The Differential Impacts of Positive and Negative Emotions on Travel-Related YouTube Video Engagement

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Content

Abstract

Despite the growing importance of video-based social media content, such as vlogs, as a marketing tool in the travel industry, there is limited research on the characteristics that enhance engagement among potential travelers. This study explores the influence of emotional valence in YouTube travel content on viewer engagement, specifically likes and comments. We analyzed 4,619 travel-related YouTube videos from eight popular tourist cities. Using negative binomial regression analysis, we found that both positive and negative emotions significantly influence the number of likes received. Videos with higher positive emotions as well as negative emotions receive more likes. However, when it comes to the number of comments, only negative emotions showed a significant positive influence, while positive emotions had no significant impact. These findings offer valuable insights for marketers seeking to optimize engagement strategies on YouTube, considering the unique nature of travel products. Further research into the effects of specific emotions on engagement is warranted to improve marketing strategies. This study highlights the powerful impact of emotions on viewer engagement in the context of social media, particularly on YouTube.

Keywords: YouTube, tourism, emotional valence, viewer engagement, social media marketing, travel marketing

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1. Introduction

Imagine that you are planning a trip to Europe and turning to YouTube for inspiration and information. Among the countless travel-related videos, two catch your attention. The first video is filled with joyous experiences, evoking awe and inspiration through positive emotions. In contrast, the second video delves into personal struggles, expressing sadness, fear, and anger while navigating the streets. Between these two videos, which one would you be more likely to click "like" and leave a comment on? Would it be the video resonating with positive emotions, or perhaps you feel more engaged with the one expressing negative emotions?

Previous research in consumer psychology and social media marketing offers diverging predictions. Positive emotional content has the potential to foster positive attitudes (Kujur and Singh, 2018; Um, 2008), resulting in engagement in advertising (Griskevicius et al., 2010) while comments and sharing of positive content may provide self-enhancement opportunities (Kujur and Singh, 2018; Tellis et al., 2019). Thus, YouTube videos that contain positive emotions are likely to induce high engagement. On the other hand, recent studies suggest that people consider negative events greater impact than positive events (Cui et al., 2012) and that negative contents tend to be perceived as more diagnostic and informative (Chen and Farn, 2020). Moreover, viewers tend to believe negative content is a sincere expression of the creator's feelings as it may not seem to have overt promotional intentions (Cheong and Morrison, 2008). Thus, driven by the belief that the content is reliable and honest, viewers may be more inclined to "like" and add comments on videos that evoke negative emotions.

Our study aims to investigate how emotional valence in YouTube travel content influences consumer engagement, including likes and comments. Previous research suggests that including positive emotions in videos can evoke positive emotional responses, impacting subsequent engagement behavior, while the perceived informational value of negative emotions can play a role in attracting viewer engagement. We anticipate that the influence of positive and negative emotions on likes and comments will differ due to the differences in the level of cognitive effort required for each action and the perceived informativeness of negative and positive emotions.

Although much previous research has explored various content characteristics that influence viewer engagement (De Vries et al., 2012; Lee et al., 2018), there remains a paucity of studies specifically investigating the emotional valence of content. Among those, most studies employed a single measure for engagement behavior (e.g., “share” for Tafesse (2020) and Tellis et al. (2019); a single composite index for Khan and Vong (2013) and Kujur and Singh(2018)). The work of Munaro et al., (2021) is similar to current research investigating the influence of emotions on likes, dislikes, and comments for

YouTube videos from the top influencers' channels. However, in their study, they employed a bipolar scale for emotion valence, assigning extremely negative emotion a value of −1 and positive emotion +1, that they could not capture the respective effect of positive and negative emotions on different engagement actions. Furthermore, most existing studies have primarily investigated the impact of YouTube advertising from brand channels (e.g., Kujur and Singh, 2018; Tellis et al., 2019). In contrast, our current research incorporated user-created videos into our analysis, given the fact that a larger quantity of user-generated content is uploaded and viewed on YouTube compared to brand advertising.

It is also important to note why the current research focuses on travel-related categories. Firstly, the impact of YouTube within the travel industry is substantial and continuously expanding. Views of travel-related videos increased by 41% in 2018 compared to 2017 (source: Think with Google, consumer insight) and they significantly influence people's travel decisions. Secondly, travel is inherently experiential in nature, leading individuals to seek indirect experiences through the perspectives of similar others. The capacity of YouTube to offer rich multimedia experiences, often in the form of user-generated content, enhances its relevance and trustworthiness as a primary source for making informed travel decisions. Furthermore, travel experiences involve hedonic emotions, yet viewers actively seek utilitarian (informative) content from travel videos. Consequently, it's likely that positive and negative emotions often coexist within a single video. Therefore, investigating the influence of emotional valence on consumer engagement is of greater significance in the context of travel categories.

To examine the influence of content characteristics, the current research collected a substantial volume of YouTube videos and conducted analyses using big-data analysis techniques. Extensive recent research in tourism that has adopted similar methodologies primarily focuses on the analysis of customer reviews of online booking sites. For instance, Park et al. (2020) conducted sentiment analysis on 105,126 customer reviews within the hotel reservation system, assessing their impact on revisit. Yousaf and Kim (2023) analyzed online reviews of hotels in New York and reported the relationship between personality traits detected from review contents and review generation, consumption, and distribution. Similarly, Amatulli et al. (2019) analyzed hotel reviews on TripAdvisor to investigate the influence of emotions on sharing behavior. Rita et al. (2022) extended this analysis to airline reviews on TripAdvisor.

In contrast to previous studies primarily dealing with customer reviews on travel product booking websites, our research focuses on YouTube videos. These videos typically have longer durations, averaging around 10 minutes, and frequently include narratives that encompass a wide spectrum of emotions within a single video. Notably, according to Google, individuals conduct three times as many searches for travel experiences compared to hotel bookings and eight times more than for flight searches (Google/Greenberg, Global, Travel Tours and Activities Survey and Behavioral Study, Dec. 2018). Our analysis of YouTube videos enables us to gain knowledge into the impact of content primarily centered on travel experiences. While several prior studies (e.g., Tafasse et al., 2020) which analyzed advertisements and vlogs included travel categories among the various topics they covered, the results did not specifically delve into the unique nature of travel video content and the motivations of viewers.

We believe understanding the interplay between positive and negative emotional content within the realm of YouTube travel videos is particularly important providing valuable insights for travel marketers and content creators to optimize engagement strategies and cater to the unique needs and preferences of their audiences.

2. Theoretical Background

2.1 Viewer Engagement Behavior

Engagement refers to a user-initiated action that leads co-creation of value (Brodie et al., 2013). Scholars have recognized that engagement encompasses not only emotional and cognitive aspects but also behavioral outcomes (Hollebeek, 2011). For this study, we specifically focus on the behavioral aspect of engagement within the context of social media, particularly YouTube.

Prior research has categorized social media engagement behavior under three stages depending on the degree of activeness: consuming, contributing, and creating (Dolan et al. 2016). Consuming represents the initial phase where viewers passively consume existing content without active contribution (e.g., viewing videos or clicking to read the description). Contributing occurs at the second level, where users engage with the content through actions like "liking" or sharing videos. Lastly, creating denotes the highest level of activity, where users generate new content, which includes writing comments.

In the current study, our primary interest lies in post-watching engagement behavior on YouTube. We focus on the actions of "like" and “comment”, as they are considered core elements of engagement, publicly visible, and measurable actions built into the social media platform. "Like“ and ”comment“ represent different levels of commitment and require varying levels of effort, with distinct mechanisms driving each action. "Like" signifies contribution according to Dolan’s classification, the lowest level of participatory action on YouTube, serving as a form of user vote expressing appreciation for content (Kahn, 2017). The action of liking only requires simple clicking which taxes minimum cognitive effort. Prior studies suggest that ”like“ is more intuitive and reflexive compared to other engagement actions (Labrecque et al., 2020; Swani et al., 2017).

Commenting, as a representative form of creating action on YouTube, differs significantly from liking in terms of effort invested and activeness. Writing comments involves multiple steps, such as clicking the comment button, composing the response, and posting it. Commenting often requires reading other comments to provide a valid response, and thus, it demands more cognitive resources and effort than liking actions (Swani and Milne, 2017). Additionally, comments are displayed under the username of the posting party, offering an opportunity for self-presentation. As a result, writing comments requires more time and cognitive resources (Sabate et al., 2014).

Due to the inherent differences between liking and commenting, factors influencing the number of likes and comments for YouTube videos may vary. For example, Kahn (2017) demonstrated that both hedonic motives (relaxation and entertainment) and utilitarian motives (information-seeking) have a positive and significant influence on "like," whereas, for the number of comments, only the information-seeking motive shows a significant impact. Similarly, Munaro et al.(2021) argue that consumers assessing likes are likely to be influenced by non-diagnostic cues such as number of followers and number of views whereas consumers assessing comments are likely to be influenced by the message contents.

2.2 Valence of Emotion

Emotions are "fuels for drives, for all motion, every performance, and any behavioral act" (Fonberg, 1986, p. 302). The impact of positive and negative emotions on consumer behavior has been widely recognized, with marketers strategically utilizing emotional appeals to influence purchase decisions (Williams, 2014). Previous studies on emotional valence have taken different approaches, treating positive and negative emotions as separate constructs or using a bipolar scale of single measures. Some argue that positive and negative emotions are independent dimensions that co-occur or vary depending on the context, suggesting that combining them on a single scale might overlook the nuances and complexity of emotions (Watson et al., 1988; Babin et al., 1998; MacCann et al., 2020). On the other hand, other studies suggest a possible trade-off between positive and negative emotions, favoring the use of bipolar approaches to capture the full spectrum of emotional experiences (Ciarrochi et al., 2015; Quoidbach et al., 2015).

Current research adopts an approach treating positive and negative emotions as separate constructs. YouTube videos offer a unique platform for diverse emotional experiences, often expressing a blend of emotions that cannot be easily confined to a single valence dimension, such as a mix of joy and sadness or curiosity and fear. It is noteworthy that, unlike short advertisements, YouTube videos tend to be long, with an average length of around 11.7 minutes according to

Statistia(2019). Similarly, the average length of YouTube travel videos collected for this study reached 9.5 minutes. Moreover, a separate measurement of positive and negative emotions allows us to account for the intensity and duration of each emotion, providing a more comprehensive understanding of their impact. Also, the current approach is consistent with prior research in emotion measurement, where behavioral measures tend to reveal an independent structure, while self-report measures often show a bipolar structure of emotional valence (Larsen and Prizmic-Larsen, 2006). In this study, we use behavioral data by extracting narrations from YouTube videos and analyze emotional valence.

Among the two valences of emotions, the influence of positive emotions on eliciting favorable responses from consumers has been well-documented in various communication settings (Teixeira et al., 2012). This phenomenon is particularly pronounced on online platforms where social sharing is common, and positive expressions are considered desirable (Utz, 2012; Moreno et al., 2011). As a result, a substantial portion of content reflecting positive emotions has been observed, rather than negative ones (Reinecke and Trepte, 2014). A similar effect has been witnessed on YouTube, as previous research has indicated that videos with positive emotional tones tend to elicit positive responses from viewers (Hasan, 2019), leading to a higher level of engagement (Kujur and Singh, 2018).

Recent studies, however, have shown that negative emotions can have a positive influence on communication effectiveness, leading to higher levels of engagement (Munaro et al., 2021; Labrecque et al., 2020). For instance, Tafesse (2020) discovered that YouTube video titles containing negative emotions tend to attract a higher number of views. These results can be attributed to the negativity bias (Baumeister et al., 2001) which suggests that negative emotions have a more profound impact on individuals than positive emotions. Additionally, negative content can be perceived as more diagnostic and informative (Chen, 2020). Such diagnosticity of negative emotional content arises from its association with authenticity and honesty. When content creators express negative emotions, it is seen as a reflection of real experiences and genuine reactions (Cheong and Morrison, 2008), fostering viewer trust and engagement.

Contents containing high levels of negative emotions may require higher cognitive resources to process (Lang et al., 2007). According to the feeling-as-information theory (Schwarz, 2012), experiencing bad moods may signal the presence of problematic situations, whereas good moods may indicate benign situations. This difference in context realization influences information processing style. Consequently, positive moods lead individuals to use less effortful and heuristic information processing, while negative moods recruit a more analytical and elaborate style of thinking (Forgas, 2013). These assumptions align with accumulating evidence in communication. For instance, Chen (2020) proposed that processing online content conveying negative emotions requires more cognitive effort from viewers than positive emotions.

2.3 Emotion and Engagement Behavior

Prior research has suggested that people are motivated to watch YouTube travel videos for two primary reasons: seeking information and seeking entertainment (Kim et al., 2016; Silaban et al., 2022) These motivations have consistently been linked to increased engagement and active participation Kim et al., 2021). Notably, research examining the relationship between viewers' motivations and their engagement behaviors on YouTube has revealed that heightened information-seeking and entertainment motivations predict different forms of engagement (Kahn, 2017).

According to the findings of Kahn (2017), both the motivation to seek information and the motivation to seek entertainment have a positive influence on the action of liking a video. However, when it comes to commenting, it appears that the only information-seeking motive exerts a significant influence. Individuals primarily driven by entertainment motives tend to engage with videos by watching, reading comments, and 'liking' content but are less inclined to take the additional step of writing comments.

While not explicitly stated in the study, it's plausible that the level of involvement varies between those who engage by 'liking' videos and those who comment. 'Liking' a video is a simple and accessible action, allowing both highly involved and less-involved individuals easily engaged, whereas composing comments demands effort and cognitive resources. Those in search of information may be actively planning upcoming trips, motivating their high involvement. Conversely, those primarily seeking entertainment are more likely to exhibit low involvement.

Drawing upon the Elaboration Likelihood Model, it becomes evident that different levels of involvement can elicit distinct styles of information processing. Individuals with high involvement tend to be influenced by central messages containing substantial information value. In contrast, those with low involvement are more susceptible to peripheral cues that evoke positive emotions. Previous research indicates that negative information often carries an authenticity and diagnostic value (Chen and Farm 2020). Consequently, it's probable that less-involved individuals are influenced by the positive emotions conveyed in YouTube videos, while highly involved viewers are more receptive to negative emotions.

Considering that 'likes' are contributed by a diverse array of consumers, ranging from highly involved potential travelers to entertainment seekers, it's likely that the number of 'likes' is influenced by both positive and negative emotions. In summary, we hypothesize the following:

H1. The level of positive emotions in YouTube videos is positively related to the number of likes for the video.

H2. The level of negative emotions in YouTube videos is positively related to the number of likes for the video.

In contrast, writing comments requires greater effort. Thus, those engage in commenting are likely to be potential travelers with higher involvement. Building on this assumption and the logic that high involvement viewers are likely to respond to negative information, we predict that contents with negative emotions have a positive influence on the number of comments that the video receives. On the contrary, positive emotional valence may not have a significant impact on the number of comments. Several prior studies support our prediction. For instance, Chmiel et al. (2011) found that posts with negative emotions can stimulate discussion and interaction, leading to more engaging and interactive conversations. Similarly, cognitively involved readers prefer double-sided reviews over one-sided (positive) reviews (Munaro et al., 2021). Accordingly, we hypothesize:

H3. The influence of the level of negative and positive emotions on the number of comments is different. Only the level of negative emotions on YouTube videos is positively related to the number of likes for the video.

3. Methodology

3.1 Sampling and Data Crawling

To test the research hypotheses, we collected a total of 4,619 videos related to eight cities from YouTube, posted between August 31, 2015, and August 31, 2020. To ensure diverse representation, we classified the world's most visited cities into three categories based on their destination image from Beerli and Martins (2004). Subsequently, we selected the top cities from each category for analysis. The city selection was based on visitor numbers in 2018, as reported by Euromonitor International in 2019. This process resulted in the following eight cities being chosen: Macau, Phuket, Miami (leisure/natural environment category), Paris, Rome, Istanbul (culture, history, and art category), London, and New York City (metropolitan category). To identify the contents related to travel, we crawled videos that contained the words "travel," "trip," or "tour" along with the name of the target city in their titles or introductory description.

For the extraction of data, we utilized the Amazon Rekognition API, a pre-trained model provided by Amazon Web Services (AWS). To obtain content features of the videos, we downloaded Web Video Text Tracks (WebVTT) files, which provided textual data from the audio content, which we then saved in Json files. Subsequently. Given the variability in video lengths, we used the median length of 9 minutes and 30 seconds as the cutoff point. Videos shorter than this duration were included entirely, while longer videos were trimmed to include only the content that fell under the time limit.

3.2 Data Collection Process

First, for each video, we collected information on the number of likes, and comments, as well as descriptive characteristics related to the video post.

Then, we employed the Linguistic Inquiry and Word Count (LIWC) software developed by Pennebaker et al. in 2015 for analysis of the textual data converted from audio contents. LIWC software offers a comprehensive dictionary with over 90 linguistic and psychological dimensions, encompassing more than 6,000 carefully categorized words and word stems. The content for each video (in text format) was tested against the LIWC sentiment analysis program and the automatically generated outcomes which include the count of vocabularies related to positive and negative emotionality.

Finally, to address the significant linguistic style differences between general user-generated (e.g., vlogs) and company/organization-generated content (e.g., promotional videos), we performed a classification of the videos into these two categories by two human coders. The coders were hired and well-trained through a detailed instruction session and a series of meetings to ensure good intercoder reliability. Two coders independently reviewed a sample of 100 selected videos and classified them based on coding guidelines. Then, through a series of multiple discussion sessions, the two assistants exchanged and discussed their results and resolved conflicts. The intercoder reliability was calculated by Holsti(1969)' s reliability coefficient. The coefficient for the content analysis was .92, which was acceptable (Wimmer & Dominick, 1997).

3.3 Variables

Table 1 presents the descriptive statistics and correlations of variables used in our study. Two dependent variables that capture viewer engagement are the cumulative number of likes and comments that each video received. Positive and Negative emotions were calculated through automated text analysis using the Linguistic Inquiry and Word Count (LIWC) software, specifically utilizing the SALEE (Syntax-Aware LexicaL Emotion Engine) module. SALEE detects emotions and sentiment in text, categorizing each emotion as negative (indicated as "badfeel" in LIWC), neutral ("ambifeel"), or positive ("goodfeel"). For our analysis, we focused on the scores of negative and positive emotions. Negative emotion represents the proportion of the text expressing negative emotions, including Boredom, Sadness, Disgust, Anger, and Fear. Positive emotion represents the proportion of the text expressing positive emotions, including Love, Joy, Amusement, Gratitude, Admiration, Calmness, and Excitement. All emotion scores fall between 0.0 and 1.0.

In addition, we included several control variables in our analysis. The posting period was calculated as the number of days from the first date of posting to the data extraction date. Video length was measured as the total duration of the video in minutes. The number of subscribers for each channel that posted the video was log-transformed. Furthermore, we recorded the creator type as 1 for videos created by general users and −1 for videos created by companies/organizations.

Tab. 3-1 Descriptive Statistics and Correlations

Continuous variables	Mean	S.D.	Min.	Max.
Number of likes	1785.98	9803.34	0.00	273,000
Number of comments	156.16	653.32	0.00	12,812
Positive emotion	.18	.14	0.00	1.00
Negative emotion	.05	.06	0.00	1.00
Posting period (days)	615.43	489.90	0.00	1,825
Length (min.)	12.15	19.93	0.17	735.00
Number of subscribers	62756.73	270708.32	0.00	15,000,000

Categorical variables	Category	N	Percent
Creator type	1(General user)	4,085	88.4%
	-1(Organization/Company)	536	11.6%

Tab. 3-2 Correlations

Continuous variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)Number of likes	1						
(2)Number of comments	.90	1					
(3)Positive emotion	.25	.00	1				
(4)Negative emotion	.07	.06	-.10	1			
(5)Posting period	.06	.06	.04	-.01	1		
(6)Length	.06	.09	-.04	.01	-.05	1	
(7)Number of subscribers	.17	.17	-.01	-.00	.07	.03	1

3.4 Analysis Model

The two dependent variables used to assess user engagement were the number of likes and the number of comments per video post (j). The model for each variable can be represented as:

(logλij)ɣij = β0 + β1 (positive_emotionj) + β2 (negative_emotionj) + β3 (posting_periodj) + β4 (lengthj) + β5 (subscriberj) + β6 (creatorj) ∈ij:

where logλij is the rate of the negative binomial distribution and ∈ij is the distributed error terms for dependent variables.

Given the overdispersion observed in multiple variables, we opted to use a negative binomial distribution for the analysis, following previous studies (Munaro et al., 2021; Hughes et al., 2019; Van Laer et al., 2018). This choice was made to achieve a better goodness-of-fit for the model, as indicated by the Akaike and Bayesian information criteria (AIC and BIC). In Table 3-3, a comparison of AIC and BIC is provided for the current model, using both a negative binomial distribution and a Poisson distribution.

Tab. 3-3 Goodness-of-fit by distribution assumption

	Poisson distribution		Negative binomial distribution	
	Likes	Comments	Likes	Comments
AIC	34,675,836.87	2,426,924.98	75,519.68	53,800.21
BIC	34,675,881.93	2,426,970.02	75,564.72	53,845.27

3.5 Result

Regarding the number of likes, both positive emotion and negative emotion showed significant positive effects, supporting H1 and H2. Controlling for other variables, an increase in positive emotions led to a higher number of likes (β = 0.985, $p < .001$). Similarly, higher levels of negative emotions also resulted in a higher number of likes (β = 5.972, $p < .001$).

In contrast, for the number of comments, the effect of positive emotion and negative emotion diverged. Only negative emotion showed a significant influence on the number of comments(β = 3.795, $p < .001$) while positive emotion did not ($p > .05$): thus, H3 is supported. As expected, a higher level of negative emotion expressed in the YouTube video content led to a greater number of comments but positive emotion did not. Table 3-4 presents the results of our analysis.

Tab. 3-4 Negative binomial regression results

Variable	likes		comments	
	B	Std. Error	B	Std. Error
Intercept	5.070***	0.053	3.305***	0.047
Positive emotion	0.985***	0.147	0.169--	0.125
Negative emotion	5.972***	0.340	3.795***	0.300
Posting period (days)	0.001***	0.000	0.001***	0.000
Length (min.)	0.043***	0.002	0.039***	0.002
LN(Number of subscribers)	0.052***	0.003	0.061***	0.003
Creator type	0.877****	0.046	0.735***	0.047
LL	-37758.838		-26893.104	
AIC	75519.676		53800.208	
BIC	75564.742		53845.273	
Observations	4,619			

4. Conclusion

The prevalence of potential travelers relying on YouTube as their primary source of travel information is steadily increasing. Recent surveys show that over 30% of Korean travelers aged 20 to 59 used YouTube to gather travel information before their trips (Source: 2023 Consumer Insight Travel Planning and Behavior Research). This study aims to investigate the factors that influence viewer engagement with travel-related YouTube videos. By analyzing a large sample of 4,619 YouTube videos, we have confirmed that the emotions expressed in these videos significantly impact viewer engagement. Moreover, we have discovered that the influence of positive and negative emotions differs depending on the type of engagement. Specifically, both positive and negative emotions in travel-related YouTube videos contribute to the increase in "likes." However, for comments, only negative emotions play a significant role.

This finding suggests that distinct modes of information processing may be triggered among viewers who choose to 'like' and those who opt to comment on YouTube videos. Clicking "like" is a simple and easy action, accessible to both highly and less-involved individuals, while writing comments may be more commonly done by highly-involved individuals. People with low involvement tend to rely on peripheral processing whereas those with high involvement tend to undergo central processing for attitude formation. These differences in the level of involvement and processing styles among viewers who engage in 'liking' and 'commenting' actions appear to lead to varying influences of negative and positive emotions.

Our results extend the findings from earlier research emphasizing the multifaceted nature of social media engagement (Laberequet et al., 2020; Munaro et al., 2021; Song et al., 2020). It underscores that when assessing the extent of engagement, 'likes' and comments should not be regarded as equivalent variables but rather as distinct components.

The current study aligns with previous research that highlights the positive influence of negative emotions. Various studies on social media have shown that negative emotions draw more attention from viewers and increase engagement (e.g., Kujur and Singh, 2018; Munaro et al., 2021). Our results also corroborate the findings from prior research by showing the role of negative comments in inducing viewers' behavioral responses.

Furthermore, this research contributes to the literature on travel marketing. While YouTube's significance in the tourism industry is growing, studies specifically focusing on this domain remain limited. The unique nature of travel products, being hedonic in nature but requiring candid and indirect information for decision-making, presents distinct challenges and opportunities for marketers.

Our study also provides valuable insights for marketing practitioners. Destination marketing organizations and companies are increasingly tailoring their content to suit specific media contexts. To ensure successful engagement from viewers, marketers must understand the characteristics of videos that attract higher attention and engagement from potential travelers. The emotional tone and presentation of content play crucial roles in achieving this. Additionally, depending on target customers' characteristics, such as temporal distance from the trip, firmness of travel plans, and motivation to watch videos, the emotional valence of the video should be adjusted accordingly.

The findings from our current research can be directly applied to YouTube marketing within the service sector. Service products are typically experiential goods, and consumers seek opportunities for indirect experiences. Consequently, communication through YouTube vlogs should exert a significant influence on viewers' purchase decisions. Building upon the insights from our research, marketers should be adept at a balance in the emotional tone of their content depending on the level of involvement of target customers.

However, it is essential to acknowledge the limitations of our research. Prior studies suggest that the influence of specific emotions may vary, even when they share similar valence. For instance, anger and fear may elicit different reactions among viewers despite both being negative emotions. Exploring such nuances in emotional effects could provide additional insights into the success of YouTube marketing strategies.

Additionally, while the current research delves into the distinct influence of positive and negative emotions, it's equally important to comprehend the intricate interplay between these emotional states. The impact of negative emotions may vary significantly depending on whether they dominate, positive emotions dominate, or both coexist at similar levels. In our dataset, it's noteworthy that the average level of negative emotions is lower than that of positive emotions. Past research has indicated that an excess of negativity has the potential to deter viewers and create unfavorable associations with content (Tafesse, 2020). Conversely, well-constructed two-sided messages, adept at presenting both positive and negative facets, tend to be more persuasive and credible (Petty et al., 2004). Therefore, future research should explore the optimal balance between positive and negative emotions that fosters sustained viewer engagement.

Another notable limitation lies in the oversight of considering the structural characteristics of comments on YouTube videos in the current research. It is important to acknowledge that comments on YouTube can take various forms and serve different purposes, such as direct responses to the video content or reactions to other users' comments. This variability introduces a level of ambiguity when interpreting the quantity of comments and their intended meanings. To advance our comprehension of the distinctions between likes and comments, future studies should emphasize an exploration of the structural dimensions of comments. This may encompass a more comprehensive analysis of comment threads and the categorization of comments into distinct types. Additionally, gaining insight into the contextual relevance of comments within the broader video discussion and unraveling the dynamics of interactions among users has the potential to furnish valuable insights into viewer engagement behavior.

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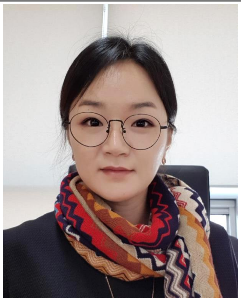	Yoo, Jinyoung (jinnieyoo@gachon.ac.kr) Yoo, Jinyoung is an associate professor of marketing in the College of Business Administration at Gachon University. Her main focus in research lies in the realms of multicultural advertising, consumer psychology, and marketing via emerging media platforms.
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유튜브 여행 동영상의 긍정적 감정과 부정적 감정이 사용자 참여에 미치는 영향

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ABSTRACT

여행 마케팅 분야에서 브이로그와 같은 동영상 기반 소셜미디어 컨텐츠의 중요성이 높아지고 있다. 그럼에도 불구하고 시청자 반응 및 참여 행동을 향상시키는 콘텐츠 특징에 대한 연구는 제한적이다. 본 연구는 유튜브 여행 콘텐츠의 나타난 감정이 시청자 참여 행동, 특히 "좋아요"와 "댓글" 작성에 미치는 영향을 연구하였다. 본 논문에서는 방문자 수가 높은 세계 8개 관광도시에 관한 여행 관련 유튜브 동영상 4,619개의 나래이션을 머신러닝으로 추출하여 텍스트화 한 후 음이항 회귀분석을 통해 분석하였다. 그 결과 긍정 감정 및 부정의 감정 모두 "좋아요" 수에 유의한 영향을 미쳤다. 즉, 동영상에서 나타난 긍정적인 감정과 부정적인 감정이 각각 높을수록 더 많은 시청자들이 "좋아요"를 클릭하는 것으로 나타났다. 댓글 수에 측면에서는 부정적인 감정만 유의한 영향을 보인 반면 긍정적인 감정은 유의한 영향을 미치지 않는 것으로 나타났다. 본 연구는 경험재인 여행 상품의 고유한 특성을 고려할 때 유튜브에서 시청자 참여를 높이고자 하는 마케터들에게 어떠한 동영상 특징이 "좋아요"와 댓글등의 참여 행동을 유도할 수 있는지를 이해하고 전략 수립에 도움을 준다는 면에서 시사하는 바가 크다. 또한 소셜 미디어, 특히 유튜브의 맥락에서 시청자 참여도에 미치는 감정의 영향력을 검증하였다. 향후에는 감정에 대한 긍정-부정의 분류를 넘어 특정 감정이 참여도에 미치는 영향에 대한 고찰을 통해 소셜 미디어 동영상에 나타난 감정의 역할에 대한 이해를 깊이 할 수 있을 것이다.

Keywords: 유튜브, 관광, 감정가, 시청자 참여, 소셜 미디어 마케팅, 여행 마케팅

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