevalence of these online marketing strategies is only expected to grow as “reaching consumers through digital media is considered to be the most promising field of development for marketing in the upcoming decade” (Smith, 2011, p. 489). An example of one of these promising marketing techniques is online influencer marketing. This marketing technique, which has rapidly become one of the most popular forms of social media advertising, can be defined as “a type of marketing that focuses on using key leaders to drive your brand’s message to the larger market” (Beall, 2017, para. 2). In other words, online influencer marketing involves brands partnering up with influential online individuals (i.e. people who have a large amount of followers on one or more social media platforms) in order to promote products and services (Lee, 2018).

Yet, the principle behind influencer marketing is nothing new – in fact, in 1955 Katz and Lazarsfeld already found that messages from the mass media do not influence audiences directly, but rather follow a ‘two-step flow’: First, opinion leaders receive information through the mass media. From there, it is passed on to the opinion followers. This theory, called the two-step flow of communication, is based on an earlier study from Lazarsfeld, Berelson, and Gaudet (1944), in which the authors researched the decision-making processes of voters during the presidential campaign of Franklin D. Roosevelt. While at first it was hypothesized that media messages would have a direct, powerful influence on voting behavior, the researchers were surprised to find that participants mentioned far more often that personal contacts were the sources that influenced their voting behavior, instead of the propaganda.

The two-step flow of communication theory is still relevant to this day in marketing practices: by focusing on the most influential people within the target audience, it is much more likely that a message will resonate with the rest of the target group (Brown & Hayes, 2008). Social media platforms in particular have become very interesting and important environments for influencer marketing due to these sites’ ability to build and maintain connections among users (Evans, Phua, Lim, & Jun, 2017; Tuten & Solomon, 2017). Moreover, in 2017 an estimated 2.46 billion people were active on social media (Statista, 2017), which illustrates the popularity and potential reach of social networking sites. Finally, it is interesting for advertisers to focus on social networking channels because younger cohorts such as generation Z (i.e. people born between 1990 - 2001) are increasingly more difficult to target effectively through traditional media (Okazaki & Taylor, 2013).

One of the most prevalent forms of online influencer marketing is the use of so-called sponsored content. Sponsored content is a type of content created by online influencers and can be found on a range of social websites, such as Instagram, YouTube and blogs. Sponsored content is often perfectly integrated into a person's social media feed, alongside the rest of their content, and has proven itself successful in the past in terms of increased purchase intention and brand recognition (Fox, 2011; McGowan, 2015). However, while often unclear to the recipient, a key difference between an influencer's 'regular' content and sponsored content is that the latter is commissioned by companies. Usually, the only way to spot this difference is when the sponsored content contains a written or spoken disclosure. However, there are multiple issues associated with these disclosures, such as inconsistencies among creators when it comes to when and where to provide one, as well as the disclosure's visibility (Wu, 2016).

As a consequence of these issues, sponsored content raises several ethical questions regarding those who are exposed to it. One of the main criticisms of sponsored content is that - without proper disclosure - it is hard for viewers to differentiate these posts from the non-sponsored content. As a result, viewers are oftentimes unaware that they are being exposed to an advertisement. This situation leads to discussions among advertisers, marketeers and academics whether this type of advertising can be considered ethical. This is especially the case when it comes to young audiences, given that these audiences are more susceptible to the manipulation effects of persuasive messages (Wyman, 2015). Moreover, there is not only a lack of guidelines regarding this type of advertising, but also a lack of uniform laws and regulations across countries. In fact, some countries do not have any official guidelines at all, with the consequence that the field of online advertising in these countries is completely self-regulatory.

One example of a country that struggles with defining and maintaining official guidelines for sponsored content is the Netherlands. There are general laws in relation to deceptive advertising which can be found in boek 6 Burgerlijk Wetboek (*book 6 of Dutch Civil Law*) (Meindersma, 2017). For example, every Dutch citizen is allowed to make a case in court when they believe that an (online) advertisement is inappropriate. However, there is a serious limitation to this right as filing a lawsuit can be very expensive and is therefore not a realistic path to follow for the vast majority of the population. Additionally, there is the Autoriteit Consument en Markt [ACM] (*Authority for Consumer and Market*). While this authority is capable of charging penalties, charging those who do not properly disclose sponsored content on social media is not on their list of priorities (Meindersma, 2017). Lastly, there is the Reclamecode Social Media (*Code for Commercials Social Media*) which is a more comprehensive overview of advertising guidelines based on the Dutch law. Those who break the rules of the Code for Commercials risk being placed on an advertising 'black list' that gets forwarded to the ACM, who in turn might decide to give a penalty. Yet, playing watchdog on social media is also not one of ACM's top priorities (Meindersma, 2017).

What becomes apparent is that there is not only a lack of detailed and uniform guidelines for the use of sponsored content, but that there are also no (strict) consequences when rules are broken. Furthermore, to this day, it is the brand behind the advertisement (and not the influencer) who is the one that receives a warning if rules are broken. In an effort to improve the current guidelines and in response to the discontent of users regarding unclarity about sponsorships, a new set of guidelines regarding sponsored content on YouTube was introduced in the Netherlands on November 21st, 2017. This set of guidelines, named the Social Code: YouTube, is an initiative of 18 Dutch YouTubers which offers YouTubers guidelines when collaborating with companies. The introduction of the Code not only simplified and clarified current guidelines, it also shifted rule-abiding responsibilities from the advertisers to the creators (Meindersma, 2017; Social Code, 2017).

1.1 Problem definition and research goal

The introduction of the Social Code: YouTube is a welcomed development in the Netherlands as previous rules regarding sponsored content were often not abided by due to confusion and/or lack of consequences. This was not only a bothersome situation for creators, but also deceptive towards viewers as many will be unaware of the fact that they are being exposed to an advertisement (Albright, 2016). The Code's main goal, therefore, is to increase the transparency of advertising in YouTube videos. However, it remains unclear if the Code will be the solution to this problem, as research still has to be conducted on the Code's effectiveness. Moreover, content creators are not obligated to join the Code, as this is done on a voluntary basis. Finally, one can wonder what happens in terms of user engagement when content shifts from perceived 'covert' advertising to 'overt' advertising due to new transparency guidelines.

While the effects of sponsored content on viewers in terms of purchase intention and brand awareness have been researched extensively (e.g. De Veirman, Cauberghe, & Hudders, 2017; Evans, Phua, Lim, & Jun, 2017; Van Reijmersdal et al., 2016), little to no research focuses on how viewers actually experience the use of this advertising strategy on social media and subsequently, react upon it. Therefore, the goal of this research was to identify how multiple indicators of user engagement are associated with different types of sponsorship situations in YouTube videos, based on the situations defined by the Social Code: YouTube. Topics that are discussed include, among others: do viewers engage differently with videos that are sponsored in comparison to non-sponsored videos, and if so, in what ways? Does providing a disclosure trigger different types of user engagement, and does the location of this disclosure influence user engagement as well? With a content analysis, both the sponsorship characteristics of a video (such as sponsorship situation, provision of disclosure, location of disclosure, etc.) as well as several indicators of user engagement (such as the amount of likes, dislikes, comments, shares, etc.) were coded and then analyzed to see if relationships between these concepts exist. Moreover, in order to provide detailed recommendations for media practitioners, this study also aimed to predict user engagement with these sponsorship characteristics.

When reading this thesis, one has to keep in mind that the term ‘user engagement’ was used to indicate a group of nine (easily) quantifiable indicators of user engagement, which are the main dependent variables in this study. Therefore, one should not interpret the term ‘user engagement’ as a single construct, as each dependent variable was unique in terms of their relationship with an independent variable. The user engagement indicators that were measured include: the amount of likes and dislikes on a video, the amount of comments that were posted on a video, the amount of times the video was shared, how many subscribers were lost or gained from a video page, the average viewing time (expressed as an absolute value and as a percentage of total video length), and finally, the levels of positive and negative sentiment in the comments. In order to make the sampled channels comparable to each other, the user engagement indicators were corrected. More specifically, the amount of likes, dislikes, comments, and shares were corrected for the amount of video views, and the amount of subscriptions driven was corrected for the amount of channel subscribers. However, this list of user engagement indicators is non-exhaustive, meaning that viewers can engage in more ways with YouTube videos than the indicators mentioned before. The reason why these specific indicators were chosen is because they can easily be measured by everyone, which is important for media practitioners who wish to use these indicators to gain insights into their own content. Moreover, if one wishes to gain insights into indicators of user engagement that are not included in this thesis, other research methods than the quantitative content analysis might be more suitable. More detailed information on this study’s user engagement indicators and how they were measured can be found in Chapter 3 of this report.

1.2 Research scope and research question

Whereas researching sponsored content on any social media platform might yield interesting results, this research focused in particular on the use of this marketing strategy in YouTube videos. The main reason why this specific social media platform was chosen is because it is the first platform for which a Social Code was developed in the Netherlands. While not everyone might consider YouTube to be a social medium, it is in fact very much so, as the platform is able to engage users to create and share user-generated content (McGowan, 2015; Thornton, 2017). Moreover, not only is

YouTube one of the most visited websites in the world (Donchev, 2017), the platform also offers new and unique possibilities when it comes to advertising in comparison to other channels (McGowan, 2015). An example of this is *TrueView*, which allows advertisers to only pay for advertising costs when viewers choose to view the (complete) advertisement.

In order to give direction to this research, this study focused on content uploaded to the channels of Dutch YouTubers. Dutch channels were chosen in particular because of the recent developments in sponsorship and disclosure guidelines in the Netherlands, as illustrated by the Social Code: YouTube (2017). Moreover, as it might be the case that YouTubers in different fields of expertise generate different types of user engagement, the choice was made to focus on one industry in particular: the beauty industry. There are multiple reasons why this industry was chosen. For example, even though the amount of money spent on influencer marketing differs per industry and company in the Netherlands, the largest budgets are currently spent by beauty, fashion, and lifestyle brands (Stallvord, 2017). Given these large budgets, it is likely that beauty, fashion, and lifestyle products are (one of) the most prevalent product categories for Dutch influencer marketing. Moreover, the majority of the initiators of the Social Code: YouTube create beauty videos, which results in the expectation that the effects of the Code can mainly be observed in this particular industry.

Lastly, the current study focused on videos in which beauty-related products were evaluated in the format of tutorials, reviews, and/or first impression videos. In other words, videos in which beauty products were featured in a vlog format were not sampled. The reason for this is that the YouTuber's opinion of a product plays a central part in the theoretical framework of this study, and vlog formats are less likely to contain an elaborate opinion in comparison to the tutorials, review, and first impression videos. Next to that, the term 'beauty product' is considered a broad concept in this study, and includes (among others) products such as make-up, skincare, and hair products/tools.

Based on the information presented above, the following research question was formulated: 'What are the relationships between sponsorship characteristics of, and indicators of user engagement around, beauty-related videos on Dutch YouTube channels?'. The corresponding hypotheses are elaborated upon in detail in Chapter 2.

1.3 Relevance

1.3.1 Scientific relevance

YouTube as a marketing tool has been previously researched in a diverse range of industries, such as the tourism industry (Reino & Hay, 2016), the tobacco/e-cigarette industry (Freeman & Chapman, 2007; Sears et al., 2017), and the online music industry (Verma, 2017). Moreover, YouTube marketing is not only useful for commercial organizations, as non-profit organizations can benefit from YouTube marketing as well. For example, a study by Pham, Farrell, Vu, Vuong, and Napier (2017) indicated that promotional videos on YouTube can aid to attract international students to universities. However, while the vast majority of studies conclude that YouTube can be an excellent tool for promoting products or services, uncertainty remains in how viewers actually filter, select and use information in their decision-making processes (Sears et al., 2017). This literature gap was also identified by the Marketing Science Institute [MSI] (n.d.-a), that listed “making sense of changing decision process(es)” as one of the research priority topics of 2016 – 2018 (para. 3). More specifically, gaining more insights into consumer processing patterns in an online environment where information is easily accessible is considered to be of utmost importance (MSI, n.d.-b).

Furthermore, research has found that product claims made in user-generated YouTube videos are different from claims made in traditional digital advertising (Sears et al., 2017). Additional research is therefore necessary on how audiences process the marketing claims made by different sources and how they react upon these (Sears et al., 2017). Moreover, taking the ‘organic’ appearance of sponsored content in mind, Evans, Phua, Lim, and Jun (2017) stated that research still needs to be conducted on consumer understanding and recognition of this type of advertising, as this “could bridge the gap between pressures from regulators and the industry” (p. 9). Sponsored content on YouTube is currently a grey area and there is thus a need for additional research that aims to identify online marketing strategies that are successful in attracting and engaging consumers through this social medium (Smith, 2011).

Another difficulty in social media marketing is measuring a campaign’s return on investment [ROI] due to a lack of robust measurement tools and plans (Kaul & Chaudhri, 2017; Kumar & Mirchandani, 2012). Whereas previous literature has suggested looking at other types of easily quantifiable information in order to determine a campaign’s ROI (such as number of sales), actual in-depth user engagement behavior with campaigns is often overlooked. In fact, looking solely at the number of sales in particular provides only limited insights into the success of the marketing campaign. In this research it was therefore decided to analyze the relationship between sponsorship characteristics and multiple indicators of user engagement. The focus of this research adds to existing literature, as it contributes to quantifying the ROI of marketing campaigns, or more specifically, sponsored content campaigns.

1.3.2 Social relevance

Influencer marketing is becoming an increasingly popular online marketing technique in the Netherlands, and there appear to be no signs regarding any decline in the extent to which it will be applied in the coming years. Stallvord (2017), who is co-owner of the first Dutch marketing agency that specialized in influencer marketing, estimated that more than 100 million euros were invested in influencer marketing in the Netherlands in 2017. Moreover, Stallvord (2017) estimated that in in the year 2017, about 15.000 Dutch influencers had one or multiple paid collaborations with companies. Not only the amount of influencers is expected to increase over the coming years, so is the amount of money spent on influencer marketing. Therefore, in order to maximize the effectiveness of sponsored content, it is important to research and understand how viewer engagement is associated with this particular type of advertising on YouTube, as the way in which users engage with the sponsored content is an indicator of the success of this marketing technique.

Different types of media professionals can benefit from these findings. For example, not only marketeers and advertisers, but also content creators on YouTube can use the insights of this thesis to create more effective and persuasive messages on social media. Lastly, the findings of this study can help improve not only the guidelines of the Social Code: YouTube, but might also give direction to the development of future Codes for other social media platforms.

2. Theoretical framework

This theoretical framework starts by discussing the concepts of user engagement and Internet participation inequality, and introduces the first sponsorship characteristic: the YouTuber's evaluation of a featured product. After that, advertising resistance by consumers and the corresponding resistance strategies they can use are presented, as these strategies aid in building the theoretical framework of this study. Then, the concept of influencer marketing on social media is discussed in greater depth, and other sponsorship characteristics are introduced (such as what different sponsorship situations exist on YouTube, as well as the provision of disclosures). Lastly, this framework introduces the use of giveaways in YouTube videos, which is an engagement-boosting strategy often used in combination with sponsored content. The final section of this framework presents a visual overview of the research model.

The hypotheses presented in this theoretical framework state 'user engagement' as the main dependent variable – however, one has to keep in mind that in this research, user engagement is *not* considered a single construct. Namely, the grouping term 'user engagement' is made up of multiple indicators, such as the amount of likes, dislikes, comments, and so on. This means that in order to keep the hypotheses clear and concise, the separate indicators for user engagement are temporarily treated as one. When presenting the results in Chapter 4, user engagement will be discussed in terms of separate indicators again. This also means that the hypotheses are deliberately chosen to be non-directional, as every single indicator of user engagement relates differently to an independent variable. A detailed discussion of which variables comprise 'user engagement' and how these variables are operationalized can be found in Section 3.3 of this report.

2.1 User engagement, participation inequality, and valence

User engagement is a construct associated with how humans interact with computer-mediated activities, or in this particular case, a YouTube video (O'Brien & Toms, 2008). User engagement is linked to what 'draws us into' particular types of content and which content is able to hold our attention. O'Brien and Toms (2008) have identified five different content characteristics that positively influence the ways in which users engage with content, including: (1) the aesthetics of the media content, (2) its affective appeal, (3) how it draws attention, (4) its meaningfulness, and finally, (5) its goal-directedness. In other words, the more the post has attractive visuals, is able to grab the user's attention, is enjoyable, is meaningful, and communicates a clear goal, the more likely the user is to engage with the content in a positive manner (e.g. posting positive comments or giving likes). Additionally, Sonderman and Tran (2013) emphasized that, next to the points mentioned above, sponsored content should also be creative and entertaining in order to be effective, as this particular type of content is becoming increasingly prevalent.

Yet, not only the characteristics of the content play a role in how a user decides to engage with it, as characteristics of the users themselves are influencing factors as well. The uses and gratifications framework [U&G] is a commonly used framework in media research and helps to understand people's motives for (social) media use. In an effort to contribute to the U&G framework, Khan (2017) has identified user motives for both YouTube participation (i.e. active users) and YouTube consumption (i.e. passive users). Khan (2017) found five different factors for YouTube participation and consumption, namely: (1) seeking information, (2) giving information, (3) self-status seeking, (4) social interaction, and (5) relaxing entertainment. Other influencing factors on user engagement include a user's anonymity, YouTube visitation frequency, and gender (Khan, 2017).

However, it is difficult to generalize the 'user' and their engagement behaviors as there exists a large participation inequality on the Internet. According to the 90-9-1 rule as coined by Nielsen (2006), 90% of users never contribute to media content (by e.g. liking, commenting, etc.) and simply lurk in the background. On the contrary, 9% of users contribute now and then, and 1% of users are responsible for almost all the visible contributions. In other words, this means that 1% of Internet users are responsible for 90% of the postings online (Khan, 2017; Nielsen, 2006).

In short, every user has different reasons to engage with a YouTube video, and multiple factors that predict user engagement have been identified by previous research. However, one factor that (to the researcher's knowledge) has not been researched in the context of sponsored content is how the valence communicated by the YouTuber might influence the user engagement of that video. Valence refers to the type of emotions that are experienced and communicated, and can be considered as a pleasure/displeasure continuum (Posner, Russell, & Peterson, 2005). According to the Interpersonal Emotion Transfer [IET] theory (Parkinson, 2011), emotions can catch on to others in two different ways: social appraisal and emotion contagion. Social appraisal occurs when the emotions of others affect how we feel about something, such as an event, product or situation. For example, talking about how anxious we are about a certain situation can make others feel anxious about that situation as well, even though they never experienced it themselves before. Contrastingly, emotion contagion is independent of a third factor such as an event, product or situation: it involves directly mirroring another person's mood. For example, we tend to feel happier after being around someone who was also very happy, without any apparent reason (Parkinson, 2011). In the context of YouTube, one could thus wonder to what extent emotion (or valence) communicated by the YouTuber is transferred to viewers and their engagement behavior. Based on this information, the following hypothesis was formulated:

H1: The valence of the YouTuber in a video is associated with the levels of user engagement of that same video.

However, this relation may not be as straightforward as it may appear: one could argue that the authenticity of the YouTuber’s valence also plays an important role. More specifically, if a YouTuber is paid (i.e. sponsored) to make a video, the authenticity of the YouTuber’s valence becomes questionable – especially when that valence is perceived to be (extremely) positive. Taking in mind that whether or not a video is sponsored is rarely communicated in the video’s thumbnail or title, a mismatch between the video’s goal and the user’s goal (i.e. motives) might occur once the video has been started by a user. It is expected in this study that especially when a user feels ‘tricked’ into watching a sponsored video, he or she is likely to resist the persuasion intent of the advertisement. In fact, this psychological resistance may in turn trigger certain types of engagement behavior. Yet, before elaborating further on this behavior, the psychological processes that occur once a viewer resists an influencer’s persuasion attempt are discussed in more detail first. The reason for this is that these psychological processes might help explain the types of user engagement behavior that can be observed in the current study.

2.2 Advertising resistance and resistance strategies

Advertisements are designed with the purpose of persuading consumers to buy a specific product or service (Fransen, Verlegh, Kirmani, & Smit, 2015). When trying to persuade a consumer, two outcomes can occur: (1) they are persuaded and their purchase intention is increased, or (2) they resist the persuasion attempt (Friestad & Wright, 1994). Persuasion attempts are resisted by audiences once they become aware of an advertiser’s intent. Multiple previous studies have researched the defensive attitudes of audiences towards advertising in traditional media (e.g. Elpers, Wedel, & Pieters, 2003; Olney, Holbrook, & Batra, 1991) as well as in new media (e.g. Panic, Cauberghe, & De Pelsmacker, 2013; Tsang, Ho, & Liang, 2004). The main reasons that are provided for resistance is that the majority of audiences is not only skeptical about the information provided in the advertisements, they also believe that the advertisements are trying to persuade them into buying something they do not want or need (Calfee & Ringold, 1994; Fransen, Verlegh, Kirmani, & Smit, 2015).

Resistance is a concept with many different definitions, but in the core of its meaning it is a reaction against change (Knowles & Linn, 2014). Fransen, Verlegh, Kirmani, and Smit (2015) have provided an overview of the types of resistance strategies consumers can use against advertisements in order to decrease the influence these persuasive message have on them. Their framework, called the ACE typology, distinguishes three different types of consumer resistance strategies: (1) avoidance strategies, (2) contesting strategies, and lastly, (3) empowering strategies. Regarding the first type, previous research has identified three different ways in which consumers can avoid advertising: (1) physical avoidance (e.g. closing a YouTube video or not clicking on certain videos at all), (2) mechanical avoidance (e.g. skipping or muting sponsored parts of the video) and (c) cognitive avoidance (e.g. ignoring information that is not congruent with one's own beliefs or 'zoning out' during sponsored parts) (Fransen, Verlegh, Kirmani, & Smit, 2015). Avoidance strategies are arguably the most difficult strategies to counter for advertisers, as the act of physical avoiding itself eliminates the possibility of communication (Fransen, Verlegh, Kirmani, & Smit, 2015).

The second type of resistance strategies, contesting strategies (also referred to in literature as 'counter-arguing'), involve challenging different components of an advertisement. For example, the advertisement's content, its source, or the persuasive techniques used are actively questioned by consumers (Fransen, Verlegh, Kirmani, & Smit, 2015). Reasons for source contesting can include that the viewer questions the source's expertise, trustworthiness or motives (Jacks & Cameron, 2003). Contesting persuasive techniques can for example result from over-exposure (Kirmani, 1997).

The final type of resistance strategies discussed in the ACE framework, called empowering strategies, is different from the other two strategies, as this type of resistance strategy is related to defending one's own dissonant beliefs instead of challenging the content of the persuasive message. This can be done in three ways: (1) by attitude bolstering (i.e. generating (new) thoughts that are in line with existing beliefs when these beliefs are challenged by a persuasive message), (2) by social validation (i.e. searching for the validation of one's beliefs in peers and significant others), and lastly, (3) by self-assertion (i.e. telling oneself that they are confident about the attitudes and behaviors that they display, and that these cannot be changed) (Fransen, Verlegh, Kirmani, & Smit, 2015). The use of empowering strategies therefore not only boosts a consumer's self-confidence, but also decreases the amount of social pressure an individual experiences in regards to conforming to the norms and values imposed by society (Fransen, Verlegh, Kirmani, & Smit, 2015).

Consumer resistance is an issue experienced by marketeers in all types of advertising. As people are becoming increasingly resistant against traditional forms of advertising (Patel, 2017), marketeers have to look for innovative ways to effectively bring their products under the attention of target groups. One of the most promising strategies of neutralizing consumer resistance is, as already elaborated upon extensively in this report, the use of influencers in advertising. The following section discusses this concept in greater depth.

2.3 The use of influencers in advertising

Influencers can be defined as “individuals who have the power to affect purchase decisions of others because of their (real or perceived) authority, knowledge, position, or relationship” (Business Dictionary, n.d., para 1). Social media influencers are not only interesting to companies due to their wide reach, but also because of their personal connection to their audiences (Dada, 2017). For this reason, followers generally perceive them as trustworthy sources of information (Sutter, 2016). Taking in mind that 92% of consumers are more likely to turn to people they trust instead of impersonal advertisements when it comes to purchasing decisions, influencers represent an effective way to bring a product under the attention of target audiences (Little, 2015; Sutter, 2016). In other words, given that consumers trust influencers due to their perceived authority, knowledge, position, or relationship, resistance in the form of source contesting is reduced. Furthermore, the use of influencers can decrease the adoption of avoidance strategies, as previous research indicated that consumers will be less likely to avoid an advertisement when it is perceived as entertaining, compared to purely informative (Elpers, Wedel, & Pieters, 2003; Olney, Holbrook, & Batra, 1991). Given that viewers choose what they watch, it can be expected that viewers will generally find the product discussions and recommendations in YouTube videos more entertaining than traditional digital advertising (to which they are increasingly becoming immune) (Patel, 2017).

There is, however, another side to the story of online influencers. As already lightly touched upon earlier in this theoretical framework, source contesting might occur when a consumer gets the feeling that an influencer is not genuine about his/her product recommendation, which significantly impacts the message’s credibility, and subsequently, its impact on viewers. Source contesting especially occurs when the influencer is considered to be biased, for example when the viewer finds out that the influencer is paid to share his or her opinion on a product (Batinic & Appel, 2013). Oftentimes, an influencer will speak very positively about a sponsored product as the influencer’s main goal is increasing the purchase intention of viewers. However, Dada (2017) found that even though sponsors prefer influencers to talk positively about their product, it is actually more effective to have influencers highlight negative aspects as well, as this makes the influencer more credible in the eyes of their audience. Therefore, the YouTuber’s valence regarding a product and the corresponding sponsorship situation are expected to have an interaction effect on user engagement. For example, one could expect that a high valence of the YouTuber will not be considered genuine when the video is sponsored, evoking negative types of engagement (e.g. giving dislikes or posting negative comments). More specifically, the current study identified four different YouTube ‘sponsorship situations’ that are possible from the perspective of the viewer: (1) Unclear sponsorship (i.e. whether a featured product is sponsored or not remains ambiguous to the viewer); (2) the

YouTuber has bought the product with their own money, (3) the YouTuber has received the product for free by a company or PR agency, but is not being paid extra to promote it, and (4) the YouTuber gets paid to promote the product (i.e. is sponsored). This information leads to the following hypothesis:

H2: The valence of the YouTuber and the sponsorship situation of a YouTube video have an interaction effect on the user engagement of that video, such that high levels of valence in sponsored videos lead to different levels of user engagement, in comparison to the other sponsorship situations.

Taking in mind that influencers are very dependent on their audiences, they have to pay close attention to the quality of their relationship with their followers and the factors that influence it. One way to improve or retain the quality of this relationship involves the YouTuber being as truthful as possible towards their followers, as telling the truth has a positive influence on trust in communities (Tompkins, 2003). In the context of sponsored content, this calls for transparency about the presence or absence of advertisements. Therefore, it is generally assumed that by disclosing the sponsorship situation, the relationship between the influencer and their followers will not be affected. The same assumption was made while designing the guidelines of the Social Code: YouTube, as content creators are encouraged by the Code to disclose whether the products they use or promote in their videos are sponsored or not. It can therefore be expected that being transparent about how the influencer received the product evokes other types of user engagement than when this is not clear. For example, the fact that the influencer is transparent about sponsorship situations might be rewarded by their followers as they appreciate the influencer being honest, whereas being secretive about sponsorship situations might trigger the opposite reaction. Based on the preceding discussion, the following hypothesis was formulated:

H3: Videos in which a disclosure for the sponsorship situation is provided generate different levels of user engagement, in comparison to videos in which no disclosure is provided.

While providing a disclosure is arguably the most ethical decision to make in terms of the code of conduct for advertising, the question remains how disclosing the use of sponsored content influences a viewer’s purchase intention, as providing audiences with a disclosure might activate their persuasion knowledge (Campbell, Mohr, & Verlegh, 2013; Evans, Phua, Lim, & Jun, 2017). Persuasion knowledge is a concept from the persuasion knowledge model developed by Friestad and Wright (1994), which refers to a “consumer's capacity to learn about persuasion over time” (p. 1). This knowledge helps consumers to respond to persuasion attempts in a way that it is in line with their own goals (Friestad & Wright, 1994). However, not every disclosure results in the activation of persuasion knowledge. For example, when it is disclosed that a Youtuber has paid for the product with their own money, there is no commercial persuasion attempt. Still, if an influencer discloses that he or she received a product for free or is being paid to feature the product in their video, persuasion knowledge might be activated among audiences. Therefore, it can be expected that the four different sponsorship situations also trigger different types of engagement, which leads to the following hypothesis:

H4: The four sponsorship situations are associated with different levels of user engagement.

2.4 Giveaways

Another strategy to get a (sponsored) product under the attention of audiences is by organizing a giveaway in a YouTube video. Online giveaways are highly engaging and can pull passive users over the threshold to become active and participate (Hoffman & Fodor, 2010). In their study, Hoffman and Fodor (2010) found that online contests or giveaways are likely to make customers more committed to a brand, reinforce the loyalty of the customer towards the brand, and even make the customer more likely to support the brand in the future (Hoffman & Fodor, 2010). These findings can be explained by the rule of reciprocation, which highlights the tendency of humans to repay (or reciprocate) to those who have given them a gift, no matter if this is tangible (e.g. a material object) or intangible (e.g. a kind deed or a generous act) (Hoeppner, 2014). Reciprocity not only explains the human urge of rewarding kind gestures, but also explains the need to punish the unkind ones (Falk & Fischbacher, 2000). Moreover, this theory not only takes into account what the consequences of the (un)kind gesture are, but also the intentions behind it. Additionally, a unique aspect of reciprocity is that the urge to repay others cannot be justified economically, meaning that we tend to always repay others, even if no future rewards from reciprocal actions arise (Falk & Fischbacher, 2000). In fact, previous research has concluded that reciprocity is such a powerful determinant of social behavior and is so pervasive in human culture, that it has even been described as "one of the most potent of the weapons of influence" (Cialdini, 2009, p. 16).

One could apply Hoffman and Fodor's (2010) findings of giveaways to the context of YouTube as well, where an influencer acts as an intermediary between the audience and the brand. Due to the rule of reciprocation, influencers are able to strengthen the bond they have with their followers by providing them with a 'gift' (i.e. do a giveaway), which will encourage followers to act favorably towards the influencer in return. As the product that is given away by the influencer is often associated with a particular brand, brands might also be able to reap the positive benefits of online giveaways. Therefore, based on the human urge to repay kind gestures and the highly engaging nature of giveaways, it can be expected that videos that contain giveaways evoke different types of user engagement than videos that do not contain one. Based on this information, the following and final hypothesis was formulated:

H5: Videos that contain a giveaway generate different levels of user engagement, in comparison to videos that do not contain a giveaway.

2.5 Research model

Figure 1 presents the research model of the current study together with the corresponding hypotheses. The research model is based on the theoretical framework as discussed in this chapter.

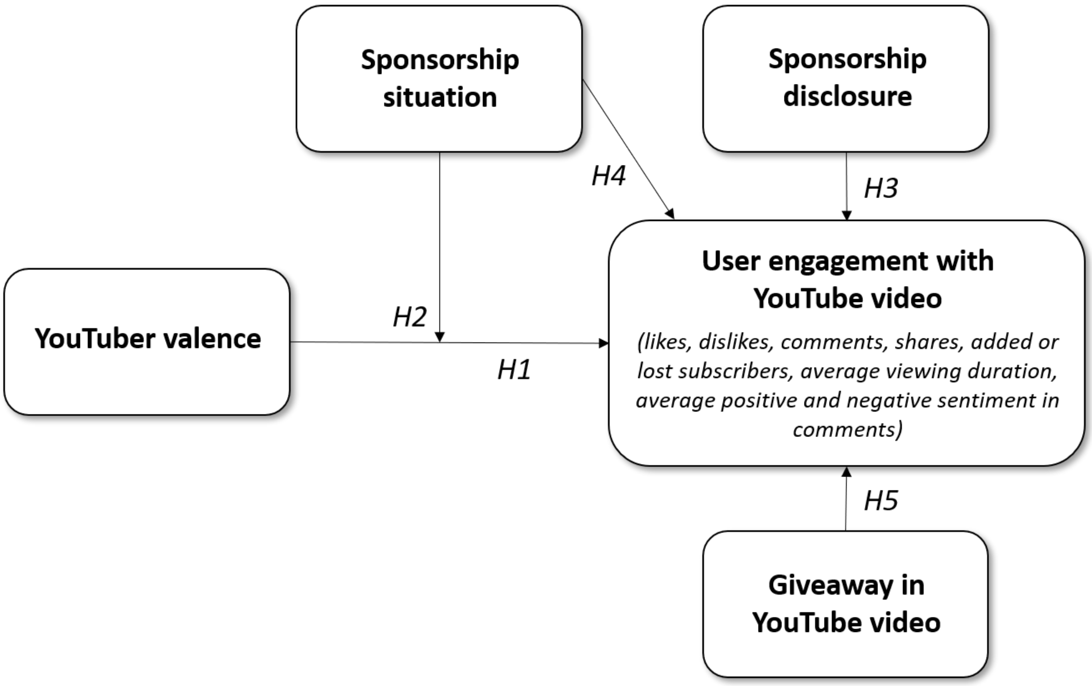

Figure 1. The conceptual model of the impact of valence, sponsorship situation, sponsorship disclosure and giveaways surrounding YouTube videos on indicators of user engagement.

3. Methodology

3.1 Research method and rationale

In order to test the hypotheses discussed in Chapter 2, this research used a quantitative and cross-sectional approach in the form of a content analysis, implying that this study was deductive in nature. Over the years, many researchers have defined the term quantitative content analysis. One of these definitions is proposed by Kerlinger (1986), who described it as a method in which communication is studied and analyzed in a systematic, objective and quantifiable manner for the purpose of measuring variables. More recent definitions of the term have included references to modern technologies such as social media and big data (Binsbergen, 2013).

Quantitative content analyses focus on manifest (i.e. literal) content – that is, the visible, countable content of a media text, rather than the (hidden) meanings behind it. Strengths of this method include (among others) low costs, unobtrusiveness and high replicability. The reason why this particular research method was chosen is because is it very suitable for quantifying user behavior. Quantifying user engagement allows the researcher to look for relationships between the sponsorship characteristics of a video (such as the sponsorship situation, if and where a disclosure is provided, a YouTuber's valence, presence of a giveaway) and indicators of user engagement, which is exactly the main goal of this study.

3.2 Sampling, units of analysis, and sample size

Guidelines for identifying an accurate sample size for quantitative content analyses are difficult to find. Therefore, to maximize statistical power while also keeping this study feasible within the time frame, a total of 300 Dutch beauty-related YouTube videos were analyzed. Before sampling the videos, the channels were sampled first: 15 Dutch YouTubers who are active in the beauty sector were selected (see Table 1). This sample was constructed through non-probability sampling, or more specifically, expert sampling. The reason for this is that complete random sampling would not generate a Dutch beauty YouTuber sample that is adequate for data analysis, as the vast majority of the population does not collaborate with companies in the form of sponsorships due to their limited reach and relatively low levels of user engagement. Therefore, in order to ensure a large enough and relevant subsample for every channel, the choice was made to select the channels through expert sampling. Some of the sampled YouTubers are part of the Social Code: YouTube (elaborated upon in Chapter 1 of this paper), which made it easier to identify a video's sponsorship situation due to the provision of a disclosure. Moreover, YouTubers with different amounts of subscribers were included to see whether or not this could be an influencing variable.

Table 1

An overview of the 15 Dutch beauty-related YouTube channels that were sampled

Channel ID	Channel Name	YouTuber Name	Amount of Subscribers
1	Beautygloss	Mascha Feoktistova	619.864
2	BeautyNezz	Joy (surname unknown)	579.166
3	VeraCamilla	Vera Camilla Lucker	268.535
4	Todaysbeautynl	Manon Tilstra	239.646
5	Jessie Maya	Jessie Bosch	205.654
6	Laura Ponticorvo	Laura Ponticorvo	144.737
7	Endless Weekend	Tara and Larissa Verbon	107.995
8	Lottelovesbeauty	Lotte de Jonge	66.757
9	MissLipglosss	Cynthia Schultz	63.145
10	Kristina K	Kristina Kirjanova	47.865
11	Forever Jade	Jade Anna van Vliet	36.412
12	Esmée Geel	Esmée Geel	32.009
13	Rachel Kromdijk	Rachel Kromdijk	9.187
14	byAranka	Aranka Haverkamp	6.516
15	Sarah Marikh	Sarah Marikh	5.128

Note. Amount of subscribers was recorded on the 29th of March, 2018.

After sampling the channels, the videos could be sampled. This was done using the following method: After opening Incognito mode in Google Chrome to ensure that previous browsing behavior did not influence the sampling process, the researcher went to youtube.com and searched for each of the influencers mentioned in Table 1. For each influencer, after clicking on their channel link in the search results, the researcher went to the Video's tab. In the top left corner, one can select which videos are presented: in this case, the choice was made to only view Uploads, causing liked videos and live streams to be excluded from the overview. In the top right corner, the filter was set to Date Added (Newest) and the view was set to a grid format rather than a list format. The reason why Date Added (Newest) was chosen over Most Popular is because the researcher aimed to measure the most recent user engagement behavior possible to maximize the relevance of this study. Moreover, taking in mind that the Social Code: YouTube was only implemented recently (i.e. November 2017) at the time of writing this thesis, the effects of these guidelines can only be observed in more recent videos. Furthermore, the Most Popular filter within channels is only based on the amount of views (i.e. the more views, the more 'popular'). Next to the fact that this filter does not take any other user engagement variables into account, these videos are also generally outdated (as it is more likely that the longer a video has been online, the more views it has received). Even though the Date Added (Newest) filter was selected, the researcher made sure the sampled videos were online for at least 30 days on the day of coding to ensure that these videos were able to be engaged with by most viewers (and thus do not receive significantly more views/comments/(dis)likes after coding). There was no maximum on the amount of days that a video was 'allowed' to be online.

After choosing these settings, the videos could be selected. One of the objectives of the current study was to investigate the YouTubers' valence regarding the products they were using. Therefore, in the sampling process, the choice was made to focus on videos that highlight the YouTubers' opinions about these beauty products, such as review videos or first impression videos. This implies that videos in which beauty products were simply 'used', and not discussed in terms of usability or likeability, were also excluded from the sample. Therefore, starting at the '30-day-online' point, the researcher looked for videos that suggested review/tutorial/first impression formats based on the thumbnail and title, and clicked on these videos to see if they fit the sampling criteria (i.e. were beauty-related and contained a clear judgement about the featured product). If this was not the case, the video was rejected from the sample. If the video fit the sampling criteria, it was added to the sample. This process was repeated until 20 videos for each channel were sampled, which resulted in a total of 300 videos.

3.3 Definitions and operationalization

The following paragraphs highlight what exact definitions were used in this study and how these definitions were operationalized. Firstly, 'sponsored content' on YouTube is defined in existing literature as the integration of "paid-by-the-brand and owned-by-the-brand messaging" in the videos of social media influencers with the goal of achieving organizational objectives (Ikonen, Luoma-aho, & Bowen, 2017, p. 165). It is important to note that within YouTube the term 'sponsored' is clearly defined as *paid* promotion (YouTube, 2018). This means that when influencers are given products for free by companies or PR agencies, but are not being paid extra to promote it, they would not label the content in which that product is featured as 'sponsored'.

The current research distinguished four different **sponsorship situations** for Dutch beauty-related YouTube videos. These situations are based on the sponsorship situations defined by the Social Code: YouTube (2017). The only way to know as a viewer which sponsorship situation is applicable to a video, is by looking at the corresponding sponsorship disclosure. Three out of four situations in this study are therefore dependent on the provision of a disclosure for the researcher to categorize them in the correct sponsorship situation. These three situations include: (1) the YouTuber has bought the featured product with their own money, (2) a YouTuber has received a particular product for free, but is not being paid to mention the product in their video, and (3) the YouTuber is being paid to promote a particular product in their video (i.e. the video is 'sponsored'). If a disclosure was not provided, the sponsorship situation remained unclear to a viewer. This (0) 'unclear' sponsorship situation was defined as the fourth possibility in this study.

As mentioned in the previous paragraph, in order for a viewer to identify which sponsorship situation applies to the video they are currently watching, users can look for a **sponsorship disclosure**. In the current study, this variable was treated as a dummy variable, in which a disclosure was either provided (1) or not (0). Additionally, four different **locations in which disclosures** for YouTube videos can be provided were identified and coded as well: Namely, there was a possibility for the YouTuber to provide (1) only a (written) disclosure in the description box, (2) only a (written and/or spoken) disclosure in the video, or (3) a disclosure in both the description box as well as in the video. Finally, there was a possibility that there is no disclosure present at all (0).

The following section describes how **user engagement** is defined and operationalized. As mentioned in Chapter 2, user engagement is associated with how humans interact with computer-mediated activities (O'Brien & Toms, 2008). Viewers can engage with YouTube videos in multiple ways, including: liking and disliking the video, commenting on the video, sharing the video, (un)subscribing from the channel that posted the video, and simply watching the video. Even though there are more possibilities of engaging with YouTube videos than the ways mentioned above (such as adding a video to a playlist, pausing or skipping sections of the video, or changing the viewing settings), the user engagement indicators chosen for this particular study were the only ones that were available for coding. In other words, since this study's method is a content analysis, the researcher was highly dependent on what data were accessible and available. Given that YouTube does not allow insight into all possible types of user engagement, not all indicators could be taken into account. Therefore, the following nine variables were defined as the indicators of YouTube user engagement: the amount of (1) **likes**, (2) **dislikes**, (3) **comments**, (4) **shares**, (5) **subscriptions driven from that particular video page**, **the average viewing time per video** (both the (6) absolute value as well as a (7) percentage of total video length), and **the levels of** (8) **positive** as well as (9) **negative sentiment in the comments**. Section 3.4 elaborates in detail on how the nine user engagement variables that were used in this study were retrieved.

3.4 Data collection procedures

The data for the content analysis were collected by coding the sampled videos. Both video content and page content were coded in order to capture the viewer experience as comprehensive as possible. An overview of the codebook used in this study can be found in Table A1 in Appendix A. Four different sources were used to retrieve both the independent as well as the dependent variables, which are elaborated upon in the following paragraphs.

Most variables could be taken directly from the video page (by either watching the video or by looking at the page itself), which is considered the first of four sources. In terms of video and sponsorship characteristics, these include the **amount of channel subscribers**, **video upload date, video category, amount of views, total video length**, whether or not a YouTuber has **additional ads enabled**, **disclosure given, disclosure location, sponsorship situation**, and **presence of giveaway**. In terms of user engagement, the amount of **likes**, **dislikes**, and **comments** could be coded from this source as well. Additionally, some creators allow viewers to look into extra detailed information about their videos, called the 'public statistics' (which is considered source number two). This information is visible by default, however, some content creators do not like to share the statistics of their videos with their audiences (or competitors) and might thus disable this feature. Yet, if this information is not disabled, viewers can access this information on a video page through the More… > Statistics button. Clicking this button reveals line graphs that show the cumulative and daily numbers of views, viewing durations, amount of subscriptions driven, and shares. As the amount of views is already coded from the video page directly, only the latter three variables are coded through this option. In other words, through this mining tool, the **average viewing time**, the **amount of subscriptions driven** from that video page (i.e. how many subscribers were lost or gained after watching the video), and the **amount of shares** were collected for every video. One of the sampling criteria for the channels (see Table 1 in Section 3.2 for the channel list) was therefore that these channels enabled viewers to view the public statistics of their videos. However, note that the public statistics button is only visible in YouTube's previous desktop layout, and not in the current desktop layout (i.e. the desktop layout active at the time of coding, which was April 2018). The previous layout could easily be restored by clicking on the personal channel icon in the top right corner, and then clicking on 'Restore classic YouTube'. Still, it is unclear how long YouTube will enable users to switch back, as the current layout might become permanent in the future (Perez, 2017).

The third set of sources that was used to establish the **sentiment in the comments** of YouTube videos was the webtool YouTube Data Tools [YTDT] (Rieder, 2017), in combination with the programs SentiStrength and Microsoft Excel 2015. YTDT can be accessed online and is able to extract data from YouTube via the YouTube API v3. One of its functionalities is to retrieve the content of comments of a video, and place these comments in a single tabular file. Hereafter, the retrieved comments for each video were analyzed with another software, named SentiStrength. SentiStrength is an opinion mining program which is able to measure positive and negative sentiment separately in short media texts (in this case, YouTube comments). The reason why this particular program was chosen over other sentiment detection programs is because SentiStrength is able to analyze sentiment at the per-comment level rather than the per-word level. Moreover, SentiStrength is free to use for academic purposes. Running a tabular file of comments in SentiStrength provides the researcher with two values per comment: One value that specifies the extent of positive sentiment, and one that specifies the extent of negative sentiment. SentiStrength's scales range from -2 to -5 to indicate negative sentiment and from +2 to +5 to indicate positive sentiment, while -1 and +1 indicate sentimental neutrality (i.e. the value '0' does not occur). Since the sentiment is most interesting from an aggregated perspective, the choice was made not to code the sentiment level per comment, but rather code the average positive and negative sentiment of all comments per video. These averages were calculated in Excel and subsequently used as analysis variables.

SentiStrength was originally developed for English texts, yet other languages are available as well, and more can easily be added to the software by hand. In the case of the current study, the Dutch dictionary for sentiment analysis was used. Whereas a Dutch dictionary was included in the download package of SentiStrength, no reliability scores in previous research could be found when using SentiStrength for the analysis of Dutch media texts. However, reliability scores for the English texts were present. To provide an indication of SentiStrength's capabilities, Thelwall, Buckley, Paltoglou, Cai, and Kappas (2010) found that when analyzing 1041 MySpace comments written in English, SentiStrength was able to predict positive emotion with 60.6% accuracy and negative emotion with 72.8% accuracy. Additionally, in another study it was concluded that SentiStrength is robust enough to accurately detect sentiment in a range of social media contexts, specifically in YouTube comments (Thelwall, Buckley, & Paltoglou, 2012).

Still, these findings do not provide a lot of insights into the reliability of SentiStrength when using the Dutch dictionary. Therefore, before using SentiStrength on Dutch comments, the researcher had to do a reliability analysis of the program. After conducting a couple of test rounds in which random YouTube comments of the sampled Dutch beauty-related videos were imported into SentiStrength, the researcher concluded based on the output that SentiStrength's sentiment analysis for Dutch texts was not as accurate as the English version. However, the program's accuracy could easily be improved since SentiStrength allows users to edit a dictionary directly. Thus, a couple of adjustments have been made to the Dutch SentiStrength dictionary. Appendix B shows a detailed logbook of which exact words were removed and added to the original Dutch SentiStrength dictionary, and also provides some notes on the overall process of improving SentiStrength's accuracy for Dutch texts.

The final source of coding consisted of one subjective 7-point semantic differential scale which measured the extent to which a YouTuber talked negatively and/or positively about a product (i.e. **YouTuber valence**). All videos were watched from beginning to end by the researcher in order to get a good indication of the overall valence conveyed by the YouTuber. Even though no parts were skipped, videos were often sped up to save time.

Lastly, since the YouTuber's valence was the only subjective scale in the codebook, an intercoder reliability test was conducted. In order to assess this scale's intercoder reliability, a second researcher was asked to code a total of 30 videos (two randomly sampled videos per channel, i.e. 2 x 15). The second researcher coded the video valence of these videos on the same 7-point scale as the first researcher. Since the valence scale can be treated as a continuous variable, a correlation coefficient was calculated to provide an indication of the intercoder agreement. This correlation was strong and positive (r = .87, p < .001) and it could therefore be concluded that this scale was sufficiently reliable when measuring a YouTuber's valence.

3.5 Analysis variables and codebook

Table 2 provides a summary and detailed overview of all the variables that were used for the data analyses. The left column in Table 2 shows the variable names, and the right column provides a definition for each variable. Moreover, in the right column it is described how these variables were manipulated or calculated in SPSS, if applicable. For example, only absolute values (Table A1 in Appendix A shows the corresponding codebook) were coded, but after coding these values may also have been corrected, adjusted, and/or used to calculate other variables in SPSS. All corrected, transformed, or calculated values were stored as separate variables, and are labeled with an * in Table 2.

Table 2

Analysis variables of the content analysis and their definitions

1. Channel and video characteristics	Definition
Channel ID	An ID (1 up to and including 15) for each separate channel.
Amount of channel subscribers	The amount of subscribers a channel had at the time of coding.
Video ID	An ID for each separate video.
Video category	The category in which the YouTube video was uploaded.
Video post date	The date on which the YouTube video was uploaded.
Date of coding	The date on which the YouTube video was coded by the researcher.
Amount of months online*	The difference (expressed in months) between the day that a video was uploaded and the day that the video was coded. The mean of this variable is 12.39, and the standard deviation 8.82.
Amount of views	The amount of views a video had at the time of coding.
Views per subscriber*	The amount of video views divided by the amount of channel subscribers was calculated in SPSS, which resulted in views per subscriber.
Amount of likes	The amount of likes a video had at the time of coding.
Likes per 1000 views*	The amount of likes divided by the amount of video views was calculated, and subsequently multiplied by 1000 in SPSS, which resulted in the amount of likes per 1000 views.
Amount of dislikes	The amount of dislikes a video had at the time of coding.
Dislikes per 1000 views*	The amount of dislikes divided by the amount of video views was calculated, and subsequently multiplied by 1000 in SPSS, which resulted in the amount of dislikes per 1000 views.
Amount of comments	The amount of comments a video had at the time of coding.
Comments per 1000 views*	The amount of comments divided by the amount of video views was calculated, and subsequently multiplied by 1000 in SPSS, which resulted in the amount of comments per 1000 views.
Amount of shares	The amount of shares a video had at the time of coding.
Shares per 1000 views*	The amount of shares divided by the amount of video views was calculated, and subsequently multiplied by 1000 in SPSS, which resulted in the amount of shares per 1000 views.
Subscriptions driven	How many people subscribed or unsubscribed to the channel from a particular video page. The (un)subscribers are merged into one cumulative value by YouTube, such as -14 or +120.
Subscriptions driven per subscriber*	The amount of subscribers lost or added from that video page divided by the amount of the amount of channel subscribers was calculated in SPSS, which resulted in subscriptions driven per subscriber.
Additional YouTube ads enabled	Influencers can play additional advertisements over their videos (i.e. monetize their videos). As the amount of ads and their content is different for every viewer, this variable was treated as a dummy variable (0 = not monetized, 1 = monetized).

Total video length	The total length of the video. YouTube expresses this in minutes, yet this value was recoded into seconds to make data analysis easier.
Average viewing duration of video	The public statistics indicate what the average video viewing time is of viewers. YouTube expresses this in minutes, yet this value was recoded into seconds to make data analysis easier.
Percentage average viewing duration / total video length *	A variable which expresses the average viewing duration as a percentage of the total video length was calculated in SPSS.
Giveaway	A dummy variable, stating if there is a giveaway present in the video (1) or not (0).
Average positive sentiment in comments	SentiStrength was used to establish the degree of positive sentiment in the comments of a video. Since this program analyzes every comment separately, an average was calculated over all comments per video in Excel.
Average negative sentiment in comments	SentiStrength was used to establish the degree of negative sentiment in the comments of a video. Since this program analyzes every comment separately, an average was calculated over all comments per video in Excel. Note that SentiStrength provides negative numbers as output for negative sentiment, yet in order to make interpretation easier and more intuitive, this variable was transformed into positive numbers.
2. Sponsorship and disclosure characteristics	
Sponsorship disclosure given	A dummy variable which states whether a sponsorship disclosure was provided (1) or not (0).
Sponsorship disclosure location	The location of the disclosure provided. If a disclosure was provided, three locations were possible: (1) in the description box of the video, (2) in the video itself, or (3) in both the description box as well as the video. If there was no disclosure, the location was coded as 0 (absent).
Sponsorship situation	The type of sponsorship situation that applied to the video. There were four possibilities: (0) it remained unclear to the viewer what the exact sponsorship situation was in a video (e.g. due the absence of a disclosure), (1) a YouTuber has bought a product with their own money, (2) a YouTuber received a product for free but does not receive any extra money for featuring this product in a video, or (3) a YouTuber was paid to advertise a product (i.e. is sponsored).
3. YouTuber valence	
YouTuber valence	What is the overall emotion communicated by the YouTuber regarding the featured product? This question is answered with the use of a single item, 7-point semantic differential scale, where (1) stands for very negative, and (7) stands for very positive. Taking in mind that this is the only subjective scale in the codebook, it was tested by another researcher to assess its intercoder reliability. This process is discussed in the final paragraph of Section 3.4.

Note. * means that this variable was created in SPSS.

3.6 Data analysis procedures

After coding all variables in Excel, the codebook was imported into IBM SPSS Statistics 24. After importing this file, multiple variables were transformed, corrected, and/or calculated first. Again, the variables labeled with an * in Table 2 indicate which variables were generated in SPSS. After doing so, the data analysis phase could start. Hypotheses 1 was tested with nine separate simple linear regression analyses. In order to protect against the type I error, a separate one-way multivariate analysis of covariance (MANCOVA) was conducted for hypothesis 1 as well. Hypothesis 2, which tested for an interaction effect of valence and sponsorship situation on the indicators of user engagement, was also tested with a one-way MANCOVA. Finally, hypothesis 3, 4, and 5 were all tested with a one-way multivariate analysis of variance (MANOVA). After testing all the hypotheses, a range of exploratory analyses were conducted as well. Tests that were used in this section include a logistic regression analysis, multiple simple linear regression analyses, a Pearson's correlation and multiple MAN(C)OVAs and ANOVAs. Lastly, multiple factorial AN(C)OVAs were also conducted to determine if the found effects were indeed separate effects. Based on the outcomes of the factorial AN(C)OVAs, a resulting model of user engagement could be produced.

4. Results

First, this chapter presents a description of the sample of this study. Then, the results of the confirmatory analyses are presented, concluding on which of the hypotheses could be accepted or rejected. Finally, the results of a range of exploratory analyses are presented, after which a visual overview of the resulting model of user engagement is provided.

4.1 Sample description

The sample consisted of 300 Dutch beauty-related videos, sampled from 15 different YouTube channels. On average, the sampled videos were 636.64 seconds long (10:37 minutes), with a standard deviation of 260.07 seconds (4:20 minutes). Regarding the average viewing time of these videos, they were watched on average for 276.23 seconds (4:36 minutes), with a standard deviation of 103.54 seconds (1:44 minutes). The videos in the sample were uploaded to four different YouTube categories: 1 video (0.3%) was uploaded to the Film & Animation category, and 2 videos (0.7%) to the Travel & Events category. Due to the extremely low numbers of videos in these categories, it appears that the videos in the latter two categories can be considered as anomalies. Contrastingly, the two largest categories were Howto & Style, which contained 150 videos (50.0%), and People & Blogs, which contained 147 videos (49.0%). Additionally, in 297 videos (99.0%) additional advertisements were enabled by the YouTuber, which means that only 3 videos in the sample (1.0%) were not monetized. Interestingly, these three videos all contained a paid sponsorship. Furthermore, 26 videos (8.7%) contained a giveaway (a group which will be analyzed more in-depth in Section 4.2.5) while the remaining 274 videos did not (91.3%). Of these 26 videos, 2 giveaways were hosted in 'unclear sponsorship' videos (7.7%), 1 giveaway in a 'YouTuber bought product with own money' video (3.8%), 14 giveaways in 'YouTuber received product for free' videos (53.8%), and 9 giveaways in sponsored videos (34.6%).

In terms of sponsorship situations, the videos in this sample were distributed as follows: in 65 videos (21.7%), the sponsorship situation remained unclear to the viewer after watching the video and reading the description box. In 92 videos (30.7%), the influencers paid for the product they discussed with their own money. In 85 videos (28.3%), the product was given to influencers for free by a company, yet they were not paid extra by that company to promote the product. Lastly, 58 videos (19.3%) contained a clear sponsorship, meaning that influencers were paid to discuss a product in their video.

In terms of disclosures given, 238 videos (79.3%) contained a written and/or spoken disclosure in either the description box, the video, or in both. That means that 62 videos (20.7%) did not contain a disclosure, with the consequence that the sponsorship situation remained unclear to viewers. Additionally, the sample contained 3 divergent cases when it comes to knowing the sponsorship situation after reading or hearing a disclosure. Namely, these three videos had a disclosure of some sort, however, these disclosures highlighted what was *not* the sponsorship situation rather than what was the sponsorship situation. More specifically, these disclosures stated that the videos were not sponsored, but did not disclose if the product was given to the YouTuber for free, or if the YouTuber bought the product with their own money. Therefore, these videos were still categorized as 'unclear sponsorship', as there was no way to know for certain that they belonged to either one of the other categories.

Furthermore, of the 238 videos that did contain a disclosure, 57 videos (23.9%) had a disclosure in only the description box, 85 videos (35.7%) had a disclosure in only the video, and 96 videos (40.3%) had a disclosure in both these locations. Figure 2 shows a bar graph of how each sponsorship situation was disclosed in this sample.

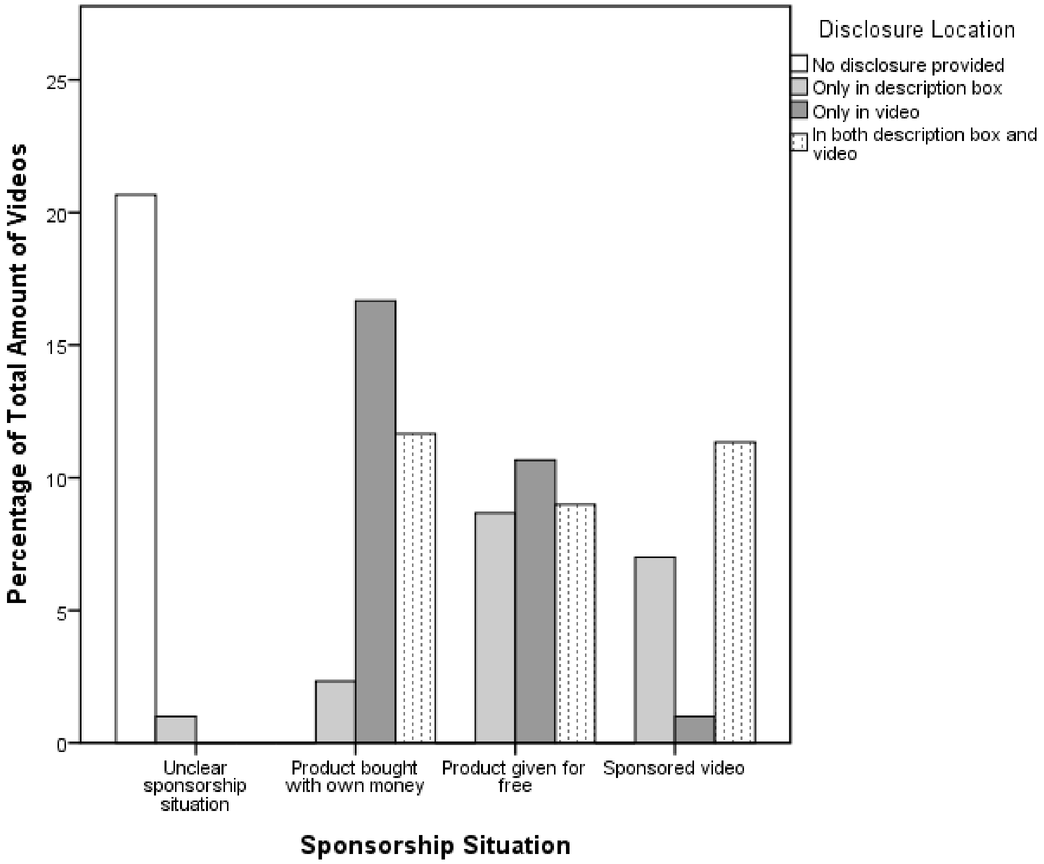

Figure 2. The disclosure locations for each sponsorship situation (expressed as a percentage of the total amount of videos).

4.2 Confirmatory analyses

The following sections discuss the hypotheses from the research model and conclude on whether or not these hypotheses could be accepted or rejected. As elaborated upon in the operationalization part of this study (Section 3.3), the variables that comprise user engagement were corrected, so that the sampled channels could be compared to each other. Therefore, the analysis variables that were used as indicators for user engagement include: the corrected amount of (1) likes, (2) dislikes, (3) comments, (4) shares, (5) subscriptions driven from that particular video page, the (6) corrected and (7) uncorrected average viewing time per video, and the extent of (8) positive as well as (9) negative sentiment present in the comments.

4.2.1 Hypothesis 1

Hypothesis 1 stated: *The valence of the YouTuber in a video is associated with the levels of user engagement of that same video.* Nine simple linear regression analyses were conducted to assess the relationship between valence and the (corrected) user engagement variables. Table 3 shows a summary of all the regression analyses. Additionally, in order to protect against the type I error for these separate tests, a one-way MANCOVA was conducted as well, with the nine user engagement variables as the dependent variables and the 'YouTuber's valence' as the covariate. The MANCOVA was significant, $F(9, 290) = 4.71$, $p < .001$; Wilk's $\Lambda = .87$, partial $\eta^2 = .128$, implying that valence had a significant effect on user engagement.

Table 3

Summary of regression analyses for the effect of the YouTuber's valence on (1) likes corrected for views, (2) dislikes corrected for views, (3) comments corrected for views, (4) shares corrected for views, (5) subscriptions driven corrected for subscribers, (6) the average viewing time per video corrected for video length, (7) the absolute average viewing time per video, and the extent of (8) positive as well as (9) negative sentiment in the comments

	Predictor: Valence		
Dependent variables	β	R^2	*F*
Amount of likes (corrected)	0.16**	.03	7.90**
Amount of dislikes (corrected)	0.12*	.01	4.14*
Amount of comments (corrected)	0.13*	.02	5.39*
Amount of shares (corrected)	0.16**	.03	7.90**
Amount of subscriptions driven (corrected)	-0.06	.00	0.90
Average viewing time (corrected)	-0.02	.00	0.12
Average viewing time	-0.25***	.06	19.24***
Positive sentiment in comments	0.23***	.05	16.75***
Negative sentiment in comments	-0.07	.01	1.57

Note. * $p < .05$, ** $p < .01$, *** $p < .001$

Based on Table 3, one can conclude that hypothesis 1 can be **largely accepted** as most variables that comprise user engagement were significantly predicted by the YouTuber's valence. The YouTuber's valence significantly predicted the (corrected) amount of likes ($\beta = 0.16$, $p = .005$), dislikes ($\beta = 0.12$, $p = .043$), comments ($\beta = 0.13$, $p = .021$), and shares ($\beta = 0.16$, $p = .005$). It also significantly predicted the (not corrected) average viewing time ($\beta = -0.25$, $p < .001$), and lastly, the average positive sentiment in the comments ($\beta = 0.23$, $p < .001$). However, the YouTuber's valence did not predict the corrected amount of subscriptions driven ($\beta = -0.06$, $p = .345$), average negative sentiment in the comments ($\beta = -0.07$, $p = .212$), and the corrected average viewing time ($\beta = -0.02$, $p = .725$).

4.2.2 Hypothesis 2

Hypothesis 2 stated: *The valence of the YouTuber and the sponsorship situation of a YouTube video have an interaction effect on the user engagement of that video, such that high levels of valence in sponsored videos lead to different levels of user engagement, in comparison to the other sponsorship situations.* A one-way MANCOVA was conducted to test for this interaction effect. The 'sponsorship situation' variable was added as a fixed factor, the 'YouTuber's valence' as a covariate, and the nine (corrected) variables that comprise user engagement as the dependent variables. In order to not repeat already discussed results, the next paragraph will only present the results of the interaction effect of valence * sponsorship situation, as the main effects for valence on user engagement are already discussed in detail in Section 4.2.1 (Hypothesis 1) and for the sponsorship situations on user engagement in Section 4.2.4 (Hypothesis 4).

The MANCOVA indicated that there was no significant interaction effect of valence and sponsorship situations on user engagement, $F(27, 830) = 1.08$, $p = .335$; Wilk's $\Lambda = .90$, partial $\eta^2 = .033$. Therefore, hypothesis 2 was **rejected**.

4.2.3 Hypothesis 3

Hypothesis 3 stated: *Videos in which a disclosure for the sponsorship situation is provided generate different levels of user engagement, in comparison to videos in which no disclosure is provided.* To test this hypothesis, a one-way MANOVA was conducted, containing the user engagement variables as dependent variables, and the 'disclosure given' variable as a fixed factor. No significant differences in user engagement based on the provision of a disclosure were found, $F(9, 290) = 1.09$, $p = .370$; Wilk's $\Lambda = .97$, partial $\eta^2 = .033$. This means that viewers do not engage differently with a video based on whether or not a sponsorship disclosure is provided, resulting in the **rejection** of hypothesis 3.

4.2.4 Hypothesis 4

Hypothesis 4 stated: *The four sponsorship situations are associated with different levels of user engagement.* Four sponsorship situation groups were compared: (1) Videos that contain an unclear sponsorship, (2) videos that feature products the YouTuber paid for with their own money, (3) videos that feature products that were given to the YouTuber for free, and (4) sponsored videos. For this hypothesis, another one-way MANOVA was conducted, in which 'sponsorship situation' was added as fixed factor and the nine variables that comprise user engagement as dependent variables.

There was a significant difference in user engagement based on the sponsorship situations, $F(27, 842) = 3.23$, $p < .001$; Wilk's $\Lambda = .75$, partial $\eta^2 = .092$. Because the MANOVA was significant, the results from the univariate ANOVAs could be examined. It was found that the sponsorship situation had a significant effect on multiple user engagement variables. For example, the (corrected) amount of dislikes was significantly different across groups, ($F(3, 296) = 2.73$, $p = .044$, partial $\eta^2 = .027$). Additionally, both the corrected average viewing time ($F(3, 296) = 6.22$, $p < .001$, partial $\eta^2 = .059$) and the uncorrected average viewing time ($F(3, 296) = 10.84$, $p < .001$, partial $\eta^2 = .099$) were found to be significantly different across sponsorship situations as well.

The variables that did not significantly differ across sponsorship situation groups were the (corrected) amount of likes ($F(3, 296) = 1.70$, $p = .167$, partial $\eta^2 = .017$), the (corrected) amount of comments ($F(3, 296) = 2.29$, $p = .079$, partial $\eta^2 = .023$), the (corrected) amount of shares ($F(3, 296) = 0.30$, $p = .827$, partial $\eta^2 = .003$), the (corrected) amount of subscriptions driven ($F(3, 296) = 2.07$, $p = .104$, partial $\eta^2 = .021$), and both the levels of positive sentiment ($F(3, 296) = 2.11$, $p = .100$, partial $\eta^2 = .021$) as well as negative sentiment in the comments ($F(3, 296) = 1.51$, $p = .211$, partial $\eta^2 = .015$).

Since the findings from the ANOVAs did not provide any insights into between which sponsorship situation groups the significant differences were exactly located, Tukey's post-hoc test was performed. Regarding the (corrected) amount of dislikes, Tukey's post-hoc test indicated that the 'sponsored video' group ($M = 1.52$, $SD = 1.26$) significantly differed from the 'product bought with own money' group ($M = 1.04$, $SD = 0.90$); $p = .043$, meaning that sponsored videos tend to receive significantly more dislikes per 1000 views than videos in which the YouTuber bought the product with their own money.

Furthermore, the mean scores for (uncorrected) average viewing time were significantly different between the 'sponsored video' group ($M = 229.74$, $SD = 82.05$) and two other groups - namely, the 'product bought with own money' group ($M = 289.61$, $SD = 101.64$); $p = .002$, and the 'product given for free' group ($M = 314.62$, $SD = 98.69$); $p < .001$. This means that sponsored videos were watched significantly shorter (in seconds) in comparison to the other two groups. Additionally, a significant difference was found between the 'product given for free' group ($M = 314.62$, $SD = 98.69$) and the 'unclear sponsorship situation' group ($M = 248.83$, $SD = 107.96$); $p < .001$. This means that videos in which a product was given for free to a YouTuber were watched significantly longer (in seconds) than videos in which the sponsorship situation was unclear. Figure 3 shows the corresponding estimated marginal means plot of the uncorrected average viewing time. The standard errors for the estimated marginal means of (uncorrected) average viewing time were: $SE_{unclear}$ = 12.25, SE_{bought} = 10.30, SE_{given} = 10.71, and $SE_{sponsored}$ = 12.97. Note that the error bars are missing in Figure 3 due to the fact that SPSS (v24) does not offer the option to add error bars to EMMEANS plots.

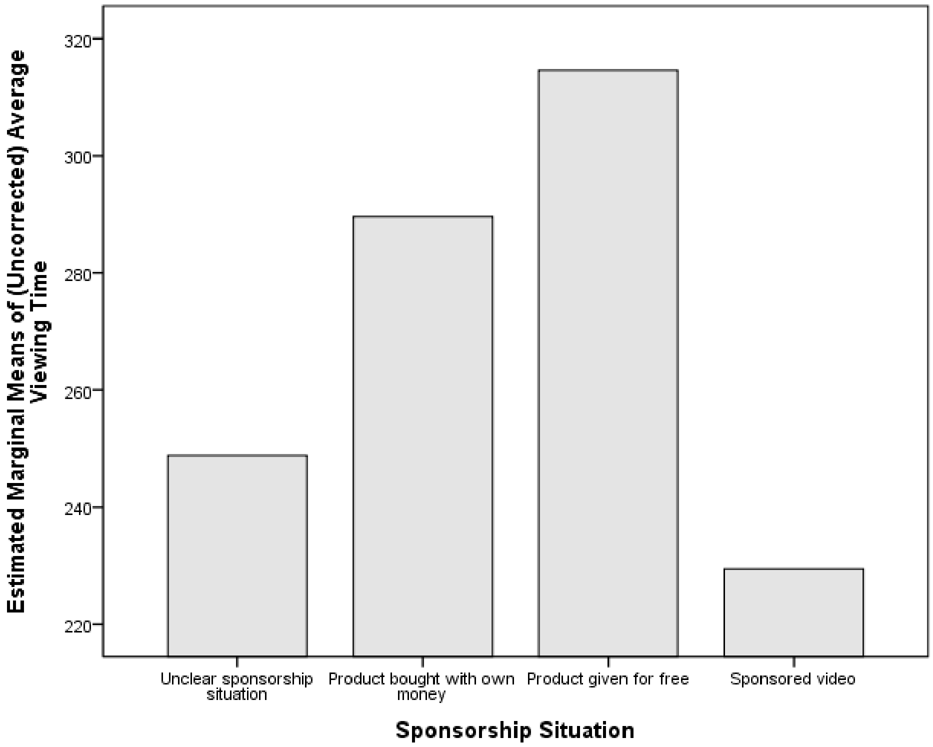

Figure 3. The estimated marginal means plot of (uncorrected) average viewing time (in seconds). Error bars are missing due to the fact that SPSS (v24) does not offer the option to add these to EMMEANS plots.

Lastly, Tukey's post-hoc test indicated the following findings for the corrected average viewing time (which is expressed as a percentage of the total video length). Significant differences in mean scores for (corrected) average viewing time were present between the 'sponsored video' group (M = 49.56, SD = 13.31) and two other groups, namely the 'product bought with own money' group (M = 42.45, SD = 8.46); p < .001, and 'product given for free' group (M = 45.13, SD = 9.18); p = .042. The difference between the 'sponsored video' group and the 'unclear sponsorship situation' group (M = 45.01, SD = 8.73) was marginally significant, p = .053. Figure 4 shows the corresponding estimated marginal means plot of the corrected average viewing time. The standard errors for the estimated marginal means of (corrected) average viewing time were: $SE_{unclear}$ = 1.22, SE_{bought} = 1.02, SE_{given} = 1.07, and $SE_{sponsored}$ = 1.29. Once more, the error bars are missing from Figure 4 due to the fact that SPSS (v24) does not offer the option to add error bars to EMMEANS plots.

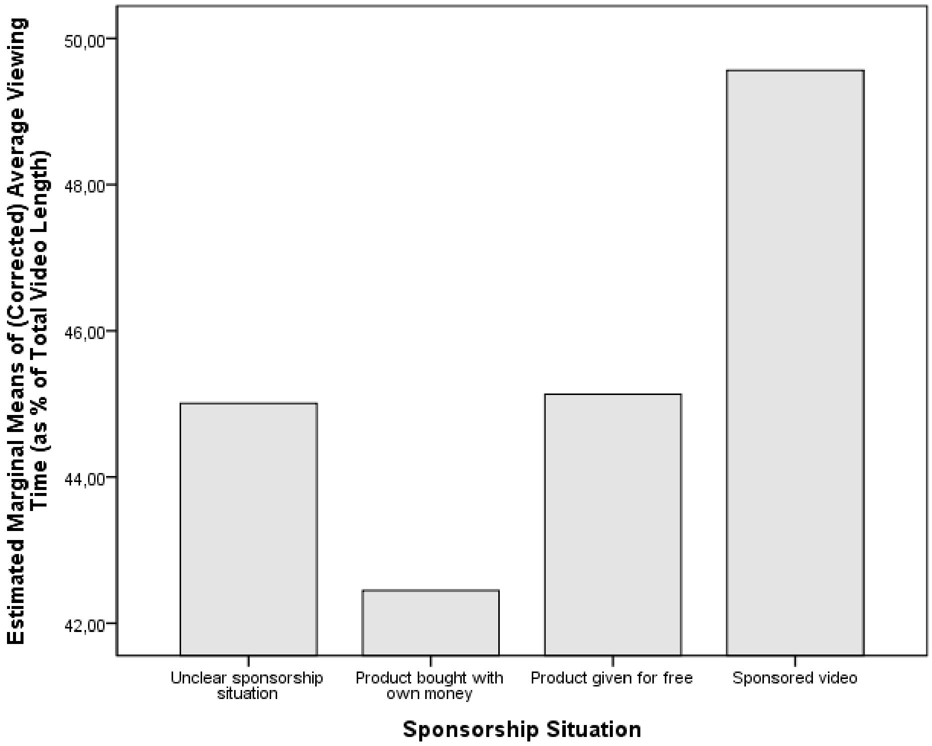

Figure 4. The estimated marginal means plot of (corrected) average viewing time (expressed as a percentage of total video length). Error bars are missing due to the fact that SPSS (v24) does not offer the option to add these to EMMEANS plots.

These findings imply that sponsored videos were watched the longest in terms of percentages of the total video length in comparison to the other sponsorship situation groups. However, this appears contradictive compared to the findings of the (un)corrected average viewing time, where sponsored videos are watched the *shortest* in comparison to the rest of the groups. An explanation for this could be that the means of the total videos lengths are also significantly different between the sponsorship situation groups. A one-way ANOVA indicated that this was indeed the case, $F(3, 296) = 13.12$, $p < .001$. Tukey's post-hoc test indicated that the 'sponsored video' group (M = 492.02, SD = 204.34) was significantly different from both the 'product bought with own money' group (M = 693.80, SD = 243.94); $p < .001$, and the 'product given for free' group (M = 721.13, SD = 255.37); $p < .001$. The 'sponsored video' group did not significantly differ from the 'unclear sponsorship situation' group (M = 574.28, SD = 267.42), $p = .250$. In other words, sponsored videos were significantly shorter in terms of total video length in comparison to videos in which the

YouTuber has bought the featured product with their own money, and videos in which the product was given to the YouTuber for free. In other words, since sponsored videos are shorter, a higher viewing percentage is reached faster than in other sponsorship situation videos, which explains why sponsored videos are significantly watched the longest (in terms of percentages) in comparison to the rest of the videos. At the same time, the short total video length of sponsored videos also explains the shortest uncorrected average viewing time.

In conclusion, hypothesis 4 can be **partially accepted** as the (corrected) amount of dislikes, and the corrected and uncorrected average viewing times differed significantly between the sponsorship situation groups.

4.2.5 Hypothesis 5

Hypothesis 5 stated: *Videos that contain a giveaway generate different levels of user engagement, in comparison to videos that do not contain a giveaway.* This final hypothesis was tested with a one-way MANOVA, with giveaway as a fixed factor and the nine (corrected) variables that comprise user engagement as dependent variables.

A significant difference in user engagement based on the presence of a giveaway was found, $F(9, 290) = 12.06$, $p < .001$; Wilk's $\Lambda = .73$, partial $\eta^2 = .272$. The separate ANOVAs indicated that there were significant differences between videos that contained a giveaway and those that did not on multiple user engagement variables. The first significant difference between groups was the corrected amount of likes ($F(1, 298) = 50.62$, $p < .001$; partial $\eta^2 = .145$), implying that videos that contained a giveaway ($M = 51.33$, $SD = 29.32$) significantly received more likes per 1000 views than videos that did not contain a giveaway ($M = 29.17$, $SD = 13.15$). Additionally, there was a significant difference between giveaway groups in the corrected amount of comments ($F(1, 298) = 92.18$, $p < .001$; partial $\eta^2 = .236$), where videos with a giveaway ($M = 31.53$, $SD = 33.39$) received more comments per 1000 views in comparison to videos without one ($M = 6.45$, $SD = 8.64$). This was also the case for the corrected amount of shares ($F(1, 298) = 7.67$, $p = .006$; partial $\eta^2 = .025$), as videos that contained a giveaway ($M = 2.26$, $SD = 5.47$) were shared significantly more often per 1000 views than videos without a giveaway ($M = 1.09$, $SD = 1.38$). Lastly, the groups also significantly differed in the level of positive sentiment in the comments ($F(1, 298) = 15.40$, $p < .001$; partial $\eta^2 = .049$), as viewers who left comments on videos that contained a giveaway ($M = 2.42$, $SD = 0.41$) used significantly more positive sentiment than viewers who left comments on videos that did not contain one ($M = 2.16$, $SD = 0.31$).

In conclusion, hypothesis 5 can be **partially accepted** as multiple significant differences in user engagement were found between videos with and without a giveaway, including the (corrected) amount of likes, comments, shares, and the level of positive sentiment in the comments. There were no significant differences between videos that contained a giveaway and those that did not in terms of the corrected amount of dislikes ($F(1, 298) = 0.35$, $p = .557$; partial $\eta^2 = .001$), the corrected amount of subscriptions driven ($F(1, 298) = 0.07$, $p = .789$; partial $\eta^2 = .000$), the uncorrected average viewing time ($F(1, 298) = 0.02$, $p = .888$; partial $\eta^2 = .000$), the corrected average viewing time ($F(1, 298) = 0.97$, $p = .326$; partial $\eta^2 = .003$), and the level of negative sentiment in the comments ($F(1, 298) = 0.90$, $p = .343$; partial $\eta^2 = .003$).

4.3 Exploratory analyses

Since the confirmatory analyses did not cover all the relationships that could be relevant to this study, a range of exploratory analyses have been conducted as well. Each section discusses exploratory analyses for a particular topic (i.e. variable). In the first section, different tests for disclosures and disclosure locations were conducted. Secondly, additional insights into the YouTuber's valence and the sentiment in the comments were generated. The exploratory analyses section is concluded by presenting the degrees of association and the resulting model of user engagement in a visual overview.

4.3.1 Disclosures and disclosure locations

For the first exploratory analysis, the researcher was interested to know if the provision of disclosures in YouTube videos has indeed become increasingly prevalent over time (arguably due to more awareness about advertising transparency in YouTube videos). In order to get a variable that illustrated the time difference between date of coding and date of uploading, SPSS's date and time wizard was used. This new variable (measured in months) was used as the predictor (independent) variable in the test, had a mean of 12.39, and a standard deviation of 8.82. The dependent variable was the provision of a disclosure. Since the dependent variable was dichotomous (a disclosure was either provided or not) and the independent variables was continuous (amount of months a video has been online), a binary logistic regression analysis was conducted.

The logistic regression model was significant, $\chi^2(1) = 13.82$, $p < .001$. The model explained between 4.5% (Cox & Snell R^2) and 7.0% (Nagelkerke R^2) of the variance in the provision of a disclosure and classified 80.7% of the cases correctly. The odds ratio was 0.95 ($p < .001$), with a 95% confidence interval of 0.92 and 0.97. This finding implies that an increase in months that a video has been online was associated with a reduced likelihood of providing a sponsorship disclosure. In other words, the more recently uploaded the video is, the more likely is it that a disclosure is provided.

The researcher was also interested to see if the disclosure locations lead to different types of user engagement. Therefore, a one-way MANOVA was conducted, with ‘disclosure location’ as fixed factor and the nine (corrected) variables that comprise user engagement as the dependent variables. As a reminder, there are four possibilities regarding disclosure locations: (0) no disclosure provided, (1) disclosure only in description box, (2) disclosure only in video, and (3) disclosure in both the description box as well as the video.

A significant difference in user engagement based on the location of a sponsorship disclosure was found, $F(27, 842) = 2.74$, $p < .001$; Wilk's $\Lambda = .78$, partial $\eta^2 = .079$. When looking at the ANOVAs, it was found that the disclosure locations had a significant effect on five out of nine user engagement variables. More specifically, the location of the disclosure was found to have a significant effect on the (corrected) amount of likes ($F(3, 296) = 3.51$, $p = .016$; partial $\eta^2 = .034$), the (corrected) amount of comments ($F(3, 296) = 4.03$, $p = .008$; partial $\eta^2 = .039$), the uncorrected average viewing time ($F(3, 296) = 3.34$, $p = .020$; partial $\eta^2 = .033$), the corrected average viewing time ($F(3, 296) = 11.91$, $p < .001$; partial $\eta^2 = .108$), and finally, the level of negative sentiment in the comments ($F(3, 296) = 4.63$, $p = .003$; partial $\eta^2 = .045$). That also means that the disclosure locations did not have a significant effect on the (corrected) amount of dislikes ($F(3, 296) = 0.08$, $p = .974$; partial $\eta^2 = .001$), the (corrected) amount of shares ($F(3, 296) = 1.46$, $p = .225$; partial $\eta^2 = .015$), the (corrected) amount of subscriptions driven ($F(3, 296) = 2.15$, $p = .094$; partial $\eta^2 = .021$), and the level of positive sentiment in the comments ($F(3, 296) = 1.91$, $p = .127$; partial $\eta^2 = .019$).

As the ANOVAs did not provide insights into between which disclosure location groups the significant differences were located, Tukey’s post-hoc test was conducted. Regarding the (corrected) amount of likes, Tukey’s post-hoc test indicated that the only significant difference for this variable is located between the disclosure location ‘only in video’ group ($M = 34.76$, $SD = 18.56$) and the ‘only in description box’ group ($M = 25.77$, $SD = 11.69$); $p = .007$, implying that videos that have their disclosure in only the video generate significantly more likes per 1000 views than videos which have their disclosure in only the description box. Furthermore, regarding the (corrected) amount of comments, Tukey’s post-hoc indicated that the ‘only in video’ group ($M = 12.90$, $SD = 20.30$) differed significantly from two other disclosure location groups: namely, the ‘only in description box’ group ($M = 5.01$, $SD = 4.31$); $p = .008$, and the ‘both in video and description box’ group ($M = 7.28$, $SD = 12.82$); $p = .044$. This means that videos that have their disclosure in only the video tend to receive significantly more comments per 1000 views in comparison to videos that have their disclosure in only the description box, and videos that have their disclosure in both locations.

The ANOVAs also indicated significant differences between disclosure location groups in both the uncorrected and corrected average viewing time. However, when looking at Tukey's post-hoc test for the uncorrected average viewing time, none of the groups differed significantly from each other, despite the significant ANOVA. The lowest p value present in the post-hoc test for uncorrected viewing time was p = .078. For the corrected average viewing time, however, multiple significant differences between groups were found. More specifically, the 'only in description box' group (M = 50.74, SD = 1.27) differed significantly from all other groups: the 'disclosure absent' group (M = 44.89, SD = 1.22); p = .005, the 'only in video' group (M = 41.00, SD = 1.04); p < .001, and the 'both in description box and video' group (M = 45.64, SD = 0.98); p = .009. This means that videos that have their disclosure in only the description box are watched the longest on average (when considering the average viewing time as a percentage of total video length) in comparison to all the other disclosure location groups. Additionally, the 'only in video' group (M = 41.00, SD = 1.04) was also significantly different from the 'both in description box and video' group (M = 45.64, SD = 0.98); p = .007, which implies that videos that have their disclosure in both the description box and video are watched longer (in percentages) than videos that have their disclosure in only the video.

Lastly, Tukey's post-hoc test was examined for the level of negative sentiment in the comments. This test indicated that the significant differences in negative sentiment between disclosure location groups were located between the 'only in video' group (M = 1.12, SD = 0.31) and two other groups, including the 'only in description box' group (M = 1.26, SD = 0.18); p = .003, and the 'in both description box and video' group (M = 1.21, SD = 0.14); p = .035. In other words, videos that have their disclosure in only the video tend to generate the lowest levels of negative sentiment in the comments, in comparison to videos that have their disclosure in only the description box and those that have their disclosure in both locations.

When interpreting these findings one has to keep in mind that they might be partly explained by the fact that certain disclosure locations are more likely to occur for some sponsorship situations than others (see Figure 2). In other words, these differences in user engagement might not necessarily be associated with the disclosure location directly, but rather with the sponsorship situation at hand.

4.3.2 Valence and sentiment

The next exploratory analysis focused on the YouTuber's valence for every sponsorship situation. For this analysis, the researcher was interested to see if the average valence of an influencer significantly differed between sponsorship situation groups. Again, there are four sponsorship situations possible: (0) unclear sponsorship situation, (1) product bought with own money, (2) product given for free, and (3) sponsored video. A one-way ANOVA indicated that there were indeed significant differences between groups, $F(3, 296) = 3.91$, $p = .009$. Tukey's post-hoc test indicated that the only significant difference in valence between groups was located between the 'sponsored video' group ($M = 6.17$, $SD = 0.65$) and the 'product bought with own money' group ($M = 5.48$, $SD = 1.55$); $p = .005$. This means that influencers tended to be significantly more positive about products that were featured in sponsored videos as opposed to videos in which they bought the products themselves.

The next exploratory analysis focused on the relationship between the amount of comments and the sentiment present in these comments. Two simple linear regression analyses were conducted: one for the average positive sentiment and one for the average negative sentiment variable. The regression equation of positive sentiment was significant, $F(1, 298) = 51.45$, $p < .001$ with an R^2 of .38, meaning that the amount of comments was predictive of the average positive sentiment in those comments ($\beta = 0.38$, $p < .001$). This was also the case for average negative sentiment, where the regression equation was also significant, $F(1, 298) = 4.41$, $p = .037$ with an R^2 of .12. This too means that the amount of comments was predictive of the average negative sentiment in those comments ($\beta = -0.12$, $p = .037$). In other words, the more comments were posted on one video, the higher the average positive sentiment in the comment section of this video tended to be, and the lower the average negative sentiment.

4.3.3 The influence of subscribers

If a YouTuber aims to become an influencer or aims to increase their effectiveness in influencer marketing, increasing the subscriber count of a channel is often one of the most sought-after goals. However, a growing subscriber count might also be associated with an increase of negative types of user engagement, as a growing audience also linked to an increased likelihood of criticism. Therefore, in order to generate insights into how predictive the amount of subscribers is of user engagement, nine additional simple linear regression analyses were conducted. Table 4 provides an overview of these tests. Once more, to protect against a type I error when conducting a multitude of separate tests, a one-way MANCOVA was performed with the user engagement variables as dependent variables and the 'amount of channel subscribers' as the covariate. This MANCOVA was significant, $F(9, 290) = 5.11$, $p < .001$; Wilk's $\Lambda = .86$, partial $\eta^2 = .137$, meaning that the amount of subscribers had a significant effect on user engagement.

Table 4

Summary of regression analyses for the effect of channel subscribers on (1) likes corrected for views, (2) dislikes corrected for views, (3) comments corrected for views, (4) shares corrected for views, (5) subscriptions driven corrected for subscribers, (6) the average viewing time per video corrected for video length, (7) the absolute average viewing time per video, and the extent of (8) positive as well as (9) negative sentiment in the comments

	Amount of subscribers		
	β	R^2	F
Amount of likes (corrected)	-0.04	.00	0.42
Amount of dislikes (corrected)	-0.04	.00	0.40
Amount of comments (corrected)	-0.11	.01	3.77
Amount of shares (corrected)	-0.22***	.05	15.35***
Amount of subscriptions driven (corrected)	-0.11	.01	3.33
Average viewing time (corrected)	0.21***	.04	13.37***
Average viewing time	0.24***	.06	17.95***
Positive sentiment in comments	-0.19**	.04	10.79**
Negative sentiment in comments	0.01	.00	0.06

Note. * $p < .05$, ** $p < .01$, *** $p < .001$

Based on Table 4, one can conclude that multiple variables were predicted by the amount of channel subscribers. For example, the (corrected) amount of shares (β = -0.22, $p < .001$), the (corrected) average viewing time (β = 0.21, $p < .001$), the (absolute) average viewing time (β = 0.24, $p < .001$), and the positive sentiment in the comments (β = -0.19, $p = .001$) were all significantly predicted by the amount of subscribers. The prediction of (corrected) amount of comments by channel subscribers was marginally significant, (β = -0.11, $p = .053$), which was also the case for the (corrected) amount of subscriptions driven (β = -0.11, $p = .069$). Variables that were not predicted by the amount of channel subscribers were the (corrected) amount of likes (β = -0.04, $p = .517$), dislikes (β = -0.04, $p = .530$), and the negative sentiment in the comments (β = 0.01, $p = .808$).

The final test for subscribers regards the views per subscriber variable. This variable illustrates how ‘loyal’ subscribers are in terms of watching the videos of the channels they are subscribed to. A Pearson’s correlation indicated a weak, negative correlation between the amount of channel subscribers and the views per subscriber, $r = -.11$, $p = .049$. This means that the more subscribers a channel gets, the less views per subscriber are generated.

4.3.4 Degrees of association and resulting model

Finally, the researcher was interested in testing whether the found effects are indeed separate effects, to come to a definitive model. To this aim, for each indicator of user engagement, a factorial AN(C)OVA (without interaction effects) was conducted, including all variables that were individually found to have a significant effect on that specific user engagement variable. Before the analyses, all variables were standardized in order to avoid multicollinearity. Moreover, in these analyses, the intercept was also excluded from the model in order to determine the statistical significance of the combined models. Lastly, the (corrected) amount of subscriptions driven was also excluded in this process, as none of the independent variables could significantly predict this user engagement variable. The results of the factorial AN(C)OVAs are presented in Table 5.

Table 5

Summary of factorial AN(C)OVAs for the effect of valence, sponsorship situation, disclosure location, giveaway, and channel subscribers on (1) likes corrected for views, (2) dislikes corrected for views, (3) comments corrected for views, (4) shares corrected for views, (5) the average viewing time per video corrected for video length, (6) the absolute average viewing time per video, and the extent of (7) positive as well as (8) negative sentiment in the comments

	Amount of likes (corrected)	Amount of dislikes (corrected)	Amount of comments (corrected)	Amount of shares (corrected)
Variable	Partial η^2	Partial η^2	Partial η^2	Partial η^2
Valence	.025**	.008	.014*	.013*
Sponsorship situation		.022		
Disclosure location	.032*		.038*	
Giveaway	.143***		.237***	.037**
Subscribers				.034**
R^2	.19	.04	.28	.08
F	11.76***	2.15	18.84***	6.59***

Note. * $p < .05$, ** $p < .01$, *** $p < .001$.

Table 5 Continued

Variable	Average viewing time (corrected)	Average viewing time (uncorrected)	Positive sentiment in comments	Negative sentiment in comments
	Partial η^2	Partial η^2	Partial η^2	Partial η^2
Valence		.037**	.039**	
Sponsorship situation	.024	.079***		
Disclosure location	.060***	.018		.045**
Giveaway			.045**	
Subscribers	.036**	.044***	.017*	
R^2	.16	.20	.11	.05
F	6.76***	8.04***	9.55***	3.47**

Note. * $p < .05$, ** $p < .01$, *** $p < .001$

As can be seen in Table 5, some relationships have become insignificant when taking into account the other found relationships. Therefore, to come to the definitive model, the analyses were repeated after step-wise excluding those predictors with the highest p value, until all predictors were significant. In the repetition of the analyses, the intercept remained to be excluded from the models in order to properly interpret the parameter estimates for the non-linear relationships, and again to determine the statistical significance of the combined models. Note that, since the variables were standardized, the parameter estimates (i.e. B's) could be interpreted as standardized parameter estimates (i.e. β's). This resulted in the definitive model with only significant predictors for all the user engagement indicators (with the exception of (corrected) amount of subscriptions driven, which could not be predicted significantly by any variable in this study). Figure 5 shows the standardized parameter estimates for these predictors in the definitive model, alongside the new values for R^2 and F, and the significance levels of the models. Dashed lines indicate negative relationships, solid lines indicate positive relationships, and dotted lines indicate non-linear relationships. Moreover, the dependent user engagement variables have a grey background, and the independent variables have a white background. Due to the number of arrows (relationships) and the corresponding readability of Figure 5, the choice was made to locate the independent variables in the middle, even though this is not usual in these types of visual overviews.

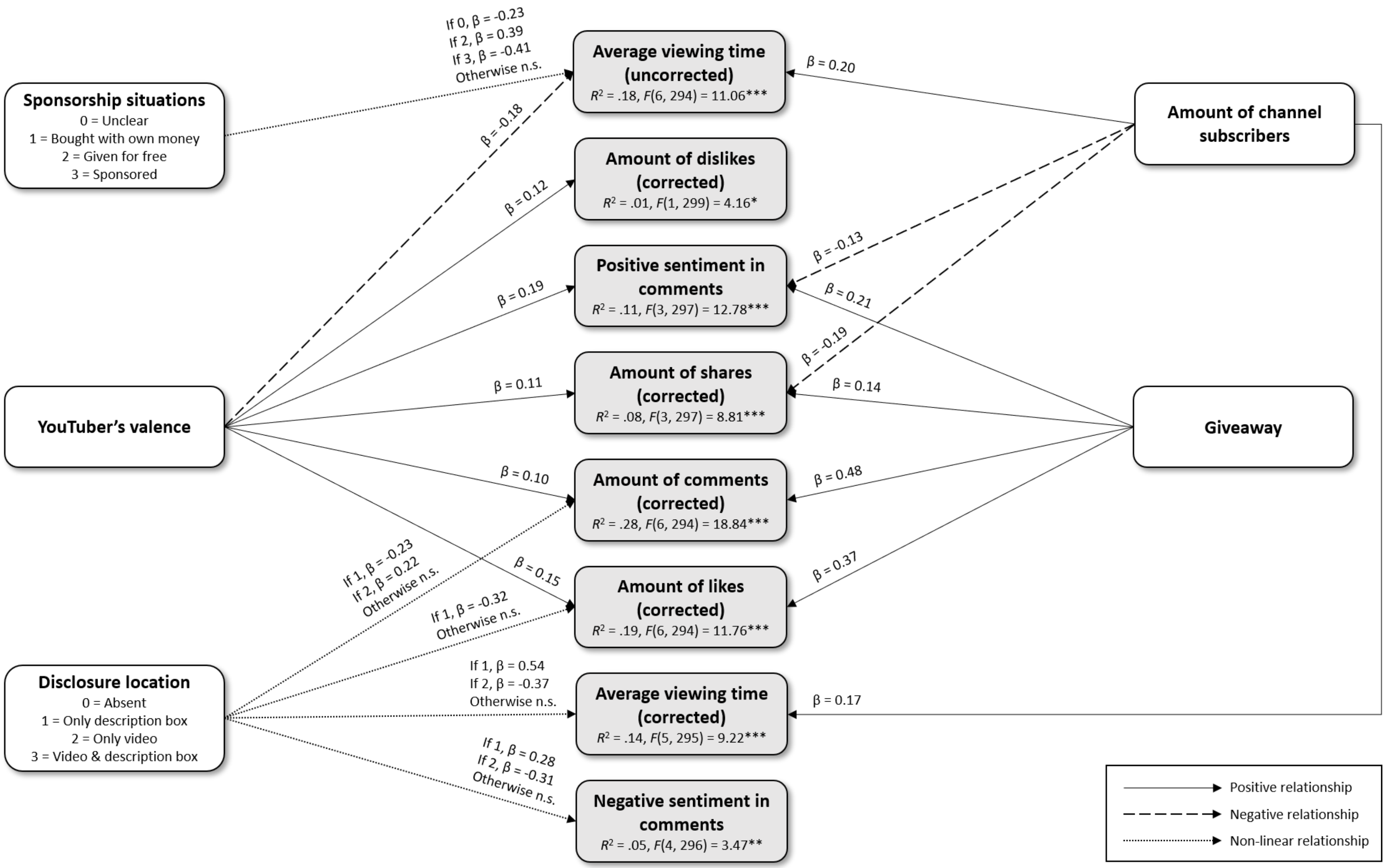

Figure 5. The resulting model of user engagement (* $p < .05$, ** $p < .01$, *** $p < .001$). All variables were standardized before the analyses, so that unstandardized *B*'s could be interpreted as standardized β's.

5. Discussion and conclusion

This research aimed to answer the following research question: 'What are the relationships between sponsorship characteristics of, and indicators of user engagement around, beauty-related videos on Dutch YouTube channels?'. The following section discusses the findings that were presented in Chapter 4, after which scientific and practical implications, recommendations for media practitioners, and limitations plus suggestions for future research are provided. Lastly, this chapter concludes by summarizing the main points of this thesis.

5.1 Discussion

As influencer marketing is on the rise, (paid) collaborations between influencers and brands are becoming increasingly prevalent in the Dutch beauty sector on YouTube. The sample of this study supports this, as 19.3% of the videos in the sample contained sponsored content, and 28.3% of the videos in the sample featured a product that was given to the YouTuber for free. However, while there exist interesting marketing possibilities for both influencers and companies on YouTube, one can argue that it is only fair that viewers of these videos are made aware of these collaborations. This opinion might be shared by content creators, as this study found that the more recently a video has been uploaded, the more likely it is that the video contains a disclosure regarding the sponsorship situation. This may be explained by an increase in awareness of covert advertising, which does not only underline the relevance of this study, but also the relevance of clear and uniform guidelines, such as the ones from the Social Code.

Still, the ongoing friction between being transparent towards followers about sponsored content and maximizing marketing efforts at the same time is a difficult one, as influencers are highly dependent on their audiences. Therefore, this study aimed to gain insights into the relationships between multiple indicators of user engagement and sponsorship characteristics, so that media practitioners can become more aware of the consequences of their marketing decisions in terms of user engagement on YouTube.

The findings of this study indicated that all indicators of user engagement that were measured (except for the amount of subscriptions driven) around beauty-related videos on Dutch YouTube channels are significantly influenced by the sponsorship characteristics of those videos and the corresponding channels. As elaborated upon in this study before, user engagement with YouTube videos can occur in many shapes and forms, yet not every type of engagement is easily accessible or measurable for researchers. Therefore, nine indicators of user engagement that are easily measurable (and thus also easily replicable by other researchers and media practitioners) were selected to create an overview of how viewers engage with videos in different sponsorship situations. Even though these nine variables are all indicators of user engagement, they all tended to behave differently in relation to the sponsorship characteristics. Therefore, one has to keep in mind when reading the term ‘user engagement’ in this study, that this term actually refers to nine separate indicators, rather than one single construct.

The most prevalent predictor of user engagement was found to be the valence of the YouTuber, as it is positively related to the positive sentiment in the comments, the (corrected) amount of comments, the (corrected) amount of likes, and the (corrected) amount of shares. This means that the more positively a YouTuber tends to talk about the featured product in a video, the higher the positive sentiment in the comments, as well as the amount of comments, likes, and shares will be. These findings can partly be explained by the Interpersonal Emotion Transfer theory, where people tend to mirror or be influenced by another person’s emotions (Parkinson, 2011). One could argue that these positive emotions translate to high levels of user engagement that are generally perceived to be positive as well, such as giving likes, posting (positive) comments, and sharing the video. However, it was also found that valence is positively related to the (corrected) amount of dislikes, and negatively related to the (uncorrected) average viewing time. This implies that when the YouTuber’s valence is high, viewers tend to spend less time watching the video, and are more likely to give the video a dislike in comparison to when the YouTuber’s valence is lower. These two findings could be explained by the assumption that influencers tend to be perceived as disingenuous when they talk (too) positively about a (sponsored) product (Dada, 2017), which is a form of source contesting (Fransen, Verlegh, Kirmani, & Smit, 2015; Jacks & Cameron, 2003). The activation of this resistance strategy could translate to user engagement that is generally perceived to be negative, such as disliking the video or watching the video for a shorter amount of time. Moreover, in this study it was found that the average level of valence tends to be the highest for sponsored videos, in comparison to the other sponsorship situation groups. The most straightforward reason for this is that a sponsored video is commissioned by companies, which want to present their products in the most positive way possible. Oftentimes, because of this, influencers refrain from mentioning critical or negative aspects about the product in such videos, causing the high levels of valence. The association with sponsored videos could explain the relationship between valence and (uncorrected) average viewing time, and valence and the (corrected) amount of dislikes as well, as sponsored videos are most likely to be resisted by viewers due to their clear persuasive message (Fransen, Verlegh, Kirmani, & Smit, 2015).

Another prevalent predictor of multiple user engagement variables in this study was the presence of a giveaway. Namely, hosting a giveaway had a positive influence on the positive sentiment in the comments, the (corrected) amount of likes, the (corrected) amount of comments, and the (corrected) amount of shares. This means that videos that contain a giveaway tend to receive more likes, comments, and shares, and also have higher levels of positive sentiment in the comment section in comparison to videos that do not contain one. This finding can mainly be explained by the highly engaging nature of giveaways (Hoffman & Fodor, 2010), especially when viewers are requested to leave behind a like or comment as part of the giveaway entry process. As one can assume that those who enter the giveaway like to win, one can also assume that these people will refrain from engaging with the video in a 'negative' manner (such as disliking or posting hate comments) as they may feel that this behavior lowers their chances of winning. Moreover, the rule of reciprocation (Hoeppner, 2014; Falk & Fischbacher, 2000) states that kind gestures are rewarded with kind gestures in return: In other words, one can assume that the act of hosting a giveaway for followers is kindly rewarded with an act of user engagement that is generally considered to be positive, such as giving a like or posting a positive comment. Lastly, in this study it was found that having a giveaway in a video can compensate for the decrease in likes and comments for certain disclosure locations, as well as for the decrease in the levels of positive sentiment in the comments when a channel grows in terms of subscribers. This again might be because of the highly engaging nature of giveaways (Hoffman & Fodor, 2010), which makes hosting one every now and then a very interesting option for boosting user engagement levels.

The amount of channel subscribers was also one of the more prevalent predictors of user engagement in this study, as it was negatively related to the positive sentiment in the comments and the (corrected) amount of shares, yet positively related to both the corrected as well as the uncorrected average viewing time. The former findings imply that the more subscribers a channel has, the less positive sentiment tends to be present in the comments, and the less shares videos tend to get. This finding can partially be explained by the expectation that the more subscribers a channel has, the more inactive subscribers are present too. That is, in the beginning, one might expect that a YouTube channel will have mostly dedicated followers (such as friends and family), but as time passes and the channel receives more followers, the percentage of dedicated followers declines. This explanation is also supported by the negative correlation between channel subscribers and the amount of views per subscriber (see Appendix C for this study's correlation matrix). Another explanation is that if a channel becomes well-known, the larger the chances are that new viewers find one or multiple videos of this channel through search engines or recommendations. As these new viewers are unfamiliar with that channel and are thus unsure of what to expect, the chances of them not sharing the video or posting a less positive (or even negative) comment in comparison to subscribers is larger.

Additionally, when it comes to the decrease in positive sentiment, one might argue that the more subscribers a channel has, the more well-known (and probably successful) the channel is, the more likely it is that a YouTuber is being criticized for merely for being popular. As people tend to use social comparison to evaluate their own successes, an influencer's success can make others envious. In fact, Hedges (2012) explained that people tend to be most envious of those similar to them (i.e. 'ordinary people' who have become famous YouTubers). Additionally, given that famous influencers are often claimed to have an exemplary role for those who watch them, everything those influencers do is assessed based on that role. As one can assume that both envy and critical feedback can translate to user engagement that is generally perceived to be more negative (such as disliking or posting a negative comment), it is no surprise to find that the higher the amount of channel subscribers is, the less positivity is conveyed in the comments and the less shares a video gets. However, the amount of subscribers was also positively related to the average viewing time (both the absolute as well as the corrected value), meaning that the more subscribers a channel has, the longer people tend to watch this channel's videos. This can be explained by the expectation that larger channels have been 'in business' for a longer amount of time, and thus know better how to create interesting content and what the preferences of their audiences are. Moreover, large channels in terms of followers are also expected to have a higher amounts of dedicated fans. So, even though larger channels get less views per subscriber, subscribers who do decide to watch the video, tend to do this longer than subscribers of smaller channels.

When looking at solely the sponsorship situations, it was found that they only affect the (uncorrected) average viewing time of a video. More specifically, when a sponsorship situation is unclear or if a video is sponsored, people tend to watch the video to a lesser extent, compared to videos that feature a product that was bought by the YouTuber. The lower average viewing time for sponsored videos might be explained by the tendency that people do not go to YouTube to see commercials (i.e. videos with the goal of selling you something) (Khan, 2017; Patel, 2017). Furthermore, one might expect that when viewers get the impression that they are looking at covert advertising while a disclosure is absent (i.e. 'unclear sponsorship' videos), they might stop the video as well. In short, due to the nature of these videos a type of avoidance strategy might be triggered (Fransen, Verlegh, Kirmani, & Smit, 2015), which leads to a lower average viewing time. However, when the video features a product that was given to the YouTuber for free, the average viewing time tends to be higher than that of videos that feature a product that was bought by the YouTuber. This might be because companies tend to send new products that still have to hit the market to influencers first before these products become available in stores for 'regular' consumers. Doing so enables influencers to create exclusive content featuring products that are new, original, and exciting, rather than predictable, unimaginative, and outdated. Taking in mind that original and creative content is valued by viewers (Sonderman & Tran, 2013), and that 'seeking information' (about new products, for example) is one of the user motives of watching YouTube videos (Khan, 2017), one can assume that videos that feature products that are not for sale yet are generally more interesting to watch than videos that feature products most people have bought by now.

The last predictor of user engagement was the disclosure location. This variable significantly predicted four user engagement indicators: the (corrected) amount of likes, the (corrected) amount of comments, the (corrected) average viewing time, and the negative sentiment in the comments. Regarding the amount of likes, it was found that videos that have their disclosure in just the description box receive less likes in comparison to videos with other disclosure locations. Based on Figure 2, one can see that (in this sample) the disclosure location 'only in the description box' is mostly associated with videos in which a product is given to a YouTuber for free, and with sponsored videos. The fact that these videos receive less likes could be explained by the fact that viewers have to make more effort to find the disclosure, which can arguably come across as a little secretive (i.e. finding out that a video is sponsored at the bottom of the description box while nothing else in the video discloses this sponsorship, might have a negative influence on people). Moreover, if a disclosure is only in the description box, it can easily be missed as not every viewer opens this box. If a video still has the 'commercial feel' of sponsored content, and viewers make no effort to find the disclosure, they might get the feeling that YouTubers are being secretive about a paid collaboration.

Regarding the amount of comments, the same effect was found for videos that have their disclosure in only the description box. Namely, these videos tend to receive less comments than videos with other disclosure locations. On the other hand, videos that provide a disclosure in only the video tend to generate the most comments in comparison to videos that disclose in a different way. A similar effect applies to the negative sentiment in the comment section: if a video has its disclosure in only the description box, the negative sentiment tends to be higher compared to videos with other disclosure locations. However, when a disclosure is only in the video, the negative sentiment tends to be lower than the sentiment in videos with other disclosure locations. Lastly, it was found that videos that have a disclosure in the description box are watched to a longer extent than videos with other types of disclosure, and that videos that have a disclosure in the video are watched shorter than videos with other types of disclosure. Even though this seems to contradict the previous findings, this finding could be explained by the activation of persuasion knowledge (Friestad & Wright, 1994). It can be argued that disclosures that are provided in the video are noticed more easily than disclosures in description boxes, which may activate the persuasion knowledge of viewers, possibly causing them to stop the video (which would be an example of an avoidance resistance strategy (Fransen, Verlegh, Kirmani, & Smit (2015)).

As becomes clear from Figure 5, the (corrected) amount of dislikes and the negative sentiment in the comments were the variables of which the least variance was explained. This could be explained by the type of audience that is watching the sampled videos. Namely, one can assume that the majority of the viewers who watch beauty-related videos is female. Khan (2017) found that females are less likely to express dissatisfaction with media content in comparison to males, which may explain why the (corrected) amount of dislikes and negative sentiment variables could not be predicted very well.

5.2 Practical and scientific implications, and recommendations

The findings of this study impact existing theory and have practical implications for media practitioners. In terms of scientific implications, the current study helped extend the understanding of user engagement in different sponsorship situations on YouTube by providing new insights. This is important as understanding user behavior is a prerequisite of any successful marketing effort (Khan, 2017). Moreover, this study provided new insights for multiple theories, especially those in the uses and gratifications framework for media research. Previous research in this framework had identified motives for users to participate (Khan, 2017) and characteristics of content (O'Brien & Toms, 2008) which trigger users to engage with it. The current study applied these theories to the context of influencer marketing on YouTube, in which they worked well. The same applies to the ACE typology by Fransen, Verlegh, Kirmani, and Smit (2015), as multiple findings could be explained with the reasoning of this framework. Moreover, the current study built upon Interpersonal Emotion Transfer theory (Parkinson, 2011), and indicated that emotion transfer might also apply to the online relationship between influencer and viewers, as valence was the most prevalent predictor of the user engagement indicators in this study. Furthermore, the researcher of the current study also wanted to test if the theory of persuasion knowledge (Friestad & Wright, 1994) is applicable to user engagement on YouTube, which might be true to some extent. In other words, sponsored videos tended to trigger the largest decrease in the (uncorrected) average viewing time, especially when combined with high levels of valence. Yet, this was the only user engagement indicator that was influenced by the sponsorship situation, implying that the effects of sponsorship situation on user engagement were limited in this study. Lastly, as it remains difficult to measure the ROI of social media marketing campaigns (Kaul & Chaudhri, 2017; Kumar & Mirchandani, 2012), this research has provided insights into the levels of user engagement that are associated with sponsored content. As mentioned before, user engagement is an indicator of the success of a marketing campaign (Khan, 2017), and generating insights into user engagement therefore provides a more comprehensive view of a campaign's success than, for example, just the number of sales generated from that particular campaign. Because this study used easily quantifiable indicators of user engagement, media practitioners are able to easily replicate the measurement techniques so that they can monitor the user engagement levels for their own campaigns. Next to that, they can now also anticipate on what to expect for user engagement levels when making certain marketing decisions (for example, how the location of the disclosure influences particular indicators of user engagement).

In terms of practical implications, practitioners can use the findings of this study to optimize their YouTube marketing and engagement strategies. This holds for both content creators as well as marketeers. Figure 5 in this report can be used by practitioners as a visual guideline for which factors influence particular indicators of user engagement, and how. The only variable that could not be predicted in this study is the (corrected) amount of subscriptions driven, which means that no recommendations regarding increasing the subscriber count of a channel could be provided. However, all other user engagement variables could be predicted to some extent, of which the amount of comments is the variable with the largest variance explained (28%). Furthermore, as active audiences increase the likelihood of a channel being found by new users through search engines, or being featured in YouTube's trending and popular lists, increasing user participation is a very sought-after goal. This study provided insights into which factors are associated with an increase in user participation, and multiple considerations and recommendations based on this study's findings can therefore be provided.

For example, the people behind the Social Code: YouTube could re-evaluate their guidelines based on the outcomes of this research as disclosure locations were found to influence some user engagement variables in a negative manner. Namely, the Code advices YouTubers to place their disclosures in the description box (except for sponsored videos, in which content creators should mention it in their videos as well). However, this study found that placing a disclosure in only the description box is associated with higher levels of negative sentiment in the comments, lower amounts of comments, and lower amounts of likes. People behind the Social Code could therefore consider asking YouTubers to disclose all types of sponsorship situations – not only the paid ones – in the video instead, as doing so is associated in this study with lower levels of negative sentiment, and higher amounts of comments. However, disclosing in the video is also associated with a lower average viewing time (arguably because of the higher likelihood of the activation of persuasion knowledge), which is a consideration YouTubers have to keep in mind when making this decision.

Additionally, practitioners who work with influencers and content creators alike can use the findings of this study (especially Figure 5) to pay extra attention to the sponsorship and video characteristics in order to maximize the chances for certain types of user engagement. Furthermore, it becomes clear that most strategic choices, even though not surprisingly, have positive as well as negative consequences. Practitioners should decide for themselves (based on the objectives they wish to achieve), what considerations they find most important. For example, if a practitioner wishes to increase the amount of subscribers of a Dutch beauty-related channel, he or she should know that it is likely that the average viewing time per video increases with the subscriber count, yet that the amount of shares and the level of positive sentiment in the comment will most likely decrease too.

Still, media practitioners who practice influencer marketing should note that even though the channels in this study mainly discuss the same topics (i.e. they are all beauty-related), every channel tends to attract different types of audiences, and therefore, user engagement. Thus, in order to maximize the effectiveness of influencer marketing, practitioners should always research the audiences of a certain influencer. The characteristics of these audiences could help explain and predict user engagement indicators to a greater extent.

5.3 Limitations and future research

Every research has its limitations. The following (non-exhaustive) discussion will point out the limitations of the current study, and provides guidelines for future research on what to look out for.

The first limitation regards the sampling process of this study. Namely, after expert sampling the 15 Dutch YouTube channels, 20 videos per channel were sampled with some very specific criteria (see Section 3.2). This caused some minor issues for testing certain hypotheses. For example, hypothesis 5 stated that there were differences in user engagement between videos that contain a giveaway, and videos that do not. Since there was no quota sampling for videos with giveaways, the group of giveaway videos was not very large (26 videos). Even though the researcher believes that this group was still large enough to have statistical power, future research could increase the size of this group by focusing on quota sampling for giveaways, and see if the findings of the current study still apply. Moreover, when researching giveaways on YouTube, the researcher noticed that giveaways are sometimes announced in the YouTube video, but then viewers were redirected to another social media platform such as Instagram or a blog if they wanted to join the giveaway. In other words, future researchers should keep in mind that the hypothesized increase in user engagement for giveaway videos might not always be visible on the video in which the giveaway is announced, but can rather be seen on the platform that ‘hosts’ the giveaway.

Another limitation in this study was the accuracy of the sentiment detection program SentiStrength. As elaborated upon in Section 3.4 (Data collection procedures) and Appendix B, the researcher tried to improve SentiStrength’s reliability and accuracy as best as possible. Nonetheless, the program still has its limitations. For example, it is unable to detect sarcasm, typos, and smartphone smileys. Future research could therefore consider using other sentiment detection programs that are able to measure sentiment at the per-comment level for similar research purposes, or dedicate a study to improving the reliability of the Dutch dictionary of SentiStrength. Moreover, next to the video itself, comments on YouTube videos can also receive ‘thumbs up’ and ‘thumbs down’. One could interpret the thumbs up and down as an ‘agree’ and ‘disagree’ with the written comment by another user (Khan, 2017). One could therefore also argue that comments with more thumbs up or down should weigh more heavily in the sentiment analysis than comments with less thumbs up or down. For example, when a certain comment is given a thumbs up, it could be argued that it should weigh twice as heavy in the calculation of the average sentiment than a comment that has not received a thumbs up. The sentiment analysis of the current study did not take this into account, yet future research definitely could take this into consideration.

The next paragraph discusses some considerations for this study, which eventually did not make it into the final codebook due to time, money or other constraints. Still, future research could consider including these variables in a content analysis, as they might help to explain more user engagement variable variance. Additionally, the (corrected) amount of subscriptions driven could not be explained by any of the variables in the current study, so the following list might provide some guidelines for future research if one of their objectives is to predict this variable. The first variable that was considered, but did not make it to be included in the codebook were affiliate links (if a viewer buys a product via such a link, a small commission is received by the YouTuber). Affiliate links are most often located in description boxes. However, to the researcher’s knowledge, it is very difficult to notice if a link is an affiliate one if no disclosure about this is provided. Still, the use of affiliate links could influence users in the sense that a YouTuber might come across as too money-focused, especially when using these types of links in combination with sponsored videos. Furthermore, another variable that was not included in the codebook of this study but could be included in future studies is the use of discount codes. Beauty YouTubers often receive discount codes from companies, which they share in their video in the hope that their followers buy the advertised product. Future research could look into if providing a discount code affects the user engagement of a video, and in what way. Additionally, future research could code more detailed characteristics of the featured products, such as the amount of (sponsored) products discussed in one video, how long the viewer is exposed to the sponsorships, the brands of the products, and the price category of these products (i.e. budget-friendly or high-end).

Additionally, some more general limitations regarding the method and the topic of research can be pointed out. For example, regarding the method used, quantitative content analyses focus on manifest (i.e. literal) content – that is, the visible, countable content of a media text, rather than the (hidden) meanings behind it. As this method is descriptive in nature, it does not reveal any underlying motives. Even though this study aimed to explain the findings with previous theory as well as possible, it could still be the case that there are other motives behind certain types of user engagement. Therefore, future research could focus on a more qualitative approach, for example in the form of interviews or focus groups, to gain more insights into why exactly users tend to display certain types of user engagement for different sponsorship characteristics. Next to that, this research is affected by the 90-9-1 rule of user participation (Nielsen, 2006), meaning that the findings of this study only apply to the engagement behavior of the 10% of users who actually participate on the Internet. As the remaining 90% of users tends to lurk in the background and very rarely to never contributes (Nielsen, 2006), no insights into their user engagement could be generated (at least not with the nine chosen indicators of this study). Future research could therefore study the opinions of the 90% group about sponsored content, in either a quantitative or qualitative manner. In addition to this, future research might think of other indicators of user engagement than the ones that were chosen for this study. The nine indicators of user engagement used in the current study are very suitable for an online content analysis, yet other researchers could use different research methods to gain insights into other indicators.

Moreover, in this research, the decision was made to focus on first impression/review videos about beauty products in order to give the study focus and direction, and to be sure that a YouTuber's valence could be coded. However, sponsored content is prevalent in more formats than just these – future research could therefore focus on user engagement in other formats as well, such as vlogs. Also, this study researched Dutch beauty YouTubers, which does not necessarily make the findings generalizable to YouTubers in other fields of expertise, nor YouTubers in other countries. Therefore, future research could study YouTubers who are active in other segments or have different demographics. Additionally, future research could establish if the relationships that are found between the variables in this study are causal relationships. Finally, in terms of replicability of this study, researchers should keep in mind that the public statistics button which was used to code certain user engagement indicators might not be available in the (near) future due to the fact it can only be accessed through the classic YouTube layout.

A final note includes the interpretation of positive and negative sentiment in the comments. Namely, the presence of positive or negative sentiment does not necessarily mean that this sentiment is directed at the YouTuber in the form of hate or praise: it only indicates that people are using words with a certain sentiment in the comments. In other words, the level of sentiment does in no way reflect what people are exactly talking about. One should therefore be careful when interpreting the average sentiment in the comment section, as one might tend to assume that high levels of negative sentiment are indicative of a lot of hate comments. While this might be true, it could also be the case that people are merely mirroring the feelings of the YouTuber in the comment section, as theorized by Interpersonal Emotion Transfer theory (Parkinson, 2011).

5.4 Conclusion

This study provided an elaborate description of the relationships between specific indicators of user engagement and sponsorship characteristics for beauty-related videos on Dutch YouTube channels. The main findings were that all indicators of user engagement (except for amount of subscriptions driven) could be predicted by the sponsorship characteristics in this study. The YouTuber's valence was the most prevalent predictor, as it significantly predicted six out of nine user engagement indicators. The visual representation of the resulting model in this thesis, which highlights the significant relations between the predictors and indicators of user engagement, provides media practitioners (such as marketeers, advertisers, and YouTube influencers) with guidelines to optimize their marketing and engagement strategies. Given that the indicators of user engagement used in this study are easily measurable and quantifiable, media practitioners should have no problems when measuring the levels of user engagement for their own personal campaigns. Based on the results of this research, recommendations for media practitioners were provided as well, including detailed recommendations for the people behind the Social Code: Youtube. Even though the Code's main goal is to encourage influencers to work with integrity when it comes to online advertising, it would be a limitation if the marketing effectiveness of the influencers would decrease based on these transparency guidelines. Therefore, recommendations were provided which made sure that the marketing efforts of influencers are not in vain, while also assuring full transparency towards viewers regarding sponsorship situations. Finally, the findings of this study also have theoretical implications, as new theoretical insights regarding the relationships between indicators of user engagement and sponsorship characteristics have been generated. New insights were also generated for multiple communication and marketing theories, such as the uses and gratifications Framework, the ACE typology, and persuasion knowledge theory, as all of these could successfully be applied to this particular research context.

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Appendix A

Table A1

Content analysis codebook

Variable	Value
Channel ID	(Positive number with no decimals)
Amount of channel subscribers	(Positive number with no decimals)
Video ID	(Positive number with one decimal)
Video category	(Category)
Video post date	(Date)
Date of coding	(Date)
Amount of views	(Positive number with no decimals)
Amount of likes	(Positive number with no decimals)
Amount of dislikes	(Positive number with no decimals)
Amount of comments	(Positive number with no decimals)
Amount of shares	(Positive number with no decimals)
Subscriptions driven	(Positive or negative number with no decimals)
Additional YouTube ads enabled?	Dummy variable → 0 = No | 1 = Yes
Total video length	(In seconds)
Average viewing duration of video	(In seconds)
Giveaway	Dummy variable → 0 = No | 1 = Yes
Average positive sentiment in comments	(Value between +1 and +5)
Average negative sentiment in comments	(Value between -1 and -5)
Sponsorship disclosure given	Dummy variable → 0 = No | 1 = Yes
Sponsorship disclosure location	0 = No disclosure given 1 = In the description box 2 = In the video 3 = In both the description box and the video
Sponsorship situation	0 = Sponsorship unclear 1 = YouTuber bought product with own money 2 = YouTuber received product for free, but is not being paid extra to promote it 3 = YouTuber gets paid to promote product (i.e. is sponsored).
YouTuber valence	1 = Very negative […] 7 = Very positive.

Appendix B

Dutch SentiStrength dictionary was adjusted by the researcher due to the fact that after performing multiple test rounds, she did not believe that the original Dutch dictionary was reliable enough in analyzing the sentiment in Dutch YouTube comments. Some general notes on this process are:

- The original English dictionary consisted of 2546 words (excluding word variations), and the original Dutch dictionary consisted of 1618 words (also excluding word variations).
- ‘Word variations’ mean the following: Some words in the dictionaries are followed by an asterisk (*). This means that SentiStrength will allocate the same sentiment to words that are very similar. For example, ‘nice*’ tells SentiStrength to label similar words with the same sentiment as the original word, such as nicer, nicest, etc. Some words were given asterisks by the researcher, so that multiple variations would be included (e.g. ‘grr’ and ‘haha’). One additional note on this is that future research should not put an asterisk with the word ‘gek’, but instead should categorize ‘gekker’ and ‘gekste’ as separate entries. The reason for this is that gek* also matches with the word ‘gekocht’, which is a word that is used often in the comment section of Dutch beauty-related videos. Doing so allocates negative sentiment to the word ‘gekocht’, which is obviously inaccurate.
- Some Dutch words were removed (neutralized) because they were categorized in the incorrect sentiment group in the eyes of the researcher (see left column of Table B1).
- Even though the original Dutch SentiStrength dictionary contains quite a bit of words, some words that are typically used in YouTube comments were missing (such as ‘leuk’ or ‘grappig’). After looking at random samples of YouTube comments of all 15 channels to see which words are typically and/or often used to describe the video’s content, the researcher added these words to the Dutch dictionary (see right column of Table B1). The corresponding sentiment of these added words was based on the sentiment given to the (closest) translations of these words in the English dictionary.
- Some Dutch words contained grammatical mistakes and were thus corrected by the researcher. For example, privileg → privilege, romanc → romance, positiv → positief, and so on.
- The process of improving was repeated until the researcher concluded that the Dutch dictionary became reliable enough regarding the sentiment in the comments. However, sentiment detection software definitely still has its limitations, which is elaborated upon in Section 5.3 of this report.

Table B1

The words that were removed and added to the original Dutch SentiStrength dictionary

Removed		Added	
Word	Sentiment	Word	Sentiment
Over	-2	Wauw/wow	+3
Niet	-3	Like	+2
Nix	-2	Dislike	-2
Geleden	-4	Grappig*	+3
Ligt	-3	Leuk*	+3
Houden	-2	Gefeliciteerd	+2
Dove	-2 (because of brand name 'Dove')	Fan	+2
Mom	-2	Lelijk*	-3
Integendeel	-2	Nice	+2
Schilderen	-4	Spontaan	+2
Vast	-2	Subscribed	+3
Vlam	-3	Voorbeeld	+2
Gevlamd	-3	Zalig*	+3
Vet	-2	Prik*	-2
		Favoriet*/fave/favo	+3
		Fijn	+2
		Top*	+2
		Tof*	+2
		Thanks/thanx/thnx/thx	+2
		Verbaasd	-2
		Schitterend*	+3
		Dik	-2
		Flawless	+3
		Allerleukst*	+3
		Beauty	+2
		Enthousiast*	+3
		Goals	+2
		Lifegoals	+3
		Vrouwelijk*	+2
		Fijn*	+2
		Ily [I love you]	+3
		Irritant*	-3
		Yes*	+2
		Origineel/originele	+2
		Trouw*	+2
		Verdient/d	+2
		Informatief	+2
		Leerzaam/leerzame	+2
		Vies/vieze	-2
		Vlekkerig	-2
		Gaaf/gave	+2
		Winnen	+2
		Helpen/geholpen	+2
		Gezellig*	+2

Appendix C

Table C1

The correlation matrix of this study

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. Amount of subscribers	1	.07	-.11*	-.04	-.04	-.11	-.22***	-.11	.08	.24***	.21***	-.07	-.19**	.01	.11	-.22***
2. Difference in days between upload and coding		1	.03	-.35***	-.06	-.12*	-.12*	-.08	-.25***	-.22***	.12*	-.07	.03	.11	-.23***	.02
3. Views per subscriber			1	-.30***	-.17**	-.15**	-.01	.69***	.07	-.05	-.11	-.02	-.08	-.27***	.04	-.06
4. Likes per 1000 views				1	.15**	.72***	.15**	-.12*	.10	.04	-.16**	.38***	.26***	-.20***	.00	.16**
5. Dislikes per 1000 views					1	.38***	.44***	-.05	-.14*	-.23***	-.11	.03	.23***	-.00	.02	.12*
6. Comments per 1000 views						1	.37***	-.06	-.03	-.13*	-.20***	.49***	.38***	-.12*	.02	.13*
7. Shares per 1000 views							1	-.01	-.15*	-.27***	-.25***	.16**	.30***	.03	-.02	.16**
8. Subscriptions driven per subscriber								1	.11	-.01	-.16**	.02	.01	-.16**	.04	-.06
9. Video length									1	.88***	-.43***	.01	-.06	-.10	.11	-.22***
10. Average viewing time										1	-.00	-.01	-.16**	-.01	.12*	-.25***
11. Average viewing time (%)											1	-.06	-.22***	.18**	.01	-.02
12. Giveaway												1	.22***	-.06	.10	.04
13. Average positive sentiment													1	-.15*	-.10	.23***
14. Average negative sentiment														1	-.02	-.07
15. Disclosure given															1	.02
16. Youtuber valence																1

Note. * $p < .05$, ** $p < .01$, *** $p < .001$