Proceedings of the 57th Hawaii International Conference on System Sciences | 2024

Exploring the Moderating Effects of Media Complexity on the Relationship between Message Content and Individual Responses in Social Media

Timothy Kaskela
Oregon State University
timothy.kaskela@oregonstate.edu

Jaeki Song
Texas Tech University
jaeki.song@ttu.edu

Abstract

Message content has been researched extensively on how it impacts social media engagement. However, there is a research opportunity to examine the moderating effect of individual media complexity components on the relationship between message content and engagement. This study examines how combinations of message content and luminosity, number of colors, and edges affect the sentiment of responses from the individual. A year of Facebook posts is collected from nine different companies. It is found that brand personality content is positively moderated by luminosity and number of colors but is negatively moderated by edges. Directly informative content is positively moderated by luminosity and negatively moderated by number of colors and edges. Practical applications of the results are outlined for increasing positive social media engagement behavior.

Keywords: social media, media complexity, engagement, luminosity, colors, edges

1. Introduction

As technological advancements have resulted in the migration of a large amount of communication, effectively constructed digital environments have become more vital for organizations. Participating in social media enables firms to enhance customer engagement, create viral posts, examine firms' value, among other advantages (Borah et al., 2020; Chung et al., 2020; Pansari & Kumar, 2017; Yang et al., 2019). Many studies have been conducted on social media interactions between companies and consumers. In particular, consumer response to issues posted by organizations on their social media has become critical in organizations' evaluations, reputations, and performance. Consumer response can vary depending on how organizations formulate and convey their issues through social media or, in other words, how organizations present content to create customers' responses (Addas & Pinsonneault, 2018; Barry & Fulmer, 2004; Munter et al., 2003). In presenting organizational issues in social media, using different combinations of media to deliver messages has become vital. This has led information systems (IS) researchers to examine the drivers behind media selection (George et al., 2013), the effects of communication medium and diversity on decision-making (Robert et al., 2018), and the effects of communication medium and culture on deception detection (George et al., 2018). In this study, we investigate another aspect of media, media complexity, and the content of a social media post. Complexity is defined as the level of redundancy within an image (Pieters et al., 2010) embedded in information posted on social media, which affects communication and task performance (Donderi, 2006b). Recent IS studies have shown that visual complexity can influence emotional response and behavior on websites (L. Deng & Poole, 2010), as well as shape attitude and brand reputation (Jiang et al., 2016). This leads us to explore the moderating effect of media complexity on the relationship between social media messages and individuals' responses.

The objective of this study is to investigate this moderating effect because of its importance in theoretical and practical implications. Theoretically, this study constructs a foundation to present how an organization formulates individuals' opinions through social media. The findings could help explain the importance of media complexity in formulating individuals' opinions. Positive opinions have been found to be vital for an organization, with impacts such as higher stock prices (S. Deng et al., 2018; Ren et al., 2022), increased loyalty (So et al., 2016), and brand reputation (Jiang et al., 2016). Understanding this moderating effect yields the potential to guide firms in developing their social media strategies. In current environments, our study reveals different approaches to formulating individuals' opinions for accelerating their acceptance of firms' products or services. Such understanding is vital to inform firms on how to

URI: https://hdl.handle.net/10125/106694
978-0-9981331-7-1

effectively allocate their social media strategies to improve responses from their customers.

These findings contribute to the IS literature by providing support for media complexity being a driver of individuals' responses in social media engagement. While social media content has been well studied in a variety of environments, there are still factors that have not been considered. Our findings bolster the role of media complexity by providing evidence of the effect on responses, as well as of the interaction of message content and media complexity. By extending the existing social media literature to consider the media complexity utilized when presenting information online, application can be extended to a variety of contexts.

2. Theoretical Background and Hypothesis Development

2.1 Social Media Consumer Engagement

The increase in the usage of social media platforms as a medium for organizations to interact with individual consumers has led to a drastic shift in communication in a digital medium. This shift is communication has led to greater understanding of the importance of the construction of a social media post and how it will impact individuals' responses to an organization's post. The importance of this construction has led to numerous studies examining various components of a social media post, including the message and media type (Li & Xie, 2020; Liu et al., 2020; Yang et al., 2019) and how they impact engagement behavior.

Social media theory development has previously utilized Uses and Gratification Theory (UGT) to lend greater understanding of usage of social networks (Chiu & Huang, 2015) and user engagement behavior based on the motivation of the end user (Dolan et al., 2016, 2019; Shahbaznezhad et al., 2021). Individuals utilize social media with different motivations and an organization can satisfy them by fulfilling these motivations (Hu et al., 2015). Two motivations for social media usage are information seeking (Chiu & Huang, 2015; Dolan et al., 2016, 2019; Hu et al., 2015) and relationship building (Chiu & Huang, 2015; Dolan et al., 2016, 2019; Hu et al., 2015). These motivations can be gratified by an organization through the creation of social media posts. Two predominant message content types for user gratification have been identified under various names but can be distilled as emotional or informative (Dolan et al., 2019; Lee et al., 2018; Meire et al., 2019). The differing nature of the individual's motivations means that social media posts need to be constructed in different ways to gratify the individual. Positive outcomes would be expected if the post construction delivered content that gratified the needs of the individual. This post construction will be examined through two components of a social media post: content message, defined for our study as the message that is intended to be conveyed, and content features, defined for our study as the manner in which the message is transmitted to the individual (Han et al., 2020).

The goal of a social media post is to convey the intended message of a social media post in such a way that it is processed accurately by the recipient of the social media post. Message content has been widely studied within the social media literature (Dolan et al., 2019; Lee et al., 2018; Tellis et al., 2019). Posts have been classified as emotional or rational posts (Dolan et al., 2019; Shahbaznezhad et al., 2021), informational or emotional (Meire et al., 2019; Tellis et al., 2019), and a construction of multiple variables related to brand personality or directly informative (Lee et al., 2018). There is overlap in the informational, rational, and directly informative post characteristics, as well as the emotional and brand personality post characteristics. The classification of social media posts in this study follows previous studies in identifying the brand personality aspects of a post, as well as the directly informative aspects of a post.

The sentiment of an individual's response would be expected to be elicited by their emotional response. It would be expected, therefore, that message content that elicits a stronger emotional response would have a higher likelihood of a response with positive sentiment. A customer's relationship is able to be built when a brand is perceived as having personality traits (Aaker, 1997; Aaker et al., 2004). An emotional connection positively impacts the perception of a brand, along with the probability of other behavioral intentions (Guèvremont & Grohmann, 2013). As previous research has ascertained the elicitation of an emotional response, we expect to find the same direct effect when a social media post includes brand personality components. Rational or directly informative content has a negative impact on the emotional response from an individual (Lee et al., 2018; Tellis et al., 2019). Staying consistent with these prior findings, this leads us to Hypothesis 1.

H1a: Brand personality content has a positive direct effect on positive responses.
H1b: Directly informative content has a negative direct effect on positive responses.

Advanced technology enables firms to incorporate complicated media in their posts with various levels of visual complexity. Visual complexity affects emotional response in environments as varied as website design (L. Deng & Poole, 2010), city skylines (Heath et al., 2000), and retail stores (Jang et al., 2018). A recent study shows that there are different facets of visual complexity that can be decomposed into two different factors: pixel and object level complexity (Shin et al., 2020). One component of visual complexity, pixel level complexity, is a peripheral cue that only induces low-level visual processes (Pieters et al., 2010; Shin et al., 2020). Pixel level complexity consists of the color, luminance, and edges within an image (Donderi, 2006a; Pieters et al., 2010; Shin et al., 2020), and has been shown to be a prominent driver of gaining both likes and shares in social media (Shin et al., 2020). Given the established measurements of pixel complexity, this study will examine the three components of pixel level complexity and their sole effects on user responses. In this study, media complexity refers to the pixel level complexity within a post in a digital platform. According to media complexity studies, it is expected that the complexity of the media at a pixel level will influence the emotional response to a post in conjunction with the content of the social media post and impact engagement behavior (Madan et al., 2018; Pieters et al., 2010; Shin et al., 2020).

Edges have been found as a measurement of complexity that increases emotional arousal as it increases (Madan et al., 2018). It is important to note that this emotional arousal could be either positive or negative, increased edges would be expected to increase the emotional response, no matter if it is positive or negative. Given these prior findings, we only expect that the number of edges will be significant, but not a positive or negative effect. This leads to Hypothesis 2a:

> H2a: The number of edges will have a significant effect on positive responses.

Color has been extensively studied within the psychological research field and has been demonstrated to impact emotional arousal and elicitation in a variety of settings (Bellizzi & Hite, 1992; Gorn et al., 1997; Valdez & Mehrabian, 1994; Warner & Franzen, 1947; Wilms & Oberfeld, 2018). As previous studies have focused on specific hues and their impact on emotional response, we will be examining colors in a from a different perspective, color complexity, or the total number of colors in an image, which leads to Hypothesis 2b.

> H2b: The number of colors will have a positive direct effect on positive responses.

Luminosity has been associated with higher levels of valence across various colors (Wilms & Oberfeld, 2018), and has led to a more positive attitude (Gorn et al., 1997). Following these previous findings, this leads to Hypothesis 2c.

> H2c: Luminosity will have a positive direct effect on positive responses.

Prior research has found that there are significant effects between text and an image within a social media post (Shin et al, 2020). Therefore, we expect that the pixel level complexity components and the text content of will have an interaction effect.

The message content of a social media post is expected to be moderated by edges. Brand personality has been shown to elicit positive emotional arousal from the end user, the increase of edges would encourage positive responses as both edges and brand personality are drivers of positive emotional response. The opposite is true for directly informative message content as it has been found to have a negative direct effect on engagement (Lee et al., 2018). The negative direct effect of directly informative message content and the impact of edges on emotional arousal would drive negative response.

Building on UGT, the goal of a post and the media complexity used in the post need to enable the optimal interpretation of the desired idea. We postulate that the directly informative content would have a higher positive response with a lower number of edges. Since the number of edges is driver of emotional response, and the directly informative content has a negative impact on sentiment, a lower number of edges would work to reduce the negative direct effect of directly informative message content.

An increased number of edges would be anticipated to strengthen the emotional response of the message content. While this is not ideal for the directly informative message content, it would be expected that a higher number of edges would have a positive moderating effect on brand personality message content. Since posts with brand personality involve the necessity of building an emotional connection, a higher number of edges would elicit higher emotional arousal, which leads to more positive individual response. This leads to Hypothesis 3a and 3b:

> H3a: The relationship between brand personality content and positive responses is positively moderated by the number of edges.
> H3b: The relationship between directly informative content and positive responses is negatively moderated by the number of edges.

It is expected that the color complexity would impact the direct effect of brand personality and directly informative content on emotional response. Given the connection between color and emotional response, as well as the connection between brand personality and emotional response, a higher number of colors would be expected to positively impact posts related to brand personality. Color complexity can lead to misperception of colors, a higher number of colors within an image would increase the possibility of this issue (Wang et al., 2020). Following the same logic for the number of edges within an image and its moderating effect on emotional response, we would also anticipate that the directly informative content would be negatively moderated by an increased number of colors. This leads us to Hypothesis 3c and 3d:

> H3c: The relationship between brand personality content and positive responses is positively moderated by the number of unique colors.
> H3d: The relationship between directly informative content and positive responses is negatively moderated by the number of unique colors.

It is expected that posts with higher brand personality and higher informational content will have more positive responses with higher luminosity. Unlike the number of colors or edges, a higher luminosity would not be expected to detract from a directly informative message. If the key difference is that an image has more luminance, it would be expected that additional filtering of unnecessary cues would not be required. Therefore, we expect that higher luminosity will follow previous literature in leading to more positive responses for both posts with higher brand personality content and higher directly informative content. This leads us to Hypothesis 3e and 3f:

> H3e: The relationship between brand personality content and positive responses is positively moderated by luminosity.
> H3f: The relationship between directly informative content and positive responses is positively moderated by luminosity.

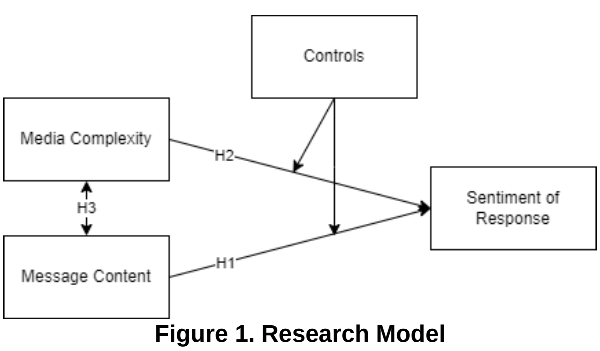

Figure 1. Research Model

3. Research Method

3.1 Data Collection

Our unit of analysis was the interaction between the individual and an organization. Our sample consisted of secondary data collected from Facebook, where organizations' posts can be observed, and their influence can be analyzed through the comments posted in response by users. The number of users on Facebook has made it a frequent platform for studies in IS research (Yang et al., 2019; Zhang et al., 2016). The observability of responses to a post is an advantage because both sides of a transmitted message are available for analysis. The construction of the message by the organization can be decomposed and assessed, and the responses to the message can be preserved and recorded.

We obtained our data from Facebook by collecting all posts containing an image from September 1, 2017, to August 31, 2018, from nine separate companies. We focus on only posts containing an image as it will allow us to examine the pixel impact of the media. We selected three companies that sell a search good (athletic shoes), three that sell another kind of search good (cell phones), and three that sell an experience good (fast-food restaurants). The good types were selected because they are widespread and well known. An experience good was included to increase the generalizability of the findings. The companies were selected by identifying the largest companies, based on revenue, for each product type. Note this excludes Apple from mobile phones as they had minimal Facebook activity.

The dependent variable for our study was the sentiment of each user's response, which has been used in previous studies in online settings (Das & Chen, 2007; W. Li et al., 2016; Mai et al., 2018), and sentiment as a dependent variable has found support for offline ramifications on a business, including having a predictive effect on sales (Gelper et al., 2018; Sonnier et al., 2011). The offline implications of sentiment as a proxy made it an ideal measure for our study.

The sentiment was calculated by utilizing the FLAIR sentiment package from Python. FLAIR is a deep learning text classifier that uses text embeddings and can be used through a GPU, reducing processing time (Akbik et al., 2019). The sentiment of each comment was classified as either negative or positive by the FLAIR package.

The image within each of the posts was collected and processed to ensure that the subsequent measures were standardized. Each calculation of the media complexity variables occurred at the pixel level, as it was found that pixel level complexity was a leading driver in both the shares (re-blogs) and likes on social media (Shin et al., 2020). Three features were considered part of visual complexity due to use in prior studies: color, luminance, and edges included in an image (Donderi, 2006a; Pieters et al., 2010; Shin et al., 2020; van der Lans et al., 2008). The media complexity calculations were based on the pixel level of the respective media type as pixel level complexity has been found to have a significant impact on the engagement with a social media post (Shin et al., 2020).

The number of colors within an image was found based on the pixel values of the image. The color of each pixel of an image was calculated based on the RGB values. Each image was converted into a matrix where each element is a vector of three elements (the RGB values). K-means clustering was conducted to calculate the number of independent clusters of RGB values within the matrix; the clusters are the distinct colors within the image. The number of clusters was determined through an iterative process from two clusters upwards. Once the distance between centroids was below a minimum threshold (denoting that the clusters were similar), the process was terminated.

To compute luminosity, the color image was converted to grayscale, and then to a matrix that contains the luminosity values for the grayscale image. A grayscale conversion of an image only contains the luminance of an image and eliminates any color. After the images were converted to a matrix, the values were summed and standardized to a value between 0 and 1, with 0 being the equivalent of a black image and 1 being the equivalent of a white image.

To calculate the number of edges, the Canny Method was utilized (Canny, 1986). The final quantification for each image standardized the edge value by determining the number of pixels that were a part of an edge divided by the total number of pixels in the image. Canny Method has been found to have better detection of edges than other edge detection algorithms and will be used for the study (Machado et al., 2015; Maini & Himanshu, 2003). This ratio (the percentage of pixels in an image considered to constitute an edge) will allow for edge comparison across all images.

3.2 Text Content Variables

The text of the social media post was classified primarily on the content variables outlined in previous studies (Lee et al., 2018). There are two categories for the content variables, directly informative variables and brand personality variables. A total of 16 variables, 8 for directly informative and 8 for brand personality, were identified in the text of each of the social media posts through a combination of natural language processing and hand coding.

The eight directly informative variables included in the study were selected from Lee et. al: *BrandMention, Deal*, *PriceComparison*, *Price, Target, ProdAvail, ProdLocation,* and *ProdMention*. However, *Brand Mention* was included in every social media post and was thus removed as a variable. The *Link* informative variable was substituted for the *ProdLocation* variable as the posts would specify that the user follow a link for a product. *Date* was a marker of the inclusion of a specific date or event in the text of the social media post. The variables *PriceComparison, Price, ProdAvail, ProdMention*, and *Deal* were specific to the mention of the price of a product in some manner. The *Target* variable was included when the text of the post was directed at a specific target audience, for example targeting students in the fall. An additional variable, *Hashtag*, was included because it was in a large number of the social media posts, giving a total of 8 directly informative variables. Finally, the Directly Informative variable was the summed value of the variables where the value of a post containing all variables was 8 and the value of one containing no variables was 0.

The brand personality variables included in the study were also selected from Lee et. al: *RemarkableFact*, *Emotion*, *Emoji*, *HolidayMention*, *Humor*, *Philanthropic*, *FriendLikely*, and *SmallTalk*. *RemarkableFact* is defined as information that is considered new or remarkable. The Emotion variable denoted if any emotional words were included within the social media text. The *Emoji* variable (redefined from the *Emoticon* variable in (Lee et al., 2018)) indicated the inclusion of an emoji within the text of the social media post. *HolidayMention* signified that the text of the social media post mentioned a holiday. The *Humor* variable denoted the inclusion of humor within the text. *Philanthropic* indicated the inclusion of text regarding philanthropic information in the social media post. The variables *FriendLikely* and *SmallTalk* were defined as text similar to what a friend would post and small talk text, which was content related to something other than the company or a product, respectively. Each of the eight variables were included in calculating the Brand Personality variable. The identification of the 16 variables of a social media post was conducted through a mix of natural language processing and hand coding.

3.2 Results

A total of 1,047 posts with at least one comment posted in reply were collected. A total of 131,559 comments were included in the analysis. The emotional response of the comment was through the FLAIR sentiment package from Python that specified data as positive or negative (mean = 0.58).

We included a number of control measures in the analysis as follows: *Time since post* was measured as the time elapsed between when the company published a post to Facebook and when the comment was posted in response. The elapsed time between the comment and the initial post was standardized to be between 0 and 1. *Post time of day* and *weekend* variables were included indicating if the corporate post was posted during one of six four-hour blocks or if it was posted during the weekend (Li & Xie, 2020). The weekend variable (mean = 0.15) had a value of 0 if the post was on a weekday and 1 if the post was on a weekend. The previous comments on a post can have a significant impact on the sentiment of a response, as such the volume and the sentiment of the prior comment on the post were controlled through *Number of Previous Comments* and *Prior Sentiment of Post*, respectively (Meire et al., 2019). The number of prior comments (mean = 314.44) indicated how many prior comments were on a post before the individual commented. The prior sentiment of the post was the sentiment of the prior comments on the post, provided there were any. If there were no prior comments on the post, the variable value was 0. The number of prior comments all log-converted as the distribution was right-skewed. A control variable was included for each of the company pages from which data was collected as we would expect perceptions to be different for each respective company. This allowed us to control for company perceptions, company page impact, and to isolate the independent variables. A variable for the number of followers for each post was collected and examined but was dropped from the models as it was highly correlated with the company control variables. Finally, a month-of-the-year dummy variable was added to control for time of year variance for each month.

Model Specification

The dependent variable of sentiment is binomial; therefore, we use logistic regression to model sentiment. The research model examined of the direct effect of *Brand Personality* and *Directly Informative* posts and the interaction between *Brand Personality* and *Directly Informative* posts with media complexity variables. First, the *Brand Personality* variable was examined to determine if there was a direct effect between posts that included brand personality components and the sentiment of responses. The *Brand Personality* variable ranged from no brand personality components (0.00) to every *Brand Personality* component (5.00). Similarly, the *Directly Informative* variable, ranging from 0.00 to 7.00, examined if there was a direct effect of the amount of *Directly Informative* components in a social media post and the sentiment of responses. However, both the *Brand Personality* and *Directly Informative* variables were right-skewed. Therefore, the log of each variable was used for the estimation of the logistic regression model. Other variables were also scaled, for example the time since post variable was scaled to be in a range between 0 and 1.

To examine the moderating variables of media complexity, the interaction coefficients for each of the media complexity variables with the *Brand Personality* and *Directly Informative* variables were examined. The change between the subsequent models was shown to be significantly different, providing evidence for the significant difference between the logistic regression model containing only control variables (Model 1) and the direct effect of the independent variables (Model 2), as well as the difference between the direct effect (Model 2) and interaction effects (Model 3) on the sentiment of responses to a Facebook post. This means that the inclusion of our independent variables and the interactions had a significant effect on the emotional responses from consumers. Table 1 shows the results of the models.

Table 1. Full Model Results

Variable	Model 1	Model 2	Model 3
Intercept	0.587*** (0.035)	0.513*** (0.037)	0.545*** (0.037)
Controls			
Post Sentiment	-0.064*** (0.019)	-0.130*** (0.023)	-0.142*** (0.023)
Previous Comments	0.018* (0.008)	0.015* (0.008)	0.032*** (0.008)
Prior Sentiment	0.142 (0.147)	0.310* (0.153)	0.507* (0.160)
Company Controls	Included		
Time Controls	Included		
Main Effects			
Brand Personality		0.125*** (0.015)	0.140*** (0.015)
Directly Informative		-0.085*** (0.013)	-0.076*** (0.014)
Edges		-0.526** (0.177)	2.714*** (0.377)
Luminosity		-0.183*** (0.036)	-0.594*** (0.069)
Number of Colors		0.021*** (0.004)	0.034*** (0.007)
Interaction Effects			
Edges * Brand Personality			-2.637*** (0.345)
Luminosity * Brand			0.208** (0.075)

Personality			
Colors * Brand Personality			0.048*** (0.006)
Edges * Directly Informative			-1.258*** (0.271)
Luminosity * Directly Informative			0.297*** (0.068)
Colors * Directly Informative			-0.050*** (0.006)
AIC	177067	176938	176721
F-test		$p < 0.001$	$p < 0.001$

Model 1 included only the control variables for and found that company controls and time controls were significant, as well as the prior sentiment of comments and the sentiment of the post itself.

Model 2 included the direct effects for our study: brand personality and directly informative variables and media complexity variables. The brand personality variable was positive and significant (0.125, $p < 0.001$), which supports Hypothesis 1a. The directly informative variable was negative and significant (-0.085, $p < 0.001$), which supports Hypothesis 1b. As previous research has found, brand personality posts have a positive impact on customer engagement and directly informative posts have a negative impact on customer engagement (Lee et al., 2018). While the sentiment of the comment was positive or negative engagement, rather than engagement alone, the results hold true. The number of edges within the media had a negative effect on the emotional response to a post (-0.526, $p < 0.05$), supporting Hypothesis 2a. The number of colors in an image had a significant effect (0.021, $p < 0.001$), supporting Hypothesis 2b. Luminosity had a significant effect on responses (-0.183, $p < 0.001$), which suggests that darker images encourage more emotional response, which does not support H2c. The direct effects of the media complexity variables suggest that a darker image with more colors and less edges would increase emotional response.

Model 3, the full model, included the main and interaction effects for our study. The direct effect of the brand personality variable was positive and significant (0.140, $p < 0.001$), while the direct effect of the directly informative variable was negative and significant (-0.076, $p < 0.001$). The number of edges of a post had a significant and large positive effect on the probability of positive sentiment (2.714, $p < 0.001$). The large coefficient in relation to the other variables was due to the nature of the variable range only having a maximum of 0.250. The number of colors within a post suggests that probability of a positive response to a post will increase as additional colors are included within a post. We found a significant negative interaction between brand personality and edges (-2.637, $p < 0.001$), which does not support Hypothesis 3a, and a significant negative interaction between directly informative and edges (-1.258, $p < 0.001$) which supports Hypothesis 3b. The negative interaction between the directly informative variable and edges was expected, but further investigation into the impact of edges within an image will be warranted. We graphed these interaction effects to better understand the joint effects, shown in Figure 2. The red solid line within each plot is the minimum logged value for brand personality or directly informative (0 in both cases). The blue dotted line within each plot is the maximum logged value for brand personality and directly informative (1.792 and 1.946, respectively). This allows the interaction plots to show the marginal effect of the results.

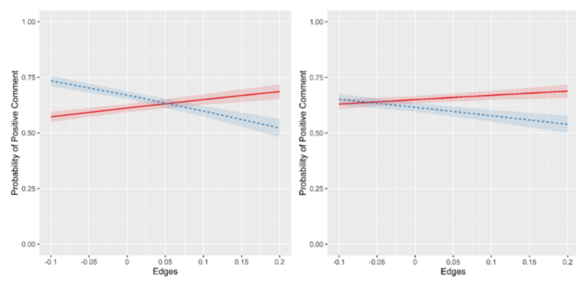

Figure 2. Number of Edges

The interaction for luminosity was positive for both brand personality and directly informative posts, supporting Hypotheses 3c and 3d. We graphed these interaction effects to better understand the joint effects, shown in Figure 3. Again, the red solid line is the minimum logged value for both variables and the blue dotted line is the maximum logged value for both variables. This allows the interaction plots to show the marginal effect of the interaction between luminosity and the brand personality and directly informative variables respectively. It is interesting to note that low and high levels of luminosity have similar probabilities of a positive comment when brand personality content is low. However, when brand personality content is high, high levels of luminosity has a significantly higher probability of a positive comment. For a post that is low on directly informative content, lower luminosity has a higher probability of a positive comment than higher luminosity. The inverse is true when directly informative content is high in a social media post.

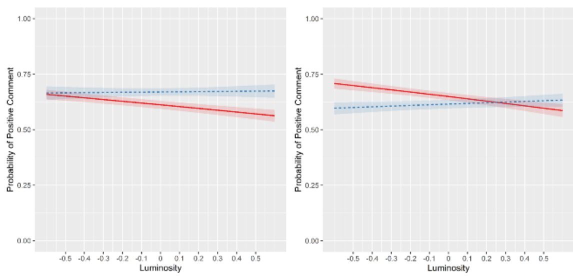

Figure 3. Luminosity

Brand personality and number of colors (0.208, p < 0.001) was found to be positive and significant, while directly informative and number of colors was negative and significant (-0.050, p < 0.001) supporting Hypotheses 3e and 3f. The interaction plots are presented in Figure 4, where the red solid line is the minimum logged value for both variables and the blue dotted line is the maximum logged value for both variables. The number of colors within an image had a significantly higher probability of a positive comment when brand personality content is higher in a social media post. The inverse is true for when a social media post has high directly informative content, a lower number of colors has an increased probability of a positive comment.

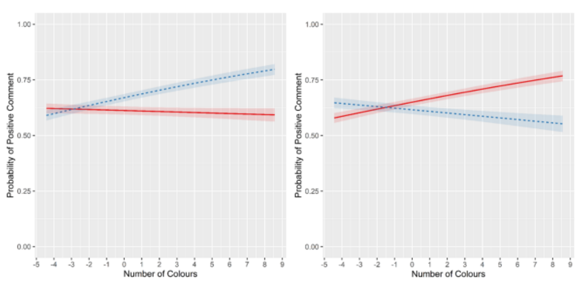

Figure 4. Number of Colors

4. Discussion and Conclusion

The study finds support for brand personality and directly informative content having a positive impact on the probability of a positive comment in response to a corporate social media post, following previous literature (Lee et al., 2018; Tellis et al., 2019). Our study extends these findings by building on the psychological effect of visual complexity (defined as media complexity in our study), measured by the number of edges, luminosity, and the number of colors in a social media post. The study also finds that the effect of brand personality and directly informative content is moderated by the three media complexity variables, lending practical guidance for the construction of social media posts that will have a higher probability of receiving a higher response from the individual.

This study works to bridge the gap between psychological theory examining visual complexity and how these components of complexity are perceived in a digital environment. The examination of luminosity, edges, and color complexity and their moderating effect on post content extends social media engagement theory to lend greater understanding to additional constructs that drive user engagement behavior. Our findings suggest that media complexity should not be considered as a single construct, measured through a proxy such as file compression size, but each of the individual components should be examined to understand their impact on engagement.

The study also found that there is an interaction effect between media complexity and social media content in addition to the direct effect examined in previous studies (Dolan et al., 2019; Lee et al., 2018; Tellis et al., 2019). When a post includes brand personality, a higher number of colors, a lower number of edges, and higher level of luminosity increases the probability of a positive response; when a post includes directly informative content, a higher level of luminosity, lower number of colors, and lower number of edges increases the probability of a positive response. In other words, the strength of each content type is partially based on the complexity of the media used to construct a post. The interactions found in this study suggest that IS scholars need to examine how different combinations of complexity and message content create different levels of emotional response.

With the migration of communication to social media, it is important to understand engagement and interactions between organizations and consumers. Our findings help extend understanding of why these interactions occur in positive or negative manners. The relationship between message content and media complexity measures shows that each measure needs to be considered separately. The number of edges should be considered within a social media post as it was found to decrease the probability of a positive comment when a post included both directly informative and brand personality content. However, there were diverging results related to the number of colors. The direct effect of brand personality content is positively moderated by an increase in the number of colors, but the direct effect of the directly informative content is negatively moderated by the number of colors. These findings offer insight on the creation of an effective social media post. Luminosity has the same positive moderating impact on both directly informative and brand personality content. A corporation should determine the content it wishes to include in a post before selecting the media complexity based on the context. Our findings help serve as a starting point for understanding this selection process.

This study has a few limitations. First, this study focuses on the image media type; further studies could examine the impact of video and audio to determine how the richness of media type would impact positive responses. Second, with the initial effectiveness of posts considered, future studies could examine whether feedback with specific comments could facilitate a greater portion of shared understanding among the commenters. It is possible that feedback from a company could change the subsequent responses from consumers.

5. References

Aaker, J. (1997). Dimensions of Brand Personality. *Journal of Marketing Research*, *34*(3), 347–356.

Aaker, J., Fournier, S., & Brasel, S. A. (2004). When good brands do bad. *Journal of Consumer Research*, *31*(1), 1–16. https://doi.org/10.1086/383419

Addas, S., & Pinsonneault, A. (2018). E-mail interruptions and individual performance: Is there a silver lining? *MIS Quarterly*, *42*(2), 381–405. https://doi.org/10.25300/MISQ/2018/13157

Akbik, A., Bergmann, T., Blythe, D., Rasul, K., Schweter, S., & Vollgraf, R. (2019). FLAIR: An Easy-to-Use Framework for State-of-the-Art NLP. *2019 Annual Conference of the North American Chapter of the Association for Computational Linguistics*, 54–59. https://github.com/zalandoresearch/flair

Barry, B., & Fulmer, I. S. (2004). The Medium and the Message: The Adaptive Use of Communication Media in Dyadic Influence. *Academy of Management Review*, *29*(2), 272–292. https://doi.org/10.5465/AMR.2004.12736093

Bellizzi, J. A., & Hite, R. E. (1992). Environmental color, consumer feelings, and purchase likelihood. *Psychology & Marketing*, *9*(5), 347–363. https://doi.org/10.1002/mar.4220090502

Borah, A., Banerjee, S., Lin, Y. T., Jain, A., & Eisingerich, A. B. (2020). Improvised Marketing Interventions in Social Media. *Journal of Marketing*, *84*(2), 69–91. https://doi.org/10.1177/0022242919899383

Canny, J. (1986). A Computational Approach to Edge Detection. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *8*(6), 679–698. https://doi.org/10.1109/TPAMI.1986.4767851

Chiu, C. M., & Huang, H. Y. (2015). Examining the antecedents of user gratification and its effects on individuals' social network services usage: The moderating role of habit. *European Journal of Information Systems*, *24*(4), 411–430. https://doi.org/10.1057/ejis.2014.9

Chung, S., Animesh, A., Han, K., & Pinsonneault, A. (2020). Financial returns to firms' communication actions on firm-initiated social media: Evidence from Facebook business pages. *Information Systems Research*, *31*(1), 258–285. https://doi.org/10.1287/ISRE.2019.0884

Das, S. R., & Chen, M. Y. (2007). Yahoo! for Amazon: Sentiment Extraction from Small Talk on the Web. *Management Science*, *53*(9), 1375–1388. https://doi.org/10.1287/mnsc.1070.0704

Deng, L., & Poole, M. S. (2010). Affect in Web Interfaces: A Study of the Impacts of Web Page Visual Complexity and Order. *MIS Quarterly*, *34*(4), 711–730. https://doi.org/10.2307/25750702

Deng, S., Huang, Z., Sinha, A. P., & Zhao, H. (2018). The interaction between microblog sentiment and stock returns: An empirical examination. *MIS Quarterly*, *42*(3), 895–918. https://doi.org/10.25300/MISQ/2018/14268

Dolan, R., Conduit, J., Fahy, J., & Goodman, S. (2016). Social media engagement behaviour: a uses and gratifications perspective. *Journal of Strategic Marketing*, *24*(3–4), 261–277.

Dolan, R., Frethey-Bentham, C., Fahy, J., & Goodman, S. (2019). Social media engagement behavior A framework for engaging customers through social media content. *European Journal of Marketing*, *53*(10), 2213–2243. https://doi.org/10.1108/EJM-03-2017-0182

Donderi, D. C. (2006a). An information theory analysis of visual complexity and dissimilarity. *Perception*, *35*(6), 823–835. https://doi.org/10.1068/p5249

Donderi, D. C. (2006b). Visual complexity: A review. In *Psychological Bulletin* (Vol. 132, Issue 1, pp. 73–97). https://doi.org/10.1037/0033-2909.132.1.73

Gelper, S., Peres, R., & Eliashberg, J. (2018). Talk Bursts: The Role of Spikes in Prerelease Word-of-Mouth Dynamics. *Journal of Marketing Research*, *55*(6), 801–817. https://doi.org/10.1177/0022243718817007

George, J. F., Carlson, J. R., & Valacich, J. S. (2013). Media Selection as a Strategic Component of Communication. *MIS Quarterly*, *37*(4), 1233–1251. https://doi.org/10.25300/misq/2013/37.4.11

George, J. F., Gupta, M., Giordano, G., Mills, A. M., Tennant, V. M., & Lewis, C. C. (2018). The Effects of Communication Media and Culture on Deception Detection Accuracy. *MIS Quarterly*, *42*(2), 551–575. https://doi.org/10.25300/MISQ/2018/13215

Gorn, G. J., Chattopadhyay, A., Yi, T., & Dahl, D. W. (1997). Effects of color as an executional cue in advertising: They're in the shade. *Management Science*, *43*(10), 1387–1400. https://doi.org/10.1287/mnsc.43.10.1387

Guèvremont, A., & Grohmann, B. (2013). The impact of brand personality on consumer responses to persuasion attempts. *Journal of Brand Management*, *20*(6), 518–530. https://doi.org/10.1057/bm.2012.58

Han, Y., Lappas, T., & Sabnis, G. (2020). The importance of interactions between content characteristics and creator characteristics for studying virality in social media. *Information Systems Research*, *31*(2), 576–588. https://doi.org/10.1287/ISRE.2019.0903

Heath, T., Smith, S. G., & Bill, L. (2000). Tall buildings and the urban skyline: The effect of visual complexity on preferences. *Environment and Behavior*, *32*(4), 541–556. https://doi.org/10.1177/00139160021972658

Hu, T., Kettinger, W. J., & Poston, R. S. (2015). The effect of online social value on satisfaction and continued use of social media. *European Journal of Information Systems*, *24*(4), 391–410. https://doi.org/10.1057/ejis.2014.22

Jang, J. Y., Baek, E., Yoon, S. Y., & Choo, H. J. (2018). Store design: Visual complexity and consumer responses. *International Journal of Design*, *12*(2), 105–118.

Jiang, Z. (Jack), Wang, W., Tan, B. C. Y., & Yu, J. (2016). The Determinants and Impacts of Aesthetics in Users' First Interaction with Websites. *Journal of Management Information Systems*, *33*(1), 229–259. https://doi.org/10.1080/07421222.2016.1172443

Lee, D., Hosanagar, K., & Nair, H. (2018). Advertising Content and Consumer Engagement on Social Media: Evidence from Facebook. *Management Science*, *64*(11), 5105–5131.

Li, W., Chen, H., & Nunamaker, J. F. (2016). Identifying and Profiling Key Sellers in Cyber Carding Community: AZSecure Text Mining System. *Journal of Management Information Systems*, *33*(4), 1059–1086. https://doi.org/10.1080/07421222.2016.1267528

Li, Y., & Xie, Y. (2020). Is a Picture Worth a Thousand Words? An Empirical Study of Image Content and Social Media Engagement. *Journal of Marketing Research*, *57*(1), 1–19. https://doi.org/10.1177/0022243719881113

Liu, L., Dzyabura, D., & Mizik, N. (2020). Visual listening in: Extracting brand image portrayed on social media. *Marketing Science*, *39*(4), 669–686. https://doi.org/10.1287/mksc.2020.1226

Machado, P., Romero, J., Nadal, M., Santos, A., Correia, J., & Carballal, A. (2015). Computerized measures of visual complexity. *Acta Psychologica*, *160*, 43–57. https://doi.org/10.1016/j.actpsy.2015.06.005

Madan, C. R., Bayer, J., Gamer, M., Lonsdorf, T. B., & Sommer, T. (2018). Visual complexity and affect: Ratings reflect more than meets the eye. *Frontiers in Psychology*, *8*, 2368. https://doi.org/10.3389/fpsyg.2017.02368

Mai, F., Shan, Z., Bai, Q., Wang, X. (Shane), & Chiang, R. H. L. (2018). How Does Social Media Impact Bitcoin Value? A Test of the Silent Majority Hypothesis. *Journal of Management Information Systems*, *35*(1), 19–52. https://doi.org/10.1080/07421222.2018.1440774

Maini, R., & Himanshu, A. (2003). Study and Comparison of Various Image Edge Detection Techniques. *International Journal of Image Processing*, *3*(1).

Meire, M., Hewett, K., Ballings, M., Kumar, V., & van den Poel, D. (2019). The Role of Marketer-Generated Content in Customer Engagement Marketing. *Journal of Marketing*, *83*(6), 21–42. https://doi.org/10.1177/0022242919873903

Munter, M., Rogers, P. S., & Rymer, J. (2003). Business E-mail: Guidelines for Users. *Business Communication Quarterly*, *66*(1), 26–40. https://doi.org/10.1177/108056990306600104

Pansari, A., & Kumar, V. (2017). Customer engagement: the construct, antecedents, and consequences. *Journal of the Academy of Marketing Science*, *45*, 294–311. https://doi.org/10.1007/s11747-016-0485-6

Pieters, R., Wedel, M., & Batra, R. (2010). The Stopping Power of Advertising: Measures and Effects of Visual Complexity. *Journal of Marketing*, *74*(5), 48–60. https://doi.org/10.1509/jmkg.74.5.48

Ren, J., Dong, H., Popovic, A., Sabnis, G., & Nickerson, J. (2022). Digital platforms in the news industry: how social media platforms impact traditional media news viewership. *European Journal of Information Systems*, 1–18. https://doi.org/10.1080/0960085X.2022.2103046

Robert, L. P., Dennis, A. R., & Ahuja, M. K. (2018). Differences are different: Examining the effects of communication media on the impacts of racial and gender diversity in decision-making teams. *Information Systems Research*, *29*(3), 525–545. https://doi.org/10.1287/isre.2018.0773

Shahbaznezhad, H., Dolan, R., & Rashidirad, M. (2021). The Role of Social Media Content Format and Platform in Users' Engagement Behavior. *Journal of Interactive Marketing*, *53*, 47–65. https://doi.org/10.1016/j.intmar.2020.05.001

Shin, D., He, S., Lee, G. M., Whinston, A. B., Cetintas, S., & Lee, K.-C. (2020). Enhancing Social Media Analysis with Visual Analytics: A Deep Learning Approach. *MIS Quarterly*, *44*(4), 1459–1492. https://doi.org/10.2139/ssrn.2830377

So, K. K. F., King, C., Sparks, B. A., & Wang, Y. (2016). The Role of Customer Engagement in Building Consumer Loyalty to Tourism Brands. *Journal of Travel Research*, *55*(1), 64–78. https://doi.org/10.1177/0047287514541008

Sonnier, G. P., McAlister, L., & Rutz, O. J. (2011). A Dynamic Model of the Effect of Online Communications on Firm Sales. *Marketing Science*, *30*(4), 702–716. https://doi.org/10.1287/mksc.1110.0642

Tellis, G. J., MacInnis, D. J., Tirunillai, S., & Zhang, Y. (2019). What Drives Virality (Sharing) of Online Digital Content? The Critical Role of Information, Emotion, and Brand Prominence. *Journal of Marketing*, *83*(4), 1–20. https://doi.org/10.1177/0022242919841034

Valdez, P., & Mehrabian, A. (1994). Effects of Color on Emotions. *Journal of Experimental Psychology: General*, *123*(4), 394–409. https://doi.org/10.1037/0096-3445.123.4.394

van der Lans, R., Pieters, R., & Wedel, M. (2008). Competitive Brand Salience. *Marketing Science*, *27*(5), 922–931. https://doi.org/10.1287/mksc.l070.0327

Wang, J., Wan, W. B., Li, X. X., Sun, J. de, & Zhang, H. X. (2020). Color image watermarking based on orientation diversity and color complexity. *Expert Systems with Applications*, *140*. https://doi.org/10.1016/j.eswa.2019.112868

Warner, L., & Franzen, R. (1947). Values of color advertising. *Journal of Applied Psychology*, *31*(3), 260–270. https://doi.org/10.1037/h0057772

Wilms, L., & Oberfeld, D. (2018). Color and emotion: effects of hue, saturation, and brightness. *Psychological Research*, *82*(5), 896–914. https://doi.org/10.1007/S00426-017-0880-8

Yang, M., Ren, Y., & Adomavicius, G. (2019). Understanding user-generated content and customer engagement on Facebook business pages. *Information Systems Research*, *30*(3), 839–855. https://doi.org/10.1287/isre.2019.0834

Zhang, K., Bhattacharyya, S., & Ram, S. (2016). Large-Scale Network Analysis for Online Social Brand Advertising. *MIS Quarterly*, *40*(4), 849–868. https://doi.org/10.25300/misq/2016/40.4.0