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Simplicity is not Key: Understanding Firm-Generated Social Media Images and Consumer Liking

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Abstract

Social media platforms are becoming increasingly important marketing channels, and recently these channels are becoming dominated by content that is not textual, but visual in nature. In this paper, we explore the relationship between the visual complexity of firm-generated imagery (FGI) and consumer liking on social media. We use previously validated image mining methods, to automatically extract interpretable visual complexity measures from images. We construct a set of six interpretable measures that are categorized as either (1) feature complexity measures (i.e., unstructured pixel-level variation; color, luminance, and edges) or (2) design complexity measures (i.e., structured design-level variation; number of objects, irregularity of object arrangement, and asymmetry of object arrangement). These measures and their interpretability are validated using a human subject experiment. Subsequently, we relate these visual complexity measures to the number of likes. The results show an inverted u-shape between feature complexity and consumer liking and a regular u-shape relationship between design complexity and consumer liking. In addition, we demonstrate that using the six individual measures that constitute feature- and design complexity provides a more nuanced view of the relationship between the unique aspects of visual complexity and consumer liking of FGI on social media than observed in previous studies that used a more aggregated measure. Overall, the automated framework presented in this paper opens up a wide range of possibilities for studying the role of visual complexity in online content.

Keywords: Social Media, Visual Complexity, Deep Learning, Image Analytics, Convolutional Neural Networks

1. Introduction

Social media platforms are becoming some of the main channels for achieving a variety of key marketing objectives, from creating awareness to facilitating sales (Batra and Keller, 2016; Kumar et al., 2013, 2016; Colicev et al., 2018; Luo et al., 2013). More and more firms actively participate on social media; they create fan pages on various platforms and generate content to improve their social media marketing strategies. However, 60% of the content generated by brands is declared as "poor and irrelevant or it fails to deliver" (Havas, 2017). As the amount of online firm-generated content (FGC), such as Instagram posts or brand tweets, continues to increase and the overall amount of content pushed to consumers explodes, it becomes more and more challenging to attain and hold the consumer's attention. To create content that is appealing to consumers requires insight in the popularity of firm-generated posts.

Finding the drivers behind the liking of FGC will improve the understanding of consumer interests and behavior. Liking behavior has been shown to have positive effects on brand evaluations (Beukeboom et al., 2015) and it can cause positive change in customers' offline behavior (Mochon et al., 2017). In addition, Kumar et al. (2016) show that liking can further improve brand evaluations and firm-generated content in general positively impacts consumer spending and overall profitability. By effectively using FGC, marketers can also positively influence their consumers' purchase behavior (Goh et al., 2013; Scholz et al., 2018). Finally, (Colicev et al., 2019) shows that visual FGC helps to build an engaged brand following and that it has a significant effect on the consideration and purchase intent of consumers

Although recent studies shed some light on the determinants of the liking and engagement with textual content in social media (Berger and Milkman, 2012; De Vries et al., 2012; Hewett et al., 2016; Stephen et al., 2015), there is very little research on the liking of predominantly visual content. This is remarkable given the growth of visual social media on platforms such as Instagram. It poses a new dimension to the challenges of the marketing manager, whose key concern is to create content that stops the consumer when scrolling through their social media content. Studies on how people perceive scenes (i.e. information that can flow from a physical environment into a perceptual system, such as images through the human eye) show that observers understand and comprehend the visual information of a scene within 100 milliseconds (Potter, 1976; Oliva, 2005). So, it is crucial that marketing managers create visual content that is likeable by the observer at the first look. Therefore, there is a need for empirical investigation of what aspects of visual content generate liking to help firms to be more effective with their visuals on social media.

In the literature, mostly in the context of advertising, we see two opposing views on how to best attract attention to visual content; on the one hand it is suggested to create simplicity (Aitchison, 2012; Book and Schick, 1997) and on the other hand, there is an emphasis on complexity (Nelson, 1994; Putrevu et al., 2004). Visual Complexity Theory (Attneave, 1954; Donderi, 2006) forms the basis of a more in-depth research in the debate between simplicity and complexity and its effect on attitude towards offline advertisements (Pieters et al., 2010). The authors show a positive as well as a negative impact for different visual complexity measures. That is, higher visual complexity in terms of basic perceptual features ("feature complexity") decreases consumers' attitude towards the ad and higher visual complexity in terms of design ("design complexity") increases consumers' attitude towards the ad. A recent study by Shin et al. (2019), investigates the impact of different image content features, including visual complexity, on social media engagement. This study finds the exact opposite, where there is a positive relationship between engagement and pixel-level complexity (i.e. feature complexity) and a negative relationship between engagement and object complexity (i.e. design complexity).

Inspired by these studies, their contrasting views, the divide we observe in the advertising literature and recent advances in computer science, we aim to empirically explain the effect of visual complexity on the liking of FGI on

Instagram. Based on previous findings, and the notion that visual complexity is not a monolithic construct (Corchs et al., 2016; Nagle and Lavie, 2020), we argue that: 1) the relationship between visual complexity and liking is most likely non-linear of nature, as opposed to the linear effects found in previous studies (Pieters et al., 2010; Shin et al., 2019). 2) By dividing the visual complexity into several individual measures we can provide a holistic view and a better understanding of the relationship between visual complexity and consumer liking.

Our study makes several contributions. First, by expanding, automating, validating and implementing the visual complexity framework as proposed by Pieters et al. (2010), we improve current knowledge in the visual marketing literature. We show that, when examining the components that constitute visual complexity individually, there are non-linear relationships between the different types visual complexity and consumer liking. It is optimal to stay in the mid-levels of feature complexity, while choosing either end of the spectrum of design complexity works best.

Second, our methods for automatically extracting information from visual content on social media create rich sources of information. Since our model provides automated insights into what content is present in different images, it provides brand managers with information on why pictures will be liked by consumers. The image analysis framework that we present can also be informative for future studies on imagery or studies that try to leverage image information.[1] In addition, we show that the individual aspects of

[1]The code for extracting the visual complexity measures and various control variables is available at: *https://github.com/Gyys1992/IJRM_visual_complexity*

visual complexity influence consumer liking above and beyond a wide range of content characteristics, such as photography attributes (Zhang et al., 2017; Zhou et al., 2018), specific types of images (extracted using multiple pre-trained convolutional neural networks), or faces.

Third, we contribute to the need for exploration of the impact of FGI on social media using a visual complexity framework on a large-scale social media dataset, (Hewett et al., 2016). Moreover, rather than stating that particular individual images are popular, we build design and feature insights about why those images are popular.

In the next section, we present our conceptual framework. After outlining the model, methodological approach and variable operationalization, we validate our measures in an experiment and summarize the results. We conclude with the theoretical contributions of our research and the managerial implications.

2. Conceptual Framework

Complexity of images has been studied extensively in different research fields such as psychology, computer science and advertising. Visual complexity has been defined in many different ways, and there is no standardized measurement of visual complexity. Palumbo et al. (2014, p. 4) best summarize visual complexity as follows: *"Visual complexity is broadly defined as the level of detail or intricacy contained within an image (Snodgrass and Vanderwart, 1980). It has been suggested that perceived complexity correlates positively with the amount of variety in a picture (Heylighen, 1997) and that it corresponds to the degree of difficulty people show when describing a visual* *stimulus (Heaps and Handel, 1999)".* In other words, complexity depends on a variety of image features ranging from basic, unstructured variation to semantic, structured variation.

Several studies have investigated ways of measuring visual complexity. A popular method for determining the visual complexity of an image has been to derive scores by asking participants to provide ratings of complexity based on a number of scales (Bonin et al., 2003; Snodgrass and Vanderwart, 1980). Palumbo et al. (2014) identify that people's ratings can be confounded and that this way of measuring is only useful for images that have already been produced, and does not provide insight into how to produce images with certain complexity characteristics. The researchers recommend using algorithms as they represent a more accurate and practical solution.

In this study, we use algorithms to automatically extract image information related to visual complexity and some additional information about the content of imagery. Table 1 lists all the automated, and interpretable[2], measures included in our framework. We categorize these variables into feature complexity or design complexity based on the way they are measured. Measures categorized as feature complexity measure the pixel-level variation of the image, whereas measures categorized as design complexity measure the

[2] All our main variables of interest are interpretable, hence their selection. The DC- and FC- Control variables are included because these two variables have been related to complexity in the past and can not be measured or approximated by any of the other variables. They are controls, because they are not interpretable or controllable by the marketer/firm. The content control variables control for the semantic content of the image, but are not visual complexity measures themselves.

variation related to the design and arrangement of objects in the image. This set of variables was derived from a more comprehensive list, see Table A.8 in the Appendix, of all different ways visual complexity has been approximated in the past. Many of these measures have been used in different studies to approximate perceived visual complexity in past research, but they have not been individually related to liking before and have not been explored in a comprehensive way. In this research, we provide a *nuanced* view of complexity that is measured in different ways and the relationship of these different measures to liking.

(Insert Table 1 about here)

Visual complexity and its effect on the liking of imagery or visual content in marketing has not been well studied, but there are two notable exceptions: Pieters et al. (2010) and Shin et al. (2019). Pieters et al. (2010) focuses on visual complexity as a characteristic of an ad and its influence on attitudes towards ads and brands. Shin et al. (2019) focuses on the effect of image characteristics, including visual complexity, on liking and reblogging behavior on social media platform Tumblr. These studies measure the visual complexity using the JPEG file size, and an additive measure to approximate the complexity related to the objects. They then study the linear relationship between these aggregate measures with the attitude of advertising and liking of Tumblr posts, respectively. Interestingly, these studies have contrasting findings, which can not be explained solely by the fact that attitude toward ads is different than liking behavior. Especially, since both these studies use the same mechanisms to hypothesize the effects.

The focal priority of this study is related to these works, however instead of using aggregate measures we investigate the individual aspects of visual complexity and their impact on liking of imagery. We split up the visual complexity into several automated and interpretable measures for the following reasons: 1) Visual complexity is not a monolithic construct (Corchs et al., 2016; Nagle and Lavie, 2020). Instead, it is constituted by many different factors. Previous studies have shown that there are many different ways to approximate the perceived visual complexity (Olivia et al., 2004; Artese et al., 2014; Corchs et al., 2016; Nagle and Lavie, 2020). These investigations highlight that each type or measure contributes to the perceived visual complexity in a unique way. 2) Visual complexity as a single construct is difficult to interpret and control. In addition, its impact on consumer liking can be difficult to disentangle. It is not clear how a manager can increase, or decrease, visual complexity as a whole. This is easier to control when visual complexity is split up into individual measures. 3) The overarching categories, feature complexity and design complexity, for the automated and interpretable measures have been shown to influence attitude and liking (Pieters et al., 2010; Shin et al., 2019). However, the linear approximations using aggregate constructs limit the implications of the findings, especially considering the contrasting findings of these two studies. We posit that instead of using aggregate constructs, splitting visual complexity up into individual, interpretable measures, and exploring non-linear relationships, we can get a better understanding of the relationship between visual complexity and consumer liking of FGI.

2.1. Feature Complexity and Design Complexity

Derived from past research (Pieters et al., 2010), we distinguish two categories of visual complexity: Feature complexity and design complexity. These categories relate to the gist of an image (Oliva, 2005). The gist of an image can be defined as the phenomenon that an observer can comprehend a variety of perceptual and semantic information from a view of a real-world environment with just a glance. In other words, the brain quickly makes sense of what we see. Oliva (2005) distinguishes perceptual and conceptual gist, where the former describes the basic image properties the brain uses to provide a structural representation of an image (feature complexity) and the latter includes the semantic information that is inferred while viewing an image or shortly after (design complexity). Furthermore, from a managerial perspective, we view feature complexity as the type of complexity that arises at the moment a picture is taken. It is a set of basic image features that can be modified using programs such as photo editing software or by simply using a filter on Instagram. On the other hand, design complexity is something in direct control of the photographer. For example, the photographer can decide to zoom in or out, or arrange objects or people to his/her preference.

The distinction between feature- and design complexity becomes even more apparent when we study the mechanism that connects them to consumer liking. Feature complexity evokes low-level visual processes and activates early layers in the visual processing system of the brain (Groen et al., 2013). Feature complexity is hypothesized to impact liking behavior through the peripheral route of persuasion (Shin et al., 2019), based on the elaboration likelihood model (Petty and Cacioppo, 1986). Design complexity, in contrast, evokes mid-level visual processes and activates later layers in the visual processing system (Groen et al., 2013). Design complexity is hypothesized to influence the liking through the central route of persuasion (Shin et al., 2019).

2.2. Feature Complexity

(Insert Figure 1 about here)

The feature complexity measures are based on low-level visual processes in the primary visual cortex (Palmer, 1999). Feature complexity represents pixel-level variation and unprocessed or unstructured image information without regards to the meaning of the image. An image is perceived more complex when there is more detail and higher variation in (a) color, (b) luminance, and (c) the quantity of edges, of an image. Feature complexity is determined when an image is taken and the basic pixel-level characteristics are encoded.

If an image has a feature complexity that is too high, it can be hard to understand the content of an image, so it is expected negatively influence attitudes at high levels (Pieters et al., 2010). Too much visual detail, is distracting from the story of the image, making it less engaging. In addition, it can mask the important aspects of an image, which makes it harder to understand what is actually depicted on the image. On the other hand, feature complexity can be experienced as a positive peripheral cue that increases physiological arousal and enhance memory (Deng et al., 2009). According to the elaboration likelihood model (Petty and Cacioppo, 1986), in an information-rich environment where information processing can be challenging and motivation to process stimuli is low, peripheral cues, such as feature complexity are necessary to persuade consumers to stop and engage (Shin et al., 2019). FGI that is low in feature complexity lacks the peripheral cues and attractive aspects to make it engaging and likeable. However, at the same time FGI that is high in feature complexity can be distracting and too difficult to process. Early work in complexity of ads by Morrison and Dainoff (1972) has indeed shown that positive attitudes toward images were highest at intermediate levels of complexity.

As a result, we expect that there is a non-linear relationship between feature complexity and liking. A certain level of complexity is needed to provide positive peripheral cues, however too much complexity might make it overly challenging to process and recognize what is depicted on the image. This negative effect of high complexity may be heightened in an environment such as social media, where a user is scrolling through content quickly, and may not have enough time to process a complex image. For these reasons, we propose the following hypothesis, with respect to feature complexity:

H1: Feature Complexity, composed of (a) color, (b) luminance, and (c) edge density, has an inverted u-shaped relationship with the liking of FGI.

Feature complexity is based on the variation in pixels in an image. More detail in the basic visual features means more computer memory is needed to store an image. Pieters et al. (2010) and Shin et al. (2019) use the amount of computer memory (i.e., JPEG file size) as their measure for feature complexity.[3] Although convenient, the file size of an image does not provide information as to what specific visual feature contributed to the complexity or consumer interaction with the image.

Therefore, we examine three basic visual features individually that together constitute the main components determining feature complexity of the image: Color, Luminance and Edge Density. We propose measures for the complexity within each of these features to develop a better understanding of their individual effects on liking. See Figure 1 for sample images of low, medium and high complexity. The complexity scores will give managers the ability to manipulate images in such a way that they can neutralize the harmful effects of one and enhance the beneficial effects of another.

(Insert Figure 2 about here)

2.3. Design Complexity

Design complexity of an image captures the complexity of the semantic information of the scene in an image. Design complexity evokes mid-level visual processes based on objects and pattern recognition (Palmer, 1999; Pieters et al., 2010). Images with a higher variation in terms of patterns and objects present are more complex.

Design complexity may impact pleasure and arousal when viewing an image that directly influences the formation of a first impression (Tuch et al., 2009). Therefore, we expect that design complexity directly impacts the

[3] In Shin et al. (2019), this is called pixel-level variation

liking of FGI on social media. Higher complexity in design has shown to improve attitude towards advertisements, due to the collative properties of an image (Palmer, 1999; Pieters et al., 2010). These studies show that intricacies in creative design make visual content more engaging to the viewer and generally more likeable. In addition, high complexity in advertising is viewed as positive because it helps slow down readers of magazines, requiring them to pay more attention to the ads (Nelson, 1994). There is no reason that this argument would not continue to hold true on social media.

Other research, however, has found negative (Shin et al., 2019), non-linear/mixed (Geissler et al., 2006; Deng and Poole, 2010), effects. The main explanation for these negative findings is that a higher design complexity requires too much cognitive effort to process and understand the ”story” of an image. The vast amount of content, and low motivation to process information, makes central cues less engaging. For this reason, Shin et al. (2019) argue that fewer central cues, or a lower design complexity in our case, are better. Work in advertising supports this notion by claiming that simplicity works, because it looks less cluttered and more ”professional” (Aitchison, 2012). In addition, simple designs are easy to recognize and process, because they activate visual processes related to object and pattern processing (Palmer, 1999). Finally, Deng and Poole (2010) highlight that higher diversity and number of visual stimuli may improve the attitude, while the order in terms of irregularity and symmetry in the arrangement negatively impacts the attitude.

The mixed findings suggest non-linearity in the actual relationship. The theoretical explanation in support of the findings in these papers focuses mostly around either end of the spectrum of design complexity and finds that either low or high design complexity has high positive effects. On the one hand, an image that is low in design complexity, has fewer central cues, looks clean, and is easy to understand and process, and is therefore likeable (Shin et al., 2019; Aitchison, 2012). On the other hand, an image that is high in design complexity, has a creative and intricate design, might slow down social media scrolling, and has collative properties, which make it likeable as well (Pieters et al., 2010; Nelson, 1994). The middle ground has neither of these qualities, so we suspect that an image either needs to be simple or more complex in the design to make it appealing and likeable. Although we suspect such a non-linearity, examining the precise relationship between design complexity and liking remains more of an empirical question. In addition, we recognize that there are boundaries, such that we do not necessarily expect that very low levels of design complexity or very high design complexity will be more likeable. We hypothesize the following with respect to the design complexity:

H2: Design Complexity, composed of (a) the number of objects, (b) irregularity of object arrangement, and (c) asymmetry of object arrangement, has a u-shaped relationship with the liking of FGI.

Pieters et al. (2010) identify six general principles of the design complexity of ads: quantity of objects, irregularity of objects, dissimilarity of objects, detail of objects, asymmetry of object arrangement, irregularity of object arrangement. Subsequently, they add all these up into a single measure for design complexity. Design complexity is calculated from scoring the images manually on these six general principles. Shin et al. (2019) create an automated measure of the total design complexity score, related only to the number of objects, by using the output of a pre-trained CNN.

Instead, we propose individual measures that capture the key elements of the design complexity of an image and investigate their relationship with liking separately. Although, Pieters et al. (2010), identify six principles of design complexity, the irregularity of objects and the detail of objects that they discuss are more reflective of pixel-level variation (feature complexity), and in empirical investigations have been shown to be closely related to the edge density, as such they are already captured in our other measures. For this reason, we do not include these in the design complexity category. Additionally, we find that it is better to combine the quantity of objects and the dissimilarity of objects into a single variable that measures the number of unique objects. This results in three automated, interpretable, measures for design complexity: (a) Number of Unique Objects, (b) Irregularity of the Object Arrangement, and (c) the Asymmetry of the Object Arrangement. See Figure 2 for sample images with low, medium and high design complexity in the three features.

To recap, we have two overarching classes of visual complexity - feature complexity and design complexity. We construct six measures within these two classes of visual complexity. We expect to find an inverted u-shape relationship between liking and feature complexity and a regular u-shape relationship between liking and design complexity. In the next section, we describe how we will empirically test the conceptual framework on Instagram data. In section 4, we then validate that our measures accurately reflect human perception.

3. Empirical Application

To test our visual complexity framework, we have gathered a rich visual social media dataset from Instagram. Instagram is one of the main social media platforms of present day, and has recently been used to study the impact of visual content by previous work (Liu et al., 2020; Rietveld et al., 2020). Our motivation for using Instagram can be found in the web appendix.

3.1. Data

Before collecting the data from Instagram, we selected which brands we would analyze based on their Gartner L2 Digital IQ index.[4] We have selected the top 1000 highest ranked brands based on this index. Subsequently, we have collected all posts of these brands over a 1-year period, starting on 05/01/2015 and ending 04/30/2016. To ensure an equal comparison between brands we have decided that out of the 1000 brands we only include brands that post at least once a week over the focal period, resulting in approximately 150,000 posts corresponding to 633 brands across 27 different industries. This selection was driven by the fact that we intend to analyze overall impact of the complexity measures across all industries. We want to understand the image aspects that drive the liking of images regardless

[4]Retrieved from: https://www.l2inc.com/about/l2-digital-iq-index

of the brand posting it or the audience it is aimed for. The posts considered for this study are FGI only, which means they are generated and posted on the accounts owned by the brand. The data can be accessed at https://uvaauas.figshare.com/articles/dataset/{extension}.[5]

3.2. Model Development

We model the liking of FGI by gathering the number of likes for each post and applying a model suitable for count data: negative-binomial (NBD) regression. Here is the model specification:

$$\begin{aligned}
log(y_{i,b}) &= \alpha + \beta_1 Color_i + \beta_2 Color_i^2 + \beta_3 Luminance_i + \beta_4 Luminance_i^2 \\
&+\beta_5 EdgeDensity_i + \beta_6 EdgeDensity_i^2 + \beta_7 FrequencyFactor_i + \beta_8 FrequencyFactor_i^2 \\
&+ \beta_9 Objects_i + \beta_{10} Objects_i^2 + \beta_{11} IrregularityOA_i + \beta_{12} IrregularityOA_i^2 \\
&+\beta_{13} AsymmetryOA_i + \beta_{14} AsymmetryOA_i^2 + \beta_{15} NumRegions_i + \beta_{16} NumRegions_i^2 \\
&\gamma_1 log(Followers_b) + \gamma_2 TextPositive_i + \gamma_3 TextNegative_i + \gamma_4 BrandControls_b \\
&+ \gamma_5 TemporalControls_i + \gamma_6 PhotographyControls_i + \gamma_7 ContentControls_i
\end{aligned} \tag{1}$$

where the i subscript indicates a particular post and the b subscript indicates the brand that posted it. The liking of posts is a non-negative integer with a high variance. It appears to follow a near power-law distribution, something that has been observed in many cases of social media prediction research (Gelli et al., 2015; Khosla et al., 2014; Mazloom et al., 2016).

[5] These are the extensions to access the data: Raw data: Data_rds/14141009, Regression input data: Final_Data/14141039, Instagram image jpeg files: Instagram_images/14153114

The majority of posts receive very few likes whereas a few posts receive up to a million likes. We observe this over-dispersion in the data, similar to other social media marketing studies (Rooderkerk and Pauwels, 2016; Rietveld et al., 2020). In addtion, we follow recommendations not to transform the count data (Cameron and Trivedi, 2005; Reitan and Nielsen, 2016). $Color_i$, $Luminance_i$, and $EdgeDensity_i$ are the main feature complexity components extracted from post i, $FrequencyFactor_i$ is added as a control variable that also measures feature complexity. $Objects_i$, $IrregularityOA_i$, and $AsymmetryOA_i$ correspond to the design complexity components.

γ_1 and γ_4 capture the brand-level effects to control for the variation due to the brands. The number of followers captures the size of the audience and the activity and hashtags measures the frequency of posting and hashtags used. We used specific measures instead of brand-level fixed effects in the form of dummies, because we want to attribute the variation in brand to observed variables.

McParlane et al. (2014) show how the time of posting affects image popularity on social media. We follow their approach by including three time-dependent dummy variables to control for time of posting - time of day, day of week and the season. Textual information is included as control variables as it is complementary to visual information for popularity prediction (Overgoor et al., 2017). Specifically, we include the positive and negative sentiment scores extracted from the image caption. Finally, we have operationalized 34 content control variables, related to photography, type of image and presence of a humane face. These are extracting using multipl pre-trained convolutional neural networks. The full model as shown in Equation 1 achieves our highest observed adjusted R-squared.

3.3. Variable Operationalization

Dependent Variable - Liking: We will focus on the consumer liking of imagery by examining how many likes an image receives on Instagram. Likes reflect well the first impression and affection consumers have with the image. The dependent variable consists of the total number of likes the image received.

Feature Complexity - Color: We measure the color complexity of an image by describing the richness of the color constitution. It consists of a linear combination of the mean and standard deviation of the pixel cloud in the color plane (Corchs et al., 2016; Hasler and Suesstrunk, 2003). We have taken the most accurate representation from Hasler and Suesstrunk (2003).[6] First, we transform the image from RGB space to CIELab colorspace. We then calculate the μ_C, σ_a, and σ_b, that represent the mean Chroma, standard deviation along the a axis, and the standard deviation along the b axis respectively. From there we can best estimate the colorfulness of image i as follows:

$$Color_i = 0.94 * \mu_C + \sqrt{\sigma_a^2 + \sigma_b^2} \tag{2}$$

Feature Complexity - Luminance: First, we extract the luminance by transforming the RGB color space to YUV from which we can calculate the luma value (Y) per pixel. We use the luminance value of each individual pixel to find all unique levels of luminance in the image. Then, we count

[6]After our validation experiment in the next section this turns out the most accurate measure for FGI on Instagram as well.

the number of pixels that contain these levels of luminance to construct the luminance variety entropy measure, as follows:

$$Luminance_i = -\sum_{j=1}^{T} n_j log(\frac{n_j}{N}) \tag{3}$$

where T is the total number of unique luminance levels. nj is the count of pixels that contain unique luminance level j. N is the number of total pixels.

Feature Complexity - Edge Density: To detect edges in the image we use the Canny edge detector (Canny, 1987). Every pixel in the image will be classified as either 0 (not on an edge) or 1 (on an edge). As a result, the edge density measure is the total number of pixels on an edge divided by the total number of pixels in an image. The edge density is denoted by the formula:

$$EdgeDensity_i = \frac{e_i}{N} \tag{4}$$

where e is the result of the binary classification of pixel i. N is the total number of pixels.

Design Complexity - Objects: He et al. (2017) proposed Mask R-CNN, using Region-Based CNNs Girshick et al. (2014) to classify regions of interests within images, to accurately detect objects within an image. In (Nagle and Lavie, 2020), the authors show that this is in fact the most effective individual predictor of visual complexity. Using a pre-trained Mask R-CNN, trained to recognize 81 different types of objects, we are able to count the total number of (unique) objects within an image.[7]

[7]Interestingly, in our validation experiment (next section) we find that when asking participants to rate the complexity of images in terms of the number of *unique* objects,

Design Complexity - Irregularity of Object Arrangement: The Feature Congestion measure of visual clutter, proposed by Rosenholtz et al. (2007), measure does not explicitly find objects, but it incorporates certain aspects of perceptual organization, such as grouping by proximity and similarity. When the appearance of one object is easily predicted from its neighbors, then there is a regular or structured arrangement of objects present. For this reason, we find that the orientation clutter reflects the irregularity of object arrangement. Using the code provide by Rosenholtz et al. (2007)[8], we compute oriented opponent energy (Bergen and Landy, 1991), which returns a bi-vector: $(kcos(2\theta), ksin(2\theta))$, at each image location and scale. θ is the local orientation and k is related to the extent to which there is a single strong orientation at the given scale and location. Orientation clutter is computed as the volume or area of an orientation distribution ellipsoid, which is the determinant of the covariance matrix of the bi-vector. The irregularity of the object arrangement is then calculated by averaging over the entire image.

Design Complexity - Asymmetry of Object Arrangement: Using the same feature congestion map, with respect to the orientation, we can calculate the vertical and horizontal asymmetry. Inspired by Zhang et al. (2017), we divide the image into two planes (top and bottom, and left and right, for vertical and horizontal respectively) and compare opposite arrangement irregularity differences. Each pixel is compared to its vertical (horizontal)

the total number of objects, instead of the total number of unique objects, better reflects the perceived complexity.

[8]The authors have provided the MATLAB code at http://dspace.mit.edu/handle/1721.1/37593

counterpart. We take the average of the vertical and horizontal asymmetry. A larger difference represents a larger asymmetry of object arrangement.

3.4. Control Variables

Feature Complexity Control - Frequency Factor: The ration the ratio between the frequency corresponding to the 99% of the image energy and the Nyquist frequency (Corchs et al., 2016).

Design Complexity Control - Number of Regions: Calculated using the mean shift algorithm (Comaniciu and Meer, 2002).

Brand Followers: The size of the audience is reflected by the number of followers of the brand posting the images. Upon inspection, we observe that the number of followers is highly correlated with the number of likes.

Brand Activity: Measured by the number of posts that the brand has created on Instagram during the measurement time period.

Time of day / day of week / season: We also incorporate time of day, day of the week, and season of the year control variables.

Number of image tags: An image tag is a reference to some other user (person or brand) within the caption or image itself.

Textual Sentiment: We include the positive and negative sentiment scores extracted from the image caption. We use Sentistrength (Thelwall et al., 2010) to calculate scores ranging from 1 (neutral) to 5 (very high valence).

Content Controls: To control for the content characteristics of the image, we have operationalized a large set of image features. First, we constructed 13 photography attributes, using some state of the art image mining methods (Zhang et al., 2017; Zhang and Luo, 2018), and added these to the regression. Second, we construct a set of most frequent types of images, and the presence of faces (humans). We operationalized this set of variables using three separate pre-trained CNNs. 1) we detected Adjective-Noun Pairs using the MVSO model (Borth et al., 2013; Rietveld et al., 2020). From the classifications, we created binary indicators for the top 10 most frequently occurring Adjective-Noun Pairs in our dataset. 2) we detected scenes using a pre-trained CNN trained to recognize 365 scenes/places (Zhou et al., 2018). We created binary indicators for the top 10 most frequently occuring scenes/places in our dataset. 3) we utilized a pre-trained VGG16 architecture CNN (Parkhi et al., 2015) to detect faces in images, creating a binary indicator for the presence of faces. For a full list and description of all these control variables we refer you to the Web Appendix.

3.5. Model Estimation

As in traditional negative binomial regression analyses, we estimated Equation 1 by maximizing the log-likelihood function. We normalized all the explanatory variables in the final model, such that their beta coefficients can be compared. We checked for multicollinearity, the variance inflation factors revealed that there is no issue.

4. Validation Experiment

Before we explore the relationship between the visual complexity and the consumer liking we need to validate whether our measures are indeed interpretable and reflective of human perception. Visual complexity has been studied, tested and validated extensively in the studies presented in Table

A.8, but the main focus of these studies has been to estimate the correlation between image features and visual complexity as a single construct. However, visual complexity is not a monolithic construct, but rather visual complexity can have different aspects. As seen in these studies, it is often a (non-)linear combination of features that best approximates the perceived visual complexity. Moreover, individual-level measures that are more closely tied to the underlying image properties are more interpretable than aggregated measures. Thus, we construct individual measures of visual complexity. The goal of this experiment is to validate these individual measures by determining if the algorithmic measurements of visual complexity match up with human perception of those same visual complexity concepts.

We follow (Shin et al., 2019) in their assumption that it can be difficult for humans to objectively judge and rate with exact numbers abstract concepts related to images. In this sense, it can be difficult for a human to generate an exact value for an image using our proposed complexity measures. It is more intuitive instead, to view this as a ranking problem. This way we can ask participants to judge pairs of images and select the image that feels most complex instead of asking them to rate an image based on the perceived complexity. For each complexity dimension, the participants can then use the set of images and compare the results, instead of scoring individual images.

To validate our proposed measures, we test if the ranking of a set of images by our automated measures correspond to those of human participants. We have sampled 900 image pairs for each complexity measure. We have sampled 300 images from between the 10th and 35th percentiles, 300 images from between the 40th and 60th percentile, and 300 images from between 65th and 90th percentile. As we are testing non-linear relationships between our visual complexity measures and liking, we want to validate comparisons of low-medium, low-high, and medium-high complexity imagery. This way we can not only compare if our measures are accurate in ranking the images, but we can also distinguish if the differences are perceived more easily between different regions of the distribution.[9]

The validation experiment was performed with 289 undergraduate students. For each participant in the survey we randomly drew 35 pairs of images out of the 900 image pairs, for each of the 6 complexity measures. Each image pair was, on average, rated by 10+ participants to ensure validity of the results. The Cronbach Alpha of our measures was .74, exceeding the commonly accepted threshold of .7 (Nunnally, 1978). The image out of the image pair that receives the majority vote is considered the image that is perceived to be most complex by human participants. We then compare the number of times our algorithmic measure agrees with the selected option by the participants as a percentage of the total image pairs. In addition, since some image pairs might be more difficult to evaluate than other we investigate as a subset those images where there is unanimous human agreement. The higher the percentage of agreement between humans and algorithms, the better the automated objective measure reflects the perceived complexity on that individual complexity dimension.

(Insert Figure 3 about here)

[9]The comparison between the different levels of complexity can be found in the web appendix

The main results of the validation experiment are summarized in Figure Appendix I. Overall, we observe that all automated measures are in over 60% agreement with the majority vote of the participants, which is comparable to findings in other studies (Shin et al., 2019). The results highlight that our measures accurately reflect the perceived complexity by humans. The results also highlight that measures such as color complexity and edge density are easier to interpret and detect by participants, than luminance and the asymmetry of the object arrangement. Intuitively this makes sense, because as humans we often talk about colors and colorfulness, whereas we don't often talk about luminance or asymmetry of object arrangements. In addition, we observe that the images that received a unanimous vote from the participants on average lead to an increase in agreement percentage of between 10% and 19% for the different complexity measures, reaching up to 96% agreement for color complexity. This means that our measures accurately predict the most complex image when humans are most easily able to agree about the complexity of the image.

5. Results

(Insert Table 2 about here)

Table 2, shows the descriptive statistics of the variables in the model. The number of likes shows a power-law distribution where the majority of posts receive very few likes and a small number of posts receive a large number of likes. The color complexity ranges from 0 to 18.41, a mean of 3.00 with a large tale on the upper end. The luminance complexity entropy measures ranges from .02 to 2.85 where the majority of posts lie between 2.5 and the maximum. The number of objects detected in the images ranges from 0 to 100. On average there are approximately 17 objects in an image. The irregularity of the object arrangement ranges from .00 to .23 with a mean of .06, whereas the asymmetry of object arrangement ranges from .00 to .92, with a mean of .24.

(Insert Table 3 about here)

Table 3 lists the correlations between our main variables of interest. The correlations between the visual complexity measures are modest, only the irregularity and the asymmetry of object arrangement are moderately correlated. We have tested for multicollinearity using variance inflator factors and we observe no issues.

(Insert Table 4 about here)

(Insert Figure 4 about here)

In Table 4, the results of four different regression analysis are listed. The "Linear-Aggregate" model is to replicate the findings of Shin et al. (2019). The "Linear-Individual" model highlights that splitting up feature- and design complexity into individual measures offers a more nuanced view of these findings. The "Quadratic-Aggregate" results support hypotheses H1 and H2, where we find that when we use the aggregate measures, as used by Pieters et al. (2010) and Shin et al. (2019), the effects are in fact non-linear. The results show that there is an inverted u-shape relationship ($\beta = 1.954, p < .01$ and $\beta = -2.467, p < .01$ for feature complexity and feature complexity squared respectively) between feature complexity and liking, thus we accept H1. On the other hand, we find that design complexity has a u-shape relationship ($\beta = -1.400, p < .01$ and $\beta = 1.716, p < .01$ for design complexity and design complexity squared respectively) with liking, accepting H2. The effects turn out to be more nuanced, however. The "Linear-Individual" model shows that for the linear findings of previous studies the effects are more nuanced. The full model "Quadratic-Individual" provides a holistic view of the relationship between visual complexity and consumer liking of FGI. The individual effects for feature complexity variables highlight that H1 is indeed fully supported and each individual variable has an inverted u-shape relationship with the liking. That is, we find positive main effects of the color ($\beta = .222, p < .05$) the luminance ($\beta = .221, p < .01$), edge density ($\beta = 1.730, p < .01$) and the feature complexity control variable frequency factor ($\beta = 1.502, p < .01$) and a negative effect of their square terms ($\beta = -.742$, $\beta = -.121$, $\beta = -2.013$, and $\beta = -.512$, with $p < .05$). Initially, the relationship between liking and these measures of feature complexity are positive, but when they increase, it prompts decreasing returns for the liking. Thus, we accept H1a (color), H2b(luminance), and H2c (edge density), there is an inverted u-shape relationship between the individual components of feature complexity and liking of social media imagery.

The top row in Figure 4 visualizes the effects for the feature complexity measures. We observe clear inverted u-shape relationships for each of these variables with consumer liking. Each variable was normalized using a min-max normalization to be within 0 and 1. The global maxima for each of these functions lies within the domain of each variables, with global maxima of .15, .91 and .43 for color, luminance, and edge density respectively indicated by the solid point and dashed line. The circles on the plot indicate the percentiles (1st, 25th, 50th, 75th, and 99th) of the distribution of the independent variables. We observe a gradual drop off for increasing values of color, and a gradual drop off for decreasing values of luminance. The edge density has a steep drop-off on either side of the maximum.

For the individual design complexity measures we find only partial support for H2. The results show negative main effects for objects ($\beta = -.177, p < .05$) the irregularity of object arrangement ($\beta = -1.143, p < .01$), and asymmetry of object arrangement ($\beta = -.304, p < .01$), but no significant effect for the design complexity control region count ($\beta = .178, p > .1$). The squared terms have positive coefficients for objects ($\beta = .111, p < .01$) the irregularity of object arrangement ($\beta = 1.1789, p < .01$), thus supporting H2a and H2b. However, we find a negative effect for squared term of the asymmetry of OA ($\beta = -.589, p < .01$), not supporting H2c. In addition, we find no effect for the our design complexity control variable region count ($\beta = -.339, p > .1$).

The bottom row in Figure 4 visualizes the effects for the design complexity measures. We observe clear u-shape relationships for objects and irregularity of the object arrangement. It is important to note the boundary conditions of our analysis. The observed range of these variables is limited and we can therefore only model the relationship within these boundaries. For example, the number of objects ranges from 0 to 100. An image with more than 100 objects is not observed and therefore we do not know its effect on liking. Zero objects are observed, but excluding zero object images from the data did not yield changes in the results. Each variable was normalized using a min-max normalization to be within 0 and 1. The global minima for two of these functions lies within the domain of each variables, with global minima of .80 and .32 for objects and irregularity of object arrangement[10]. We observe an inverted u-shape relationship for the asymmetry of object arrangement with a global maximum of -.26 for asymmetry of object arrangement. This is outside of the domain for this variable. The estimated number of likes is monotonically decreasing for the entire domain of the asymmetry of object arrangement, so the relationship with liking is, in fact, negative.

To summarize, the results show all aspects of feature complexity influence liking in an inverted u-shape type of relationship, fully supporting H1 including a, b, and c. Design complexity as a whole has a u-shape relationship with liking, supporting H2, but we only find support for H2a (objects) and H2b (irregularity of the object arrangement) individually. Combining the estimated coefficients with a plot, we find a negative relationship between the asymmetry and liking of consumers, which suggests that just a symmetrical design for images is strongly related with consumer liking, not supporting H2c.

[10]These minima do not lie close to the means of each normalized variable

5.1. Robustness Checks

To test the robustness of our model, we also investigated the robustness of inclusion of content control variables, the size of the effects of our visual complexity variable, confirmed the predictive validity of our model, and examined a generic brand-level fixed effects model. Our results show strong correlations and these additional analyses simply strengthen those findings. The results neither confirm nor disconfirm a direct causal effect.[11]

(Insert Table 5 about here)

Robustness against inclusion of controls variables: First, we included the temporal controls. As observed in Table 5, there is no significant change in the results. Second, we added the photography controls to the regression. In Table 5, we observe that the absolute numbers change slightly, though the direction of the effects remain the same. Finally, we added a set of most frequent types of images, and the presence of faces (humans) to the model. Table 5 shows that our results are robust to the inclusion of these 34 content control variables. The visual complexity effects are present above and beyond the types of images and photography attributes. The full length table with coefficients for the content control variables can be found in Table C.11.

(Insert Table 6 about here)

[11]We have also performed analyses at the industry level and observed some minor changes only.

Model Fit: As observed in Table 6, the Negative Binomial Regression fits the data better than a Poisson regression. This was expected due to the overdispersion that we observe in the number of likes variable. There is a very long tail in the distribution: Few posts obtain a large volume of likes, whereas the vast majority of posts obtain few likes.

(Insert Table 7 about here)

Predictive Validity: To assess the predictive validity of our model, we split the data in 20% test set and 80% training set. We predict the liking for the test dataset using our trained model, the results in Table 7 are the average for 5-fold cross validation. We investigate the predictive power of our negative binomial regression using the visual complexity measures we propose, and compare them to three benchmark models. As observed in Table 7, the rank correlation is .9319, which is very high. The measure indicates a high level of predictive validity. The RMSE is quite high as well, which shows that it is much easier to predict the relative ranking of a certain posts than it is to predict the exact number of likes. Especially posts with an extremely high number of likes are difficult to predict and this increases the RMSE. Most importantly, we observe that compared to the benchmarks our model performs better. The predictive validity combined with the interpretability of our method over the benchmarks highlights the importance of our framework.

Size of effects: We observe an inverted u-shape relationship between the measures of feature complexity and the liking of social media imagery. These results suggest that we would be able to find the optimum for both these measures that would lead to the highest number of expected likes when keeping all other factors the same. As an examination of the effect size we explored what this optimization effect would be for choosing the optimal image over a non-optimal image and we observe that improving feature complexity to its theoretical optimum would increase the expected number of likes by 19%. Given that the average likes on an image in our brand set is 4138, this would result in an increased number of likes of 786 on average. A quick and easy way for brands to improve the feature complexity of an image is to apply a filter based on the complexity scores. We explored the effect of choosing the right filter and we observe that just by choosing the right filter would improve the expected number of likes by 3%, see Appendix B and Figure Appendix B for an illustration. That means this would result in an increased number of likes of 125 on average. It is important to note that applying a filter takes less than a second since it involves simply clicking on the appropriate filter. This means that the ROI for either minor uses of our model is high.

Brand-level fixed effects: We have chosen to include specific brand-level fixed effects to account for the fact that brands have very different social media capabilities from each other. The specific brand-level fixed effects that we include are post frequency and the number of followers. However, we also examined a negative binomial model with fixed-effects for each individual brand, but it does not lead to a change in our conclusions.[12]

[12] We considered moving the control variable of number followers to be part of the DV

6. Discussion

In this paper, we expanded, automated, and scaled up the existing visual complexity framework proposed by Pieters et al. (2010). Subsequently, we have investigated the influence of each individual measure on liking behavior on Social Media. We observed an inverted u-shape relationship of feature complexity, including its individual components, with liking, fully supporting Hypothesis 1 - 1a,1b, and 1c. In contrast, we observed a u-shape relationship of design complexity, including two out of three of its individual components, with liking, thus supporting Hypothesis 2 - 2a and 2b.

6.1. Theoretical Implications

This paper has two major theoretical contributions. First, we show that the relationship between the two visual complexity categories and consumer liking is not linear. Previous theory has established that feature complexity negatively influences attitudes (Pieters et al., 2010), while other research has shown that feature complexity provides positive peripheral cues (Shin et al., 2019). Our results suggest truth in both findings, such that the optimum level of feature complexity is somewhere in the mid-region, depending on its specific aspects color, luminance, or edge density. The same two studies (Pieters et al., 2010; Shin et al., 2019) and others are also contrasting in their findings on design complexity.We find that both extremes of the design complexity spectrum have high positive impact on liking.

(i.e., dividing likes by number of followers), but this would not fully control for other aspects of this variable, such as brand strength and resources, and so such a specification would prevent us from identifying the true effect of the image.

Our second contribution is showing that visual complexity is not a linear, monolithic construct and can therefore not be captured by a single additive measure. Instead of using aggregated measures for feature and design complexity, we developed and validated a set of measures that provides us with a more nuanced and interpretable view of the relationship between liking and visual complexity. We observe that all three aspects of feature complexity (i.e., color, luminance, and edge density) influence the liking of FGI uniquely in an inverted u-shape manner. For design complexity, we observed a u-shape relationship with liking for the number of objects and the irregularity of the object arrangement, but a strictly negative relationship between asymmetry and liking.

6.2. Methodological Implication

We have developed a framework that enables researchers to study image-based social media in a similar manner to the way they study text-based social media. Our automated measures, both aggregate and individual, have been validated in an experiment to ensure that they accurately represent how visual complexity is perceived. From here, we have identified the aspects of social media imagery that lead to liking rather than the particular images that are liked. This gives us theoretical principles, based on visual complexity theory (Attneave, 1954; Donderi, 2006), about how to design image-based social media that advertisers and marketing managers can benefit from. We extracted aspects of photos that influence liking regardless of the nature of the image. Our results are robust to including a wide variety of content characteristics as control variables in our regression.

6.3. Managerial Implications

The combination of understanding how different aspects of feature- and design complexity influence liking and the automated extraction of this information directly from images enables a powerful tool for content managers (Kumar et al., 2016). For example, we show that using the feature complexity measures, content managers can improve liking by 3% with just a few additional clicks. Figure B.5 and Appendix B illustrate a potential guide to using Instagram filters. Unlike feature complexity, design complexity needs to be considered before the photo is taken. The analysis suggests to use a regular and simple design, using a unique object or a regular arrangement of multiple objects in the image, but to be aware of their symmetrical arrangement and orientation.

6.4. Limitations and Future Research

Our dependent variable, liking, has limitations. For instance, we cannot know who likes a post and some likes hold more value than others. This so-called "image journey" is a problem that requires a much richer dataset to know exactly how much extra exposure a single like has generated.

In addition, moderators such as brand strength or brand familiarity could potentially change the relationship between visual complexity and liking. When users are familiar with a brand, the impact of image complexity on liking could change. Brands could investigate whether the general findings are applicable to their brand. Different users could also have different preferences, which remains to be explored in future work.

Our complexity framework opens up possibilities for a wide range of applications. Managers, policy makers, and marketing professionals alike can extract large amounts of information from images and use this information to better understand their consumers and optimize their content for the ”good” of the consumer. Image analytics at scale can offer key insights in understanding the diffusion of online FGI and we encourage future exploration of the possible applications.

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7. Tables

Table 1: List of image statistics used in this paper - Feature Complexity (FC), Design Complexity (DC) and Controls. The FC and DC are controls, because they are more difficult to interpret.

Type	**Measure**	**Reference**
FC	Color Complexity	Artese (2014), Corchs (2016), Hasler (2003)
FC	Edge Density	Cavalcante (2014), Corchs (2016), Rosenholtz (2007)
FC	Luminance Entropy	Cavalcante (2014)
DC	Object Count	Oliva (2001), Pieters (2010)
DC	Object Arrangement asg	Oliva (2001), Pieters (2010)
DC	Object Arrangement Irregularity	Pieters (2010)
DC - Control	Region Count	Comaniciu (2002)
FC - Control	Frequency Factor	Corchs (2013), Corchs (2016)
Content Control	Photography measures	Zhang (2017), Zhang (2018)
Content Control	Face Detection	Parkhi (2015)
Content Control	Adjective-Noun Pairs	Borth (2013)
Content Control	Scenes	Zhou (2014)

Table 2: Descriptive Statistics

Variable	mean	sd	min	max
Likes	4,138	30,694	0	935,690
Color	3.00	1.75	.00	18.41
Luminance	2.48	.49	.02	2.85
Edge Density	.09	.03	.00	.35
Frequency Factor	.42	.04	.00	.49
Objects	17.38	20.51	0	100
Irregularity of OA	.06	.02	.00	.23
Asymmetry of OA	.24	.11	.00	.92
Region Count	56.51	30.11	0	1,320
Followers	168,751	1,679,190	15	46,098,258
Text Sentiment Positive	1.74	.89	1	5
Text Sentiment Negative	1.23	.56	1	5

Table 3: Correlation Matrix

	1	2	3	4	5	6	7	8	9	10	11
1 Likes											
2 Edge Density	.04**										
3 Luminance	.02*	.45**									
4 Frequency Factor	.04**	.42**	.06**								
5 Color	-.02**	.08**	.22**	-.02**							
6 Irregularity of OA	-.06**	.21**	-.02**	.26**	.08**						
7 Region Count	-.03**	.18**	.28**	.16**	.18**	.42**					
8 Objects	-.03**	.12**	.16**	.06**	.04**	.17**	.32**				
9 Asymmetry of OA	-.08**	.16**	.13**	.21**	.11**	.75**	.36**	.16**			
10 Followers	.92**	.05**	.02**	.04**	-.07**	-.15**	-.04**	-.08**	-.13**		
11 Text Sent. Pos.	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	
12 Text Sent. Neg.	.00	-.01*	.00	-.01*	.01	.00	.00	.00	.00	.00	.06**

Table 4: Negative binomial for 4 different specifications of visual complexity. The first two columns are linear estimations using a linear combination and individual specification, respectively. The second two columns are quadratic estimations using the same two specifications.

	Linear-Aggregate	Linear-Individual	Quadratic-Aggregate	Quadratic-Individual
Feature Complexity	.590*** (.023)		1.954*** (.062)	
Edge Density		.461*** (.028)		1.730*** (.085)
Luminance		.139*** (.015)		.221*** (.073)
Color		−.179*** (.043)		.222** (.089)
Frequency Factor		.707*** (.031)		1.502*** (.245)
Feature Complexity^2			−2.467*** (.103)	
Edge Density^2				−2.013*** (.126)
Luminance^2				−.121** (.050)
Color^2				−.742*** (.153)
Frequency Factor^2				−.512*** (.155)
Design Complexity	−.413*** (.025)		−1.400*** (.090)	
Objects		−.070*** (.010)		−.177*** (.029)
Irregularity of OA		.147*** (.044)		−1.143*** (.179)
Asymmetry of OA		−.702*** (.039)		−.304*** (.108)
Region Count		.026 (.102)		.178 (.141)
Design Complexity^2			1.716*** (.155)	
Objects^2				.111*** (.032)
Irregularity of OA^2				1.789*** (.236)
Asymmetry of OA^2				−.589*** (.199)
Region Count ^{2}				−.339 (.437)
Log(Followers)	.922*** (.001)	.920*** (.001)	.921*** (.001)	.921*** (.001)
Text Sentiment Positive	.004** (.002)	.004** (.002)	.004** (.002)	.004** (.002)
Text Sentiment Negative	−.003 (.003)	−.003 (.003)	−.003 (.003)	−.003 (.003)
(Intercept)	−1.502*** (.036)	−2.006*** (.049)	−1.532*** (.039)	−2.373*** (.101)
Photography Controls	✓	✓	✓	✓
Content Controls	✓	✓	✓	✓
Temporal Controls	✓	✓	✓	✓
Brand Controls	✓	✓	✓	✓
Observations	147,963	147,963	147,963	147,963
Adjusted R-Squared	.438	.452	.446	.453

Note: *p<.1; **p<.05; ***p<.01

Table 5: Stepwise regression, by introducing more controls in each step to highlight the robustness of our results.

	Stepwise Regression			
	Incl. Brand	**Incl. Temporal**	**Incl. Photography**	**All**
Feature Complexity				
Edge Density	2.036*** (.084)	2.036*** (.084)	1.728*** (.085)	1.730*** (.085)
Edge Density^2	−2.316*** (.125)	−2.316*** (.125)	−1.938*** (.125)	−2.013*** (.126)
Luminance	.311*** (.071)	.311*** (.071)	.175** (.073)	.221*** (.073)
Luminance^2	−.181*** (.047)	−.181*** (.047)	−.103** (.050)	−.121** (.050)
Color	.240*** (.065)	.240*** (.065)	.265*** (.089)	.222** (.089)
Color^2	−.796*** (.137)	−.796*** (.137)	−.717*** (.152)	−.742*** (.153)
Frequency Factor	1.236*** (.241)	1.236*** (.241)	1.360*** (.245)	1.502*** (.245)
Frequency Factor^2	−.356** (.152)	−.356** (.152)	−.382** (.154)	−.512*** (.155)
Design Complexity				
Objects	−.140*** (.028)	−.140*** (.028)	−.169*** (.029)	−.177*** (.029)
Objects^2	.111*** (.032)	.111*** (.032)	.109*** (.032)	.111*** (.032)
Irregularity of OA	−1.348*** (.170)	−1.348*** (.170)	−1.177*** (.178)	−1.143*** (.179)
Irregularity of OA^2	2.037*** (.228)	2.037*** (.228)	1.849*** (.236)	1.789*** (.236)
Asymmetry of OA	−.328*** (.099)	−.328*** (.099)	−.342*** (.108)	−.304*** (.108)
Asymmetry of OA^2	−.477** (.194)	−.477** (.194)	−.569*** (.199)	−.589*** (.199)
Region Count	.248* (.140)	.248* (.140)	.184 (.141)	.178 (.141)
Region Count^2	−.392 (.437)	−.392 (.437)	−.290 (.437)	−.339 (.437)
Log(Followers)	.923*** (.001)	.923*** (.001)	.922*** (.001)	.921*** (.001)
Text Sentiment Positive	.004** (.002)	.004** (.002)	.004** (.002)	.004** (.002)
Text Sentiment Negative	−.003 (.003)	−.003 (.003)	−.003 (.003)	−.003 (.003)
(Intercept)	−2.507*** (.099)	−2.507*** (.099)	−2.379*** (.101)	−2.371*** (.101)
Brand Controls	✓	✓	✓	✓
Temporal Controls		✓	✓	✓
Photography Controls			✓	✓
Content Controls				✓
Observations	147,963	147,963	147,963	147,963
Adjusted R-Squared	.445	.446	.446	.453

Note: *p<.1; **p<.05; ***p<.01

Table 6: Overview of model fit of Poisson vs. Negative Binomial Regression

Model	**Log Likelihood**	**AIC**	**BIC**
Negative Binomial	-952,709	1,905,545	1,906,179
Poisson	-62,437,559	124,875,244	124,875,868

Table 7: RMSE and Spearman Rank Correlation for out of sample prediction using our method compared to a model with visual content contral variables only and Pieters et al., Shin et al. and Corchs et al. benchmarks

	RMSE	**SRC**
Controls only	15,529	.9278
Corchs	15,057	.9318
Pieters	15,225	.9309
Shin	15,275	.9307
This paper	**14,913**	**.9319**

8. Figures

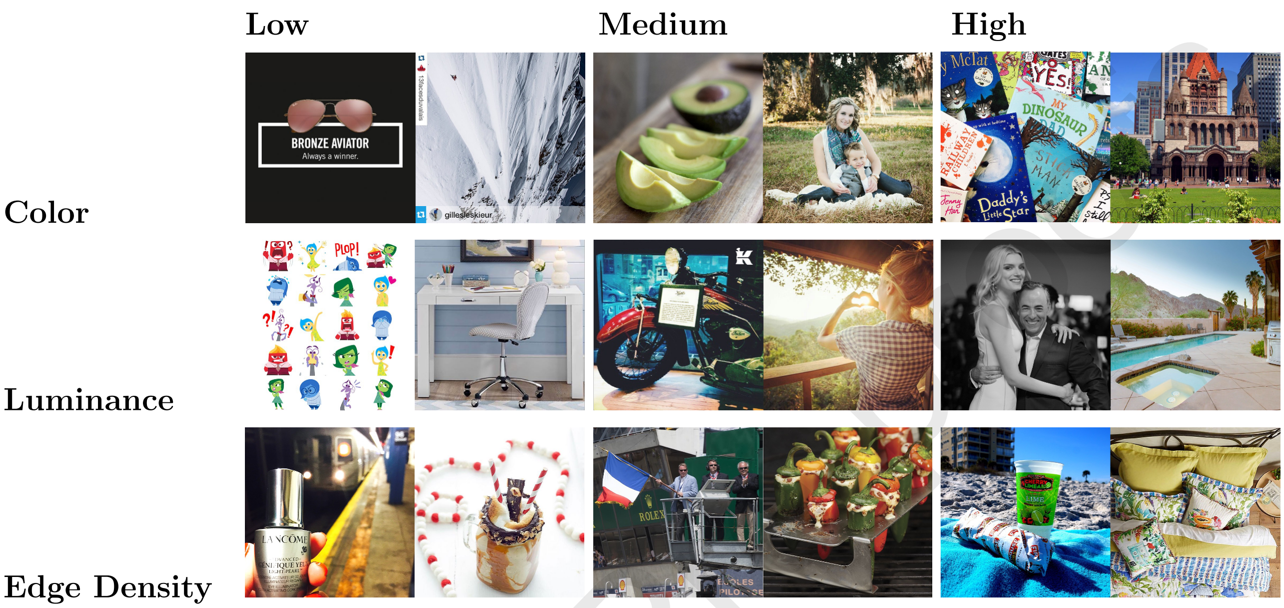


Figure 1: Sample images of low, medium and high complexity for each individual measure of feature complexity.

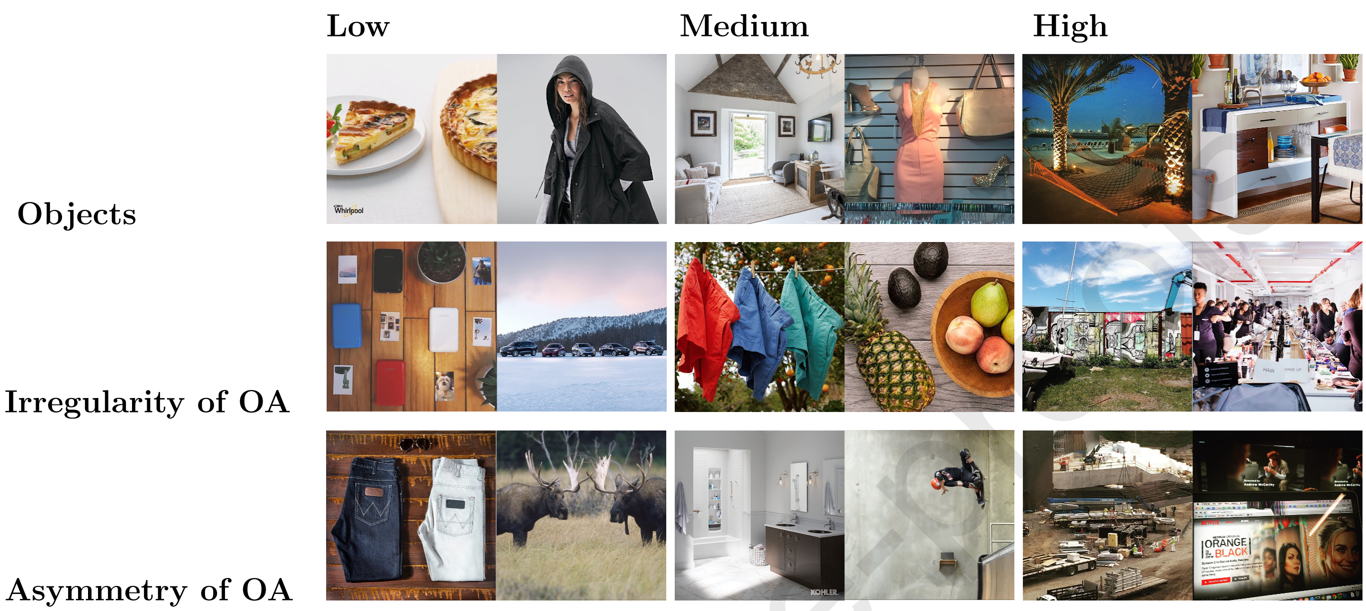


Figure 2: Sample images of low, medium and high complexity for each individual measure of design complexity. Number Objects, Irregularity of Object Arrangement, Asymmetry of Object Arrangement

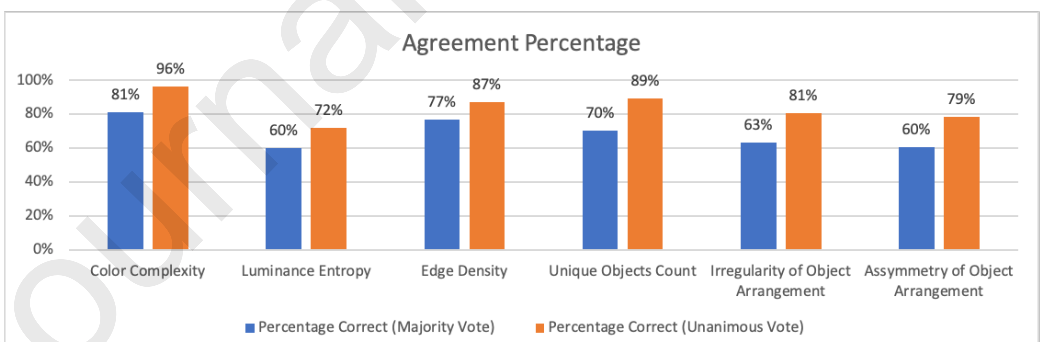


Figure 3: Agreement percentages between the predicted scores and the participants' votes. The blue bars represent the agreement between the majority vote and the automated measures. The orange bars represent the agreement between images that received a unanimous vote and the automated measures.

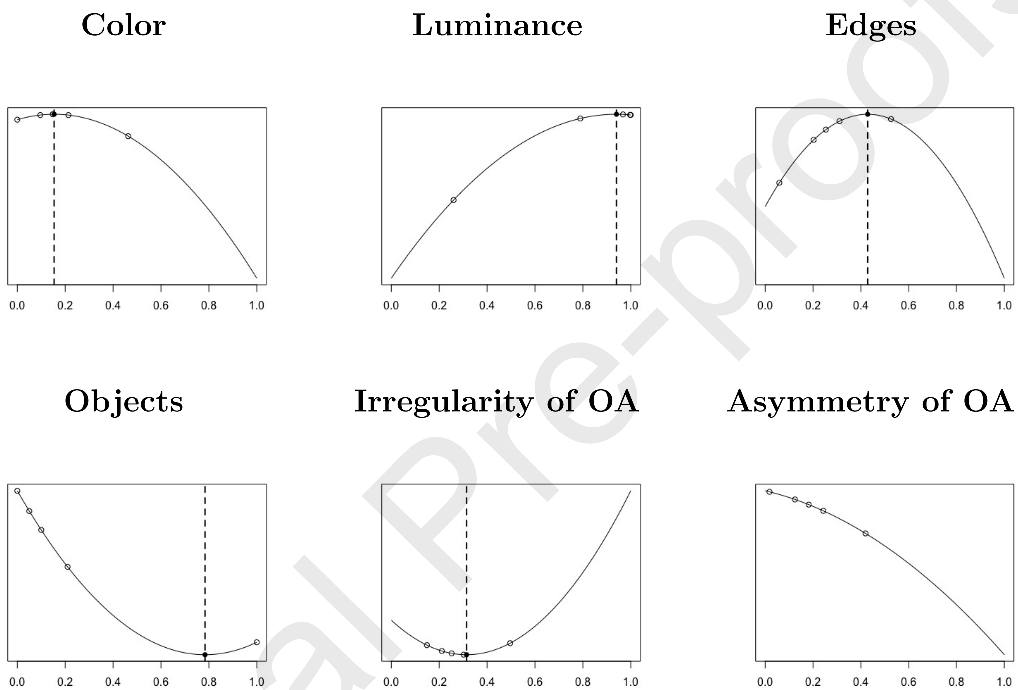


Figure 4: Visualization of the effects for each individual measure. The variables in the regression analysis are normalized to be between 0 and 1. The y-axis represents the estimated number of likes, all else being equal. The circles on the plot represent the percentiles (1%, 25%, 50%, 75%, 99%) of the distribution of the independent variable. The dashed line and the solid point indicate the global maximum/minimum.

Appendix A. Visual Complexity

Table A.8: Comprehensive list of visual complexity approximations and measures. The automated and interpretable visual complexity measures used in the paper are derived/chosen from this list of complexity measures on the basis of interpretability and correlation.

Category	**Complexity Measure**	**Reference**	**Interpretability**
Feature	Color Count	Artese (2014), Corchs (2016)	Yes
Feature	Color Entropy	Artese (2014), Corchs (2016)	Yes
Feature	Color Harmony	Artese (2014), Corchs (2016)	Yes
Feature	Colorfulness	Corchs (2016), Hasler (2003)	Yes
Feature	Contrast (G)	Cavalcante (2014), Corchs (2016), Haralick (1973)	No
Feature	Correlation (G)	Corchs (2016), Haralick (1973)	No
Feature	Edge Density	Corchs (2016), Rosenholtz (2007)	Yes
Feature	Energy (G)	Corchs (2016), Haralick (1973)	No
Feature	Frequency Factor	Corchs (2016), Corchs (2013)	No
Feature	Homogeneity (G)	Corchs (2016), Haralick (1973)	No
Feature	JPEG File Size	Corchs (2016), Corchs (2013), Forsythe (2011)	No
Feature	Luminance Entropy	Cavalcante (2014)	Yes
Design	Object arrangement	Pieters (2010)	Yes
Design	Object count	Oliva (2004)	Yes
Design	Object irregularity	Pieters (2010)	Yes
Design	Region Count	Comaniciu (2002)	No
Feature/Design	Clutter	Rosenholtz (2007)	Yes
Feature/Design	Deep Neural Network	Nagle (2020), Machado (2015)	No

Appendix B. Filter Guide

Figure B.5: Visualization of the filter guide. Given a picture and it's complexity score, we can apply potential filters and analyze the new complexity scores. From there, we can select the optimal filter, (no filter included as option), applying the filter leads to a predicted increase of 3% for the top picture and 1.5% for the bottom picture. We picked low and high colorfulness pictures for our illustration. The predicted likes increase is out-of-sample prediction, and we used these posts' actual values for all other variables.

A quick and easy way for brands to improve the feature complexity of an image is to apply a filter based on the complexity scores. We explored the effect of choosing the right filter and we observe that just by choosing the right filter would improve the expected number of likes by 3%. That means this would result in an increased number of likes of 125 on average. Figure Appendix B, illustrates the process of a filter guide. Based on the feature complexity scores of these images, we explore a set of potential filters. Then, we analyze what the new complexity scores would be after applying these potential filters. The filter (no filter as part of the options), that brings us closest to the optimal values for each of the individual would provide us with the highest predicted number of likes. We can then select the optimal filter based on the predicted scores. In the examples, that gets us to an increase of 3 % (1.5 %) for the top (bottom) image in predicted likes, all non-image characteristics being equal. We used actual posts and their corresponding scores for all variables. It is important to note that applying a filter takes less than a second since it involves simply clicking on the appropriate filter. The calculation of the feature complexity scores for all potential filters also takes less than a second. An automated tool, therefore, would quickly be able to apply the best filter based on the visual complexity of the image.

Appendix C. Web Appendix - Descriptives and Regression

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1 Edges																				
2 Color	.57*																			
3 Luminance	.45*	.63*																		
4 Irregularity of OA	.21*	.10*	-.01*																	
5 Objects	.12*	.26*	.17*	.17*																
6 Asymmetry of OA	.16*	.21*	.14*	.75*	.16*															
7 Diagonal Dominance	-.01*	-.02*	-.02*	.01*	-.02*	.00														
8 Rule of Thirds	-.05*	-.07*	-.04*	-.06*	-.04*	-.05*	.21*													
9 V. Physical Dominance	.06*	.09*	.06*	.06*	.06*	.06*	.01*	.26*												
10 H. Physical Dominance	.02*	.03*	.01*	.06*	.04*	.00	.02*	.21*	.13*											
11 H. Color Balance	-.29*	-.50*	-.42*	-.24*	-.19*	-.39*	.03*	.04*	.00	.02*										
12 V. Color Balance	-.30*	-.50*	-.41*	-.30*	-.18*	-.48*	.03*	.05*	-.07*	.08*	.56*									
13 FG Size Diff	.05*	.06*	.00	.10*	.10*	-.01*	-.01*	-.03*	.06*	.05*	-.07*	-.11*								
14 FG Color Diff	-.19*	-.30*	-.26*	-.03*	-.06*	-.04*	.03*	.08*	-.02*	.01*	.27*	.25*	-.48*							
15 FG Texture Diff	-.13*	-.26*	-.24*	-.08*	-.09*	-.11*	.01*	.04*	-.02*	.01*	.23*	.26*	-.35*	.32*						
16 Brightness	-.19*	-.24*	-.28*	.14*	-.13*	.04*	.03*	.05*	-.03*	-.02*	.18*	.18*	-.02*	.05*	.12*					
17 Saturation	.13*	.44*	.29*	-.03*	.06*	.02*	.00	-.05*	.03*	.03*	-.18*	-.15*	-.02*	-.09*	-.09*	-.25*				
18 Contrast	.05*	.28*	.08*	.19*	.09*	.18*	.01*	.00	.07*	.07*	-.26*	-.22*	.06*	.07*	-.04*	-.06*	.53*			
19 Clarity	-.27*	-.33*	-.33*	.14*	-.15*	.05*	.02*	.05*	-.04*	-.02*	.18*	.18*	-.04*	.10*	.14*	.94*	-.27*	-.06*		
20 Warmth	.20*	.28*	.23*	.08*	.06*	.09*	.00	-.02*	.03*	.00	-.11*	-.12*	.01*	-.11*	-.08*	.01*	.09*	.04*	-.01*	

Table C.9: Correlation between visual complexity and photography control variables.

Note: Brightness was removed from analysis due to collinearity with clarity.

Table C.10: Descriptive Statistics

Variable	mean	sd	min	max
Dependent Variable				
Likes	4,138	30,694	0	935,690
Feature Complexity				
Color	3.00	1.75	.00	18.41
Luminance	2.48	.49	.02	2.85
Edge Density	.09	.03	.00	.35
Frequency Factor	.42	.04	.00	.49
Design Complexity				
Objects	17.38	20.51	0	100
Irregularity of OA	.06	.02	.00	.23
Asymmetry of OA	.24	.11	.00	.92
Region Count	56.51	30.11	0	1,320
Textual Sentiment				
Text Sentiment Positive	1.74	.89	1	5
Text Sentiment Negative	1.23	.56	1	5
Hashtags	4.31	5.24	0	39
Brand Specific				
Followers	168,751	1,679,190	15	46,098,258
Posts	232	155	52	990
Photography				
Diagonal Dominance	.69	.24	0	1
Rule of Thirds	.59	.12	0	1
Physical Dominance (Vertical)	.83	.14	0	1
Physical Dominance (Horizontal)	.85	.13	0	1
Color Balance (Vertical)	.79	.08	0	1
Color Balance (Horizontal)	.75	.09	0	1
Figure-Ground Size Diff	.39	.35	0	1
Figure-Ground Color Diff	.32	.20	0	1
Figure-Ground Texture Diff	.15	.11	0	1
Saturation	.30	.17	0	1
Contrast	.45	.16	0	1
Clarity	.49	.25	0	1
Warmth	.25	.22	0	1
Content Controls (Binary)				
Crazy car	.02	.13	0	1
Classic castle	.03	.16	0	1
Hot girls	.01	.11	0	1
Outdoor party	.01	.09	0	1
Busy office	.01	.08	0	1
Amazing food	.01	.09	0	1
Hot cup	.01	.11	0	1
Cute animals	.01	.08	0	1
Outdoor wedding	.02	.13	0	1
Favorite team	.004	.06	0	1
Art studio	.004	.06	0	1
Bakery/shop	.03	.17	0	1
Beach	.01	.10	0	1
Clean room	.04	.20	0	1
Coffee shop	.01	.11	0	1
Desert/sand	.01	.10	0	1
Museum/indoor	.02	.14	0	1
Nursery	.02	.14	0	1
Ocean	.01	.07	0	1
Playroom	.03	.16	0	1
Face	.25	.43	0	1
Temporal Controls (Binary)				
Afternoon	.30	.46	0	1
Evening	.39	.49	0	1
Night	.18	.39	0	1
Weekend	.19	.40	0	1
Spring	.10	.30	0	1
Summer	.31	.46	0	1
Fall	.33	.47	0	1

Table C.11: Full set of results with coefficients for all control variables. Full length of Table 4

	Quadratic-Individual
Feature Complexity	
Edge Density	1.730*** (.085)
Luminance	.221*** (.073)
Color	.222** (.089)
Frequency Factor	1.502*** (.245)
Feature Complexity^2	
Edge Density^2	−2.013*** (.126)
Luminance^2	−.121** (.050)
Color^2	−.742*** (.153)
Frequency Factor^2	−.512*** (.155)
Design Complexity	
Objects	−.177*** (.029)
Irregularity of OA	−1.143*** (.179)
Asymmetry of OA	−.304*** (.108)
Region Count	.178 (.141)
Design Complexity^2	
Objects^2	.111*** (.032)
Irregularity of OA^2	1.789*** (.236)
Asymmetry of OA^2	−.589*** (.199)
Region Count ^{2}	−.339 (.437)
Brand Specific	
Log(Followers)	.921*** (.001)
Posts	−.287*** (.003)
Text	
Text Sentiment Positive	.004** (.002)
Text Sentiment Negative	−.003 (.003)
Hashtags	.024*** (.0004)
Temporal Controls	
Afternoon	−.011* (.006)
Evening	.022*** (.006)
Night	.074*** (.007)
Weekend	.047*** (.005)
Spring	−.217*** (.007)
Summer	−.230*** (.005)
Fall	−.197*** (.005)
Photography Controls	
Diagonal Dominance	−.016** (.008)
Rule of Thirds	.116*** (.018)
Vertical Physical Dominance	.018 (.014)
Horizontal Physical Dominance	.006 (.016)
Horizontal Color Balance	−.415*** (.027)
Vertical Color Balance	.108*** (.033)
FG Size Difference	.077*** (.007)
FG Color Difference	.115*** (.012)
FG Texture Difference	−.010 (.020)
Saturation	.002 (.024)
Contrast	−.008 (.018)
Clarity	−.123*** (.010)
Warmth	−.086*** (.009)
Content Controls - ANP	
Crazy car	.043*** (.015)
classic castle	.053*** (.013)
Hot girls	.052*** (.017)
Outdoor party	.013 (.021)
Busy office	−.042* (.023)
Amazing food	−.061*** (.020)
Hot cup	−.038** (.018)
Cute animals	.021 (.023)
Outdoor wedding	.042*** (.014)
Favorite team	−.034 (.032)
Art studio	−.005 (.031)
Bakery/shop	−.045*** (.012)
Content Controls - Places365	
Beach	.108*** (.019)
Clean room	−.088*** (.010)
Coffee shop	−.024 (.018)
Desert/sand	.047** (.018)
Museum indoor	.051*** (.014)
Nursery	−.047*** (.014)
Ocean	.106*** (.026)
Playroom	.091*** (.012)
Content Controls - Face VGG16	
Face	−.055*** (.005)
(Intercept)	−2.401*** (.099)
Observations	147,963
Adjusted R-Squared	.453
Overdispersion θ	1.96*** (.007)
Note:	*p<.1; **p<.05; ***p<.01

Appendix D. Web Appendix - Instagram

Instagram allows users to generate content and share this content with other users across the platform. Unlike text-based or mixed media social media platforms, Instagram is considered a visual social media platform meaning that its main focus is visual content - imagery in particular. A user shares (posts) an image with a short description (caption) on their Instagram page. Users can choose to 'follow' other users, in which case new photos from a user they follow will automatically show up in their feed. Typically, users follow dozens, hundreds, or even thousands of other users or brands that are (actively) generating content. The followers can show appreciation of the content posted by 'liking' it, which they do by clicking on a heart-shaped icon, or double tapping on the image. Users can also comment on other users' photos.

After taking a photo, a user has several ways to quickly edit it before sharing it on Instagram. One of Instagram's most popular features is the possibility of adding a filter to a photo. These filters add a certain visual effect to the photo, for example turning the photo into a black and white photo or intensifying shadows and brightening highlights. On Quora[13], Instagram CEO and founder Kevin Systrom describes filters as follows: *"Our filters are a combination of effects - curve profiles, blending modes, color hues, etc. In fact, I usually create them in Photoshop before creating the algorithms to do them on the phone"*. Instagram allows users to take, edit and share

[13]Retrieved from: https://www.quora.com/What-do-the-different-image-filters-on-Path-Instagram-Oink-etc-actually-do/answer/Kevin-Systrom

a photo within seconds. We perceive that these filters will be relevant for manipulating the feature complexity of the imagery.

Additionally, users can make use of hashtags (a topic marker starting with a '#' character, such as #selfie or #nature) in their description of the photo which allows the specific posts to be found by other users and brands can use it to target a specific audience. This is similar to the way hashtags are used on Twitter to mark the topic of a tweet. Additionally, users can tag other users in the image or in the description, which means that they will get a notification that they have been tagged in that post. For example, if an image is a group shot with multiple people in it, it is common practice to tag those people who have an Instagram account. This means that the post is now not only visible on the page of the user that generated the posts, but it is also visible on the page of the tagged users.

Instagram is one of today's most popular social media platforms with over 800 million active monthly users (Mathison, 2018). Its users have shared over 50 billion photos to date and share an average of 95 million photos and videos per day. They "like" about 4.2 billion posts each day. It has also shown to be a particularly interesting platform for brands. In 2016, almost 50% of US brands were using Instagram for social media marketing and this has risen to over 70% recently (Osman, 2018). A social media study conducted by Forrester (Elliott, 2014) reviewed how the top 50 global brands market on social networks. Forrester evaluated 11.8 million user interactions on 2,489 posts made by 249 branded profiles and collected data on how many top brands use each social network, how many followers they've collected, how often they post, and how often users interact with their posts. They found that the average number of Instagram followers for a top brand in 2016 was already over 1 million. The next section describes the Instagram dataset we have created.

Appendix E. Web Appendix - Convolutional Neural Networks and Content Controls

Figure E.6: Visualization of Mask RCNN object detection for low, medium and high number of objects.

In the last decade, researchers in computer science have developed the ability to automatically extract conceptual information from a large number of images. This information has shown to be particularly useful in a number of research fields. Recently, we have also seen an adoption of these methods for marketing research, especially in online settings where image data is often used. In this paper, we use CNNs to extract the object complexity and the content control variables. CNNs are powerful deep learning networks developed primarily for image recognition. CNNs have been successful in identifying objects in images, such as faces, humans and animals, or scenes such as park, coffee shop, beach etc. Convolutions are effective at extracting image features, because they are a type of filter that is applied multiple times to different parts of the image. The CNN uses only a small set of parameters that need to be estimated to detect similar features in multiple locations in an image. Nowadays, we can use large datasets with labeled images and the increasingly cheap nature of computer power to learn the parameters in convolutions at a large scale. The CNNs have several types of layers (mathematical manipulations) to extract different types of information from an image. The CNN architecture builds up a large amount and variety of information from the image and combines all of these different types of information to enable identification of complex concepts in the image. By scanning over a large number of pre-labeled images and adjusting weights the CNN can "learn" how to recognize the labeled information in the images of the training set. We use four different pre-trained CNNs to extract our content information. Three of these are pre-trained classifiers that classify an image as belonging to a certain class, the fourth is an object localization classification. Instead of classyfing an image as a whole, it first determines regions of interest that are then classified to be of a certain class. First, we will explain the mask RCNN architecture and how we use it to extract the number of objects. Then, we'll discuss the three pre-trained image classifiers that we use to create our binary content indicators.

More recently, object localization (i.e. detecting and localizing multiple objects within an image, instead of classifying an entire image) has become more accurate. He et al. (2017) proposed Mask R-CNN, using Region-Based CNNs Girshick et al. (2014) to classify regions of interests within images, to accurately detect objects within an image. In (Nagle and Lavie, 2020), the authors show that this is in fact the most effective individual predictor of visual complexity. Using a pre-trained Mask R-CNN, trained to recognize 81 different types of objects, we are able to count the total number of (unique) objects within an image. Figure Appendix E, visualized the output of object detection using Mask RCNN. We use the latest MaskRCNN architecture, Inception ResNet V2 Mask RCNN trained on the coco dataset. As shown, it does not alwasys detect all objects, nor does it classify them perfectly. However, our validation experiment does show that it accurately reflects the perception when we simply count the number of detection boxes from the classifier. In future research, once these models become faster and more accurate, we expect that the object complexity score will be more accurate. In addition, one could use the distribution of the detected objects for the irregularity of object arrangement and asymmetry of object arrangement as well.

For the constuction of the content indicators, we use three CNNs trained to recognize, scenes, adjective-noun pairs and faces. For the places/scenes classification we use a deep neural structure trained on previous images of different locations, called the Places Database (Zhou et al., 2018). The Places Database consists of 10 million scene photographs, all labeled with scene semantic categories. It comprises a diverse list of types of environment encountered in the world. For instance, scenes include: Lobby, Jacuzzi, Dorm Room, and Building Facade. The deep learning model accurately identifies 365 scene categories depicted in images. Similar to object detection, the pre-trained CNN returns a probability score for each of the 365 scene categories in the image. The final result is a distributional representation of the identification of scenes for every hotel image in our dataset. We detected adjective-noun pairs using the MVSO model (Borth et al., 2013). The model accurately identifies 1200 adjective-noun pairs. The binary indicators for both these variables were constructed by simply selecting the top 10 most frequent classes from both of these pre-trained CNNs applied to our dataset. From there, an indicator would indicate 1 if the image was classified as being one of these top 10 most frequent scenes or adjective-noun pairs. Lastly, for the face detection, we used a CNN pre-trained to recognize faces (Parkhi et al., 2015). In case the model detects a face in the image, we assign a 1 to the face indicator.

Appendix F. Web Appendix - Alternative Complexity

These 11 measures evaluate visual complexity measures proposed in Corchs et al. (2016). The measures found in other papers, are either highly similar or create a combination of filters and compression. We are already dealing with compressed imagery, so we can only use the file size as a measure for compression. They find a correlation of r=.81 with perceived complexity of participants from a linear combination of these measures. M7 and M9 correspond to the edge density and color as we use them. M5 and M8 are visual complexity controls that we incorporate in our paper. M11 was not used, because this is closely related to the photography controls. Finally, M6 is what both the other benchmark papers (Pieters et al., 2010; Shin et al., 2019) use as their measure for the feature complexity.

- **M1**: Contrast; it measures the intensity contrast between a pixel and its neighbors over the whole image.
- **M2**: Correlation; it measures how correlated a pixel is to its neighbors over the whole image.
- **M3**:Energy; it is the sum of squared elements in the GLCM.
- **M4**:Homogeneity, it measures the closeness of the distribution of elements in the GLCM with respect to the GLCM diagonal.
- **M5**:Frequency Factor, it is the ratio between the frequency corresponding to the 99% of the image energy and the Nyquist frequency (highest possible frequency in an image).
- **M6**:Compression Ratio, which is the JPEG file size.

- **M7**: Edge Density, same as the edge density measure in our study.
- **M8**: Number of regions, computed with the superpixel-based fast fuzzy C-means image segmenation as proposed by Lei et al. (2018) (more advanced method than proposed in (Corchs et al., 2016).
- **M9**: Colorfulness; it consists in a linear combination of the mean and standard deviation of the pixel cloud in the color plane (Artese et al., 2014).
- **M10**:Number of Colors; measures the number of distinct color in the RGB image.
- **M11**:Color Harmony, based on the perceived harmony of color combinations. It is composed of three parts: the chromatic effect, the luminance effect, and the hue effect. The image is split up into 10 segments, based on (Lei et al., 2018), each with their average color. We then take the minimum of the harmony of each segment compared to all others.

Appendix G. Web Appendix - Photography Attributes

As control variables for our study we compute the photography attributes used in Zhang et al. (2017) and Zhang and Luo (2018). The attributes are split up into three main categories: Color, Composition and Figure-Ground Relationship.

Appendix G.1. Composition

First, we compute a saliency map of the image, assigning a saliency score to every pixel in the image. Then, we use the superpixel algorithm to segment the image into 10 main regions.[14] The salient region in the image is the segment with the highest average saliency score.

- **Diagonal dominance** We calculate the distance between the center of the salient region to each of the two diagonals of a photo. The diagonal dominance is the negative of the minimum of these two distances.

- **Rule of thirds** We calculate the distance from the center of the salient region to each of the four intersections of the two horizontal lines and the two vertical lines that evenly divide the photo into nine parts. The rule of thirds score is the negative of the minimum of these distances.

- **Physical visual balance** We calculated two physical visaul balance measures: vertical and horizontal. We calculated the weighted saliency centroid from a weighted average centroid. We weigh the centroid of each of the 10 segments by the average saliency score to find the weighted center of the image. The vertical (horizontal) physical visual balance is than the distance from that center to the horizontal (vertical) line splitting the image into two halves.

- **Color visual balance** We calculated two scores for color visual balance: vertical and horizontal color visual balances. Each pixel is com-

[14]we chose to do the segmentation like (Zhang and Luo, 2018) to match previous work, instead of the superpixel-based fast fcm used above

pared to its vertical (horizontal) counterpart. The score is the average euclidean distance of each pixel pair.

Appendix G.2. Figure-ground relationship

Figure refers to the foreground, and ground refers to the background, of a photo. For the first three figureground relationship features, we first use the Grabcut algorithm (Rother et al., 2004) to identify the figure and background of each photo. In the following, we explain how we extract each attribute for figureground relationship.

- **Size difference** We take the difference between the number of pixels of the figure and that of the background, normalized by the total number of pixels of the photo.

- **Color difference** We first calculate the average RGB vectors for figure and ground. Then the color difference is the Euclidean distance between the two RGB vectors.

- **Texture difference** Difference in edge density between the figure and the ground.

Appendix G.3. Color

- **Brightness** is the average of the value dimension of HSV across pixels (Datta et al. 2006).

- Saturation is the average of saturation cross pixels.

- **Contrast of brightness** was calculated as the standard deviation of the value dimension of HSV cross pixels.

- **Clarity** A pixel is defined to be of enough clarity when the Value of the HSV is more than .7.
- **Warm** hue the warm hue level for the photo is the proportion of warm hue (i.e., red, orange, yellow) pixels in a photo.
- **Colorfulness** - We already have this measure as part of our visual complexity framework.

Appendix H. Web Appendix - Validation Experiment - Additional Analyis

Table H.12: Agreement percentages when sampling from different ranges of the distribution: Low, medium and high. In bold are the highest percentages per row.

Type	Low - Medium	Medium - High	Low - High
Color Complexity (Majority Vote)	82%	72%	**89%**
Color Complexity (Unanimous)	96%	91%	**99%**
Luminance Entropy (Majority Vote)	56%	**63%**	61%
Luminance Entropy (Unanimous)	**83%**	67%	69%
Edge Density (Majority Vote)	83%	61%	**86%**
Edge Density (Unanimous)	83%	63%	**92%**
Unique Objects Count (Majority Vote)	67%	71%	**73%**
Unique Objects Count (Unanimous)	86%	87%	**91%**
Irregularity of Object Arrangement (Majority Vote)	62%	56%	**72%**
Irregularity of Object Arrangement (Unanimous)	79%	75%	**87%**
Assymmetry of Object Arrangement (Majority Vote)	47%	66%	**68%**
Assymmetry of Object Arrangement (Unanimous)	64%	73%	**94%**

In Table H.12 we present the agreement percentages for images pairs where we sampled from different ranges of the distribution, which is relevant for our study as we are investigating non-linear relationships with the liking. We observe that for 5 out of 6 measures the agreement percentage was highest for the low vs. high comparison. This means that when there is a larger difference between the automated complexity scores it is generally easier to judge by the participants. For the luminance entropy, we observe that it was harder for participants to distinguish between images sampled from low and medium ranges. In addition, we observe that for the asymmetry of the object arrangement, the low and medium range images were hard to distinguish, whereas the low vs. high, and medium vs. high resulted in 68%

agreement, increasing to 94% in case of unanimous vote. For the rest of the measures the agreement percentages are to be expected, with the highest scores for low vs. high and still large percentage even when comparing the low and high range images to medium range images. Overall, we can conclude that the measures accurately reflect the perceived complexity, and that a bigger difference between the measures makes it easier to distinguish between images. Only low and medium measures asymmetry of object arrangement are not distinguishable, which needs to be taken into consideration in the analysis.

Appendix I. Web Appendix - Validation Experiment Set Up

Welcome to the survey. Today, you will see two images at a time. For each image pair you will have to click which image out of the two is more complex based on the explained criterion. First, we will explain what Visual Complexity is and how you can determine which of the two images is more complex. Second, we will explain each of the six (6) criteria in detail. After the explanation of a criterion, a random image pair will be shown to you and you will have to judge, based on the given criterion, which image is most complex. You will do this 33 times per criterion.

Visual Complexity is broadly defined as the level of detail or intricacy contained within an image. It has been suggested that perceived complexity correlates positively with the amount of variety in a picture and that it corresponds to the degree of difficulty people show when describing an image.

You judge the image pairs based on your perceived complexity within the described criterion.
For example, for color you pick the image that you feel to be the most colorful or for objects you pick the image that you feel to have the most different objects.

Today you will judge the complexity of images within the following 6 criteria:
1. number of colors / colorfulness
2. amount of detail / number of edges
3. darkness/lightness variation or luminance variation
4. number of unique objects
5. irregularity of the object arrangement / clutter
6. asymmetry of the arrangement of objects.

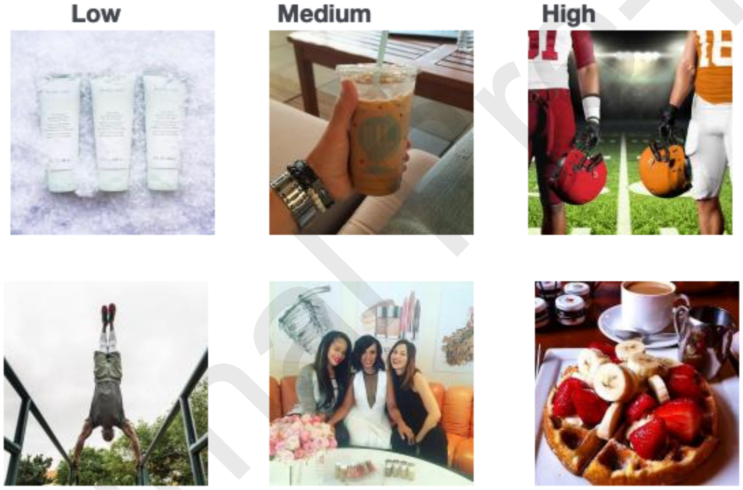
Make sure to judge each image in its entirety and not just a part of an image.

Color Complexity

In the following block of questions, you will pick the image that feels most complex in terms of color. The color complexity reflects how much variation there is in the number of colors or how colorful an image feels. An image that is more complex in terms of color has a higher number of different colors and looks more colorful.

See below for examples of low, medium and high color complexity.

Low | Medium | High

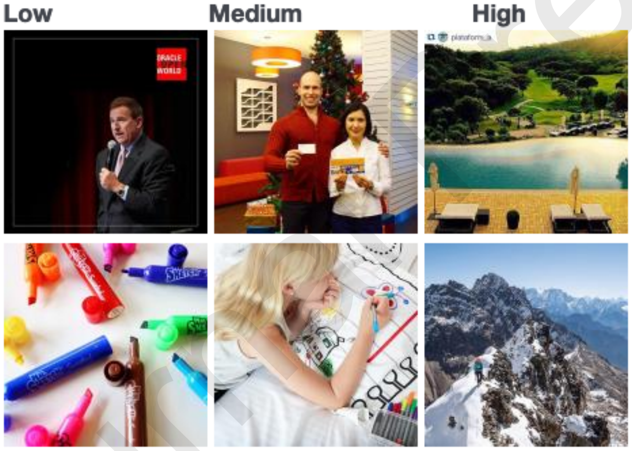


Edge Density

In the following block of questions, you will pick the image that feels most complex in terms of Edge Density. Edges are changes or discontinuities in an image. The more edges and texture an image has the higher edge density. An image that is more complex in terms of edge density has a higher number edges and looks more detailed, whereas an image that is less complex is smoother or uniform and has less details.

See the examples below:

Low **Medium** **High**



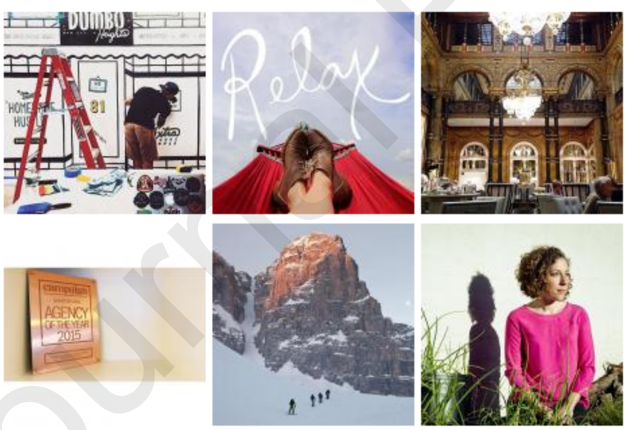
Luminance Complexity

Luminance is another word for brightness. Luminance complexity reflects how many different brightness levels (from very dark to very bright) there are in an image.

In the following block of image pairs, you will pick the image that feels most complex in terms of brightness. An image that is complex in terms of brightness has a lot of different levels of brightness, whereas an image that is not complex or simple in terms of brightness has a consistent and uniform brightness level that doesn't change much throughout the image.

See the examples below:

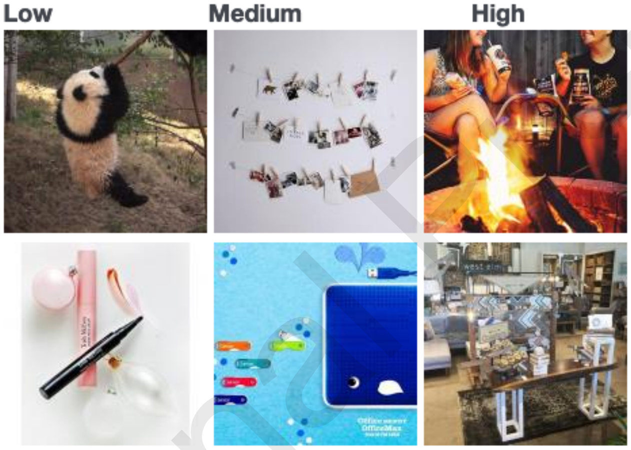
Low **Medium** **High**



Number of unique objects

In the following block of questions, you will pick the image that feels most complex in terms of unique objects. Choose the image that has the most unique objects. An image that is complex in terms of unique objects has a lot of different objects, whereas an image that is not complex in terms of unique objects has only a small number different objects. See the examples below:

Low **Medium** **High**



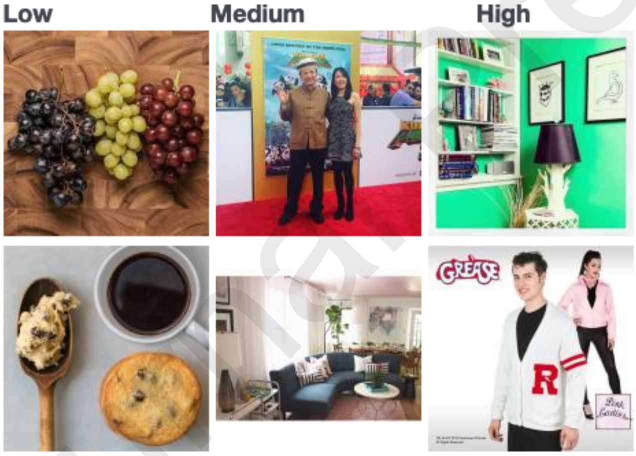
Next

Irregularity of Object Arrangement
In the following block of questions, you will pick the image that feels most complex in terms irregularity of the object arrangement. Object arrangement is where objects are placed in the image.

An image that is more complex in terms of the irregularity of the arrangement has objects (even if they are the same) placed randomly across the image, seems to have little structure and is more cluttered, whereas an image that is less complex or simpler in the irregularity of the object arrangement seems more structured and less cluttered.

See the examples below:

Low **Medium** **High**

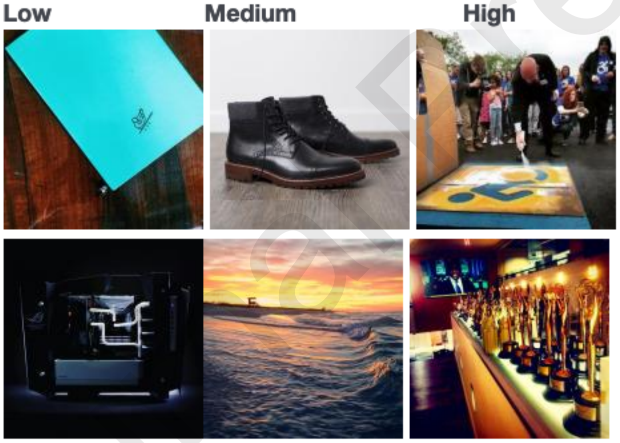


Asymmetry of Object Arrangement

In the following block of questions, you will pick the image that feels most complex in terms of the asymmetry of the object arrangement. Object arrangement is where objects are placed. An image that is more complex in the asymmetry of the object arrangement is less symmetric in the spatial placement of objects, whereas an image that is simpler or less complex in the asymmetry of the object arrangement seems more symmetric in the way objects are placed within the image.

See examples below:

Low **Medium** **High**



Which image is more complex in terms of unique objects? (click on the image)

Appendix J. Web Appendix - Brands

Table J.13: Brand list

Brand	**Industry**
A&W Restaurants	Foodservice
Abbott	Pharmaceuticals & life sciences
ABC	Media
Abercrombie & Fitch	Fashion & Personal Care
Abercrombie kids	Fashion & Personal Care
Accenture	Professional services
Ace	Retail/e-tail
Advance Auto Parts	Retail/e-tail
Advanced Micro Devices	Technology - General
Affinia	Sports, Leisure & travel
Aflac	Financial services & insurance companies
Air Jordan	Fashion & Personal Care
Airbnb	Sports, Leisure & travel
Airwick	Personal and household appliances
Alaska Airlines	Sports, Leisure & travel
Alcoa	Industrial products & services
Alex and Ani	Retail/e-tail
Alexander Wang	Fashion & Personal Care
Alexion Pharmaceuticals	Pharmaceuticals & life sciences
Allen Edmonds	Retail/e-tail

Allergan	Pharmaceuticals & life sciences
Allstate	Financial services & insurance companies
Altera	Telecom and IT
Amazon.com	Retail/e-tail
American Apparel	Retail/e-tail
American Express	Financial services & insurance companies
American Giant	Fashion & Personal Care
American Greetings	Retail/e-tail
ampm Mini Market	Foodservice
Andaz	Sports, Leisure & travel
Anki	Sports, Leisure & travel
Anna Sui	Fashion & Personal Care
Anthropologie	Retail/e-tail
Anyperk	Professional services
Anytime Fitness	Sports, Leisure & travel
AOL	Media
Applebee's	Foodservice
Arby's	Foodservice
Arm & Hammer	Personal and household appliances
Armor Holdings	Professional services
Assassin's Creed	Media
AT&T	Telecom and IT
Athenahealth	Professional services
Athleta	Fashion & Personal Care
Autodesk	Telecom and IT

AutoNation	Automotive
Autozone	Retail/e-tail
Avanade	Telecom and IT
Avaya	Telecom and IT
AVEDA	Fashion & Personal Care
Badgley Mischka	Fashion & Personal Care
Baldor Electirc	Industrial products & services
Ball Corporation	Industrial products & services
Banana Boat	Fashion & Personal Care
Banana Republic	Retail/e-tail
Bank of America	Financial services & insurance companies
Barbie	Toys industry
Barneys New York	Retail/e-tail
Baskin-Robbins	Foodservice
Bass Pro Shops	Retail/e-tail
Bath & Body Works	Retail/e-tail
Bed Bath & Beyond	Retail/e-tail
Best Western	Sports, Leisure & travel
Betty Crocker	Media
Beverly Hills Polo Club	Fashion & Personal Care
BFGoodrich	Tire & Rubber
Bill & Melinda Gates Foundation	Non profit organisations
Bing	Telecom and IT
Black + Decker	Personal and household appliances
Blendtec	Personal and household appliances

Bloomberg	Professional services
Blue Teach	Education
Bobbi Brown	Fashion & Personal Care
Bojangles' Restaurants Inc.	Foodservice
Bose	Technology - General
Boston Market	Foodservice
Briggs & Stratton	Industrial products & services
Bright Horizons	Education
Brooks	Personal and household appliances
Brooks Brothers	Retail/e-tail
Buckle	Retail/e-tail
Buffalo Wild Wings	Foodservice
Buick	Automotive
Build-A-Bear Workshop	Retail/e-tail
Bulova	Fashion & Personal Care
Burger King	Foodservice
Burton	Sports, Leisure & travel
CA Technologies	Telecom and IT
Cabela's	Retail/e-tail
Cadillac	Automotive
Call of Duty	Sports, Leisure & travel
Calvin Klein	Fashion & Personal Care
Camden Property Trust	Real Estate
Capital One	Financial services & insurance companies
Caress	Fashion & Personal Care

Carglass	Professional services
Carhartt	Fashion & Personal Care
Caribou Coffee	Foodservice
Carl's Jr. Restaurants	Foodservice
Carnival	Sports, Leisure & travel
Carter's	Fashion & Personal Care
CB Richard Ellis Group	Financial services & insurance companies
CB2	Retail/e-tail
CBS Corporation	Media
CH2M	Construction & construction materials
Champion	Fashion & Personal Care
Chevrolet	Automotive
CHG Healthcare Services	Human resources
Chico's	Retail/e-tail
Chili's	Foodservice
Chipotle	Foodservice
Chiquita	Agriculture, forestry, fishing
Chrysler	Automotive
Chubb	Financial services & insurance companies
Chuck E. Cheese	Sports, Leisure & travel
Church's Chicken	Foodservice
CiCi pizza	Foodservice
CIGNA Corp	Pharmaceuticals & life sciences
Cinnabon	Foodservice
Circle K	Retail/e-tail

Cisco	Telecom and IT
Citibank	Financial services & insurance companies
Citrix	Telecom and IT
Clarion	Sports, Leisure & travel
Clarisonic	Fashion & Personal Care
Clean & Clear	Fashion & Personal Care
Clinique	Fashion & Personal Care
Clorox	Personal and household appliances
CNN	Media
Coinstar	Retail/e-tail
Coldwater Creek	Retail/e-tail
Coldwell Banker Real Estate	Real Estate
Cole Haan	Fashion & Personal Care
Columbia Sportswear	Fashion & Personal Care
ComCast	Telecom and IT
Comfort Suites	Sports, Leisure & travel
Conrad Hotels	Sports, Leisure & travel
Convergys	Professional services
Cooper Tire	Tire & Rubber
Cottonelle	Fashion & Personal Care
Coty	Fashion & Personal Care
Country Inns & Suites	Sports, Leisure & travel
Crabtree & Evelyn	Fashion & Personal Care
Craftsman	Retail/e-tail
Crate and Barrel	Retail/e-tail

Crayola	Personal and household appliances
Crocs	Fashion & Personal Care
Crowne Plaza Hotels & Resorts	Sports, Leisure & travel
CSX	Sports, Leisure & travel
Culver's Franchising System	Foodservice
Cunard	Sports, Leisure & travel
CustomInk	Retail/e-tail
Cyanogen	Telecom and IT
David Weekley Homes	Real Estate
David Yurman	Fashion & Personal Care
Dean & Deluca	Retail/e-tail
Deere & Company	Construction & construction materials
Dell	Telecom and IT
Delta Air Lines	Sports, Leisure & travel
Denny's	Foodservice
Derek Lam	Fashion & Personal Care
Dermalogica	Fashion & Personal Care
DeWALT	Construction & construction materials
Dick's Sporting Goods	Retail/e-tail
Digium	Telecom and IT
Discovery Communications	Media
Disneyland	Sports, Leisure & travel
Dixie	Personal and household appliances
DKNY	Fashion & Personal Care
DLA Piper	Professional services

Dodge	Automotive
Dolby	Technology - General
Dollar General	Retail/e-tail
Domino's	Foodservice
DoSomething.org	Non profit organisations
DoubleTree	Sports, Leisure & travel
Dreamworks Animation	Media
Dress Barn	Retail/e-tail
Duck Tape	Personal and household appliances
Dun & Bradstreet	Telecom and IT
Dunkin Donuts	Foodservice
Earth Friendly Products	Personal and household appliances
Earthbound Farm	Agriculture, forestry, fishing
Eastern Mountain Sports	Retail/e-tail
Eastman Kodak	Industrial products & services
Eddie Bauer	Fashion & Personal Care
Edelman	Professional services
Electronic Arts	Media
Elie Tahari	Fashion & Personal Care
Elizabeth Arden	Fashion & Personal Care
Embassy Suites	Sports, Leisure & travel
Energizer	Personal and household appliances
Esprit	Retail/e-tail
Esri	Telecom and IT
Essie	Fashion & Personal Care

Esso	Energy & chemical
Este Lauder	Fashion & Personal Care
Ethan Allen	Personal and household appliances
Expedia	Sports, Leisure & travel
Express Employment Professionals	Human resources
Fairmont Hotels	Sports, Leisure & travel
Family Dollar	Retail/e-tail
Fastenal	Industrial products & services
FastSigns	Industrial products & services
Febreze	Personal and household appliances
Firehouse Subs	Foodservice
Firestone	Tire & Rubber
Fitbit	Personal and household appliances
Flickr	Telecom and IT
Food Network	Media
Forbes	Media
Ford	Automotive
Forever 21	Retail/e-tail
Foursquare	Telecom and IT
FOX news	Media
Free People	Retail/e-tail
Fresh	Fashion & Personal Care
GAP	Fashion & Personal Care
Garmin	Technology - General
Gartner	Professional services

GE Appliances	Personal and household appliances
Geico	Financial services & insurance companies
Genentech	Pharmaceuticals & life sciences
General Assembly	Education
General Tire	Tire & Rubber
Gensler	Professional services
Georgia-Pacific	Industrial products & services
Gibson Guitar	Personal and household appliances
Gilt Groupe	Retail/e-tail
Girls Scouts of the USA	Non profit organisations
Gmail	Telecom and IT
GMC	Automotive
GoDaddy.com	Telecom and IT
Goddard Systems	Education
Gold's Gym	Sports, Leisure & travel
Goodyear Tire	Tire & Rubber
GoPro	Technology - General
Great Clips	Fashion & Personal Care
Groupon	Professional services
Gymboree	Retail/e-tail
H.E.B.	Retail/e-tail
Hallmark	Retail/e-tail
Hampton by Hilton	Sports, Leisure & travel
Hanes	Retail/e-tail
Hardee's	Foodservice

Harley-Davidson	Automotive
Harry & David	Retail/e-tail
Harry Winston	Fashion & Personal Care
Hartford Financial Services	Financial services & insurance companies
Harvard University	Education
Hasbro	Toys industry
Hautelook	Retail/e-tail
Hayneedle	Retail/e-tail
HBO	Telecom and IT
Herbal Essences	Fashion & Personal Care
Hertz	Sports, Leisure & travel
Hills	Petfood & Care
Hilton Hotels & Resorts	Sports, Leisure & travel
Hilton Worldwide	Sports, Leisure & travel
Holiday Inn	Sports, Leisure & travel
Holiday Inn Express	Sports, Leisure & travel
Home Instead Senior Care	Professional services
Honeywell International	Consortia & organizations
Houzz	Professional services
HSN	Media
HubSpot	Professional services
Hulu	Media
Humana	Financial services & insurance companies
Hyatt Hotels & Resorts	Sports, Leisure & travel
Hyatt Regency	Sports, Leisure & travel

IBM	Telecom and IT
Ideo	Professional services
Iman Cosmetics	Fashion & Personal Care
Inc. Magazine	Media
Intel	Telecom and IT
Intercontinental Hotels	Sports, Leisure & travel
Intuit	Telecom and IT
IZOD	Fashion & Personal Care
Jack In The Box	Foodservice
James Corner Field Operations	Professional services
Jawbone	Personal and household appliances
Jazzercise	Sports, Leisure & travel
Jeep	Automotive
Jenn-Air	Personal and household appliances
Jersey Mike's Subs	Foodservice
JetBlue	Sports, Leisure & travel
Jimmy John's gourmet Sandwich Shops	Foodservice
Jo Malone	Fashion & Personal Care
Jockey	Fashion & Personal Care
John Varvatos	Fashion & Personal Care
Johnson's baby	Fashion & Personal Care
Johnston & Murphy	Retail/e-tail
Joie De Vivre	Sports, Leisure & travel
JW Marriott	Sports, Leisure & travel
K-Swiss	Fashion & Personal Care

KAYAK	Sports, Leisure & travel
KBR	Construction & construction materials
Keen	Fashion & Personal Care
Kenmore	Personal and household appliances
Kentucky Fried Chicken	Foodservice
Keurig	Personal and household appliances
Kiehl's	Fashion & Personal Care
Kimley-Horn & Associates	Professional services
Kimpton Hotels & Restaurants	Sports, Leisure & travel
Kindle	Personal and household appliances
Kirkland Signature	Food & Beverage
KitchenAid	Personal and household appliances
Kleenex	Fashion & Personal Care
Kmart	Retail/e-tail
Kohler	Industrial products & services
Kroger	Retail/e-tail
L.L. Bean	Retail/e-tail
La Prairie	Fashion & Personal Care
La-Z-Boy	Retail/e-tail
Lan	Sports, Leisure & travel
Lands' End	Retail/e-tail
Laura Mercier	Fashion & Personal Care
Layne Christensen	Construction & construction materials
LegalZoom	Professional services
Lennar	Construction & construction materials

Leo Burnett	Professional services
Levi's	Fashion & Personal Care
LifeBridge Health	Non profit organisations
LinkedIn	Telecom and IT
Listerine	Fashion & Personal Care
Lockheed Martin	Technology - General
Long John Silver Restaurants	Foodservice
Lowe's	Retail/e-tail
Lucky Brand	Fashion & Personal Care
Lucy	Retail/e-tail
Lunds & Byerly's	Retail/e-tail
Lycra	Fashion & Personal Care
Mac Tools	Construction & construction materials
Madewell	Retail/e-tail
Marathon Oil	Energy & chemical
Marmot	Fashion & Personal Care
Marriott International	Sports, Leisure & travel
Marsh & McLennan	Financial services & insurance companies
Mary Kay	Fashion & Personal Care
Massachusetts Mutual Life Insurance	Financial services & insurance companies
Massage Envy	Professional services
Matco Tools	Industrial products & services
Mathnasium Learning Centers	Education
Mayo Clinic	Non profit organisations
McDonald's	Foodservice

McKesson	Pharmaceuticals & life sciences
MD Anderson Cancer Center	Non profit organisations
Medtronic	Technology - General
Meijer	Retail/e-tail
Meridian Health	Non profit organisations
Merle Norman	Fashion & Personal Care
Merrell	Fashion & Personal Care
Merry Maids	Professional services
Method	Personal and household appliances
Methodist Hospital System	Non profit organisations
MetroPCS	Telecom and IT
MGA Entertainment	Toys industry
MGM Resorts International	Sports, Leisure & travel
Michael Kors	Fashion & Personal Care
Microsoft	Telecom and IT
Microsoft Advertising	Telecom and IT
Microsoft Office	Telecom and IT
Microsoft Studios	Sports, Leisure & travel
Miller Industries	Automotive
Milliken	Industrial products & services
Minuteman Press	Professional services
Mobil	Energy & chemical
Moe's Southwest Grill	Foodservice
Monsanto	Agriculture, forestry, fishing
Morgan Stanley	Financial services & insurance companies

Motorola	Telecom and IT
Mountain Hardwear	Retail/e-tail
Mrs Meyer's Clean Day	Personal and household appliances
MTV	Media
Murad	Fashion & Personal Care
Nair	Personal and household appliances
National Geographic	Media
National Guard	Government & public services
Nautica	Fashion & Personal Care
NBA	Media
NBC	Media
NESN	Media
NetApp	Technology - General
Netflix	Media
Networked Insights	Telecom and IT
Neutrogena	Fashion & Personal Care
New Balance	Fashion & Personal Care
New York Times	Media
Newegg	Retail/e-tail
Newell Rubbermaid	Personal and household appliances
News Corporation	Media
NFL Players	Sports, Leisure & travel
Northern Trust	Financial services & insurance companies
Northrop Grumman	Technology - General
Northwestern Mutual	Financial services & insurance companies

Norwegian Cruise	Sports, Leisure & travel
NRG Energy	Energy & chemical
Nugget Market	Retail/e-tail
Nutrisystem	Professional services
Nvidia	Telecom and IT
NYX Cosmetics	Fashion & Personal Care
Oakley	Fashion & Personal Care
Office Depot	Retail/e-tail
OfficeMax	Retail/e-tail
Ogilvy & Mather	Professional services
Old Navy	Retail/e-tail
Old Spice	Fashion & Personal Care
Omnicom Group	Professional services
OnBase by Hyland	Telecom and IT
ONeill	Fashion & Personal Care
OPI	Fashion & Personal Care
Oracle	Telecom and IT
Orbitz	Professional services
Origins	Fashion & Personal Care
Overstock.com	Retail/e-tail
Owens Corning	Industrial products & services
Oxo	Personal and household appliances
Palmolive	Fashion & Personal Care
Pampers	Fashion & Personal Care
Papa John's	Foodservice

Papa Murphy's	Foodservice
Paramount	Media
park inn	Sports, Leisure & travel
Patagonia	Fashion & Personal Care
Paychex	Professional services
Paycom	Telecom and IT
Payless ShoeSource	Retail/e-tail
PayPal	Financial services & insurance companies
PBS Kids	Media
PBTeen	Retail/e-tail
Pedigree	Petfood & Care
Perini	Construction & construction materials
Perricone MD	Fashion & Personal Care
PG&E	Energy & chemical
Philosophy	Fashion & Personal Care
Physicians Formula	Fashion & Personal Care
Pier 1 Imports	Retail/e-tail
Pillsbury	Media
Pink Ribbon	Non profit organisations
Pixar	Media
Pizza Hut	Foodservice
Planet Fitness	Sports, Leisure & travel
Plato's Closet	Retail/e-tail
Pond's	Fashion & Personal Care
Pottery Barn	Retail/e-tail

Pottery Barn Kids	Retail/e-tail
Power Home Remodeling Group	Professional services
Princess Cruises	Sports, Leisure & travel
Proactiv	Fashion & Personal Care
Proenza Schouler	Fashion & Personal Care
Progressive	Financial services & insurance companies
PuroClean	Professional services
Qtips	Personal and household appliances
Qualcomm	Industrial products & services
Quicken Loans	Financial services & insurance companies
Quiznos Sub	Foodservice
RadioShack	Retail/e-tail
Radisson Hotels Worldwide	Sports, Leisure & travel
rag & bone	Fashion & Personal Care
Ralph Lauren	Fashion & Personal Care
Ram	Automotive
Ray-Ban	Fashion & Personal Care
Raytheon	Technology - General
Razor	Personal and household appliances
Razorfish	Professional services
RE/Max	Real Estate
Reader's Digest	Media
Redbox	Retail/e-tail
Reef	Fashion & Personal Care
REI	Retail/e-tail

Remington	Personal and household appliances
Renaissance Hotels	Sports, Leisure & travel
Restoration Hardware	Retail/e-tail
Revlon	Fashion & Personal Care
Revolution Foods	Professional services
Reynolds	Personal and household appliances
Rite Aid	Retail/e-tail
Ritz-Carlton	Sports, Leisure & travel
Road & Track	Media
Rockport	Fashion & Personal Care
Rockstar Games	Sports, Leisure & travel
Rockwell Collins	Technology - General
Rosewood Hotels & Resorts	Sports, Leisure & travel
ROSS Stores	Retail/e-tail
Royal Caribbean Cruises	Sports, Leisure & travel
Russell	Fashion & Personal Care
Salesforce.com	Telecom and IT
SanDisk Corporation	Personal and household appliances
Sassoon	Fashion & Personal Care
Saturn	Automotive
Saucony	Fashion & Personal Care
Schecter	Music
Scholastic.com	Education
Scientific American	Media
Scotch-Brite	Personal and household appliances

Scripps Health	Non profit organisations
Seagate Technology	Technology - General
Sears	Retail/e-tail
Seventh Generation	Personal and household appliances
Sherwin-Williams	Construction & construction materials
Sigma-Aldrich	Technology - General
Signarama	Professional services
Skechers	Fashion & Personal Care
Skinceuticals	Fashion & Personal Care
Skype	Telecom and IT
Smashbox	Fashion & Personal Care
Smith International	Construction & construction materials
Smoothie King	Foodservice
Snap Fitness	Sports, Leisure & travel
Snap-on Tools	Personal and household appliances
SolarCity	Construction & construction materials
Sonic Drive In Restaurant	Foodservice
Sonos	Personal and household appliances
Sony Music Entertainment	Music
Sony Pictures	Media
SoulCycle	Sports, Leisure & travel
SpaceX	Technology - General
Spiegel	Retail/e-tail
Sport Clips	Fashion & Personal Care
Sportvision	Media

Sprint	Telecom and IT
Square	Telecom and IT
St. jude Children's Research Hospital	Non profit organisations
St. Regis Hotels	Sports, Leisure & travel
Starbucks	Foodservice
State Farm	Financial services & insurance companies
Stayfree	Fashion & Personal Care
Steve Madden	Fashion & Personal Care
Stew Leonard's	Retail/e-tail
StriVectin	Fashion & Personal Care
Subway	Food & Beverage
Supercuts	Fashion & Personal Care
Sybase	Telecom and IT
Sylvan Learning	Education
Symantec	Telecom and IT
System4	Professional services
Taco Bell	Foodservice
Talbots	Retail/e-tail
Target	Retail/e-tail
TE Connectivity	Technology - General
Teach For America	Education
TED	Media
TEKsystems	Human resources
Tenaris	Energy & chemical
TEVA	Fashion & Personal Care

Texas Instruments	Technology - General
Texas Roadhouse	Foodservice
The Boston Consulting Group	Professional services
The Home Depot	Retail/e-tail
The North Face	Retail/e-tail
The UPS Store	Logistics & Mail
The Washington Post	Media
Theory	Fashion & Personal Care
Thermo Fisher Scientific	Technology - General
Ticketmaster	Professional services
TLC	Media
Tom Ford	Fashion & Personal Care
Tom's of Maine	Fashion & Personal Care
Tommy Bahama	Fashion & Personal Care
Tommy Hilfiger	Fashion & Personal Care
Topps	Sports, Leisure & travel
Tory Burch	Fashion & Personal Care
Tractor Supply Company	Retail/e-tail
Travelodge	Sports, Leisure & travel
TripAdvisor	Sports, Leisure & travel
Trish McEvoy	Fashion & Personal Care
True Religion	Fashion & Personal Care
True Value	Retail/e-tail
TRW Automotive Holdings	Industrial products & services
Tupperware	Personal and household appliances

Tylenol	Pharmaceuticals & life sciences
U by Kotex	Fashion & Personal Care
U.S. Bank	Financial services & insurance companies
U.S. Polo Assn.	Fashion & Personal Care
UGG Australia	Fashion & Personal Care
Ultimate Software	Telecom and IT
Under Armour	Fashion & Personal Care
Unicef	Non profit organisations
Union Pasific Railroad	Sports, Leisure & travel
United Continental Holdings	Sports, Leisure & travel
United Country Real Estate	Real Estate
Universal Music	Media
Universal Pictures	Media
UPS	Logistics & Mail
US Marine Corps	Government & public services
USAA	Financial services & insurance companies
Valvoline	Energy & chemical
Vanderbilt University	Education
Vanity Fair	Personal and household appliances
Vaseline	Fashion & Personal Care
Vector	Technology - General
Verizon	Telecom and IT
Veterans United Home Loans	Financial services & insurance companies
VH1	Media
Viking	Personal and household appliances

Vince Camuto	Fashion & Personal Care
Vineyard Vines	Retail/e-tail
Visiting Angels	Professional services
Vizio	Personal and household appliances
VMware	Telecom and IT
Vogue	Media
W Hotels	Sports, Leisure & travel
Wachovia	Financial services & insurance companies
Waffle House	Foodservice
Waldorf Astoria	Sports, Leisure & travel
Walgreens	Retail/e-tail
WaMu	Financial services & insurance companies
Warner Bros	Media
Waters	Technology - General
Weather Channel	Media
WebMD Health	Media
WeightWatchers	Professional services
Wendy's	Foodservice
West Elm	Retail/e-tail
Western Union	Financial services & insurance companies
WeWork	Professional services
Whataburger	Foodservice
Whirlpool	Personal and household appliances
Whiskas	Petfood & Care
White House — Black Market	Retail/e-tail

Wikipedia	Media
Williams-Sonoma	Retail/e-tail
Windows	Telecom and IT
Windstar Cruises	Sports, Leisure & travel
Wingstop Restaurant	Foodservice
Workday	Telecom and IT
World Bank Group	Financial services & insurance companies
Wrangler	Fashion & Personal Care
Wyndham Hotels and Resorts	Sports, Leisure & travel
Xbox	Personal and household appliances
Xcel Energy	Energy & chemical
Yahoo!	Telecom and IT
Yelp	Telecom and IT
YouTube	Media
Zales	Retail/e-tail
Zaxby's Franchising	Foodservice

Simplicity is not Key: Understanding Firm-Generated Social Media Images and Consumer Liking - ***Highlights***

1. This research presents automated measurements for capturing the visual complexity of social media imagery.
2. The relationship between visual complexity and consumer liking on social media is not linear.
3. Visual complexity is not a linear, monolithic construct and can therefore not be captured by a single additive measure.
4. The relationship between visual complexity and consumer liking on social media is best interpreted using its individual components.
5. Image analytics at scale can offer key insights in understanding the diffusion of online visual content.