Image Mining: Exploring the Impact of Video Content on the Success of Crowdfunding

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Abstract

This study aims to better understand the role of visual content in the likelihood of supporting crowdfunding projects. We propose an image mining procedure for collecting, identifying, and classifying visual concepts. This procedure detects communities in the visual concepts' network, allowing researchers to classify objects into contextual clusters for further inferences. In Study 1, we explored 11,264 video frames from 652 crowdfunding projects on Kickstarter.com using Clarifai's image recognition tool. By the Louvain method of community detection, we identified 38 contextual clusters of visual concepts. From those, we found that the "workspace" cluster positively linked to crowdfunding projects' success, while the "event" cluster negatively was related. In addition, in Study 2, we conducted an experiment to examine the impact of the two visual contexts on consumer investors' intent to support crowdfunding projects and found evidence supporting our initial findings.

Keywords: Visual data, image mining, image data, unstructured data, crowdfunding

1. Introduction

In the age of Web 2.0, users contribute a gigantic volume of information through channels such as social media, blogs, and online reviews. These user-generated data are mainly in the form of figures, texts, pictures, and videos. In recent years, image-based content (e.g., pictures and videos) has emerged as the most popular electronic information means, especially on social media platforms, such as Facebook, Instagram, Pinterest, Snapchat, TikTok, and Twitter. As noted by Business Insider, by 2021, video content is estimated to represent 82% of all internet traffic, up from 73% in 2016 (Business Insider, 2017). A recent report by Hootsuite highlights that the 800 million monthly active users of the emerging social media platform TikTok spend an average of 46 minutes per day watching 15-second videos (Hootsuite, 2020). The reason behind such prevalence of visuals is rather intuitive: processing visual information is much less effortful than symbolic ones such as figures and text (Lurie & Mason, 2007). As the old saying goes, *a picture is worth a thousand words*. For instance, a study found that tweets with images received 150% more retweets than tweets without images (Cooper, 2016).

Over the last few years, marketing researchers and practitioners have exploited the richness of online public data, primarily in numeric and textual format. However, despite its popularity, the utilization of visual content remains at an early stage. After all, the main obstacle is that this type of unstructured data is inherently qualitative. Thus, it is extremely challenging to process and make inferences upon a large amount of visual information effectively and efficiently. Nevertheless, at the dawn of the artificial intelligence (AI) era, we propose an image mining procedure that combines the usage of machine learning image recognition tools and network analysis frameworks to overcome this obstacle.

This paper aims to exploit large-scale visual content publicly available online and investigate its influence on the viewer's behavior. To do so, we collect and process a set of videos and obtain mutually related visual concepts using image recognition tools. Based on the normalized co-occurrences of these concepts, we construct a network of visual content and identify clusters, in which concepts are closely related, by the Louvain method of community detection. Each of these clusters may represent a visual context that appears in the set of videos. Finally, we suggest inferences on how the information belonging to different visual contexts influences the viewers' behavior.

Based on the visual data analysis of 652 videos collected from a leading crowdfunding platform, Kickstarter.com, we found two visual contextual clusters significantly related to the crowdfunding project's success, i.e., reaching the project's funding goal within its funding period. Presenting visual information from the context of "event" (featured by keywords such as "actor," "actress," "administration," "leader," "rally," "crowd") will backfire on the project's fundraising. However, visual information from the context of "workspace" (featured by keywords such as "office," "toy," "teamwork," "cooperation) can benefit the crowdfunding campaign. We further implemented an experiment to examine the impact of visual context on consumer investors' intent to support crowdfunding projects and found evidence supporting our initial findings. The proposed image mining method can help marketers better understand consumers' online behavior at large, especially in platforms such as social media and crowdfunding. Our empirical results also provide substantial implications for crowdfunders' campaign strategy.

2. Theoretical Background

2.1. Visual Information as Unstructured Data

Visual information is considered as a form of unstructured data, together with text and audio information (Sudhir, 2016). Rizkallah (2017) estimates that unstructured data account for 80% of those currently held by companies, including documents, messages, social media posts, pictures, videos, and audio. Unstructured data is also growing 15 times faster than structured data (Narayanan & Ramesh, 2012). In the past decade, marketing researchers and practitioners have been exploiting large-scale data from consumer forums, blogs, product reviews, and more recently, in search engines and social media. Since analyzing a large volume of communication content is challenging (Godes et al., 2005), early studies often used quantitative summaries of consumer data, such as the total number of comments and overall product ratings, to approximate the exchanged ideas (Chevalier & Mayzlin, 2006; Chintagunta et al., 2010; Dellarocas et al., 2007; Chen et al., 2011; Godes & Mayzlin, 2004; Liu, 2006). More recent research focuses on the meaning of customer-generated verbal content and develops various text mining methodologies (Alaparthi & Mishra, 2021; Humphreys & Wang, 2018; Jurafsky et al., 2014; Lopez et al. 2020; Lee & Bradlow, 2011; Netzer et al., 2012).

Thanks to the development of information technologies, including advanced smartphones, 4G and 5G networks, and social media platforms, visual content has become more popular as an information carrier in the era of Web 2.0. Despite its popularity and prominence in practice, online visual content has still been underexplored in marketing academic research. Among the few studies of visual content, Xiao and Ding (2014) examined the effects of facial features in print advertising. Liu et al. (2020) considered the color, shape, and texture of brand image portrayed in social media. Zhang et al. (2018) analyzed the shot length, camera motion, sound loudness, and sound pitch of videos. Bui (2021) used geo-tagged photos to study spatiotemporal behavior and visitors' preferences at shopping locations. Dzyabura and Peres (2021) collected user-generated collages to study consumer associations of U.S. national brands. The objective of the current study is to explore the contextual patterns of visual content by leveraging the recent advances in image recognition technology and examine their impact on consumers. Specifically, we are interested in mining the visual content created by nascent businesses (startups and small businesses) on consumer-to-consumer (C2C) platforms such as crowdfunding.

2.2. Visual Information in Crowdfunding

Crowdfunding has become a widespread practice for entrepreneurs and startups to seek financial support for their innovations (Agrawal et al., 2015; Kuppuswamy & Bayus, 2017; Mollick, 2014). In the face of barriers to traditional funding sources, including banks and venture capital, entrepreneurs and startups can now raise financial support from online communities of consumer investors, i.e., backers or crowdfunders (Agrawal et al., 2015; Kuppuswamy & Bayus, 2017). Crowdfunding makes an excellent setting for our study for multiple reasons. First, crowdfunding campaign backers face high uncertainty when making investment decisions, as crowdfunding projects are mostly at the early stage and inherently risky. For instance, Mollick (2014) found that among 247 successful projects in the design and technology categories on Kickstarter.com (i.e., those successfully raised their funding goal and promised to deliver products), a great majority of them (about 75%) were delayed, and some (about 4%) did not deliver at all. Furthermore, crowdfunders are primarily inexperienced in investing in new projects and lack knowledge about specific product development. Therefore, they rely heavily on the limited information provided on the project webpage to evaluate the quality of the new product and the credibility of the project creator. This situation makes the amount, quality, and receiver-friendliness of the project information, critical for crowdfunding success.

Second, visual information plays a significant role in promoting entrepreneurs' crowdfunding ideas. For example, Kickstarter's creator handbook suggests that images and videos are "a huge help for bringing people inside your story" (Kickstarter.com/help/handbook). Research also shows that more visual impressions help consumers distinguish between products and thus make choices more easily (Jia et al., 2014; Lurie & Mason, 2007; Townsend & Sood, 2011). Fundamentally speaking, increased visual processing of items in a consideration set fosters disambiguation and differentiation by providing more information about product features (Bloch et al., 2003; Capenter et al., 1994). As explained later in more detail, our data also suggest that having a video is positively related to the funds raised by a crowdfunding project.

Third and lastly, since most project creators, if not all, are startups and small businesses, alternative channels to reach their targeted crowdfunders are limited. Besides, the effectiveness of project creators' promotion efforts can be conveniently gauged by the outcome of crowdfunding, either the success or the amount of money pledged. Crowdfunding, thus, makes an ideal context for empirically examining the influence of visual content and providing implications for marketers at large. Below, we introduce an image mining procedure that is applicable in crowdfunding and other general settings.

3. The Image Mining Method

We propose the following procedure of collecting, identifying, and classifying information in the user-generated visual content, including pictures and videos.

3.1. The Image Mining Procedure

Step 1. Downloading visuals: Source videos/pictures from a given website.

Step 2. Segmenting video: Slice the video into a sequence of pictures by frame or second.

Step 3. Extracting objects: Label visual concepts that appear in pictures using an image-recognition tool (e.g., Clarifai, Google Cloud Vision, IBM Watson).

Step 4. Identifying clusters: Build a contextual network of co-occurrences of objects appearing in the images. By detecting communities in the network, classify objects into contextual clusters for further inferences.

Fig. 1 shows an example of the first three steps of image mining on the video of a crowdfunding project, Foamzoo, on Kickstarter.com. First, we started the procedure by downloading the project's 2 minutes 24-second video from its webpage and then segmented the video by second into 125 pictures (including the one at time 0). Second, we uploaded each picture to Clarifai's image recognition tool through its application programming interface (API). Lastly, the API outputs 20 concepts identified in the picture with the highest probabilities. The extracted information can be further analyzed at the level of second, ten seconds, the whole video, etc. For this study, we use second as the fundamental analysis level and look for co-occurrences of pairs of visual concepts in each second of the videos.

<Insert Figure 1 here>

3.2. Network and Community Detection

Our next step of analysis is based on the measure of co-occurrences of concepts. The co-occurrences help us find the patterns of objects appearing in different contexts of images to construct a contextual network. For instance, if the concepts "desk" and "chair" are found together frequently, we should define that 'desk' and 'chair' have a strong dyadic connection. However, using simple co-occurrences has limitations because, for an object frequently appearing in a given set of videos, its co-occurrences with almost any other object will be greater than that of an object appearing less frequently (Netzer et al., 2012). For instance, in our data described later, the concept “desk” appeared with “computer” 1,563 times, while there were only six co-appearances of the concept “cord” with “computer.” However, project videos show “desk” 2,863 times in the data, while “cord” was shown only eight times. Thus, once we normalize for the mere occurrences of the concepts, we find that the likelihood of "computer" appearing in a video frame that has a “cord” is much greater than for such a concept appearing in a video frame that has a “desk.”

Such normalization is called Lift (Turney & Littman, 2003; Netzer et al., 2012). Lift is the ratio of the actual co-occurrence of two terms to the frequency with which we expect to see them together. The Lift between concepts X and Y can be calculated as

$$\text{Lift}(X,Y) = \frac{P(X,Y)}{P(X)\cdot P(Y)},$$

where $P(X)$ is the probability of concept X appearing in a video frame randomly selected form the whole dataset. $P(X,Y)$ is the probability that both concept X and concept Y appear in a video frame randomly selected form the whole dataset. Particularly, if concept X is identified in n video frames, $P(X)$ can be further derived as

$$\frac{\sum_{i=1}^{n} p_i(X)}{N},$$

where $p_i(X)$ is the probability of concept X existing in video frame i, predicted by the image recognition tool, and N is the total number of video frames in the data. Similarly, if concept X and concept Y are identified together in m video frames, $P(X,Y)$ can be found by

$$\frac{\sum_{j=1}^{m} p_j(X)\cdot p_j(Y)}{N}.$$

Based on the dyadic connections defined by Lift, we build up a network of concepts from visual content. To classify these visual concepts, we can further detect their clusters in the network based on the strength of the connections between visual concepts. These clusters are inherently contextual because more closely related concepts are, by definition, more likely to appear in the same video frame. In other words, clusters of concepts can be seen as different visual settings in which the crowdfunding project creators present their ideas and products. In the following section, we will identify the contextual clusters and explore their impacts on the crowdfunding outcomes.

4. Study 1: Exploratory Study on the Impact of Video Content

4.1. Data

Data for this study were collected from Kickstarter, one of the most popular crowdfunding platforms in the world. We collected all the 847 projects presented in the English language (to rule out the influence of language) created from 11/12/2016 to 11/17/2016. We monitored these projects across their funding period (the maximum was 60 days) and excluded 10 projects, as these were canceled by the project creators. We ended up with 837 projects, among which 652 projects used videos to introduce their crowdfunding ideas. A t-test shows that having a video was positively related to the funds raised (*t-statistic* $= 2.3$, $p = .021$).

For each project, we collected its category, funding goal, and creator's information, including the number of projects they had created, succeeded, and backed before the present campaign. The project's funding period ranged from 2 to 60 days, with a mean of 32 days. When the project ended, we recorded the funds pledged and found whether the funding goal was achieved (success or not). Overall, 46.5% of projects in the data succeeded. The average funding pledged was $32,630 for all projects and $66,930 for successful ones.

We collected and processed the video content of the crowdfunding projects by following the image mining method proposed in §3 using Clarifai's image-recognition general model. Clarifai, founded in 2013, is a commercially available image-recognition tool and has been used in recent marketing studies on image data (Dzyabura & Peres, 2021, Nanne et al., 2020). Clarifai's general model could identify at least 11,000 concepts, including objects (e.g., woman, man, sunshine, ocean), ideas/themes (e.g., education, leisure, togetherness, urban), and emotions/feelings/moods (e.g., joy, cute, confidence, cold) (Johnson, 2018). Clarifai's identification accuracy was reported to be around 89.3% (Jaakonomäki et al., 2017).

We obtained 100,264 video frames from the 652 projects and 20 concepts with corresponding probabilities for each frame. From those, we identified 2,595 distinct concepts and 180,295 distinct co-occurred pairs of concepts identified from these visual contents. Based on the measurement of Lift defined earlier, we built up the contextual network of concepts and used Kamada and Kawai's (1989) spring-embedded algorithm to illustrate it in a network plot available at https://photos.app.goo.gl/nMxWnbDmzM5SB1gH8[1]. This algorithm minimizes the stress of the spring system connecting the nodes in the network so that concepts that are more often shown in the same context (have higher Lift) appear closer to one another in the graph. In this plot, the size of each node was scaled by the square root of the appearance frequency of the concept.

To detect the communities in the network, we adopted the Louvain method, which is commonly used to extract communities from large networks (Blondel et al., 2008). In the

[1] The network plot is only available online due to its large size. Readers can zoom in to see the details in the figure through the link provided. Loading the details may require some time.

Louvain method of community detection, clustering optimization is achieved by maximizing network modularity, i.e., maximizing the relative density of edges inside communities with respect to edges outside communities. In the network plot, concepts labeled by the same color belong to one cluster. We found a total of 46 clusters in the network. We then calculated the percentage of concepts belonging to each cluster in each video frame, and for each video, took the average of the frame-level percentages to get a cluster score, a number between 0 and 1. A high (low) cluster score of a video indicates the video's high (low) relevance to the corresponding cluster. We present the descriptive statistics of variables for projects with videos in Table 1. The top 15 most frequent concepts for each cluster are presented in Appendix A. Based on the most frequent concepts, we were able to recognize the visual contexts that 38 clusters stand for. We present these contexts with corresponding clusters in Table 1.

<Insert Table 1 here>

4.2.Model and Results

We adopt a logistic model to examine the impact of visual contexts on the probability of project success. Specifically, we model the probability of project p's success as a logit function given by:

$$P\left(Success_p = 1\right) = \frac{\exp\,(X_p\vec{\beta})}{1 + \exp\,(X_p\vec{\beta})} \tag{1}$$

where X_p denotes a vector of explanatory variables for project p, including the percentage of all visual contextual clusters as well as the project's and the project creator's characteristics. $\vec{\beta}$ denotes the vector of coefficients to be estimated. The empirical specification for $X_p\vec{\beta}$ is given by

$$X_{ip}\vec{\beta} = \beta_0 + \mu_{c,p} + \sum_{n=1}^{38} \beta_n Cluster_{k_n,p} + \beta_{37} VideoLength_p + \beta_{38} Goal_p + \beta_{39} FundingPeriod_p + \beta_{40} TimeToDeliver_p + \beta_{41} Failed_p + \beta_{42} Succeeded_p + \beta_{43} Backed_p \quad (2)$$

where $\mu_{c,p}$ denotes the crowdfunding project category fixed effect. $Cluster_{k_n,p}$ denotes the percentage of one of the 38 identified visual contextual cluster contained in the project p's video, i.e., the cluster score. We incorporate four additional project-specific variables: $VideoLength_p$, $Goal_p$, $FundingPeriod_p$, and $TimeToDeliver_p$. $VideoLength_p$ denotes the length of the project video in seconds. $Goal_p$ denotes the amount of funding that the project creator is aimed to raise for project p in dollars. $FundingPeriod_p$ denotes the length of the funding period in days. $TimeToDeliver_p$ denotes the length of time from the end of the funding period to the outcome deliver time promised by the project creator. To control the experience of the project p's creator, we include three variables of $Failed_p$, $Succeeded_p$, and $Backed_p$, which capture the number of projects that the project creator has failed, succeeded, and backed in the past, respectively.

We estimated our proposed model and present the estimation results of the model in Table 2. Among the 38 clusters, we found $Cluster_{15}$, shown in Fig. 2 A, negatively related to the success of crowdfunding ($\beta=-12.73, p<.05,$), whereas $Cluster_{37}$, shown in Fig. 2 B, positively related to the success of crowdfunding ($\beta=33.33, p<.05$). Interestingly, these two clusters of visual concepts represent two typical settings that crowdfunding entrepreneurs may conveniently use for their campaign videos in various consumer product categories. In Fig. 3, we created a word cloud for each of them, in which the sizes of concepts are scaled by the square root of its frequency in our data. $Cluster_{15}$, the "event" setting, was featured by keywords "actor", “actress”, “administration”, “election”, “leader”, “crowd”, etc. It was relevant to a visual scene that involves a character pitching the crowd during a planned public or social occasion. The estimation results suggested that using this type of scene in a video was likely to harm the crowdfunding campaign. On the other hand, $Cluster_{37}$, the “workspace” setting, included keywords such as “office,” “toy,” “teamwork,” “cooperation,” and was related to a setting involving the collaboration of people in a working space. Our result indicated that this type of visual context would help crowdfunding projects to succeed.

<Insert Figure 3 here>

The different impacts of event and workspace settings may be due to several reasons. First, consumer investors may feel more comfortable with product presentations in a more casual environment, such as a workspace, than an event setting. Past research has shown that the physical environment plays a vital role in consumer experience for generating positive sentiment, such as enjoyment (e.g., Hightower et al., 2002; Yang et al., 2002). We expect a similar impact from the visual environment in which products are shown in videos. Second, consumer investors may use the visual setting as an implicit cue to formulate the project creator's credibility. Compared to the event setting, the workspace setting is more consistent with the project’s product development process and teamwork. Furthermore, backers may perceive a healthy financial well-being of the crowdfunding project when the project creators seem to have established a workspace. Backers will thence generate more trust towards the project (Ganesan, 1994). Third, consumer investors are more likely to relate the product to their personal user experience when it is presented in a familiar visual environment, such as a workspace. As a result, they may perceive a higher value of the product and appreciate its unique features more due to higher involvement levels (Lemke et al., 2010). Thus, we speculate that consumer investor's enjoyment of watching crowdfunding campaign videos, trust in the crowdfunding project, the perceived value of the product, and perceived innovativeness would mediate the effect of the two identified visual contexts.

<Insert Figure 3 here>

In addition, we found that the coefficient of project goal (*Goal*) was significantly negative ($\beta = -4.54\times10^{-6}$, $p<.05$); the coefficient of *FundingPeriod* was also negative and significant ($\beta = -2.29\times10^{-2}$, $p<.05$). These results suggested that (i) the larger amount of money that a project creator was aimed to obtain, the less likely the project was likely to achieve its funding goal; (ii) the longer the funding period, the less likely the project would succeed. The negative impact of the funding period might be because projects with weak marketability strategically extended the funding period in the hope of gathering more support. However, the chance for these projects to succeed remained small due to their low value for the consumers. The impact of *VideoLength* and *TimeToDeliver* were not significant. For project creator-specific variables, we found the number of projects that failed (*Failed*) to be negative and significant ($\beta = -.69$, $p<.01$). The number of projects succeeded by the project creator (*Succeeded*) significantly enhanced the success of the focal project ($\beta = .69$, $p<.01$). In other words, the project creators' success experience might serve as a critical signal for backers to make their investment decisions. The impact of the number of projects backed by the creator (*Backed*) was not significant. Four other identified contextual clusters showed one-tail significance. They were $Cluster_{16}$ "Fire" ($\beta = -16.87$, $p<0.08$), $Cluster_{18}$ "Holiday" ($\beta = -20.20$, $p<0.06$), $Cluster_{20}$ "Flying" ($\beta = -37.72$, $p<0.06$), and $Cluster_{25}$ "Battle" ($\beta = 15.02$, $p<0.07$). These results might reflect the tastes of the backer population. For example, projects with the highest cluster scores of $Cluster_{25}$ "Battle" were mostly related to video and tabletop games and film and video production. The battle actions highlighted in the campaign videos might help attract the young generation backers active on Kickstarter.com. Project videos highlighting visual elements related to fire, holiday, and flying themes might be less appealing to most backers on the platform.

The main findings of the exploratory study on the impact of video content suggest that using an event setting ($Cluster_{15}$) could be detrimental to crowdfunding campaign success while using a workplace setting ($Cluster_{27}$) could enhance the project's success. In addition, longer crowdfunding projects and larger monetary goals are less likely to get funded. Finally, our study suggests that creators' past successes enhance the likelihood of the current project success. Below, we include an experimental study to explore our key findings further.

5. Study 2: Experimental Study on the Impact of Video Context

5.1. Experimental Design

To examine the causal impact of the visual contexts on the likelihood of success in crowdfunding, we designed a two-group random assignment experiment. We first recorded two videos of a hypothetical crowdfunding campaign, which are identical in terms of the main character and the speech content but adopt different visual contexts. Second, we randomly assigned participants to watch one of the two crowdfunding campaign videos with either the event visual context or the workspace one. After watching the video, participants were asked about their intent to support the campaign. Participants' responses were then compared between the two groups to find if there was a significant difference.

To actualize the two visual contexts in our experiment, we set up two physical spaces representing (1) an event venue, including a podium and a projector, and (2) an office of a startup co-working space. Next, we recruited an entrepreneur with experience in pitching to diverse audiences (e.g., other entrepreneurs, investors, etc.) to serve as an actress in the two fictitious crowdfunding campaign videos. Finally, we recorded a video of the entrepreneur in each of the two cluster settings.

Both videos were recorded in February 2019. In the first video, the entrepreneur pitched a crowdfunding solution (a green tea teacup set) to a group of people from a podium, replicating the event context. Fig. 4 A shows an image from the first video. In the second video, the entrepreneur pitched the same crowdfunding solution. However, the location was in a staged office that includes several elements from a relaxed, working space, such as collectible items, board games, a magnetic glass whiteboard, a Nespresso machine, a tea kettle, magazines and newspapers, laptops, and most importantly three co-workers, to represent the workspace context (see Fig. 4 B). The authors crafted a 2-minute script for the campaign, and the entrepreneur closely followed it in both videos. Below, we provide such a script.

<Insert Figure 4 here>

> *Numerous benefits of enjoying a cup of green tea have been identified by researchers, including, among others: Improved health, increased fat burning, enhanced physical performance, and even living longer (Gunnars, 2018). According to Boston's nutritionist Beth Reardon, green tea's health benefits are all about catechins–antioxidants that fight and may even prevent cell damage. Green tea is rich in catechins! (Spencer, 2019). Unfortunately, brewing a nice cup of green tea on the go is difficult and complicated.*
>
> *Hi, I'm Dr. Ashley Smith [this is a fictitious name], and I'm the founder and CEO of The Tiny Teacup Company. After four successful Kickstarter campaigns for green tea lovers last year, we're here one more time to introduce our latest product innovation, the West Lake Tea Set.*

Named after the majestic West Lake in Hangzhou, China – one of the most beautiful cities on earth, and even described in the 13th century by Marco Polo as "the city of heaven" (Tang, 2019), the West Lake Tea Set is designed to completely enhance your green tea drinking experience wherever you are.

The West Lake Tea Set was crafted by our team of designers and engineers in our labs in Milan and Shanghai and will be manufactured in San Francisco, California. It comes in a water-resistant travel box made out of indestructible canvas and includes a soft Napa leather strap for easy carrying. Once you open your West Lake Tea Set, you will enjoy an authentic Chinese porcelain set of cups and kettle, with beautiful motives from the West Lake.

The set includes:

- *Two cups, so you can share your green tea with anyone on the go,*
- *A stainless-steel filter that works with bagged and loose-leaf tea, and*
- *A beautiful silicon sleeve to enjoy your green tea at any temperature.*

Many people drink green tea from a mug. But, did you know that there are several advantages from drinking green tea from a small, sipping cup as opposed to a mug?

- *It encourages us to drink slowly and helps us to concentrate on the tea.*
- *These are easier to clean*
- *Green tea cools faster*
- *You can enjoy multiple infusions without becoming full*
- *You can share your tea with someone else (Caicedo, 2018)*

Support our Kickstarter campaign. The West Lake Tea Set will retail for $59 plus shipping. Right now, you can get yours for $29 with free shipping.

Enjoy your green tea!

After recording, we edited the videos using iMovie software (Apple.com). The lengths of the videos were almost the same, video 1 at 2:09 and video 2 at 2:12. We ran a test to confirm how closely the videos represent $Cluster_{15}$, the event context, and $Cluster_{37}$, the workspace context, respectively, by following the method used in Study 1. Video 1 was found to have an event cluster score ($\text{Cluster}_{\text{event},1}$) of 0.1019 and a workspace cluster score ($\text{Cluster}_{\text{worksapce},1}$) of 0.0171, while video 2 was found to have an event cluster score ($\text{Cluster}_{\text{event},2}$) of 0.0070 and a workspace cluster score ($\text{Cluster}_{\text{event},2}$) of 0.0458. These results confirmed that between the two videos, video 1 contained far more visual cues that belongs to the event cluster ($\text{Cluster}_{\text{event},1} >> \text{Cluster}_{\text{event},2}$), and video 2 contained far more of the "workspace" cluster ($\text{Cluster}_{\text{worksapce},2} >> \text{Cluster}_{\text{worksapce},1}$). We then uploaded the two videos to the YouTube video platform (YouTube.com) and subsequently attached these videos in a survey administered on Qualtrics.com. In the survey, we adopted a randomizer in the question flow to randomly assign online participants to watch one of the videos. Right after a participant watched the video, we first measured each participant's intent to support the projects using a 4-item scale. We then measured the four mediating variables, i.e., the enjoyment of watching the video, the trust on the project, the perceived value, and the perceived innovativeness (see §5.2).

5.2. Measurement

The items of measurement are presented in Table 3. To estimate consumer's intention to support, we developed 1 item (*ITS 1*) and adopted three items from Chang and Chen (2008) (*ITS 2 - ITS 4*). In addition, we developed four items (*ENJ 1 - ENJ 4*) to measure the enjoyment of watching the video. We then adopted four items (*TRST 1 - TRST 4*) from Sirdeshmukh, Sing, and Sabol (2002) to assess trust, four items (*VL 1 - VL 4*) from Wu et al. (2014) to estimate perceived value, and four items (*INNV 1 - INNV 4*) from Avlontis and Salavou (2007) to measure perceived innovativeness.

5.3. Data Collection

A pretest of the questionnaire was performed to determine the content validity of measurement scales (Hair et al., 2006). We applied the questionnaire to five business professors whose research area is related to the scales included in our survey. Some alterations were conducted based on their suggestions. We finalized our questionnaire and recruited participants for our experiment from Amazon Mechanical Turks (AMT), a marketplace in which individuals are compensated with a fee in exchange for completing diverse tasks, including responding to academic research. Numerous studies have used AMT in the past and have been published in outlets such as *Journal of Marketing* (Aydinli et al., 2014; Giebelhausen et al., 2014; Sirianni et al., 2013) *and Journal of Marketing Research* (Goldstein et al., 2014), among others.

We required our participants to be designated as "Mechanical Turk Masters" (identified as high performers by AMT) to ensure the quality of responses. In addition, their location was limited to the US to ensure that participants have similar benchmarks when evaluating the crowdfunding project. The AMT respondents were offered a small compensation for completing this task. A total of 149 responses were collected in November 2019. Of these, 115 surveys were usable, and the remaining were dropped because of unengaged or incomplete responses, resulting in an effective response rate of 77.18%. The data description of the sample is presented in Table 3. We found high reliability for all constructs measured by multi-item scales (*Cronbach's* $\alpha > 0.90$, presented in Table 3). For the following statistical tests, we used the average value of items to represent each construct.

<Insert Table 3 here>

5.4. Models and Results

To assess the impact of visual context, we first conducted a t-test on the intention to support (ITS) between the workspace visual context group and event visual context group. We found that the group watching the workplace version video yielded a significantly higher level of intent to support the crowdfunding project ($t = 2.642, p<0.01$).

Following the three steps proposed by Baron and Kenny (1986), we further examined the proposed mediation relationships. In step 1, we regressed intent to support (*ITS*) on workplace visual context (*WVC*) to confirm that *WVC* was a significant predictor of *ITS*:

$$ITS = \rho_{10} + \rho_{11}WVC + \varepsilon_1.$$

In step 2, to confirm that *WVC* was a significant predictor of each mediator, we regressed the four proposed mediators, enjoyment of watching the video (*ENJ*), trust on the project (*TRST*), perceived value (*VL*), and perceived innovativeness (*INNV*) on *WVC*:

$$ENJ = \rho_{210} + \rho_{211}WVC + \varepsilon_{21},$$

$$TRST = \rho_{220} + \rho_{221}WVC + \varepsilon_{22},$$

$$VL = \rho_{230} + \rho_{231}WVC + \varepsilon_{23},$$

$$INNV = \rho_{240} + \rho_{241}WVC + \varepsilon_{24}.$$

Lastly, in step 3, we regressed *ITS* on *WVC* and the four mediators to confirm that (1) the mediating variables were significant predictors of *ITS* and (2) the significant impact of *WVC* found in step 1 was reduced or turn insignificant:

$$ITS = \rho_{30} + \rho_{31}WVC + \rho_{32}ENJ + \rho_{33}TRST + \rho_{34}VL + \rho_{35}INNV + \varepsilon_3.$$

$\varepsilon_1, \varepsilon_{21}, \varepsilon_{22}, \varepsilon_{23}, \varepsilon_{24}$ and ε_3 are the corresponding residuals in each equation.

The estimation results of the three-step regression are presented in Table 4. In Step 1, we re-confirmed that the visual context was a significant predictor of participants' intent to support the crowdfunding project (ρ_{11}=0.8460, p<0.01). In Step 2, we found that workplace visual context significantly improved participants' enjoyment of watching the video (ρ_{211}=0.5405, p<0.05), trust on the project (ρ_{211}=0.5761, p<0.01), perceived value (ρ_{211}=0.7672, p<0.01), and perceived innovativeness (ρ_{211}=0.5364, p<0.05). Finally, in Step 3, we found (1) positive and significant impact of enjoyment of watching the video (ρ_{32}=0.4260, p<0.01), perceived value (ρ_{34}=0.3361, p<0.01), and perceived innovativeness (ρ_{35}=0.4406, p<0.01), and (2) insignificant impact of workplace visual context (ρ_{31}=0.2410, p>0.24). These results suggest that enjoyment of watching the video, perceived value, and perceived innovativeness mediate the causal relationship between workplace visual context and consumer's intent to support the crowdfunding project. Trust was found negative and insignificant (ρ_{33}=-0.2071, p>0.19) and thus not qualified as a mediator. Nevertheless, the mediating effect of trust might be underestimated because participants of the experiment did not actually invest their money into the project. Compared to a hypothetical experiment, consumers making actual purchases are likely to have a higher level of involvement, i.e., the internal state of personal relevance or importance regarding the purchase (Park & Young, 1986). As consumers become more involved in the purchase, they engage more extensively in their information searching (Petty et al., 1983). As a result, the consumers may perceive higher risks from sources such as novel technologies adopted by the project and the complexity of the manufacturing process, which makes the consumers' trust on the crowdfunding campaign more critical in their final purchase decision making.

<Insert Table 4 here>

6. Discussion

6.1. Contributions

This paper contributes to marketing research and practice by introducing an image mining procedure by which information contained in big visual data can be detected, classified, and interpreted. To overcome the obstacles in utilizing large-scale image content, we suggest marketing researchers and practitioners utilize the commercialized AI vision tools to recognize visual concepts, build a co-occurrence-based network of visual concepts, and detect clusters of concepts to identify visual contexts. Based on the video data from Kickstarter.com, we find two visual contexts significantly related to crowdfunding success. Presenting visual information from the context of "event" (featured by keywords such as "actor," "actress," "administration," "leader," "rally," "crowd") will backfire on the project's fundraising. However, information from the context of "workspace" (featured by keywords such as "office," "toy," "teamwork," "cooperation) can benefit the crowdfunding campaign.

To further examine the causality from visual contexts to the success of crowdfunding, we conducted an experiment. We controlled for all crowdfunding project and creator factors and manipulated the main visual context in which the project videos are recorded. We found that visual context indeed had a significant impact on participants' willingness to back the project. Also, we found enjoyment in watching the video, perceived value, and perceived innovativeness mediated the impact. The empirical findings enrich the crowdfunding literature by identifying two critical visual contexts commonly used in campaign videos and examining the underlying mechanism of how the visual contexts influence consumer decisions.

6.2. Managerial Implications

The proposed procedure can be conveniently applied to online platforms such as Instagram, Pinterest, and TikTok, where visuals are the most popular form of postings. With the flood of pictures and videos rushing in every day, marketing researchers have numerous opportunities to investigate the impact of visual contexts on consumer engagement activities such as views, likes, and click-throughs. Combining with the earlier advances in text mining methods (Humphreys & Wang, 2018; Jurafsky et al., 2014; Lee & Bradlow, 2011; Netzer et al., 2012), marketing researchers are now capable of analyzing consumer's interaction more comprehensively. For example, future research may tap into the interactions of Web users' communications in different media, such as text and pictures. Another direction for future research is to explore both audio and visual information contained in videos.

The empirical findings of the negative influence of event context and the positive influence of the workspace context also have managerial implications on marketing communication. With limited resources, entrepreneurs and startups are usually restricted to the environment to take photos and record videos to introduce their products. Between two typical convenient settings, our discovery suggests that presenting products in a workspace setting works significantly better than in an event setting. Entrepreneurs and startups may apply this conclusion in their promotion activities to enhance the effectiveness of communication.

6.3. Limitations and Future Research

Our research has some limitations. First, Study 1 uses data extracted from Kickstarter.com, a rewards-based platform. As highlighted by Ramos (2014), there are additional crowdfunding types of platforms, such as equity-based, lending-based, and donation-based platforms. Future research could explore the role of video on other types of crowdfunding platforms. Second, data collected for our second study are limited to the US consumer population. Josefy et al. (2017) noted that, in some crowdfunding campaigns, geographical location accounts for the variance among relevant variables. Future research should explore the impact of video information on crowdfunding success in other markets with different cultural, social, and economic attributes. Third, Janiszewski (1990) suggests that the preattentive (subconscious) processing of visual contexts in print advertisements (e.g., newspaper and magazine layout, other competing ads, supporting information within the ad) interferes with the comprehension and memory of the attended materials (e.g., discount information). Thus, a manipulation check could be conducted at the end of Study 2 to examine whether the participants perceived the two videos differently and identified them to be “event” or “workspace” context. By doing so, we could better understand if the visual contexts in videos influence consumer decisions consciously or not. Finally, the impact of contextual information in videos may depend on consumer’s individual characteristics, such as personality, purchase situation, and economic status. Therefore, we suggest future research on video contexts to address the diversities in the consumer population and provide insights on segmentation and targeting strategies for video development in crowdfunding campaigns.

References

Agrawal, A., Catalini, C., & Goldfarb, A. (2015). Crowdfunding: Geography, social networks, and the timing of investment decisions. *Journal of Economics & Management Strategy, 24(2),* 253-74.

Alaparthi, S., & Mishra, M. (2021). BERT: A sentiment analysis odyssey. *Journal of Marketing Analytics, 9(2),* 1-9.

Aydinli, A., Bertini, M., & Lambrecht, A. (2014). Price promotion for emotional impact. *Journal of Marketing, 78(4),* 80-96.

Avlonitis, G. J., & Salavou, H. E. (2007). Entrepreneurial orientation of smes, product innovativeness, and performance. *Journal of Business Research, 60(5),* 566-575.

Baron, R. M., & Kenny, D. A. (1986). The moderator-mediator variable distinction in social psychological research – conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology, 51(6),* 1173-1182.

Bloch, P. H., Brunel, F. F., & Arnold, T. J. (2003). Individual differences in the centrality of visual product aesthetics: concept and measurement. *Journal of Consumer Research, 29(3),* 551–65.

Blondel, V. D., Guillaume, J. L., Lambiotte, R., & Lefebvre, E. (2008). fast unfolding of communities in large networks. *Journal of Statistical Mechanics: Theory and Experiment, 2008 (10),* 10008-20.

Bui, T. H. (2021). Discovering shopping visitors' behavior and preferences using geo-tagged social photos: A case study of Los Angeles City. *Journal of Marketing Analytics, 9(2),* 127-143.

Business Insider Intelligence (2017). *Video will account for an overwhelming majority of internet traffic by 2021*. https://www.businessinsider.com/heres-how-much-ip-traffic-will-be-video-by-2021-2017-6.

Caicedo, R. (2018). *5 Reasons why it's better to drink tea in small cups*. https://www.myjapanesegreentea.com/why-its-better-to-drink-tea-in-small-cups.

Carpenter, G. S., Glazer, R., & Nakamoto, K. (1994). Meaningful brands from meaningless differentiation: The dependence on irrelevant attributes. *Journal of Marketing Research, 31(8),* 339–50.

Chang, H. H., & Chen, S. W. (2008). The impact of online store environment cues on purchase intention: Trust and perceived risk as a mediator. *Online Information Review, 32(6),* 818-841.

Chen, Y., Wang, Q., & Xie, J. (2011). Online social interactions: A natural experiment on word of mouth versus observational learning. *Journal of Marketing Research, 48(2),* 238-54.

Chevalier, J. A., & Mayzlin, D. (2006). The effect of word of mouth on sales: Online book reviews. *Journal of Marketing Research, 43(3),* 345-54.

Chintagunta, P. K., Gopinath, S., & Venkataraman, S. (2010). The effects of online user reviews on movie box office performance: Accounting for sequential rollout and aggregation across local markets. *Marketing Science, 29(5),* 944-57.

Cooper, B. B. (2016). *How Twitter's expanded images increase clicks, retweets and favorites.* Buffer Social. https://blog.bufferapp.com/the-power-of-twitters-new-expanded-images-and-how-to-make-the-most-of-it.

Dellarocas, C., Zhang, X. M., & Awad, N. F. (2007). Exploring the value of online product reviews in forecasting sales: The case of motion pictures. *Journal of Interactive Marketing, 21(4),* 23-45.

Dzyabura, D., & Peres, R. (2021). Visual elicitation of brand perception. *Journal of Marketing, 85(4),* 44-66.

Ganesan, S. (1994). Determinants of long-term orientation in buyer-seller relationships. *Journal of Marketing, 58(2),* 1-19.

Giebelhausen, M., Robinson, S. G., Sirianni, N. J., & Brady, M. K. (2014). Touch vs. tech: When technology functions as a barrier or a benefit to service encounters. *Journal of Marketing, 78(4),* 113-124.

Godes, D., & Mayzlin, D. (2004). Using online conversations to study word-of-mouth communication. *Marketing Science, 23(4),* 545-60.

Godes, D., Mayzlin, D., Chen, Y., Das, S., Dellarocas, C., Pfeiffer, B., Libai, B., Sen, S., Shi, M., & Verlegh, P. (2005). The firm's management of social interaction. *Marketing Letters, 16(3/4),* 415-25.

Goldstein, D. G., Suri, S., McAfee, R. P., Ekstrand-Abueg, M., & Diaz, F. (2014). The economic and cognitive costs of annoying display advertisements. *Journal of Marketing Research, 51(6),* 742-752.

Gunnars, K. (2018). *10 Proven Benefits of Green Tea*. https://www.healthline.com/nutrition/top-10-evidence-based-health-benefits-of-green-tea#section8.

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. (2006). *Multivariate data analysis.* Pearson Prentice Hall Upper Saddle River, NJ.

Hightower Jr, R., Brady, M. K., & Baker, T. L. (2002). Investigating the role of the physical environment in hedonic service consumption: An exploratory study of sporting events. *Journal of Business Research, 55(9),* 697-707.

Hootsuite (2020). *Social Media Trends 2020*. https://hootsuite.com/pages/social-media-trends-2020-report

Humphreys, A., & Wang, R. J. H.(2018). Automated text analysis for consumer research. *Journal of Consumer Research, 44(6),* 1274-1306.

Jaakonmäki, R., Müller, O., & Vom Brocke, J. (2017, January). The impact of content, context, and creator on user engagement in social media marketing. *Proceedings of the 50th Hawaii international conference on system sciences*.

Janiszewski, C. (1990). The influence of nonattended material on the processing of advertising claims. *Journal of Marketing Research, 27(3),* 263-278.

Josefy, M., Dean, T. J., Albert, L. S., & Fitza, M. A. (2017). The role of community in crowdfunding success: Evidence on cultural attributes in funding campaigns to "save the local theater". *Entrepreneurship Theory and Practice, 41 (2),* 161-182.

Jia, J. S., Shiv, B., & Rao, S. (2014). The product-agnosia effect: How more visual impressions affect product distinctiveness in comparative choice. *Journal of Consumer Research, 41(2),* 342-60.

Johnson, K. (2018). *Clarifai improves general model 1.5 with machine-labeled datasets.* https://venturebeat.com/2018/10/04/clarifai-improves-general-model-1-5-photo-recognition-software-with-machine-labeled-datasets/.

Jurafsky, D., Chahuneau, V., Routledge, B. R., & Smith, N. A. (2014). Narrative framing of consumer sentiment in online restaurant reviews. *First Monday, 19(4).*

Kamada, T., & Kawai, S. (1989). An algorithm for drawing general undirected graphs. *Information Processing Letters, 31(1),* 7-15.

Kuppuswamy, V., & Bayus, B. L. (2017). *Does my contribution to your crowdfunding project matter*. *Journal of Business Venturing, 32,* 72-89.

Lee, T. Y., & Bradlow, E. T. (2011). Automated marketing research using online customer reviews. *Journal of Marketing Research, 48(5),* 881-94.

Lemke, F., Clark, M., & Wilson, H. (2011). Customer experience quality: An exploration in business and consumer contexts using repertory grid technique. *Journal of the Academy of Marketing Science, 39(6),* 846-869.

Liu, L., Dzyabura, D., & Mizik, N. (2020). Visual listening in: Extracting brand image portrayed on social media. *Marketing Science 39(4),* 669-686.

Liu, Y. (2006). Word of Mouth for Movies: Its dynamics and impact on box office revenue. *Journal of Marketing, 70(3),* 74-89.

Lopez, A., Guerra, E., Gonzalez, B., & Madero, S. (2020). Consumer sentiments toward brands: the interaction effect between brand personality and sentiments on electronic word of mouth. *Journal of Marketing Analytics, 8(4),* 203-223.

Lurie, N. H., & Mason, C. H.(2007). Visual representation: implications for decision making. *Journal of Marketing, 71(1),* 160-77.

Mollick, E. (2014). The dynamics of crowdfunding: An exploratory study. *Journal of Business Venturing, 29,* 1-16.

Nanne, A. J., Antheunis, M. L., van der Lee, C. G., Postma, E. O., Wubben, S., & van Noort, G. (2020). The use of computer vision to analyze brand-related user generated image content. *Journal of Interactive Marketing, 50,* 156-167.

Narayanan, A., & Ramesh, N. (2012). *Benefitting from big data leveraging unstructured data capabilities for competitive advantage*. Booz & Company.

Netzer, O., Feldman, R., Goldenberg, J., & Fresko, M. (2012). Mine your own business: Market-structure surveillance through text mining. *Marketing Science 31(3),* 521-43.

Ramos, J. (2014). Crowdfunding and the role of managers in ensuring the sustainability of crowdfunding platforms. *European Commission Joint Research Centre Scientific and Policy Reports, 85752*.

Rizkallah, J. (2017). The big (unstructured) data problem. *Forbes*. https://www.forbes.com/sites/forbestechcouncil/2017/06/05/the-big-unstructured-data-problem.

Sirdeshmukh, D., Singh, J., & Sabol, B. (2002). Consumer trust, value, and loyalty in relational exchanges. *Journal of Marketing, 66(1),* 15-37.

Sirianni, N. J., Bitner, M. J., Brown, S. W., & Mandel, N. (2013). Branded service encounters: strategically aligning employee behavior with the brand positioning. *Journal of Marketing, 77(6),* 108-123.

Sudhir, K. (2016). The exploration-exploitation tradeoff and efficiency in knowledge production. *Marketing Science, 35(1),* 1-9.

China Highlights (2019). *The top 10 most beautiful places in China.* https://www.chinahighlights.com/travelguide/most-beautiful-places.htm.

Townsend, C., & Sood, S. (2011). The impact of product design on choice: A dual-process explanation. *Proceedings of the Society for Consumer Psychology.*

Turney, P. D., & Littman, M. L. (2003). Measuring praise and criticism: inference of semantic orientation from association. *ACM Transactions on Information Systems, 21 (4),* 315-46.

Wu, L. Y., Chen, K. Y., Chen, P. Y., & Cheng, S. L. (2014). Perceived value, transaction cost, and repurchase-intention in online shopping: A relational exchange perspective. *Journal of Business Research, 67(1),* 2768-2776.

Xiao, L., & Ding, M. (2014). Just the faces: Exploring the effects of facial features in print advertising. *Marketing Science, 33(3),* 338-352.

Yang, S., Allenby, G. M., & Fennell, G. (2002). Modeling variation in brand preference: The roles of objective environment and motivating conditions. *Marketing Science, 21(1),* 14-31.

Zhang, Q., Wang, W., & Chen, Y. (2020). Frontiers: In-consumption social listening with moment-to-moment unstructured data: The case of movie appreciation and live comments. *Marketing Science, 39(2),* 285-295.

Table 1. Descriptive Statistics of Variables for Projects with Videos (N=652)

Variable	Unit	Mean	SD.	Variable	Unit	Mean	SD.
Success	Binary	0.53	0.50	Cluster 19 “Music”	Ratio	3.33×10^{-2}	6.84×10^{-2}
Fund Raised	US $	32790.70	224731.83	Cluster 20 “Flying”	Ratio	2.24×10^{-3}	6.55×10^{-3}
Created	Count	0.54	1.66	Cluster 21 “Filming”	Ratio	6.85×10^{-3}	1.08×10^{-2}
Succeeded	Count	0.38	1.43	Cluster 22 “Model”	Ratio	1.90×10^{-2}	2.67×10^{-2}
Failed	Count	0.15	0.68	Cluster 23 “Factory”	Ratio	1.16×10^{-3}	3.43×10^{-3}
Backed	Count	6.62	24.26	Cluster 24 “Street”	Ratio	9.57×10^{-3}	1.63×10^{-2}
Goal	US $	30081.63	159101.53	Cluster 25 “Battle”	Ratio	9.55×10^{-3}	1.64×10^{-2}
Funding period	Day	32.27	10.25	Cluster 26 “Cycling”	Ratio	1.73×10^{-3}	5.30×10^{-3}
Time to deliver	Day	127.56	105.29	Cluster 27 “Fashion Accessories”	Ratio	2.58×10^{-3}	6.86×10^{-3}
Video length	Second	152.78	100.03	Cluster 28 “Watch”	Ratio	4.45×10^{-3}	2.28×10^{-2}
Cluster 1	Ratio	2.24×10^{-2}	2.97×10^{-2}	Cluster 29 “City”	Ratio	5.62×10^{-3}	1.24×10^{-2}
Cluster 2 “Party”	Ratio	1.02×10^{-2}	2.40×10^{-2}	Cluster 30	Ratio	6.51×10^{-3}	9.77×10^{-3}
Cluster 3	Ratio	5.20×10^{-2}	5.79×10^{-2}	Cluster 31 “Food”	Ratio	3.74×10^{-3}	1.28×10^{-2}
Cluster 4 “Homemade food”	Ratio	3.00×10^{-3}	1.35×10^{-2}	Cluster 32 “Schedule”	Ratio	7.82×10^{-4}	2.65×10^{-3}
Cluster 5 “Business”	Ratio	1.21×10^{-2}	2.25×10^{-2}	Cluster 33 “Crafting”	Ratio	2.11×10^{-2}	2.25×10^{-2}
Cluster 6 “Fashion”	Ratio	4.74×10^{-2}	4.20×10^{-2}	Cluster 34 “Transportation”	Ratio	9.95×10^{-3}	2.27×10^{-2}
Cluster 7 “Outdoor”	Ratio	3.65×10^{-2}	4.74×10^{-2}	Cluster 35 “Healthcare”	Ratio	2.94×10^{-3}	6.69×10^{-3}
Cluster 8 “Telecom”	Ratio	1.02×10^{-2}	8.82×10^{-2}	Cluster 36 “Martial Arts”	Ratio	2.27×10^{-6}	5.79×10^{-5}
Cluster 9 “Tourism”	Ratio	7.67×10^{-3}	1.55×10^{-2}	Cluster 37 “Workspace”	Ratio	4.93×10^{-3}	8.62×10^{-3}
Cluster 10 “Nature”	Ratio	2.19×10^{-2}	3.24×10^{-2}	Cluster 38 “Construction”	Ratio	1.61×10^{-3}	4.88×10^{-3}
Cluster 11 “Design”	Ratio	8.78×10^{-2}	7.52×10^{-2}	Cluster 39	Ratio	5.90×10^{-3}	1.09×10^{-2}
Cluster 12 “Space”	Ratio	3.61×10^{-2}	4.83×10^{-2}	Cluster 40	Ratio	2.34×10^{-4}	1.46×10^{-3}
Cluster 13	Ratio	1.08×10^{-3}	4.92×10^{-3}	Cluster 41 “Lake and Farm”	Ratio	9.87×10^{-4}	5.79×10^{-3}
Cluster 14 “People”	Ratio	0.23	0.13	Cluster 42 “Battery”	Ratio	2.07×10^{-5}	3.52×10^{-4}
Cluster 15 “Event”	Ratio	8.41×10^{-3}	2.15×10^{-2}	Cluster 43	Ratio	4.65×10^{-3}	7.98×10^{-3}
Cluster 16 “Fire”	Ratio	6.79×10^{-3}	1.24×10^{-2}	Cluster 44 “Crane”	Ratio	5.08×10^{-6}	1.30×10^{-4}
Cluster 17 “Sports”	Ratio	2.55×10^{-2}	3.83×10^{-2}	Cluster 45	Ratio	6.24×10^{-6}	1.59×10^{-4}
Cluster 18 “Holiday”	Ratio	7.41×10^{-3}	2.15×10^{-2}	Cluster 46 “Laundry”	Ratio	1.36×10^{-6}	2.61×10^{-5}

Table 2. Impact of Visual Contextual Clusters on Project Success (N=652)

Variable	Coefficient	SD.	Variable	Coefficient	SD.
Intercept	0.3518	1.575	Cluster 18	-20.20*	10.36
Cluster 15	-12.73**	5.614	Cluster 19	2.074	2.240
Cluster 37	33.33**	13.25	Cluster 20	-37.72*	19.35
Video length	1.706×10^{-4}	9.587×10^{-4}	Cluster 21	8.366	10.30
Goal	-4.544×10^{-6}**	1.881×10^{-6}	Cluster 22	6.008	4.638
Funding period	-2.289×10^{-2}**	9.773×10^{-3}	Cluster 23	0.287	34.80
Time to deliver	5.874×10^{-4}	9.625×10^{-4}	Cluster 24	1.036	6.663
Failed	-0.686***	0.236	Cluster 25	15.02*	8.051
Succeeded	0.685***	0.153	Cluster 26	-11.49	18.75
Backed	8.988×10^{-3}	7.147×10^{-3}	Cluster 27	16.16	14.68
Cluster 2	4.669	5.561	Cluster 28	-1.750	4.167
Cluster 4	-3.277	9.079	Cluster 29	-16.15	10.16
Cluster 5	5.343	4.509	Cluster 31	3.642	10.37
Cluster 6	-1.981	3.199	Cluster 32	36.71	36.14
Cluster 7	5.138	3.814	Cluster 33	1.250	5.543
Cluster 8	-3.168	2.218	Cluster 34	4.297	5.102
Cluster 9	-3.243	6.589	Cluster 35	-11.15	14.28
Cluster 10	-2.849	4.231	Cluster 36	-9.573×10^{3}	5.972×10^{5}
Cluster 11	0.973	2.689	Cluster 38	24.90	26.35
Cluster 12	2.091	2.672	Cluster 41	-35.79	26.01
Cluster 14	0.294	1.962	Cluster 42	91.46	280.2
Cluster 16	-16.87*	9.403	Cluster 44	4.423×10^{3}	2.663×10^{5}
Cluster 17	1.949	3.106	Cluster 46	-2.364×10^{3}	3.267×10^{3}

*: p-value ≤ .10, **: p-value ≤ .05, ***: p-value ≤ .01.

Table 3. Measurement and Descriptive Statistics

Construct	Item	Mean	SD.	Cronbach's α
Intent to Support (*ITS*)	*1. How likely would you support this project?*	3.12	1.90	0.96
	2. I intend to use the crowdfunding campaign to buy the product.	2.90	1.82	
	3. I expect to purchase from the crowdfunding campaign in the future.	3.10	1.88	
	4. It is likely that I will transact with the crowdfunding campaign in the near future.	3.26	1.86	
	Average	3.11	1.76	
Enjoyment (*ENJ*)	*1. I enjoy watching the campaign video.*	4.52	1.63	0.92
	2. The crowdfunding campaign video makes me feel good.	4.16	1.55	
	3. I like the way that the presenter introduced the product.	4.71	1.56	
	4. I feel comfortable listening to the presenter.	5.31	1.43	
	Average	4.68	1.38	
Trust (*TRST*)	*1. I feel that the crowdfunding campaign is dependable.*	4.97	1.40	0.91
	2. I feel that the crowdfunding campaign is competent.	5.24	1.37	
	3. I feel that the crowdfunding campaign is of high integrity.	5.26	1.29	
	4. I feel that the crowdfunding campaign is responsive to customers.	5.03	1.25	
	Average	5.12	1.18	
Value (*VL*)	*1. The crowdfunding campaign offers a good economic value.*	4.10	1.66	0.95
	2. The product I would purchase from the crowdfunding campaign is a good buy.	3.99	1.82	
	3. The products I would purchase at the crowdfunding campaign are worth the money paid.	4.09	1.82	
	4. You get what you pay for at the crowdfunding campaign.	4.39	1.67	
	Average	4.14	1.60	
Innovativeness (*INNV*)	*1. The product offers more possibilities.*	3.94	1.66	0.93
	2. The product offers unique, innovative features.	3.97	1.69	
	3. The product covers more customer needs.	4.05	1.52	
	4. The product has more uses.	3.68	1.58	
	Average	3.91	1.46	
Workplace Visual Context	*1 = workspace, 0 = event*	0.50	0.50	

Table 4. Regression Results of Mediation Test

IV \ DV	Step 1	Step 2				Step 3
	Intent to Support	Enjoyment	Trust	Value	Innovativeness	Intent to Support
Intercept	2.680*** (0.227)	4.403*** (0.182)	4.833*** (0.152)	3.754*** (0.206)	3.640*** (0.206)	-1.061** (0.458)
Workplace Visual Context	0.846*** (0.320)	0.542** (0.254)	0.576*** (0.214)	0.767*** (0.290)	0.536** (0.270)	0.241 (0.205)
Enjoyment						0.426*** (0.121)
Trust						-0.207 (0.158)
Value						0.336*** (0.110)
Innovativeness						0.441*** (0.111)
Adjusted R^2	0.050	0.030	0.052	0.050	0.025	0.636

*: p-value ≤ .10, **: p-value ≤ .05, ***: p-value ≤ .01.

Figure 1. Image Mining Procedure

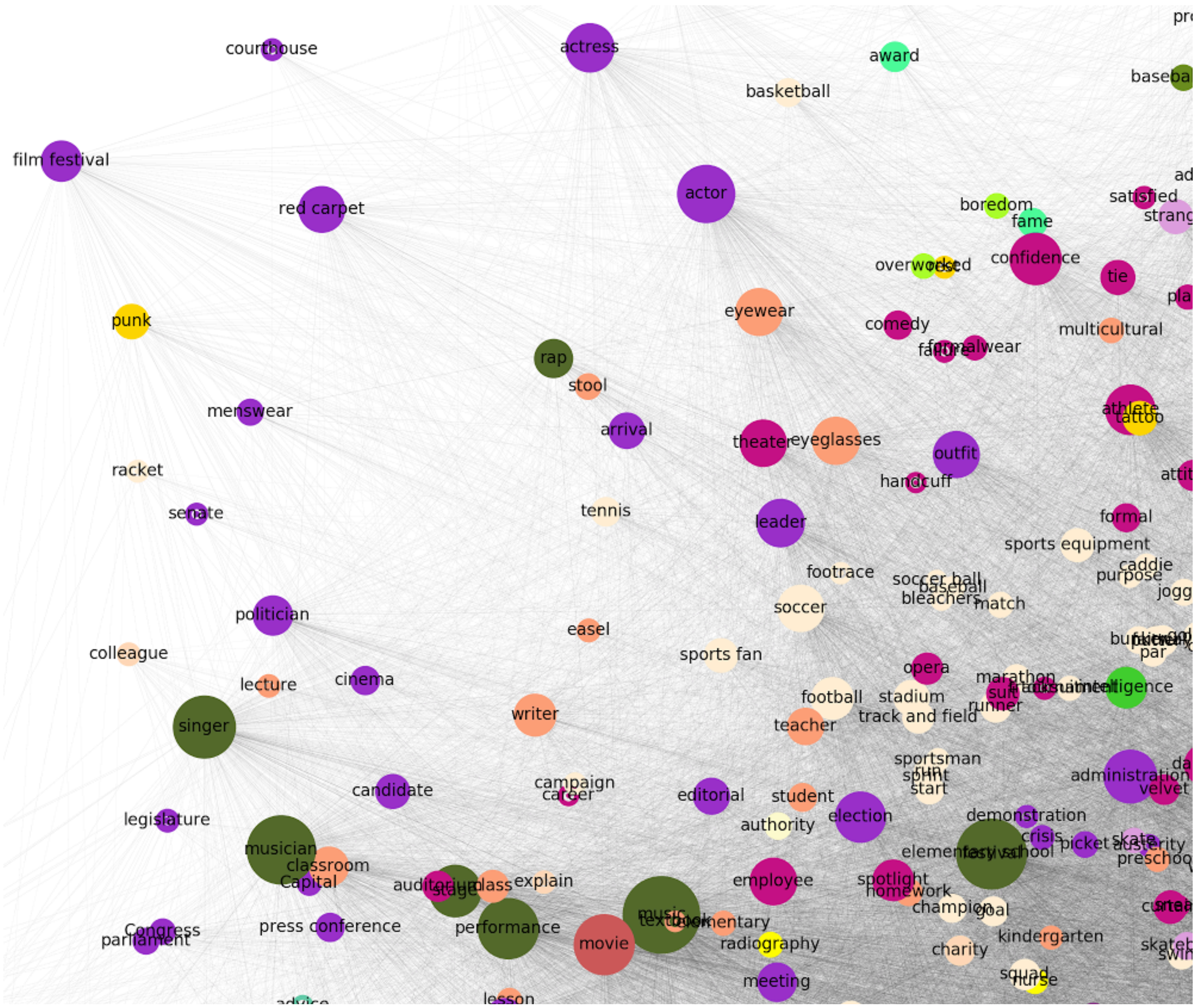
CONCEPT	PROB	CONCEPT	PROB	CONCEPT	PROB
child	0.956	woman	0.964	child	0.973
people	0.95	child	0.957	people	0.942
family	0.925	people	0.948	education	0.938
education	0.907	adult	0.942	woman	0.902
woman	0.898	man	0.924	business	0.895
squad	0.89	togetherness	0.906	man	0.858
man	0.886	education	0.901	family	0.857
sport	0.868	table	0.898	room	0.856
young	0.853	horizontal	0.883	horizontal	0.842
room	0.853	family	0.878	school	0.837
exercise	0.853	room	0.871	adult	0.83
boy	0.853	lifestyle	0.86	teamwork	0.827
fun	0.852	indoors	0.84	sit	0.818
school	0.828	sit	0.828	young	0.803
indoors	0.826	business	0.823	little	0.784
person	0.819	happiness	0.804	indoors	0.782
girl	0.813	side view	0.792	table	0.782
lifestyle	0.802	young	0.792	togetherness	0.781
adult	0.8	furniture	0.772	girl	0.761
teamwork	0.798	fun	0.77	boy	0.754

...

CONCEPT	PROB	CONCEPT	PROB	CONCEPT	PROB
man	0.955	people	0.96	people	0.974
people	0.931	woman	0.957	adult	0.972
young	0.928	hand	0.944	hygiene	0.971
one	0.924	adult	0.943	woman	0.965
isolated	0.9	one	0.942	cleaner	0.951
person	0.899	person	0.879	hose	0.943
desktop	0.897	desktop	0.875	family	0.931
looking	0.856	man	0.861	bathroom	0.926
business	0.854	human	0.845	faucet	0.923
adult	0.846	family	0.834	desktop	0.913
portrait	0.835	wear	0.828	hand	0.911
equipment	0.814	indoors	0.819	sport	0.902
sit	0.814	medicine	0.808	person	0.902
work	0.813	vertical	0.791	care	0.899
vertical	0.812	hygiene	0.785	house	0.893
leisure	0.807	cleaner	0.768	spray	0.887
casual	0.798	color	0.761	bottle	0.885
fun	0.792	H2O	0.752	clean	0.881
sport	0.777	drink	0.75	wet	0.874
active	0.768	equipment	0.747	vertical	0.859

Figure 2. Contextual Network of Video Content in the Data.

A. *Cluster₁₅* “Event” in purple ● located in the top left of the network plot



B, Cluster$_{37}$ "Workspace" in apricot located in the middle left of the network plot

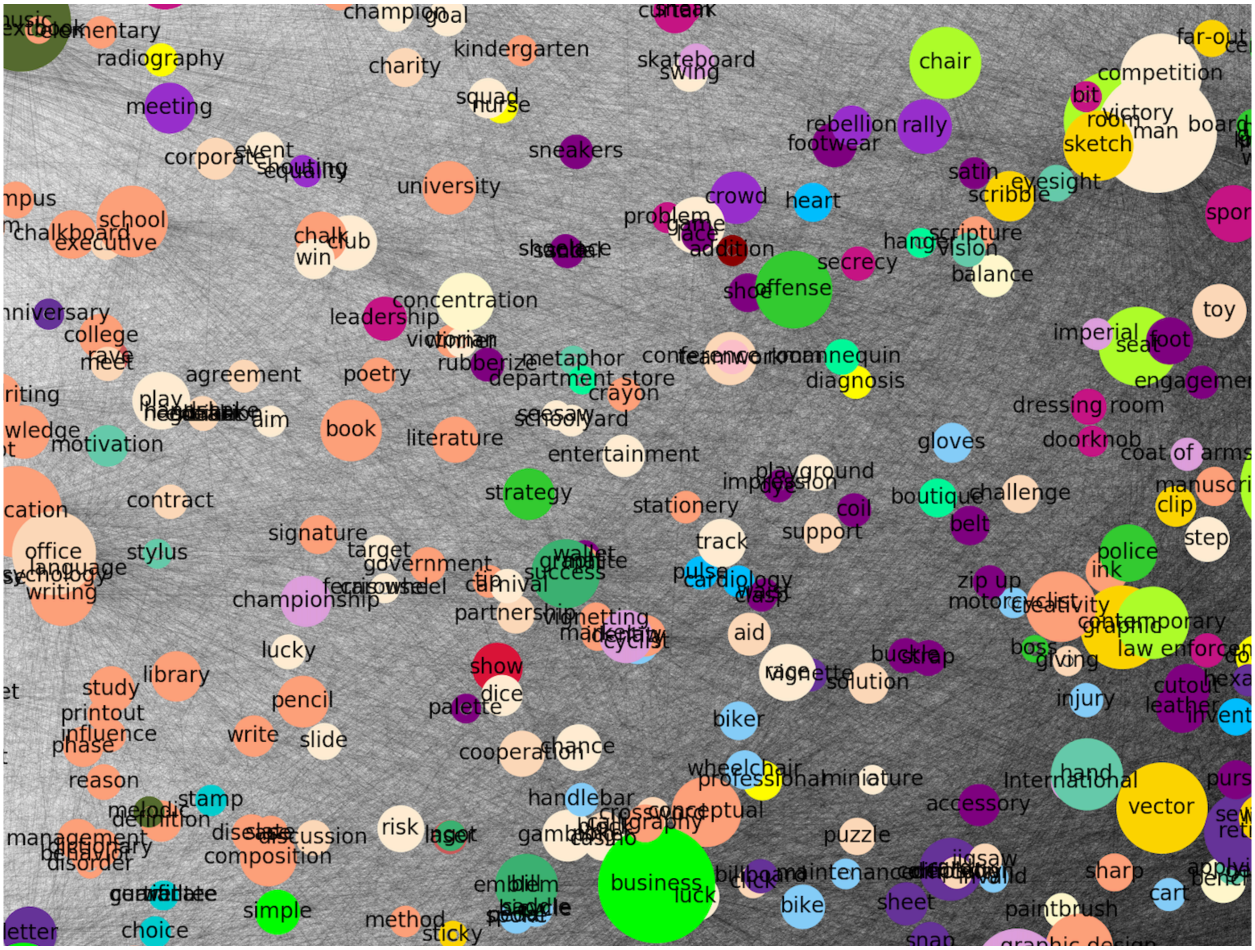
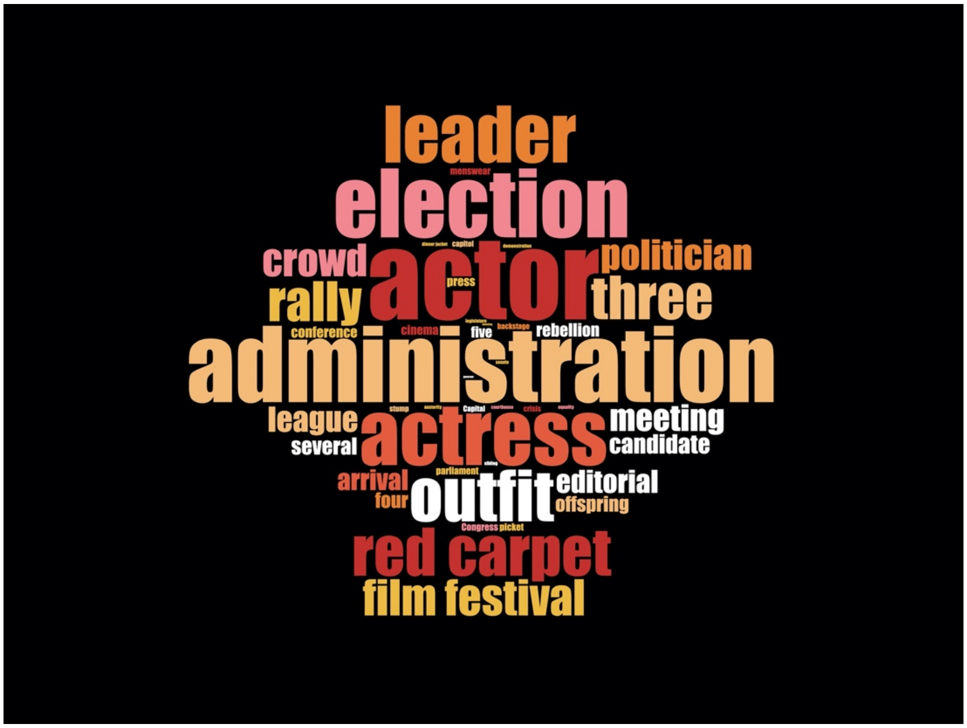


Figure 3. Word Clouds of *Cluster$_{15}$* and *Cluster$_{37}$*

A. *Cluster$_{15}$* — The Event Setting



B. *Cluster$_{37}$*— The Workspace Setting

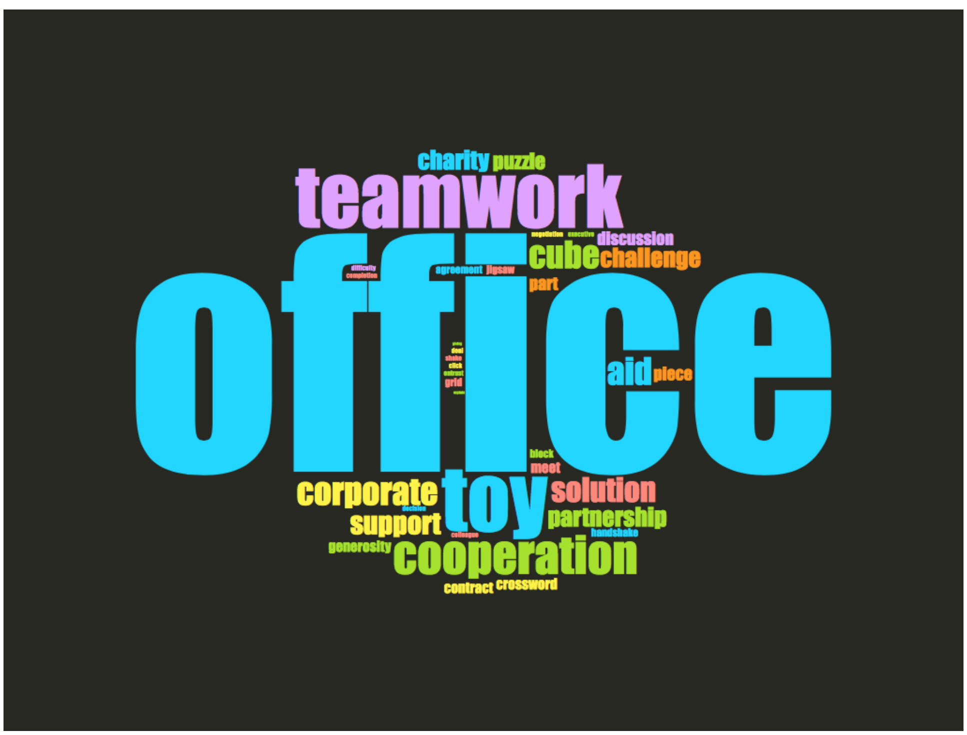


Figure 4. Experimental Setup for Two Visual Contexts

A. The Event Setting

B. The Workspace Setting

Appendix A. Top 15 Most Frequent Concepts of the 46 Clusters.

Concept	Frequency	Concept	Frequency	Concept	Frequency	Concept	Frequency
Cluster 1		Cluster 2 “Party”		Cluster 3		Cluster 4 “Homemade Food”	
sit	8397.60	dawn	1518.80	illustration	18776.78	close-up	1268.59
looking	7851.03	still life	1385.82	art	14062.53	grow	411.05
two	5853.77	drink	1374.41	vector	11744.06	delicious	324.52
sitting	3030.02	health	1368.38	graphic	7448.38	healthy	304.47
fair weather	2986.13	glass	1115.55	water	6008.06	refreshment	234.05
cute	2541.13	party	961.66	sketch	2826.35	nutrition	203.40
sun	1823.31	restaurant	893.82	sea	2249.68	sweet	182.94
studio	1175.98	coffee	775.59	environment	1946.36	epicure	129.24
mammal	1132.98	traditional	755.14	silhouette	1896.00	bowl	117.82
veil	1021.51	bar	641.80	beach	1789.66	sugar	107.57
snow	935.27	clean	534.87	ocean	1458.80	chocolate	101.64
funny	917.33	treatment	526.41	fall	1313.22	tasty	78.87
animal	895.47	ice	397.78	seashore	1282.36	diet	72.68
friendship	773.46	wine	305.31	vacation	1023.66	cereal	67.87
weather	769.53	cup	302.52	river	762.20	homemade	66.55
Cluster 5 “Business”		Cluster 6 “Fashion”		Cluster 7 “Outdoor”		Cluster 8 “Telecom”	
commerce	3342.44	wear	31957.46	outdoors	22244.87	business	41555.25
success	2554.70	fashion	10278.97	travel	13285.93	technology	18475.72
stock	2417.99	side view	5796.75	daylight	8564.67	education	11901.75
finance	1835.84	window	4822.76	sky	8310.34	computer	8051.12
money	1740.30	person	3889.32	landscape	7473.01	internet	7577.00
bill	1503.90	architecture	3501.95	sunset	1743.39	child	7324.35
shopping	1444.74	building	3012.80	mountain	1110.06	text	6869.23
exhibition	1382.93	fine-looking	2344.07	sand	991.60	connection	4521.76
market	974.32	home	2250.75	rock	963.77	modern	4452.23
police	832.11	confidence	2249.31	dusk	828.08	communication	4157.44
shop	757.97	athlete	1822.85	scenic	698.42	school	3143.04
safety	712.84	casual	1620.82	fog	687.15	template	2885.69
option	572.02	serious	1409.66	stone	382.87	creativity	2879.75
counter	509.47	facial hair	1347.71	bald	358.32	conceptual	2817.29
wealth	300.38	employee	1289.92	sight	309.56	telephone	2798.41
Cluster 9 “Tourism”		Cluster 10 “Nature”		Cluster 11 “Design”		Cluster 12 “Space”	
motion	2713.04	nature	12117.86	no person	33393.58	light	15119.21
painting	1578.73	summer	7296.73	desktop	26235.52	abstract	12097.68
religion	1518.28	color	4891.18	design	16442.56	dark	9882.89
tourism	931.54	tree	3592.12	symbol	8954.36	wallpaper	3917.60
evening	785.54	park	3485.25	paper	8673.47	science	2872.83
museum	748.71	bright	2341.50	pattern	6855.30	background	2796.60
dancing	544.26	leaf	1449.71	retro	5758.02	moon	2565.27
sculpture	300.00	flora	1152.75	sign	5376.76	astronomy	2303.14
gold	289.33	flower	838.96	old	3774.76	eclipse	1586.91
ornate	279.34	garden	795.16	shape	3006.42	crescent	1439.91
fantasy	275.22	outside	638.00	empty	2977.04	space	1191.62
Halloween	271.17	season	509.11	texture	2854.98	illuminated	1170.14
tourist	237.28	elderly	486.56	vintage	2271.39	Luna	1068.51
tower	200.59	elder	91.23	blank	1935.10	exploration	787.82
dancer	189.13	bouquet	61.30	document	1746.22	planet	447.50

Concept	Frequency	Concept	Frequency	Concept	Frequency	Concept	Frequency
Cluster 13		Cluster 14 “People”		Cluster 15 “Event”		Cluster 16 “Fire”	
lid	1268.95	people	70189.64	actor	4092.66	blur	6035.80
cap	592.59	adult	58255.86	administration	2638.47	danger	1094.77
sewing	46.42	man	47270.10	election	1982.01	energy	988.52
bobbin	39.96	one	46925.45	actress	1581.40	flame	872.69
fisherman	18.95	indoors	45383.71	leader	1434.52	smoke	634.02
repair	14.56	portrait	44463.67	outfit	1191.79	hot	413.25
pastime	14.45	woman	39055.75	red carpet	1137.56	knife	250.68
baseball cap	13.95	room	20380.95	three	710.54	heat	189.74
spiral	11.11	facial expression	19108.25	rally	602.54	luminescence	164.34
angler	2.93	furniture	12863.03	film festival	518.28	burnt	134.00
dressmaker	2.87	girl	12395.16	crowd	463.88	meat	99.37
rod	2.86	family	10455.25	politician	439.35	fireplace	83.60
fishing rod	2.82	happiness	6891.80	meeting	377.27	burn	54.27
bait	2.80	relaxation	5908.04	league	337.65	magic	45.03
hook	2.79	table	5761.27	editorial	244.00	warmly	42.51
Cluster 17 “Sports”		Cluster 18 “Holiday”		Cluster 19 “Music”		Cluster 20 “Flying”	
fun	6002.04	decoration	3466.94	music	18742.72	bird	1463.62
grass	2801.60	celebration	1999.57	festival	11769.64	adventure	554.70
action	2606.82	winter	1875.36	musician	10403.62	airplane	332.70
soccer	1227.66	Christmas	1091.70	singer	6307.11	aircraft	329.58
field	907.04	shining	1034.73	performance	5431.51	airport	322.81
play	880.80	candle	368.82	concert	3890.07	entertainment	100.94
race	807.22	thread	274.62	stage	2296.64	fly	98.30
game	805.13	gift	234.14	instrument	2267.40	flight	88.54
football	661.29	satisfaction	197.21	band	1605.86	hallway	72.52
club	654.06	purple	146.61	guitar	1038.15	air	70.57
lawn	579.46	surprise	101.38	pop	910.03	ceiling	45.56
golf	494.83	romantic	97.18	piano	826.53	mall	40.98
gambling	433.36	necklace	95.38	guitarist	705.60	feather	40.21
golfer	314.45	spectrum	89.10	audience	538.31	absence	38.78
luck	294.24	trendy	83.70	stringed instrument	450.90	lobby	36.62
Cluster 21 “Filming”		Cluster 22 “Fashion Model”		Cluster 23 “Factory”		Cluster 24 “Street”	
movie	5365.65	young	7276.61	container	1192.44	street	3703.72
equipment	4547.70	beautiful	3570.74	beer	100.05	road	2440.35
plastic	1067.25	model	3348.67	storage	99.69	shadow	1720.22
television	915.79	hand	3294.32	robot	79.84	monochrome	1549.02
focus	473.10	face	3220.35	warehouse	79.69	graph	671.48
lens	215.83	enjoyment	2734.45	spacecraft	47.82	guidance	643.39
tool	182.97	togetherness	2339.96	fuel	39.84	identity	510.96
zoom	75.18	love	2164.48	gasoline	38.70	auto racing	504.63
engine	63.45	pretty	1811.86	natural gas	32.03	spherical	450.95
gear	50.96	human	1261.43	fossil fuel	21.61	ball-shaped	417.42
aperture	44.34	hair	1161.75	pipe	15.15	traffic	401.79
video recording	41.54	sexy	864.63	basement	14.63	flag	398.31
journalist	29.80	elegant	759.73	tub	14.42	championship	389.49
shutter	27.85	sunglasses	721.38	distillery	14.24	soil	328.55
flash	26.28	eye	677.85	brewery	14.22	freedom	315.58

Concept	Frequency	Concept	Frequency	Concept	Frequency	Concept	Frequency
Cluster 25 “Battle”		Cluster 26 “Cycling”		Cluster27 “Fashion Accessories”		Cluster 28 “Watch”	
group	6972.22	security	1012.50	style	1081.67	number	1648.02
offense	4886.58	collection	491.89	jewelry	598.49	round	840.99
military	1661.42	wheel	485.35	leather	425.47	time	714.37
battle	1178.49	bike	142.71	couple	334.39	precision	575.58
war	806.12	cyclist	109.49	luggage	318.62	classic	522.97
ceremony	709.73	gloves	61.32	wedding	292.55	clock	401.18
intelligence	538.85	protection	56.06	foot	225.25	watch	315.15
weapon	454.62	motley	51.71	cutout	196.07	arrow	239.06
strategy	415.21	wheelchair	48.49	footwear	150.00	analogue	224.50
army	225.02	biker	45.51	bag	135.63	timer	172.37
uniform	211.06	rope	20.59	handle	120.01	deadline	161.21
gun	131.96	brake	19.78	accessory	96.10	minute	159.55
soldier	116.48	chain	19.77	case	70.25	dial	150.32
combat	88.22	lock	14.88	belt	53.99	alarm clock	140.44
force	66.10	injury	13.94	purse	49.58	countdown	112.34
Cluster 29 “City”		Cluster 30		Cluster 3 “Food”		Cluster 32 “Schedule”	
city	4831.98	calamity	670.46	food	3043.55	many	953.86
urban	2176.88	storm	310.96	growth	698.15	calendar	52.84
reflection	1602.27	mist	201.01	cooking	649.86	future	51.52
cityscape	497.19	accident	193.50	meal	308.42	monthly	44.10
skyscraper	388.54	abandoned	145.50	vegetable	228.98	annual	40.15
skyline	359.27	recycling	95.61	dinner	194.04	schedule	34.63
town	357.02	pollution	86.39	lunch	145.69	date	30.87
watercraft	226.57	crystal	46.06	plate	136.89	fiber	24.01
bridge	154.23	flood	41.69	freshness	126.88	diary	23.49
downtown	139.93	garbage	34.01	chef	109.54	pile	21.03
boat	110.90	waste	33.35	dish	97.82	batch	19.69
ship	93.37	trash	28.80	ingredients	55.57	daily	19.17
harbor	47.74	steam	26.27	pot	53.08	planner	17.87
sail	42.23	broken	17.29	kind	44.89	agenda	17.05
pier	40.03	full	13.79	herb	44.86	almanac	13.28
Cluster 33 “Crafting”		Cluster 34 “Transportation”		Cluster 35 “Healthcare”		Cluster 36 “Martial Arts”	
horizontal	11645.64	vehicle	5187.67	medicine	2786.70	martial arts	1.58
wood	6851.67	transportation system	3387.18	healthcare	1678.74	boxer	1.54
industry	5919.50	car	2138.72	hospital	469.38		
vertical	4540.02	sound	1030.81	patient	168.71		
wall	1845.42	production	979.12	doctor	162.58		
concentration	902.17	pavement	497.20	medical practitioner	152.10		
wooden	819.91	control	464.15	biology	148.73		
grinder	786.70	show	357.56	laboratory	75.88		
preparation	773.92	driver	321.71	professional	58.97		
skill	614.77	drive	289.78	scientist	44.59		
simplicity	505.11	fast	235.60	scrutiny	44.25		
bench	181.74	nightlife	214.10	chemistry	33.45		
board	152.29	classical music	175.20	surgery	31.56		
craft	139.36	violin	136.17	microbiology	28.32		
artisan	130.91	speed	109.62	sparse	18.76		

Concept	Frequency	Concept	Frequency	Concept	Frequency	Concept	Frequency
Cluster 37 “Workspace”		Cluster 38 “Construction”		Cluster 39		Cluster 40	
office	7610.23	machinery	773.70	data	4345.86	pool	242.05
toy	573.42	work	642.03	element	2437.29	aquatic	29.32
teamwork	509.82	machine	552.54	service	1091.20	reptile	26.69
cooperation	187.75	expression	464.24	power	818.14	monster	25.98
aid	108.51	ground	81.18	electricity	348.33	camouflage	8.72
cube	90.58	truck	63.08	wire	135.57	shell	7.53
corporate	90.42	heavy	26.01	phonograph record	124.74	turtle	5.57
solution	73.00	dig	24.50			dinosaur	5.08
support	57.50	shovel	11.45			lizard	4.91
charity	49.57	trowel	6.95			snake	4.76
partnership	43.31	tractor	6.12			tortoise	2.99
challenge	42.21	spade	5.86			slow	2.95
puzzle	33.18	bulldozer	3.80			species	2.75
part	28.93	scoop	3.75			vertebrate	1.83
piece	24.67	power shovel	3.68				
Cluster 41 “Lake and Farm”		Cluster 42 “Battery”		Cluster 43		Cluster 44 “Crane”	
lake	788.73	battery	17.24	image	5711.88	crane	3.35
rural	490.92	charger	8.94	label	1112.77	grandstand	1.71
agriculture	474.96	alkaline	2.90	badge	23.72	cargo container	0.79
swan	8.61	recharge	2.86	umbrella	23.15		
poultry	8.29	charge	2.81	emblem	20.71		
waterfowl	5.55	cylinder	2.66	application	19.81		
hen	2.95			choice	6.30		
chicken	2.94			stamp	5.31		
farmyard	2.85			shield	2.97		
cockerel	2.63			envelope	2.75		
duck	2.61			well	2.68		
goose	2.44			certificate	2.67		
Thanksgiving	0.86			guarantee	2.64		
				premium	2.60		
Cluster 45		Cluster 46 “Laundry”					
Broadway	3.35	laundry	4.12				
tram	1.68	clothesline	0.89				