Pictures that are Worth a Thousand Donations: How Emotions in Project Images Drive the Success of Online Charity Fundraising Campaigns? An Image Design Perspective

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Abstract. Charity fundraising is increasingly relying on online platforms such as crowdfunding platforms. However, overwhelmingly, crowdfunding campaigns do not meet their goals. Therefore, it is imperative to examine how to improve the success of charity fundraising campaigns. In this paper, we focus on the design of project images on a crowdfunding website, which portray the themes and contents of the projects. Employing the Stimulus-Organism-Response (S-O-R) model, we investigate the relationships between image attributes (S) and image emotions (O), and between image emotions (O) and campaign outcomes (R). We develop and train a deep neural network model to identify the emotions conveyed in the images, and then implement it to project images from a popular crowdfunding platform. We apply the obtained image emotions together with the objective image attributes and the project outcome metrics to explore from a design perspective, what image attributes evoke the image emotions, and how image emotions are related to the success of charity fundraising projects. Our results confirm these relationships and further suggest that the roles of image emotions on the success vary with project characteristics such as the project budget and category. In addition, the image emotions of competing projects on the crowdfunding platform are found to reduce the project's performance. In an extended study, we conduct an online randomized controlled experiment by manipulating image attributes to reexamine the causal relationships and verify the mediating roles of positive and negative empathies between image emotions and campaign outcomes. This research contributes to the charity fundraising literature from a novel perspective of emotions in project images. It presents new and unique findings regarding the mediation roles of positive and negative empathies, and the limitation of sadness emotions in certain types of charity fundraising. In addition, our findings provide useful insights for practitioners to design successful online charity campaigns.

Keywords: Charity Fundraising, Crowdfunding, Project Images, Deep Learning, Emotions, Empathy.

1. INTRODUCTION

Philanthropy is flourishing. Americans donated a record of $471 billion to charitable causes in 2020, and individuals contributed about 78% of all dollars given to charity (Giving USA, 2021). Among all charitable sectors, the "public-society benefit" sector led the way with the highest double-digit growth. As online giving grows to the highest share of total giving (Blackbaud Institute 2020 Charitable Giving Report), charity fundraising is increasingly relying on online platforms to solicit contributions. As an online marketplace for a large number of charity fund seekers and general public potential donors, crowdfunding has become a popular way of soliciting small funds from the general public because crowdfunding is an open, easy-access, and popular funding mechanism that accumulates negligible singular funds from a considerable number of individuals into a significant amount (Ahlers et al., 2015; Allison et al., 2015; Mollick, 2014; Ordanini et al., 2011). Although many people turn to crowdfunding to support their projects financially, not every campaign is funded successfully, partially due to the fierce competition among fundraisers. For example, more than 60% of Kickstarter campaigns fail to reach their goals (Kickstarter Stats July, 2021); on Indiegogo.com, another major crowdfunding platform, the unsuccessful rate is even over 80% (Liu, 2018). Given the large number of charity campaigns competing for prospective donors' support on a crowdfunding website, it is imperative to study how to improve the successfulness of charity fundraising campaigns on a crowdfunding platform.

Echoing this need, crowdfunding studies (Ahlers et al., 2015; Allison et al., 2015; Burtch et al., 2013; Mollick, 2014; Zheng et al., 2014) have focused on identifying key factors that influence the success of crowdfunding projects, and particularly, project setting parameters such as duration, amount, and preset goal. We take a different view and focus on the *project images*[1] that portray the themes and contents of the projects with visual designs and are featured on the funding website (see Figure 1). Representing the campaign, project images appear on the project pages, at the start of the project videos, and in project searches. Kickstarter reminds project designers to consider a project image thoughtfully, as "it's the first part of your project people will see — you'll want to make a good first impression" (Kickstarter Handbook, 2021). In the crowdfunding scenario, images can be important since users are unable to inspect the featured project in person. Evidence from e-commerce studies concludes that images have a profound effect on online environments. Peck and Childers (2003) found that online product images can increase consumers' perceived quality. In addition, Kelly et al. (2002), Bland et al. (2007), Goswami et al. (2011), Chung et al. (2012), Di et al. (2014) and Zhang et al. (2021) have shown that product images do play important roles in influencing users' trust, risk perception, attitudes and purchase intentions in terms of click-through rate and conversion rate. Images can elicit intense emotions (Lang et al., 1993), and the various emotions evoked by images are critical to encourage someone to take an action or not (Casas & Williams, 2019). Thus, project images are of great importance in attracting backers' attention to a project, triggering their emotions, and motivating them to pledge.

[1] This term is adopted from Kickstarter.com, and it is termed "campaign card image" by Indiegogo.com.

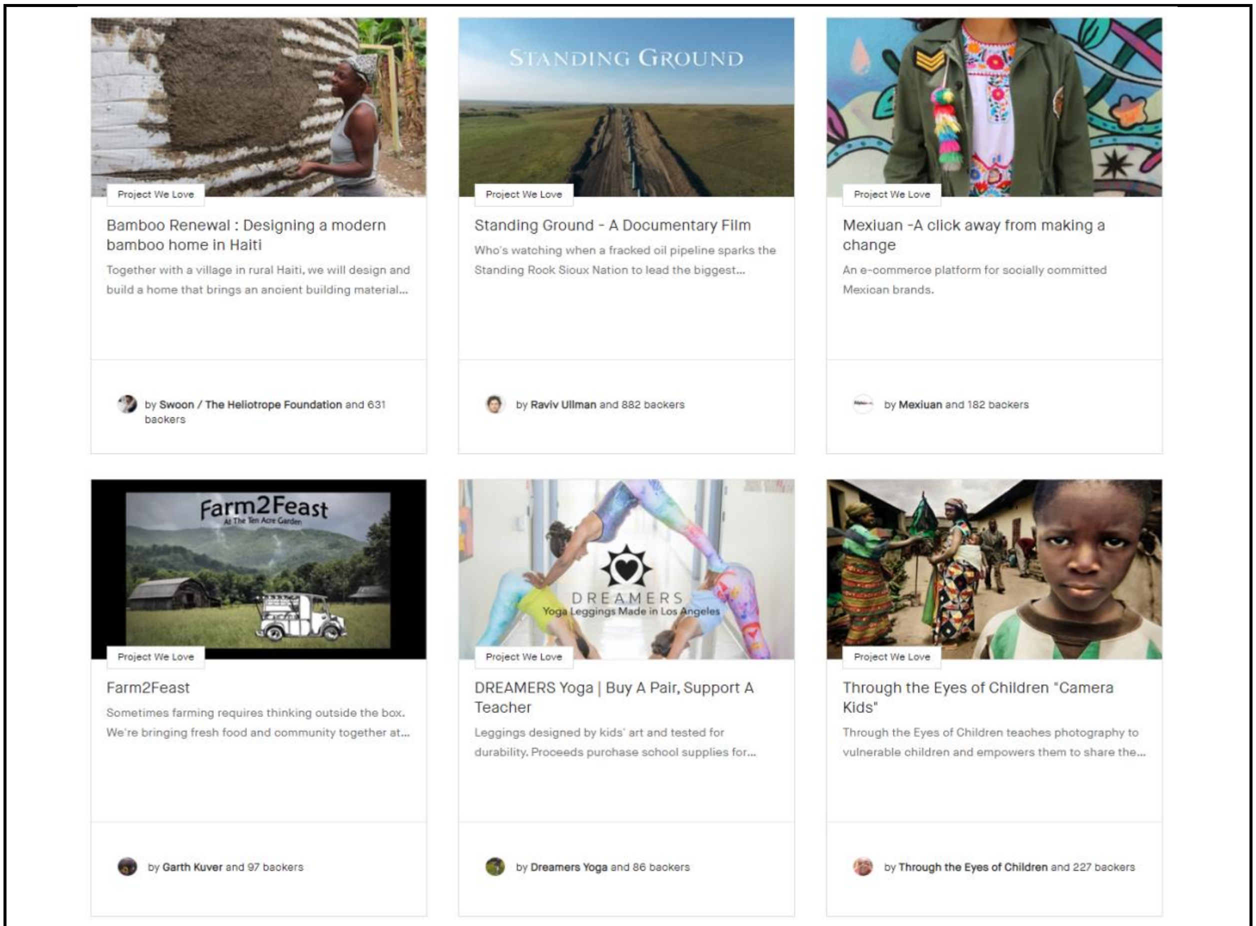


Figure 1. Examples of Project Images in the Public Benefit Category on Kickstarter.com

This study complements the literature by investigating how to improve the performance of charity fundraising campaigns through designing project images to arouse backers' emotions and subsequently influence their behaviors. Specifically, we investigate the following questions: First, how design attributes of a project image, such as color, content, and composition, are related to image emotions? Second, are emotions evoked by a project image affecting charity crowdfunding performance? If so, what is the mechanism? What are the quantitative effects?

We develop our research model based on the Stimulus-Organism-Response (S-O-R) framework in the context of charity fundraising campaigns: the image attributes as the external stimuli, the image emotions evoked by the project images as the organisms, and campaign outcomes as the responses. Philanthropy literature (Boulding, 1962; Batson & Shaw, 1991; Andreoni, 1989) proposes different theories, i.e., exchange theory, empathy-altruism hypothesis, and warm glow theory to explain the motivation to donate, which all emphasize empathy as the source of individuals' charity donation behaviors. Inspired by this literature, we hypothesize that negative and positive empathies play pivotal roles in the effects of image emotions on charity crowdfunding donations. Two sets of hypotheses are proposed based on the relationships between stimuli and organisms, and between organisms and responses, respectively. We obtain objective and reliable measurements of image emotions with a machine learning model and conduct empirical and experimental analyses to seek answers to the research questions. We expect to understand the relationships between emotions in project images and campaign success, and to provide fundraisers practical suggestions about how to design fundraising project images when launching charity crowdfunding projects.

This model is first verified through empirical analyses based on data collected from the "Public Benefit" category of Kickstarter.com. We develop a state-of-the-art deep neural network-based classifier to predict general viewers' emotional reactions (e.g., amusement, contentment, fear, sadness) categorized by Machajdik and Hanbury (2010), which are referred to as "image emotions." To understand the relationships between image attributes and image emotions, we also apply image analysis tools to measure several objective image attributes such as composition, color, and content (Wang et al., 2013; Zhang et al., 2021; Yang et al., 2013). We also use the data from

Kickstarter.com to verify the relationship between image emotions and campaign performance. Furthermore, we conduct an online randomized controlled experiment to verify the hypotheses. We also develop measurements of positive and negative empathies based on Light et al. (2019) and Andreychik and Migliaccio (2015) to verify their roles. The results supported the hypotheses that image attributes can stimulate the participants' positive and negative emotions, leading to empathic reactions, and in turn influencing their pledge intention.

This study contributes to the literature and practices in the following ways:

First, we are among the first studies that demonstrate how emotions evoked by project images play a critical role in the success of charity crowdfunding campaigns. Prior e-commerce studies have shown that images on a website significantly influence consumers' perceived quality, trust, risk perception, attitudes and purchase intentions in terms of click-through rate and conversion rate (Bland et al., 2007; Chung et al., 2012; Di et al., 2014; Goswami et al., 2011; Kelly et al., 2002). Charity promotion advertising literature on image emotions (Burt and Strongman 2005, Small and Verrochi 2009) has mainly focused on emotions evoked by human content and/or human facial expressions on the ad images. Compared with the literature, our study identifies a more comprehensive set of image attributes and emotions by developing a cutting-edge deep learning model, and expands the research scope of image emotions beyond self-reported affects aroused purely by human facial expressions on the images. We employ multiple methodologies and tools that provide new ways in studying emotions. For example, we implement machine learning techniques (i.e., deep learning, image analysis, and text mining) to identify and quantify objective image design factors and emotion measurements to enable empirical and experimental examinations of their relationships and impacts on charity crowdfunding performance.

Second, this research provides several new and unique findings that shed light on the underlying mechanism through which the image emotions lead to charity campaign outcomes. Traditional literature on philanthropic donation with visual ads (Bagozzi & Moore, 1994; Burt & Strongman, 2005; Change & Lee, 2009; Small & Verrochi, 2009) has predominantly focused on the role of negative emotions or sympathy on motivating donors' contribution decisions and showed that negative emotions are more effective than positive or neutral emotions in motivating donations. Our results differ from the traditional view in two ways: (1) we empirically show that negative emotions such as sadness are not always effective in motivating donations. We find that sadness evoked by project images only significantly motivates donation behaviors in *low-budget* or *educational* type of campaigns, while positive emotions such as contentment can significantly enhance the charity crowdfunding outcomes of *high-budget*, or *community* or *environment* types of campaigns. (2) We find that positive emotions give rise to positive empathy, which also triggers philanthropic donation behaviors. Our experimental results support the mediation roles played by positive (negative) empathy between positive (negative) emotions and donation decisions. Such findings present new evidence and mechanism to the charity donation literature regarding how emotions motivate donation behaviors.

Finally, managerially, our findings provide actionable and measurable guidance to charitable fundraisers for improving campaign performance through an optimal design of project images. This research suggests that viewers' emotions can be stimulated by image design through color attributes (e.g., warm hue and saturation) and content design (e.g., humans and animals), and that emotions can give rise to empathy which will motivate philanthropic behaviors. This research implements objective measurement of image attributes to better understand the connection between an image and the emotions it evokes. Our results suggest that specific attributes of the project images can influence the viewer's emotions. The findings create a bridge from a more aesthetic and intuitive understanding of photographic imagery to a more quantifiable understanding of how emotions influence fundraising performance in a crowdfunding scenario.

The rest of the paper is organized as follows. Literature review summarizes existing literature and related theories and discusses our research model in light of earlier works. Empirical study section describes our machine learning algorithms that identify emotions in the charity fundraising project images, and our empirical analyses based on data collected from Kickstarter.com. The next section introduces the experiment and additional studies to further verify our expanded research model. Then we discuss the implications, and finally, we conclude the paper and discuss limitations and directions for future research.

2. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

We review two main streams of relevant literature, namely, images and philanthropic donation, and propose our research model based on the S-O-R framework.

2.1 Literature on Images

Images are powerful means of online communication. Since consumers cannot directly observe or inspect the real products or the charity crowdfunding projects offered or featured on the Internet, images can present information in a more digestible way (Trope & Liberman, 2010). Project images play vital roles in charity crowdfunding campaigns. They convey detailed and explicit information about the projects to the backers, draw visitors' attention and guide their line of sight, and trigger the viewers' emotions and can affect the campaign success.

2.1.1 Literature on Image Emotions and Image Analytics. Images are commonly considered in the literature to cause emotional arousal. For example, Carroll (2003) stated that emotional response is crucial in a viewer's responses to artwork, Silvia (2005) suggested that there is an intimate relationship between art and emotions, and Barry (2006) posited that emotions should be involved in aesthetic appreciation.

Our work builds on this literature of image and emotion and expands on other innovative developments in machine learning to analyze images. As a useful method, machine learning can enhance the analysis of unstructured visual data such as images (Shin et al., 2020). We develop machine learning algorithms to recognize the emotions in project images. As artificial intelligence has advanced and deep learning has achieved great success in almost every domain, researchers have proposed and implemented a variety of deep neural network-based models to understand image semantics. Many custom models created by researchers, have proven themselves effective in many downstream business applications. For example, Zhang et al. (2021) leverage large-scale image analytics and develop convolutional neural network models to estimate Airbnb property demand. Liu et al. (2020) develop deep convolutional neural networks to measure brand attributes (e.g., glamorous, rugged, healthy and fun) from images and then apply the classifiers to brand-related images posted on social media to measure what consumers are visually communicating about brands. Based on the literature, we leverage a similar classification model in the deep learning framework and tailor it to our specific context — emotion detection. Our deep learning model described in the next Section differs from the existing ones in that we use both *pixel-level* and *mid-level features* as inputs and can therefore predict image emotions with higher accuracy than state-of-the-art baselines, such as You et al. (2016) and Rao et al. (2019).

2.1.2 Literature on Image Attributes. While the literature of philanthropic fundraising with visual ads (Buri & Strongman, 2005; Chang & Lee, 2009; Small & Verrochi, 2009) has mainly focused on human content and human facial expressions on the images, we adopt a richer set of image attributes from the previous image-related literature in e-commerce (Goswami et al., 2011; Chung et al., 2012; Zhang et al., 2021) and image classification (Machajdik & Hanbury, 2010; Wang et al., 2013). The attributes include color, content, compositions, and main element-background relationship (See detailed metrics and definitions in Table 1).

Color affects viewers' emotional feelings (Valdez & Mehrabian, 1994). For instance, red is generally perceived as hazardous (Braun et al., 1994), and green as trustworthy (Aslam, 2006). There are two color space models in image processing and computer vision applications: RGB and HSV. The RGB color model is an additive model that defines color in terms of a combination of primary colors: Red, Green, and Blue. The HSV color space (illustrated in Figure 2) is designed by computer graphics researchers to align more closely with the way human vision perceives color-making attributes. It has been more popularly adopted by the image literature (Machajdik & Hanbury, 2010; Chung et al., 2012; Wang et al., 2013; Zhang et al., 2021). In the HSV model, *Hue* represents color that is measured in degrees in the range of 0° to 360° with warm color hues less than 30° or greater than 110° according to Wang et al. (2013) and Zhang et al. (2021); *Saturation* is for shade that describes the depth or intensity of the color in the image; and Value for *brightness*, i.e., the overall lightness or darkness of the image. A high *contrast of brightness* indicates an uneven distribution of brightness across all pixels in the images, which makes the content appear sharp to viewers. Increasing the contrast level will result in brighter highlights and darker shadows.

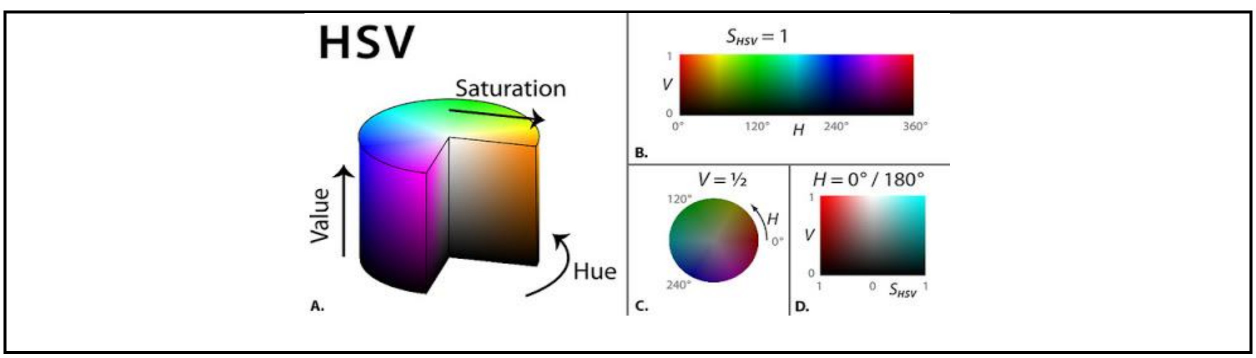


Figure 2. Illustration of the HSV Color Space
(Adapted from https://commons.wikimedia.org/wiki/File:Hsl-hsv_models.svg)

Burt and Strongman (2005), Change and Lee (2009), Machajdik and Hanbury (2010), and Small and Verrochi (2009) used the content of *human* and *human faces* in the images to classify or manipulate emotions. Several established guidelines about image composition attributes *diagonal dominance*, *symmetry*, *visual balance color* and *rule of thirds* are laid out in the professional photography book of Freeman (2007) and adopted in Zhang et al. (2021). In addition, the difference between the main element and the background will make the main element more stand out, which is measured by the *size difference*, *color difference* and *texture difference* (Goswami et al., 2011; Wang et al., 2013; Zhang et al., 2021). We illustrate the composition and main element-background relationship attributes in greater details in Appendix D. Zhang et al. (2021) considered the whole set of image attributes of the property images on the Airbnb website and showed that the color attributes as well as the composition and figure-ground difference all increase the property demand, except that the contrast of brightness has a negative effect on demand.

In our charity crowdfunding setting, image attributes can not only help backers cognitively evaluate the content in the project images but also stimulate backers as visual stimuli. Burt and Strongman (2005), Chang and Lee (2009), and Small and Verrochi (2009) experimentally demonstrated that human content and their facial expressions in images are contagious to viewers' emotions. Therefore, instead of focusing on either image or emotion solely, we combine the findings of extant research to employ a richer set of image attributes as antecedences of emotions, and propose Hypothesis 1:

Hypothesis 1: ***Image attributes of charity fundraising project images affect the emotions in charity fundraising project images.***

To explore more specific relationships between image attributes and the emotions the image evokes, we consider several key images attributes, such as color (saturation, brightness, and warm hue) and content (with human, with human face, and with animals).

Literature has suggested that color attributes affect viewers' emotional reactions. Wilms and Oberfeld (2018) used skin conductance and heart rate to biologically confirm that the color attributes, such as saturation, brightness, and hue, stimulate human emotions. Color attributes are found to be important features to predict emotions of artistic photos by Wang et al. (2013). Hemphill (1996) stated that bright colors can elicit positive emotions while dark colors can elicit negative emotions. Hanada (2018) reported an association between hues and emotions using correspondence analysis. Kaya and Epps (2004) showed hues that can be seen in nature elicit positive emotional responses of viewers. The results of Kaya and Epps (2004) reveal a mechanism about how emotions are formed by hues. That is, hues that can be related to things about which people have positive perception or experience before, such as nature, will arouse positive emotions. Therefore, we argue that since most people perceive warm hues as positive cues, warm hues are expected to evoke positive emotions and suppress negative emotions.

With a similar hue, different saturation and brightness bring out different emotions, and saturation is found to have a stronger effect on emotions than hue (Manav, 2007). Gao et al. (2007) reported that saturation and brightness induce more emotional reactions than hue and culture factors. Since people are more likely to prefer vivid and bright colors, saturation and brightness are concluded to be positively correlated to viewers' pleasure (Valdez & Mehrabian, 1994). Thus, we expect that saturation and brightness of project images elicit positive emotions and suppress negative emotions. Accordingly, we summarize the above literature and propose the following sub-hypotheses under H1:

H1_saturation: ***Higher saturation of charity fundraising project images will evoke positive emotions and suppress negative emotions.***

H1_brightness: ***Higher brightness of charity fundraising project images will evoke positive emotions and suppress negative emotions.***

H1_warmHue: ***Higher warm hues of charity fundraising project images will evoke positive emotions and suppress negative emotions.***

Image content can likewise affect viewers' emotions. In an animal conservation context, Whitley et al. (2021) surveyed over a thousand respondents and found that those exposed to the animal portraits reported lower positive emotions and no significant change in negative emotions. Those effects could be due to the viewers' concerns about the animals. Since our charity crowdfunding setting is similar to that in Whitley et al. (2021), we expect that having animals in images will attenuate positive emotions while not affecting negative emotions.

On the other hand, having humans in images might also affect viewers' emotions. For example, the charity advertising literature (Burt & Strongman, 2005; Chang and Lee, 2009; Small & Verrochi, 2009) has conducted experiments to show the effect of a picture in the ads. And the pictures in those studies depict a person in need typically trigger negative emotions or sympathy in order to motivate the responsiveness of potential donors. Hence, humans in project images are supposed to stimulate negative emotions.

Besides human in project images, Burt and Strongman (2005) and Small and Verrochi (2009) further focused on human faces and found that human faces can express emotions via emotion contagion. And when donors see the sad faces of victims, they are more likely to donate. By Machajdik and Hanbury (2010) and Dupré et al. (2020), "although the expression of the face is very important in order to distinguish between the moods of a picture, algorithms that can effectively recognize the emotional expression of a human face in static images are not yet fully mature." Considering that those people are in need of help given the charity fundraising context, even if their facial expressions demonstrate positive emotions, the contrast may highlight the distressed situation and evoke pity of the backers. Thus, we hypothesize that showing human faces in project images could arouse sadness emotion. Thus, we propose the following hypotheses:

H1_animal: ***Having animals in a charity fundraising project image will suppress positive emotions.***
H1_human: ***Having humans in a charity fundraising project image will evoke negative emotions.***
H1_face***: Having human faces in a charity fundraising project image will evoke sadness emotion.***

Although the literature suggests possible relationships between image attributes and emotions, many studies (Jacobs et al., 1991; Whitley et al., 2021) suggest that the same image attribute might elicit different emotions in various contexts. Thus, in this study we still need to explore the effect of images attributes on emotions in a charity crowdfunding scenario.

2.2 Literature on Philanthropic Donation

Traditional donation literature (Bagozzi & Moore, 1994; Burt & Strongman, 2005; Change & Lee, 2009; Fisher et al., 2008; Small & Verrochi, 2009) studying emotional influence on donations has mainly focused on or emphasized the negative emotions evoked by charity promotion ads. The image attributes considered in this stream of literature are primarily human content and human facial expressions. They show that negative emotions tend to be more effective than positive or neutral ones in motivating the responsiveness of penitential donors. In the public service ad scenario, Bagozzi & Moore (1994) conducted two experiments with anti-child abuse TV ads soliciting donation to help. They showed that ads that can stimulate negative emotions (i.e., anger, sadness, fear and tension) will lead to the empathic reaction of viewers and will in turn trigger their decisions to help. With a field study of televised blood donation drives, Fisher et al. (2008) found that negative emotions rather than positive ones can motivate donation behaviors, especially when people think they are helping others. In the context of child poverty charity promotion, Chang and Lee (2009) revealed that a negatively framed message that arouses viewers' self-relevance, consciousness and sympathy led to greater donation intentions than a positive appeal, especially when they are congruent with a negative pictorial presentation. Burt and Strongman (2005) found that images of people that provoke negative emotions (e.g., sadness) in respondents generate significantly larger donations of time and money for poverty reduction compared to other types of images. Small and Verrochi (2009) demonstrated that appeals depicting victims with a sad (versus happy or neutral) facial expression were more effective at eliciting prosocial behavior, and that the relationship between emotion expression and donation behavior was mediated by sympathy.

While previous research (Fisher et al., 2008; Small & Verrochi, 2009) has shown that the positive emotion of joy or happiness does not increase or even decrease willingness to help by reducing sympathy, Liang et al. (2016) showed that the positive emotion of strength evoked by text content of a donation ad can inspire people to donate. And combining this positive emotion with the negative emotion of sadness is more effective as a means of persuading people to donate.

Thus, we propose our Hypothesis 2 about the effect of image emotions on the performance of charitable crowdfunding projects.

Hypothesis 2: ***Emotions triggered by the charity fundraising project image affect the project's performance.***

To investigate the mechanism more explicitly, we specifically consider the mediation role of empathy in our model based the philanthropic donation literature, a long existing topic area in economics, marketing, and psychology. We extend this literature by considering a full spectrum of emotions, and both negative and positive empathy.

Philanthropic donation literature has proposed and verified three major motives and drivers of people helping others by donating to worthy causes. Some studies (Boulding, 1962; Drollinger, 2010; Reece, 1979; Sargeant, 1999) use the *exchange theory* in economics to explain the giving behaviors. That is, philanthropy occurs when benefits (e.g., glow of righteousness, sense of community with others) to the helper outweigh the costs (e.g., donations after tax deduction). Besides the above rational or selfish view of philanthropic behaviors, Batson and Shaw (1991) proposed the *empathy-altruism hypothesis* which holds that people help others in need out of genuine concern for the well-being of the other person, or empathic concern, regardless of what they can gain from it. In addition to altruism, Andreoni (1989, 1990) explained the motives of charity giving by the *"Warm Glow" theory*, which refers to a mixture of egoism and altruism. That is, besides donors receive utility from the fact that other people benefit from the public good, donations to public goods may also be caused by the expected warm glow (i.e., emotional reward of joy and satisfaction from the act of giving itself) they might receive by giving, which implies there might be "impure altruism" (Andreoni, 1989). Warm glow giving was verified with a lab experiment conducted by Crumpler and Grossman (2008) and in an empirical study of blood donation by Ferguson et al. (2012).

Though these theories propose different accounts of motive to give, they share a unanimous view on the critical role of *empathy* on the donors' contribution behaviors. Boulding (1962) defined empathy as "putting oneself in another's place, for feeling the joys and the sorrows of another as one's own" and regarded it as the source of the "genuine philanthropy". Batson and Shaw (1991) further emphasized the power of empathy in evoking truly altruistic motivation "with an ultimate goal of benefiting those for whom empathy is felt". Andreoni et al. (2017) found that empathy is likely to increase warm glow and is the key reason behind giving.

We especially focus on how empathy drives backers' behaviors in an online charity fundraising setting. Emotion contagion can play a pivotal role in the forming of empathy (Choi et al., 2016; Nezlek et al., 2001). Empathy can be generated by either seeing others in need (negative empathy) or valuing others' well-being (positive empathy). Bagozzi and Moore (1994) found that negative emotions can lead to *negative empathy* and then the decision to help, which demonstrates a general idea about how emotion and empathy work in a philanthropic context. When negative emotions are evoked by the project images, participants might empathize with those in need and have negative empathy in mind and they will be motivated to help so as to relieve themselves from the negative emotions (Cialdini et al., 1987). While negative empathy might be based on compassion and pity, positive empathy refers to "understanding and vicariously sharing others' positive emotions" and can be generated by observing or giving someone else a good experience through helping (Morelli et al., 2015). Prior studies mainly focus on negative empathy. Recent studies in psychology (Morelli et al., 2015; Sallquist et al., 2009) call for the attention to investigate positive empathy as a separate concept. Sallquist et al. (2009) found a positive relationship between positive emotion and *positive empathy*, and a positive association between positive empathy and social competence. Positive empathy can lead people to engage in prosocial behaviors and "gain the good feeling of sharing vicariously in the job of the needy individual's relief" (Batson & Shaw, 1991; Morelli et al., 2015). Thus, we include both negative and positive empathies in Hypothesis 2 to explain the mechanism of how image emotions are related to project performance and propose the following extended hypotheses:

Hypothesis 2a: ***Negative emotions of the charity fundraising project image lead to negative empathy.***
Hypothesis 2b: ***Positive emotions of the charity fundraising project image lead to positive empathy.***
Hypothesis 2c: ***Negative empathy enhances the charity crowdfunding project's performance.***
Hypothesis 2d: ***Positive empathy enhances the charity crowdfunding project's performance.***

2.3 Stimulus-Organism-Response (S-O-R) Model

The Stimulus-Organism-Response (S-O-R) model describes a framework of how individuals react to external environmental stimuli. The model describes human reactions in three steps: after receiving an external stimulus (S), individuals will generate an affective reaction and internal emotional state (O); depending on the stimulus, an emotional state (O) is generated in their minds internally, which in turn affects the individuals' actual behavior (R) (Mehrabian and Russell 1974). The S-O-R model is widely used in discovering consumer behaviors in different settings that include both offline and online environments. In the offline environment, Singh et al. (2014) have employed the S-O-R model to reveal how atmospheric factors in physical retail stores, such as the store design, affect consumer behavior in the store. In the online shopping scenario, Animesh et al. (2011) employed this framework to illustrate how customers' intention to repurchase or revisit is formed by such stimuli as the technological and spatial environments of the virtual world, and the color scheme of the online stores (Ettis, 2017; Peng & Kim, 2014). The S-O-R model has also been adopted in the social network scenario to explore why users discontinue Facebook usage (Luqman et al., 2017). The generalizability of the S-O-R model is further supported by the meta-analytical study of Vieira (2013). They all supported the strong associations among stimulus, emotion, and response.

We employ the S-O-R model to explore how backers react to stimuli, namely, the project images in charity crowdfunding. Our research model has three key components: the objective image attributes (Wang et al., 2013; Yang et al., 2013; Zhang et al., 2021) serve as the external stimuli, and the image emotions (Machajdik and Hanbury 2010) extracted from the project images are the organism or emotional state, which in turn affect the viewers' participating in the crowdfunding campaign (response). The overall research model based on the S-O-R framework is summarized in Figure 3.

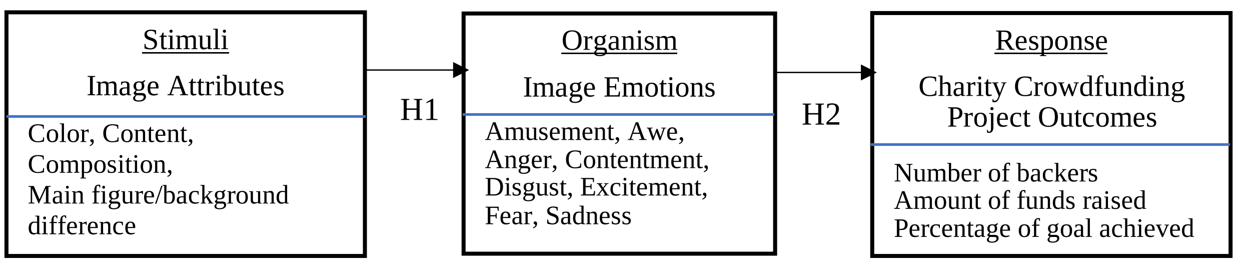


Figure 3. The Proposed Research Model

Incorporating the mechanism of empathy discussed above into the proposed model, we obtain an extended research model depicted in Figure 4, which includes the negative and positive empathy between image emotions and charity crowdfunding outcomes.

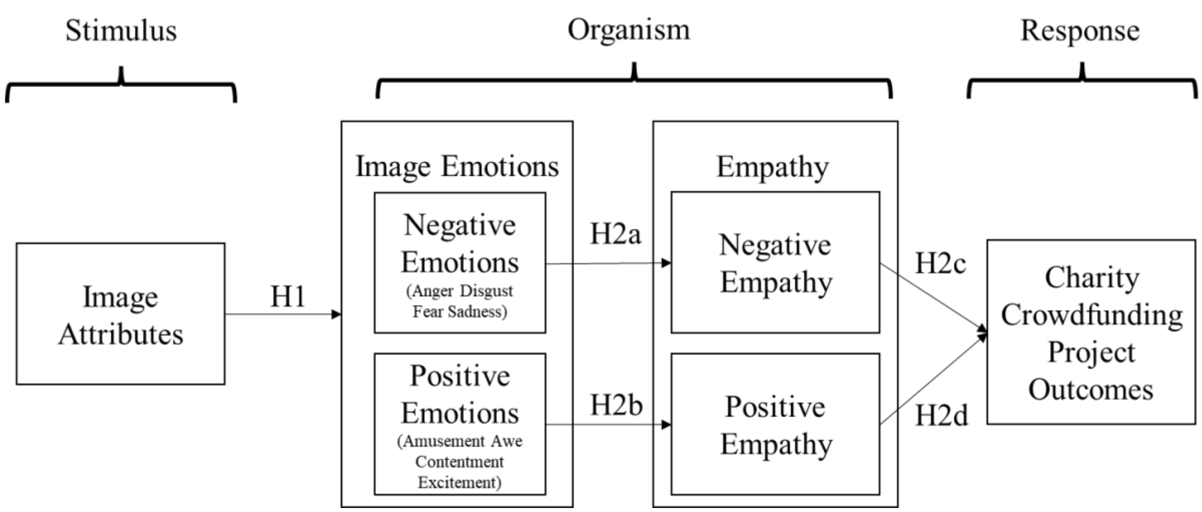


Figure 4. The Extended Research Model

To our best knowledge, this study is the first to examine how design factors of project images drive image emotions, which also affect the performance of crowdfunding projects. To highlight the contribution of this study, we summarize and contrast our study with the related literature in Appendix A.

3. EMPIRICAL STUDY

We collected the project images and other project-related information, such as preset funding targets, participant numbers, total amount raised, and textual descriptions from the "Public Benefit" category on one of the most popular crowdfunding platforms Kickstarter.com to empirically test the relationships between image attributes and emotions in the project images (sub-hypotheses in H1), and between image emotions and backers' pledge behavior (H2). Public benefit belongs to the "public-society benefit" sector of charity based on Giving USA (2021) and is a preset category that can be found on Kickstarter's Explore page. We obtain a total of 840 projects available in that category at the time of research (August 2017).

We focus on how Kickstarter projects attract and seek funding from potential backers who browse the website via categories or by searching keywords on the listing page. We first conduct a preliminary study to show that project images play an important role in attracting backers' attentions among competing campaigns.

3.1 Preliminary Analysis of Project Images on a Crowdfunding Platform

One feature of crowdfunding that distinguishes it from other fundraising methods (e.g., door-to-door, direct mail, special events, online fundraising pages) is that it allows multiple competing fundraising projects to appear on the same webpage simultaneously and compete head-to-head for backers. Therefore, it is critical to know what attracts a potential donor's attention on a crowdfunding page. We conduct a preliminary analysis (refer to Appendix B for details) by asking each participant to select one area that attracts their attention the most on a given webpage with 12 projects from a crowdfunding website and on a single-project page. The heatmap of all the participants (Figure 5) demonstrate that participants pay more attention to the image areas, which highlights the importance of images in a crowdfunding platform.

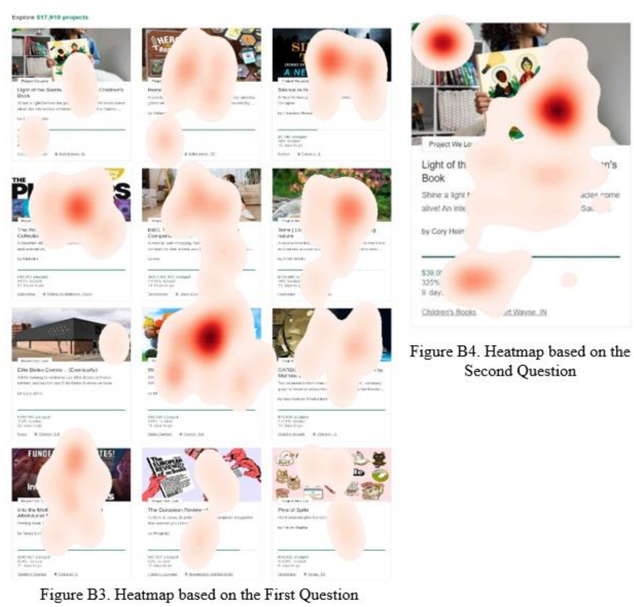


Figure 5. Attention Heatmap in the Preliminary Analysis

These results conclude that project images are the most attention-catching among all the web elements about a crowdfunding project. Yet, they are insufficiently examined by the previous literature. Our study expands the scope of the existing crowdfunding studies by examining the impact of project image designs on the performance of charity crowdfunding campaigns.

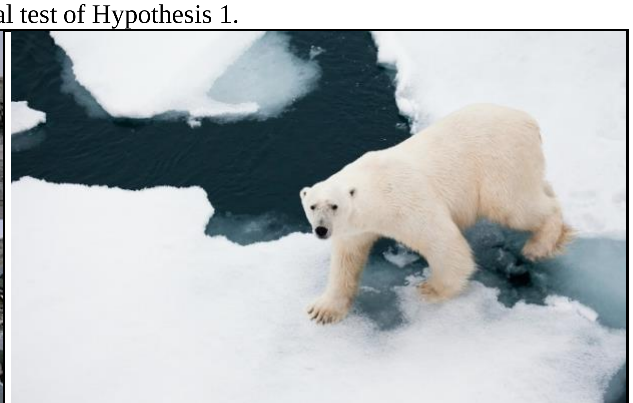
3.2 Extracting Emotions from Project Images

Since image emotion is central to this study, we start from presenting our emotion detection via deep learning. We adopt a well-defined set of emotions from Machajdik and Hanbury (2010), which includes amusement, anger, awe, contentment, disgust, excitement, fear and sadness. This set of emotions was developed based on the image emotion work of Mikels et al. (2005) as well as the basic emotion set proposed by Ekman et al. (1987).

We build a deep neural network-based model to predict emotions for project images. Please refer to Appendix C for detailed model architecture and execution. The training and validation data sets are from a set of human-labeled images created by You et al. (2016) (Figure C1 in Appendix C). Our mixed deep neural model (Figure C2 in Appendix C) learns to classify image emotions by fusing different aspects of images, primarily from low-level and mid-level features. The low-level features are pixel-level values in the RGB space, and the mid-level features include adjective noun pairs (ANPs) and tag words (i.e., objects contained in images) extracted via Google Vision API[2]. These low/mid-level features used to detect emotions make our model different from the previous studies (Machajdik & Hanbury, 2010; Small & Verrochi, 2009) and existing emotion detection APIs. First, our model does not rely on facial expressions or the presence of human beings in the image. Second, our model can identify eight different emotions while these APIs were trained and tested on a subset of eight emotions (e.g., Google only has joy, sorrow, anger, and surprise). Compared with various baseline models, our method achieves the best prediction performance (Table C2 in Appendix C).

We apply this learned optimal classifier to our project image dataset to predict their emotions. Figure 6 presents a few examples of predicted emotions of images in our project image dataset. For each of the eight emotions of every project image, the classifier provides a degree ranging from 0 to 100 (the higher the degree, the more likely the image is associated with that emotion). Our emotion measurements are not derived from any image attributes that will be used as independent variables in Model (1), but solely from the semantics of images (i.e., objects, ANPs and pixel values). Emotions capture and reflect the relations among higher-level elements, while attributes are alternative representations of raw image pixels. Thus, our emotion measurements are independent of the measurements of image attributes, supporting the empirical test of Hypothesis 1.

a. Amusement: 0.17, Anger: 0.04, **Awe: 98.12**, Contentment: 0.67, Disgust: 0.16, Excitement: 0.10, Fear: 0.49, Sadness: 0.26.



b. Amusement: 2.49, Anger: 2.20, Awe: 0.31, **Contentment: 79.96**, Disgust: 3.48, Excitement: 5.77, Fear: 1.90, Sadness: 3.89.

[2] Compared with the other image recognition services such as Amazon AWS Rekognition, IBM Watson Visual Recognition and Microsoft Azure Computer Vision, Google Vision is reported to provide the highest accuracy in tagging image contents, and the tags generated by Google Vision are the closest to those summarized by human (Ali 2019 and Enge 2019).

c. Amusement: 0.06, Anger: 9.66, Awe: 0.14, Contentment: 3.13, Disgust: 1.2, Excitement: 0.31, Fear: 2.12, **Sadness: 83.38**.	d. Amusement: 0.35, Anger: 3.94, Awe: 0.24, Contentment: 0.22, Disgust: 13.29, Excitement: 1.64, **Fear: 66.81**, Sadness: 12.06.

Figure 6. Examples of Project Images from Kickstarter.com and Their Predicted Emotions

3.3 Hypothesis 1 Testing: Empirical Results

To understand image emotions from a design point of view and to provide practical guides, we leverage the image attribute variables to investigate how they can explain the variances of image emotions (H1).

3.3.1 Measuring Image Attributes. To provide actionable implications to practice, we take a systematic approach to choose the image attributes based on the literature (Freeman, 2007; Small & Verrochi, 2009; Wang et al., 2013; Zhang et al., 2021). Following these standards, we propose the following four major components of image attributes, as summarized in Table 1.

Table 1. Image Attributes and Definitions

Component	Attributes	Operational Definitions
Color	Warm Hue	Pixels with warm color hue in the overall pixel count.
	Saturation	Average saturation value of all pixels in the HSV color space
	Brightness	Average brightness value of all pixels in the HSV color space
	Contrast of Brightness	Standard deviation of the brightness values of all pixels in the HSV color space
Image content	Text	There are textual contents in the images.
	Human	There are human beings in the images.
	Human Face	There are human faces in the images.
	Animal	There are animals other than humans in the images.
Composition	Diagonal Dominance	Distance between the main figure and the two diagonal lines
	Symmetry	The main figure distributed evenly on the left and the right
	Visual Balance Color	Color of the pixels across the central vertical line is distributed evenly
	Rule of Thirds	Distance between the main figure and two equally spaced vertical lines
Main element-background relationship	Size Difference	Size proportion of the main element in the whole image (0-100)
	Color Difference	Color difference between the main element and the background
	Texture Difference	Texture difference between the main element and the background

Based on the guidelines by Wang et al. (2013) and Zhang et al. (2021), we include such color-related attributes as warm hue, saturation, brightness, and contrast of brightness in this study. All of these color metrics are based on the HSV. *Warm hue* is defined as the proportion of pixels with warm color hues in the overall pixel count according to Wang et al. (2013). It is measured on a 100.0 scale. *Saturation* describes the depth or intensity of the color in the image. *Brightness* refers to the overall lightness or darkness of the image. *Contrast of brightness* is measured by the standard deviation of the brightness values of all the pixels. Following Burt and Strongman (2005), Change and Lee (2009), Small and Verrochi (2009), and Whitley et al. (2021), we consider the presence of *human*, *human faces*, or *animals* on project images as another image attribute. Additionally, following Yuan et al. (2016), we also include the presence of *text* on project images as an image attribute. These attributes are manually extracted by two domain experts. Following Zhang et al. (2021), we also consider image composition attributes such as *diagonal dominance*, *symmetry*, *visual balance color*, and *rule of thirds* and the attributes of *size difference*, *color difference* and *textual difference* about Relationship of Main Element and Background (Appendix D).

We use the popular image processing package, Python Pillow, to obtain the attributes of all the project images in our data sample. The descriptive statistics are presented in Table 2.

Table 2. Descriptive Statistics of the Image Attributes (N = 840)

Image Attributes		Min	Max	Mean	Std. Dev.
Color	Warm hue	0.21	100	70.37	25.05

	Saturation	0	0.97	0.28	0.18
	Brightness	1.40	254.47	140.50	49.51
	Contrast of brightness	17.85	117.95	60.12	15.55
Image Content	Animal in image	0	1	0.05	0.22
	Human in image	0	1	0.35	0.48
	Human Face in image	0	1	0.13	0.34
	Text in image	0	1	0.50	0.50
Composition	Diagonal dominance	-30.46	-0.15	-6.62	5.73
	Symmetry	-3246	0	-468.36	405.89
	Visual balance color	-296.14	-2.48	-90.67	36.81
	Rule of thirds	-45.27	-0.78	-21.84	7.58
Main Element-background Relationship	Size difference	0.31	69.33	5.20	5.53
	Color difference	1.86	408.39	122.39	85.57
	Texture difference	0	0.12	0.09	0.07

3.3.2 Hypothesis 1 Testing Empirical Findings. To test the sub-hypotheses of Hypothesis 1, we analyze the relationships between image attributes and the derived image emotion metrics at the project level, i (i = 1, 2…840). To do so, we model each of the image emotions as the dependent variable $ImageEmotion_{ki}$ (k = 1, 2…8), and the image attributes as independent variables, represented by $ImageAttribute_{ni}$ (n =1, 2… 16). We formally express the regression model in Equation (1).

$$ImageEmotion_{ki} = \alpha_k + \sum_n \beta_{kn} \cdot ImageAttribute_{ni} + \varepsilon_{ki} \quad (1)$$

where α_k and ε_{ki} are the constant term and error term of emotion k, respectively, and β_{kn} is the coefficient term of emotion k and image attribute n. The VIF statistics are in the range of 1.031 to 1.834, suggesting that multicollinearity is not detected. We use seemingly unrelated regressions (SUR) to estimate all eight equations in Table 3. We also provide the standardized results in Table E1 in Appendix E.

Table 3. Results of Using Image Attributes to Explain the Variance of Image Emotions (N = 840)

	Amuse-ment	Awe	Content-ment	Excite-ment	Anger	Disgust	Fear	Sadness
Saturation	**6.374***	1.283	1.625	**7.159***	-1.959	**7.456***	**-8.849*****	**-13.089*****
Brightness^2	**-0.001*****	**-0.001*****	**0.000***	0.000	**0.001*****	0.000	**0.000*****	0.000
Brightness	**0.145****	**0.194*****	**0.081***	0.078	**-0.340*****	0.058	**-0.142*****	**-0.074***
Warm hue	0.014	-0.012	-0.024	**0.082*****	0.048	-0.029	**-0.037****	**-0.041****
Animal in image	**-7.214*****	-4.235	**14.313*****	**-5.947****	4.294	-3.723	0.628	1.883
Human in image	0.356	**-3.941*****	-1.554	**10.865*****	**4.159****	**-6.693*****	-1.192	**-1.999****
Human Face in image	**-7.251*****	**-4.780****	**5.335*****	**3.754***	**5.756****	**-3.610***	**-2.160***	**2.955****
Contrast of brightness	-0.041	0.067	-0.022	0.021	0.085	**-0.105****	0.048	-0.054
Text in image	**-3.942*****	**-6.274*****	**-2.786*****	-0.736	16.307	-1.927	0.505	-1.149
Diagonal dominance	-0.001	0.163	**-0.194*****	-0.005	-0.067	0.015	0.047	0.042
Symmetry	0.000	0.000	0.000	0.001	0.003	0.000	**-0.002***	-0.002
Color balance	-0.011	**0.095*****	0.019	0.009	**-0.042***	**-0.081*****	0.016	-0.003
Rule of thirds	0.108	**-0.174***	0.086	-0.041	0.045	0.065	-0.087	-0.002
Size difference	-0.056	-0.166	0.111	-0.061	0.164	0.091	**-0.142***	0.059
Color difference	-0.010	-0.013	-0.001	-0.005	**0.028*****	0.001	-0.001	0.001
Texture difference	4.398	-9.978	4.833	8.983	-12.527	-5.956	**9.350***	0.897
Constant	8.752*	8.680	5.226	-0.631	18.682***	10.338*	24.064***	24.888***
R^2	8.2%	12.1%	13.1%	15.2%	25.1%	7.9%	6.1%	5.2%
Adj. R^2	6.3%	10.3%	11.3%	13.5%	23.6%	6.0%	4.2%	3.2%

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The results reported in Table 3 suggest that overall, image attributes can explain the variance of each emotion. Higher saturation in the project image is found to be positively related to positive emotions such as amusement and excitement, and negatively related to negative emotions fear, and sadness, which are consistent with *H1_saturation*. However, saturation also increases disgust. That is probably because over-saturation can make an image gaudy and unnatural. Thus, *H1_saturation* is partially supported. Given the valid range of brightness, our results show that higher brightness can significantly elicit amusement, awe, contentment, and suppress anger, fear, and sadness. These findings are consistent with our hypothesis. Thus, *H1_brightness* is supported. The results also demonstrate that a higher warm hue in the image color can increase positive emotions such as excitement while decreasing negative emotions such as fear and sadness. These results support *H1_warmHue*.

Based on our results, having animals in images can suppress amusement and excitement, which supports *H1_animal*. However, it also increases contentment. This is because while concerning for them in the charity crowdfunding scenario, most people feel satisfied when seeing animals. Thus, *H1_animal* is partially supported. Our results suggest that having humans in project images only increases the negative emotion anger but reduces disgust and sadness. We also observe that it arouses positive emotion excitement and suppresses awe. Thus, *H1_human* is partially supported. This contradicting result could be due to the following two reasons: (1) unlike the images of human portraits used in the literature, the project images in our charity crowdfunding campaign dataset are generally not dominated by human faces (only 38.4% of the project images with human show faces) but the contents that fit with the campaign theme; (2) our identification of emotions are not solely based on facial expressions but on the overall image design. Thus, unlike humans in the previous philanthropic fundraising studies (Burt & Strongman, 2005; Chang & Lee, 2009; Small & Verrochi, 2009) that were portraited in need to stimulate sympathy, humans in the charity crowdfunding project images are usually not dominant content of the images. On the other hand, we found that existence of human face significantly evokes the sadness emotion. Hence, *H1_face* is supported.

As a result, our approach can detect the evoked emotions of images in a more comprehensive and unbiased way. The sample images in Figure 6 confirm our findings about the relationships between image attributes and emotions. Consistent with the above empirical results in Table 3, the high brightness in Figure 6(a) arouses the awe emotion; the polar bear in Figure 6(b) stimulates the contentment emotion of the viewers; the grayscale image of Figure 6(c) has a low level of saturation, together with the human faces, leading to a strong emotion of sadness; and the relatively low warm hue and low brightness contribute to the fear emotion in Figure 6(d).

3.4 Hypothesis 2 Testing: Empirical Results

We apply the charity fundraising project data from Kickstarter to test Hypothesis 2.

3.4.1 Metrics and Measurements

Crowdfunding Performance

Following the prior crowdfunding literature (Ahlers et al., 2015; Allison et al., 2015; Burtch et al., 2013; Hobbs et al., 2016; Kang et al., 2016; Mollick, 2014; Yuan et al., 2016; Zheng et al., 2014), we adopt the three most commonly used metrics: (1) the total *amount* of funds the project raised, (2) *No. of Backers* that measures the number of individuals (registered accounts on the platform, to be precise) who contribute financial support to the crowdfunding project, and (3) *percentage* of goal achieved. Every crowdfunding project has a preset funding target. Projects can achieve various percentages of this target within the fundraising period.

Emotions of Competing Projects

Considering the competing nature of crowdfunding projects, projects that are listed at the same time on the crowdfunding platform are inevitably competing for the attention of the backers, because the projects that appear on the Internet platform simultaneously are only one “click” away. Thus, based on the starting and ending time and date, for each project in our dataset, we find all the projects that share overlapping durations with it and define them competing projects. We count the number of these competing projects *#Competing projects* and include it in Model (2). For each emotion type, we also calculate the average emotion score in the same emotion type of all the competing projects. For example, for charity fundraising campaign *i*, suppose that there are *n* competing projects (i.e., with some overlap duration with project *i*), the average Amusement score of competing projects is calculated by: $Competing\_Amusement_i = \frac{\sum_{j \neq i}^{n} Amusement_j}{n}$.

Control Variables

According to the crowdfunding literature (Allison et al., 2015; Garimella et al., 2017; Hong et al., 2018; Lin & Viswanathan, 2015; Mollick, 2014), we control such variables as *Preset Goal*, *Campaign Duration*, *Length of Text Description*, *Number of Images* and *Number of Videos* in the full project description on the project page. Considering our research context, we also control emotions of *text* descriptions (including *anxiety*, *anger*, and *sadness*) obtained by the LIWC software (Yin et al., 2014), and *project popularity* to account for the variation in the attractiveness of the themes. The project popularity is measured via the following procedure. We first extract the topmost frequent terms in text descriptions of all the sample projects, as shown in the word cloud in Figure 7. Then we use Google Trends index to approximate the relative popularity of each keyword during the project period. A final popularity score for each project is computed based on the sum of the Google Trends scores of the selected words appearing in the project description. Each keyword will be only counted once, while different keywords are summed up.

Figure 7. Word Cloud of Top Popular Terms in Crowdfunding Project Descriptions

We summarize the descriptive statistics of our data regarding variables in Table 4.

Table 4. Descriptive Statistics of Variables of Crowdfunding Projects (N = 840)

	Attributes	Variables	Min	Max	Mean	Std. Dev.
Dependent Variables	Outcome of projects	No. of Backers	0	94,770	319.02	637.53
		Amount (K$)	0	815.6	27.67	59.81
		Percentage (%)	0	3,534.61	141.80	240.06
Independent Variables	Emotion in project images	Amusement	0.022	85.822	11.930	15.584
		Awe	0.015	98.117	7.362	17.821
		Contentment	0.030	91.264	6.914	11.456
		Disgust	0.023	98.181	11.802	18.192
		Excitement	0.048	95.099	16.182	17.792
		Fear	0.187	68.037	11.332	11.015
		Sadness	0.046	83.381	10.185	11.583
	Emotion in Competing Projects	#Competing projects	0	106.00	33.58	19.75
		Competing Amusement	0	67.44	11.98	4.14
		Competing Awe	0	26.61	7.40	3.32
		Competing Contentment	0	28.50	6.90	2.52
		Competing Disgust	0	38.48	11.71	4.03
		Competing Excitement	0	32.29	16.38	4.24
		Competing Fear	0	19.76	11.22	2.29
		Competing Sadness	0	20.65	9.96	2.74
Control Variables	Emotion in text description	Anxiety	0	9.09	0.082	0.650
		Anger	0	9.38	0.186	0.979
		Sadness	0	10	0.202	1.030
	Project characteristics	Preset Goal (K$)	0.015	1,500	27.60	69.10
		Project popularity	0	213.03	32.71	38.74
		Length of Text Description	73	4,565	946	632.19
		No. of Images	0	72	7.59	10.19
		No. of Videos	0	7	0.85	0.64
		Campaign Duration	5	91	33.46	10.99

3.4.2 Empirical Findings. To verify Hypothesis 2, we perform an empirical analysis at the project level, i, for each dependent variable $Performance_{pi}$ (p = 1, 2, 3), i.e., number of backers, amount raised, and percentage of fundraising goal achieved, respectively. We express the model in Equation (2) and summarize the results in Table 5 (standardized results in Table E2 in Appendix E).

$$Performance_{pi} = a_p + \sum_k \left(b_{pk} ImageEmotion_{ki} + c_{pk} Competing_{ImageEmotion_{k,i}} \right) + \sum_l d_{pl} Control_{li} + e_{pi} \quad (2)$$

where $ImageEmotion_{ki}$ (k = 1, 2…7) represents the score of the kth emotion in the image emotion set in project image of project i, and $Competing\_ImageEmotion_{k,i}$ is the average score of the kth emotion of the competing projects of i. Since all eight emotion scores add up to 100, we drop one of the emotions "anger" to remove multi-collinearity. $Control_{li}$ represents the control variable l (l = 1, 2… 9) of project i. We applied log transformation to the variables of textual anxiety, textual anger, textual sadness, and goal to handle the skewed distribution. In the equation regarding performance p, a_p and e_{pi} are the constant and error terms, respectively, and b_{pk}, c_{pk} and d_{pl} are the coefficients of image emotion k of own image and competing images, and control l, respectively.

The findings of this empirical study suggest that:

(1) The contentment emotion in a project image has a statistically significantly positive effect on all three outcome metrics. If the contentment score in project image increases by 1 unit, the average number of backers is expected to increase by approximately 4, the average amount raised is expected to increase by $286, and the average ratio of achieved amount to preset goal is expected to increase by 1.901%. This result is unique in the literature of charity fundraising with visual ads, which primarily emphasized the importance of negative emotions. However, it supports the empathy-altruism or the "Warm Glow" theories in the philanthropic donation literature, which explain people's prosocial behaviors out of pure altruism or emotional rewards of joy. This finding suggests that if the project image conveys the satisfying and happy feelings by making someone else happy, then it will attract more people to participate in the crowdfunding project and contribute more.

(2) Sadness exhibited in images is significantly and positively associated with the number of backers and the amount raised. If the sadness in project image is increased by 1 unit, the average number of backers is expected to increase by about 7 and the average amount raised is expected to increase by $373. This result suggests that the sad emotion in a project image can arouse the feelings of pity, sympathy, tenderness, or sorrow, which drive the viewers to be willing to contribute to the funding project. This finding is consistent with the previous literature where the emotion of sadness has a positive effect on the success of fundraising (Small & Verrochi, 2009).

Table 5. Effects of Image Emotions on Crowdfunding Performance (N = 840)

	Backer #	Amount (K$)	% of goal achieved	Backer #	Amount (K$)	% of goal achieved
Amusement	0.510	0.004	0.147			
Awe	-1.445	0.046	-0.081			
Contentment	**3.76****	**0.286***	**1.901****			
Disgust	-1.218	-0.069	-0.146			
Excitement	-1.22	-0.111	-0.111			
Fear	**-5.123****	-0.305	-1.348			
Sadness	**6.727*****	**0.373****	0.713			
#Competing projects	-0.843	**-0.176***	**-1.112****			
Competing Amusement	**-10.312***	-0.470	0.830			
Competing Awe	-6.235	-0.964	-0.810			
Competing Contentment	**-24.207*****	-0.995	**-8.370****			
Competing Disgust	-1.215	-0.223	3.147			
Competing Excitement	-2.735	0.346	1.736			
Competing Fear	**-21.979****	-0.947	**-6.866***			
Competing Sadness	-4.318	**-1.283***	-3.331			
Anxiety in text description	11.337	1.473	-5.422	10.626	2.214	0.946
Anger in text description	30.919	-0.161	-7.222	28.411	0.321	-4.225
Sadness in text description	83.405	0.542	16.967	**100.503***	2.163	22.597
Preset Goal	**128.862*****	**16.463*****	**-48.869*****	**133.231*****	**16.560*****	**-47.108*****
Project popularity	0.781	0.014	0.131	0.708	0.011	0.083

Length of text description	**0.141*** **	**0.006***	**0.028***	**0.131*** **	**0.006***	**0.028***
No. of Images	**5.609** **	**0.852*** **	**3.506*** **	**5.664** **	**0.875*** **	**3.569*** **
No. of Videos	**158.295*** **	**16.325*** **	**37.076*** **	**176.390*** **	**17.222*** **	**44.574*** **
Duration	-1.236	-0.056	-0.160	0.109	0.082	-1.227
Constant	-471.503	-104.664***	647.706***	-1221.875***	-150.147***	500.619***
R^2	26.0%	30.8%	13.0%	21.6%	28.4%	9.5%
Adj. R^2	23.8%	28.7%	10.4%	20.8%	27.6%	8.6%

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

(3) Fear in project images reduces the number of backers. If fear increases by 1 unit, the average number of backers is expected to drop by about 5. This finding aligns with studies in the medical literature showing that fear is a critical factor that inhibits people from donating blood (France & France, 2018). Fear may be associated with distrust, which makes people reluctant to accept new technology (Hsiao, 2003). Consistent with the literature, we do observe that fear makes backers balk.

(4) Competition effect is confirmed. The number of competing projects is shown to significantly reduce the funds raised and percentage of goal reached. The image emotions of competing projects, e.g., amusement, contentment, fear, and sadness, are hurting the performance of the focal charity fundraising projects.

(5) Adding the emotion variables of the focal project and the competing projects increases the adjusted R^2 of the models, which suggests significant effect of emotions in charity crowdfunding.

The above empirical results support Hypothesis 2 that emotions in project images impact the success of crowdfunding projects.

3.4.3 Moderation Effects of Project Budget and Project Category.

We conduct additional empirical tests of Model (2) with sub-samples of charity fundraising campaigns of divided by project types. Mollick (2014) suggests that crowdfunding project characteristics such as project category and budget are significant factors to consider when launching and designing a crowdfunding project. Since the budget and the category of the charity projects cannot be directly obtained from the crowdfunding platform, to study the possible moderation effects of these characteristics, we hired two experts who have experiences in charity crowdfunding campaigns to evaluate the project budget and to assign the project category based on the project description. The raters were first asked to evaluate the budget of the projects on a 1-7 Likert scale (higher rating indicates a higher budget). The ratings from both experts are highly correlated with a Cohen's Kappa 0.672, suggesting a substantial agreement between the experts (Landis & Koch, 1977). We follow the budget rating to divide all the projects in our sample dataset by the average rating of 3.557 into two groups: 348 high-budget projects and 492 low-budget projects. We re-examine Model (2) with the split samples by budget level and present the results in Tables 6 (standardized results in Table E3 in Appendix E).

Table 6. The Effects of Image Emotions on Crowdfunding Performance by Budget

	High Budget			Low Budget		
	Backer #	**Amount (K$)**	**% of goal achieved**	**Backer #**	**Amount (K$)**	**% of goal achieved**
Amusement	-0.032	-0.024	1.405	0.583	0.022	-0.591
Awe	-1.422	0.214	0.551	-1.389	-0.122	-0.511
Contentment	**10.376*** **	**0.753*** **	**3.692*** **	-1.884	-0.100	0.320
Disgust	-1.325	0.079	0.685	-0.995	-0.162	-0.562
Excitement	-1.827	-0.126	-0.074	-1.555	-0.139	-0.150
Fear	-2.155	-0.149	-0.609	**-7.347*** **	-0.367	**-1.760***
Sadness	0.560	0.110	0.379	**10.223*** **	**0.495** **	0.768
#Competing proj.	-1.038	-0.209	-1.205	-0.357	-0.150	**-1.524*** **
Competing Amusement	**-18.551** **	-1.103	-4.449	-3.618	-0.117	**5.692** **
Competing Awe	8.394	-0.286	1.689	-10.130	-0.966	-1.066
Competing Contentment	**-54.676*** **	**-3.119** **	**-21.297*** **	-9.403	0.115	-2.300
Competing Disgust	14.979	0.850	7.238	-7.997	-0.760	0.444
Competing Excitement	1.729	0.887	2.497	-2.451	-0.008	1.363
Competing Fear	-15.077	-1.381	-6.412	**-22.126***	-0.729	**-7.855***
Competing Sadness	-3.430	-1.161	-6.192	-6.026	**-1.779***	-3.190

Anxiety in text description	48.173	5.346	-30.495	39.481	3.204	23.753
Anger in text description	12.160	2.027	-17.314	68.509	0.570	-6.547
Sadness in text description	140.919	-1.521	-17.815	5.482	0.969	44.588
Preset Goal	**117.163*** **	**15.313*** **	**-52.006*** **	**128.533*** **	16.966	**-47.000*** **
Project popularity	0.538	-0.044	-0.324	0.631	0.034	**0.405***
Length of text description	0.049	0.005	0.023	**0.183*** **	0.005	**0.030***
No. of Images	**11.000** **	**0.990** **	**4.589** **	4.423	**0.896*** **	**2.843*** **
No. of Videos	**217.307*** **	**22.659*** **	**37.021***	**106.445** **	**10.281** **	**45.562*** **
Duration	1.861	0.021	-0.437	-1.903	-0.043	0.565
Constant	-583.380	-102.632**	768.585***	-491.284	-100.143**	575.896***
N	348	348	348	492	492	492
R^2	32.7%	36.1%	14.7%	27.6%	30.7%	18.5%
Adj. R^2	27.7%	31.3%	8.3%	23.8%	27.1%	14.3%

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The results in Table 6 show that the relationship between image emotions and the performance of charity crowdfunding projects varies with the budget level: for high-budget campaigns, only the contentment emotion is significantly effective in driving the success, while the amusement and contentment emotions of the competing campaigns' images hurt their performance; for low-budget campaigns, the sadness emotion of project images significantly attracts more backers and increases the pledge amount, fear reduces the backer number and percentage of goal achieved, and the number of competing projects and the fear and sadness of competing project images also impair the focal campaign's outcomes.

These results suggest that different emotions, positive or negative ones, motivate the donation behavior in different ways, because they are mediated by different types of empathies. While sadness has been proven as an effective tool to arouse sympathy which induces donation behaviors by a large body of experimental studies with visual promotion ads, there lacks extensive evidence about positive emotion like contentment evoked by images causing donations. The budget amount signals the size, cost, challenge level to deliver, and the success probability of a crowdfunding project (Mollick, 2014). The low-budget campaigns tend to be smaller projects that are easier to achieve and anticipate smaller amount from individual backers. Thus, the negative sadness emotion plays a dominant role for low-budget campaigns because it can effectively arouse the sympathy of backers and incentivize them to donate, but in a relatively smaller amount of pity money. On the other hand, projects with a higher budget imply a larger contribution amount and a higher uncertainty of success. Contentment is a feeling of happiness and satisfaction with contributing to public causes and cultivates the backers' self-esteem. Contentment may have a lower influential level than sadness. For example, Videras and Owen (2006) demonstrated that contributing to environmental causes increased life satisfaction of individuals with moderate to high levels of social responsibility while it had no significant effect on life satisfaction of those with low levels of social responsibility. The satisfaction level of charity donation increases with the amount. For example, Dunn et al. (2008) found a positive effect of overall giving to charity and spending money on others on life satisfaction. Thus, contentment may induce greater donations. Our findings suggest that contentment induces positive empathy, which provides greater incentive to the backers to pledge more and be more contented with their giving to the high-budget campaigns.

Based on the nonprofit categories defined in Giving USA (2021), experts also classified each project into the following categories: Community, Environment, Education, Arts and Culture, Animal Welfare, Business, Food, and Medical (one project may belong to multiple categories). We selected the top three categories (Education, Community, and Environment) to ensure enough observations to conduct the empirical tests. We re-examine Model (2) with each category and present the results in Table 7 (standardized results in Table E4 in Appendix E).

Table 7. The Effects of Image Emotions on Crowdfunding Performance by Project Category

	Community			Environment			Education		
	Backer #	**Amount (K$)**	**% of goal achieved**	**Backer #**	**Amount (K$)**	**% of goal achieved**	**Backer #**	**Amount (K$)**	**% of goal achieved**
Amusement	0.996	0.084	**1.118** **	3.430	-0.121	2.818	-1.674	-0.053	**-1.09***
Awe	-0.674	-0.085	-0.088	1.961	0.007	0.066	-2.065	-0.071	-0.563
Contentment	**4.190** **	**0.884*** **	0.068	**20.997*** **	**1.186*** **	**5.887** **	-4.64	-0.285	0.017
Disgust	-0.816	-0.041	-0.166	2.505	-0.032	0.076	-1.486	0.027	-0.251

Excitement	0.442	-0.013	-0.427	2.999	0.259	-0.949	-2.68	-0.137	0.445
Fear	-2.055	-0.131	-0.439	1.891	0.204	-2.923	-6.527	-0.440	-0.210
Sadness	0.260	-0.083	-0.165	6.601	0.053	0.784	**15.954*** **	**1.181*** **	0.468
#Competing proj.	-0.441	-0.181	-0.689	2.090	0.144	-0.086	1.582	0.022	0.517
Competing amusement	-5.815	-0.903	-1.448	**-48.417***	**-3.745****	-15.398	8.194	0.615	2.340
Competing awe	-3.590	-0.929	-0.702	-14.550	-0.742	-0.791	-1.766	-0.15	**5.538****
Competing contentment	**-28.317*** **	-1.416	-1.525	**-109.23****	**-5.352****	**-40.110****	-7.122	0.134	**7.277****
Competing disgust	**-18.045****	**-2.426*** **	-4.198	-1.627	-0.941	6.839	7.042	0.200	**7.169*** **
Competing excitement	**-19.093****	**-1.705****	-2.804	-16.037	-1.216	1.498	2.263	0.342	**5.143****
Competing fear	**-27.039****	**-2.385***	-7.517	-6.196	-2.404	-4.222	-26.847	-1.762	4.772
Competing sadness	2.012	-1.690	-4.051	-53.330	**-3.585***	-19.587	22.548	1.037	**7.023****
Anxiety in text description	1.091	1.699	-8.846	221.109	24.729	-85.419	44.735	1.049	-1.428
Anger in text description	-8.987	4.212	13.016	-128.148	-11.004	-4.435	53.131	2.175	-13.963
Sadness in text description	**175.696*** **	0.352	1.474	99.699	12.140	13.948	16.126	1.552	31.793
Preset Goal	**120.273*** **	**16.778*** **	**-36.023*** **	**117.610***	**17.525*** **	**-61.242****	**169.452*** **	**16.971*** **	**-29.633*** **
Project popularity	0.588	-0.046	0.063	-0.446	-0.072	-0.391	0.989	0.031	0.085
Length of text description	0.050	0.002	0.003	**0.255****	**0.019****	0.073	**0.145***	0.007	0.022
No. of Images	-2.039	-0.094	2.783	13.020	0.273	3.868	1.929	0.496	-0.483
No. of Videos	**136.215*** **	**15.921*** **	20.342	**313.388*** **	**25.578*** **	72.100	78.513	9.557	**50.521*** **
Duration	-2.042	-0.250	0.327	-9.799	-0.637	-2.030	-5.129	-0.399	-0.833
Constant	75.124	-10.283	677.206***	769.528	3.563	1200.366	-1417.045*	-145.813**	-53.03
N	206	206	206	134	134	134	254	254	254
R^2	43.6%	50.1%	16.5%	40.2%	51.3%	24.4%	30.1%	38.0%	23.7%
Adj. R^2	36.1%	43.5%	5.5%	27.0%	40.5%	7.7%	22.8%	31.6%	15.7%

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Results in Table 7 suggests that positive and negative emotions should also be applied differently according to the category of charity fundraising projects. More specifically, we show that contentment has a significantly strong influence on donation to community and environmental types of charity fundraising campaigns because backers gain satisfaction and develop a sense of achievement by contributing to social benefits and complying with social norms (Sugden 1999); and for education projects, the negative sadness emotion plays an important role in attracting a large number of backers and making them donate.

The above findings extend the traditional charity literature (Liang et al., 2016; Small & Verrochi, 2009) by examining how various emotions sparked by project images affect backers' donation behaviors differently for campaigns with diverse attributes in an online crowdfunding platform.

Our results in the above empirical analyses support the S-O-R model that emotions in project images are influenced by image attributes, and they are related to the project performance.

4. EXPERIMENT OF DESIGN ATTRIBUTES ON IMAGE EMOTIONS

To further verify the empirical results, we conduct an online randomized controlled experiment with image attribute manipulations, with additional studies in Appendix G.

4.1. Experiment Design

We create a crowdfunding project that raises funds to humanely trap, neuter, and return stray cats. This made-up project contains a project image of a stray cat and an identical short textual description of the project. The objective of this experiment is to further verify the effects of attributes of project images on the participants' emotions, and the impacts of image emotions on the participants' pledge intentions in a crowdfunding project. The project image and description are attached in Appendix F. The experiment is administered through the QuestionPro platform to host the experiment and collect response data.

Based on the results of our empirical analyses and the feasibility, we choose to test the effects of warm hue and saturation attributes separately. We drop the treatment of the other color attribute, i.e., brightness, because a user's perceived image brightness is influenced by the screen brightness setting, which is usually determined on an individual basis, so that the realized brightness of the treated pictures may be distorted and deviate from our original setup. Moreover, we do not choose the other image attributes due to the technical difficulty in treating any of those attributes alone without significantly altering all other attributes.

To minimize the change of other image attributes due to the manipulation on warn hue or saturation, we only treat one color attribute in one group. That is, we manipulate warm hue (High vs. Low) with two groups of participants and saturation (High vs. Low) with another two groups. Although it is still inevitable to change the color, the variation is minimized. Each subject is assigned to view one of the project images and the associated same textual description. After reading through the fundraising project, subjects are asked to rate their emotional response in a 7-point Likert scale (Machajdik & Hanbury, 2010) and whether they are willing to pledge for such a charity project. This experiment is created online and distributed through Amazon Mechanical Turk (MTurk). To ensure all participants are proficient in English and maintain the quality of the sample, we require all participants to be located in the US and have a historical approval rate over 95%.

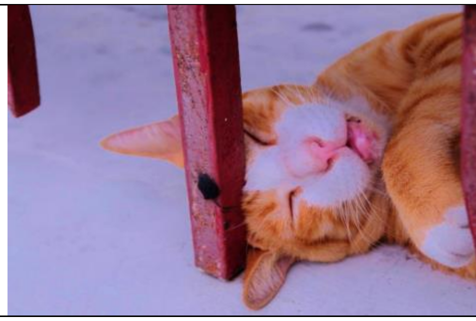
Table 8. Manipulation on Warm Hue

Manipulation	Warm hue: High	Warm hue: Low
Image		
Warm hue value	99.996	58.761

In Test 1, we manipulate the warm hue attribute in the stray cat's image. We use Pillow, a Python imaging library, to change the warm hue property of the image. Then we use our algorithm to verify the manipulation on warm hue is successful. The cat images with high or low warm hue are shown Table 8. In Test 2, saturation is manipulated by Pillow as well. Then we use our algorithm to measure the saturation and check the manipulation is successful. The images with high or low saturation are shown in Table 9.

Table 9. Manipulation on Saturation

Manipulation	Saturation: High	Saturation: Low

Image		
Saturation value	0.409	0.296

4.2 Experiment Findings

In this study, we collected 257 samples from MTurk in April 2021. After removing invalid sample such as participants who never browse any crowdfunding platforms before, we obtain 177 samples. The descriptive statistics of the full sample are shown in Table 10. The "Education" and "Income" variables are evaluated based on the classifications given in Table B1 in Appendix B.

Table 10. Descriptive Statistics in the Full Sample (N = 177)

Variable	Min	Max	Mean	Std. dev.
Pledge Intention	0	1	0.531	0.500
Positive Empathy (Average)	1	6.80	4.95	1.322
Negative Empathy (Average)	1	6.67	4.46	1.396
Amusement	1	7	3.469	1.803
Awe	1	7	3.079	1.720
Anger	1	7	3.740	1.706
Contentment	1	7	4.136	1.704
Disgust	1	7	3.412	1.807
Excitement	1	7	3.746	1.846
Fear	1	7	3.243	1.740
Sadness	1	7	4.006	1.743
Age	18	65	38.650	10.593
Education	1	8	4.706	1.203
Income	1	12	6.559	3.017
Gender (1 = Male, 0 = Female)	0	1	0.627	0.485

Each participant is randomly assigned to one of the four controlled groups. The descriptive statistics of each group is presented in Table 11. The demographic variables, e.g., age, education, income and gender, of each group are statistically equal (the *p*-value of the chi-square test of homogeneity are in the range of 0.116 to 0.667), validating that the sample groups are randomized.

Table 11. Descriptive Statistics of the Experiment Data in Each Group

	Warm hue				Saturation			
Treatment	**High**		**Low**		**High**		**Low**	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Pledge Intention	0.350	0.484	0.730	0.449	0.440	0.502	0.550	0.503
Positive Empathy (Avg)	4.784	1.309	5.338	1.059	4.621	1.359	4.951	1.457
Negative Empathy (Avg)	4.239	1.342	4.809	1.325	4.226	1.331	4.465	1.511
Amusement	3.050	1.632	3.270	1.899	4.130	1.609	3.450	1.877
Awe	2.510	1.644	3.100	1.704	2.740	1.697	3.700	1.648
Anger	3.160	1.675	4.020	1.657	3.920	1.562	3.750	1.818
Contentment	3.490	1.835	4.460	1.414	4.590	1.618	3.960	1.786

Disgust	2.730	1.661	3.710	1.879	3.050	1.820	3.890	1.672
Excitement	3.410	1.755	3.850	1.989	4.260	1.697	3.510	1.836
Fear	2.620	1.534	3.420	1.944	2.900	1.569	3.770	1.648
Sadness	3.570	1.692	4.290	1.868	3.490	1.571	4.430	1.658
Age	39.510	10.519	39.980	11.157	36.150	10.051	38.680	10.488
Education	4.920	1.256	4.540	1.304	4.510	1.167	4.850	1.081
Income	7.050	3.274	6.350	2.809	6.870	3.113	6.170	2.953
Gender	0.540	0.505	0.650	0.483	0.720	0.456	0.600	0.494
N	37		48		53		39	

Figure 8 illustrates the comparisons of the group mean of each emotion reported by the participants after viewing a treated project image. We further employ independent sample *t*-tests and Mann-Whitney tests to statistically verify whether changing an image attribute, i.e., warm hue or saturation, can make differences to each of the evoked emotions when the participants view the project images. The results (*t* values and *U* values) are presented in Table 12.

Table 12. Results of Independent Samples

***T*-Test**			**Mann-Whitney Test**		
Treatment	**Warm hue**	**Saturation**	**Treatment**	**Warm hue**	**Saturation**
Amusement	-0.554	**1.853***	Amusement	840.50	**820.50* +**
Anger	**-2.358****	4.465	Anger	**624.50** -**	983.50
Awe	-1.609	**-2.711****	Awe	**693.50* -**	**698.50***-**
Contentment	**-2.668*****	**1.732***	Contentment	**613.50** -**	859.00
Disgust	**-2.502****	**-2.281****	Disgust	**624.00** -**	**737.50** -**
Excitement	-1.085	**1.991****	Excitement	765.50	**798.50* +**
Fear	**-2.107****	**-2.571****	Fear	**688.50* -**	**720.00** -**
Sadness	**-1.845***	**-2.767*****	Sadness	**667.00** -**	**694.50***-**

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

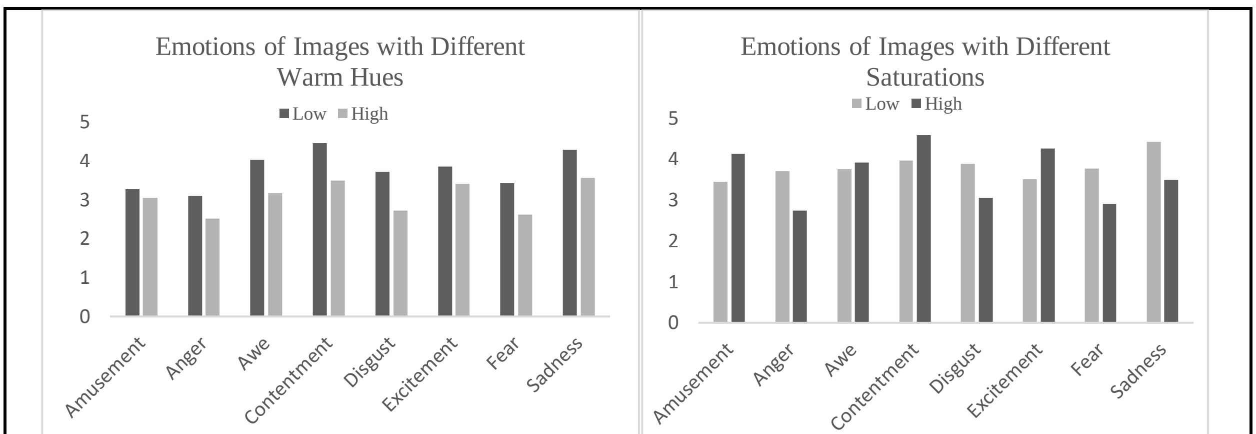


Figure 8. Comparisons of Emotions under Warm Hue and Saturation Manipulations

The findings in Figure 8 and Table 12 suggest that a low warm hue project image evokes stronger anger, contentment, disgust, fear and sadness emotions than the high warm hue one; and that a high saturation image evokes stronger positive emotions such as amusement, contentment, and excitement while a low saturation image evokes most negative emotions disgust, fear and sadness plus awe. These results from the warm hue and saturation treatments are generally consistent with our empirical results of Hypothesis 1 Testing. These results provide experimental supports for our empirical results from Kickstarter and further verify Hypothesis 1.

4.3 Emotions' Effect on the Pledge Intention

We pool all the data points from the four groups to further explore the mechanism between emotions and pledge intention (a proxy of outcome). We add the reported positive empathy and negative empathy to test Hypotheses 2a and 2b with our experiment data. Positive empathy ($Positive\_Empathy_j$) and negative empathy ($Negative\_Empathy_j$) are latent variables which are measured by valid scales. Adapting from the literature (Andreychik & Migliaccio, 2015; Light et al., 2019), we develop our scale to measure positive and negative empathy by the items listed in Table F2 in Appendix F.

To further explore the mechanism between emotions and pledge intention (a proxy of outcome). We add positive empathy and negative empathy in this model. We first investigate the effect of image emotions ($Image\_Emotion_{kj}$ $k = 1, 2\ldots8$) on positive empathy and negative empathy, respectively. We express the model with Equations (3) And (4).

$$Positive\_Empathy_j = \gamma^P + \sum_{k\in\{positive\ emotins\}} \delta_k^P \cdot Image\_Emotion_{kj} + \epsilon_j^P \quad (3)$$
$$Negative\_Empathy_j = \gamma^N + \sum_{k\in\{negative\ emotions\}} \delta_k^N \cdot Image\_Emotion_{kj} + \epsilon_j^N \quad (4)$$

where superscript P and N represent positive and negative empathy, respectively. γ and ϵ_j are the constant and error terms respectively, and δ_k is the coefficient of image emotion k.

Then we perform a logistic regression at the user level to predict participants' pledge intention ($Pledge\_Intention_j$) based on their reported positive and negative empathy. We express the model with Equation (5). We estimate Equations (3)-(5) and provide the results in Tables 13 and 14.

$$logit\left(Pledge_{Intention\,j}\right) = \theta + \omega^P \cdot Positive_{Empathy\,j} + \omega^N \cdot Negative_{Empathy\,j} + \sum_l \rho_l \cdot Control_{lj} + \epsilon_j \quad (5)$$

where $Control_{lj}$ represents the control variable l (l =1, 2… 7) of participant j. θ and ϵ_j are the constant and error terms respectively, and ω^P, ω^N and ρ_l are the coefficients of positive empathy, negative empathy, and control l respectively.

Table 13. Effects of Image Emotions on Empathy (N = 177)

		Positive Empathy	**Negative Empathy**
Positive Emotions	Amusement	**-0.182****	
	Awe	**0.123***	
	Contentment	**0.153****	
	Excitement	**0.242*****	
Negative Emotions	Anger		0.124
	Disgust		-0.060
	Fear		0.126
	Sadness		**0.136***
	Constant	3.582***	3.326***
	R^2	0.201	0.127
	Adj. R^2	0.182	0.107

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 14. Effects of Image Empathy on the Pledge Intention (N = 177)

Variables		**Pledge Intention**
Empathy	Positive Empathy	**0.755*****
	Negative Empathy	**0.597*****
Control Variable	Income	-0.029
	Edu	0.159
	Age	0.006
	Gender	0.080
	WarmHue_High_Dummy	-0.644
	WarmHue_Low_Dummy	0.821
	Saturation_High_Dummy	-0.008
Constant		-7.305***
Cox and Snell R^2		0.345

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Based on our results in Table 13, all positive emotions except amusement have positive effects on positive empathy. Only sadness significantly leads to negative empathy. This shows the dominant role of sadness in a philanthropic context. The reason why amusement is negatively significant is that people may not expect to empathize with others' amusement in a philanthropic context. Thus, H2a and H2b are partially supported. The logistic regression results in Table 14 suggest that both positive and negative empathy have significantly positive effects on pledge intention, which supports H2c and H2d.

To validate our empirical results, we also test the direct effect of emotions on the intention to pledge. The results are presented in Table 15. We check the VIF in all models, and the largest VIF is 3.628. Thus, collinearity should not be a concern. The logistic regression results in Table 15 suggest that both positive emotions of contentment and excitement, and negative emotions of sadness and fear are effective in increasing the odds of pledge intention, which is consistent with our empirical results and verifies Hypothesis 2.

Table 15. Effect of Image Emotion on the Pledge Intention (N = 177)

Variables		Pledge Intention
Image Emotions	Amusement	0.079
	Awe	-0.329
	Anger	0.008
	Contentment	**0.351****
	Disgust	0.094
	Excitement	**0.294***
	Fear	**0.404****
	Sadness	**0.303****
Control Variables	High_WarmHue_Group (Dummy)	-0.431
	Low_WarmHue_Group (Dummy)	**0.909***
	High_Saturation_Group (Dummy)	-0.580
	Income	0.000
	Education	-0.066
	Age	0.011
	Gender	-0.509
Constant		-4.291***
Cox and Snell R^2		0.302

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The findings show that our experimental results are consistent with the empirical results, where contentment and sadness both have positive effect on the pledge intention. However, counter to the empirical results, the fear emotion has a positive effect on pledge intention, too. By checking participants' feedback, we found some participants either hates or even fear cats. This might add some extra effect on the fear emotion. The feedback also revealed that some participants are very into saving stray cats, which might cause the significance of excitement emotion. Those are the limitation of this experiment since it is under one specific scenario. To check the robustness of the findings, we conduct more studies with more charity project scenarios.

The Mediation Role of Empathy. Bagozzi and Moore (1994) proposed the possible mediator role of empathy between emotion and decision to help. We use Process (Hayes, 2017) to test the significance of the mediation effect. We only test those emotions which have direct and significant effect on empathy and pledge intention in this analysis, since this is the basic requirement for the existence of mediation effect exists. Thus, only Contentment, Excitement, and Sadness are tested here separately with positive empathy and negative empathy, respectively. The process adopts 5,000 bootstrapping to estimate the 99% confidence interval of the mediation effect. Therefore, if zero is not included in the 99% confidence interval, we conclude the mediation effect is significant. Based on Table 16, we conclude the mediation effects of positive and negative empathy are significant.

Table 16. Results of Empathy Mediation Tests

Dependent Variable	Pledge Intention					
Mediator	Positive Empathy			Negative Empathy		
Independent Variables	Effect	LLCI (99%)	ULCI (99%)	Effect	LLCI (99%)	ULCI (99%)
Contentment	**0.278***	0.110	0.566			

Excitement	**0.286***	0.134	0.550			
Sadness				**0.230***	0.060	0.556

Note: LLCI= lower limit of confidence interval, ULCI= upper limit of confidence interval

4.4. Additional Study

To show the generalizability of our findings to other categories of charity crowdfunding projects, we select another three projects from the charity categories of Animal, Art & Culture, Education, Medical and Environment from Kickstarter.com. We present the details in Appendix G. The findings support the conclusions we draw from the previous experiment.

5. DISCUSSIONS

5.1 Theoretical Implications

We explore the behaviors of potential donor on a charity crowdfunding platform in response to the emotional arousal brought by project images. The empirical results support the hypotheses proposed based on the S-O-R model that the image attribute (S) can affect the emotion of project images (O), and the emotion of project images (O) can further affect the crowdfunding performance (R). We also proposed an extended model in which positive and negative empathy are mediators between positive and negative emotions and donation behaviors, respectively. Our experiment results verify this extended model.

Previous research has shown that emotions generated from text descriptions (Liang et al., 2016) or facial expressions (Burt & Strongman, 2005; Small & Verrochi, 2009) on charity advertisements can increase people's donation to charitable organizations. Yet the fast growth of crowdfunding calls for research that considers the roles of various emotions, especially image emotions, in driving backers and donations to the online charity fundraising platforms. To contribute to this line of research, we study how emotions evoked by project images affect the performance of charity crowdfunding projects.

Emotions are considered to be important responses from viewers who express their aesthetic appreciation to artwork (Barry, 2006; Carroll, 2003). However, due to individual heterogeneity, viewers tend to hold different subjective viewpoints toward artwork, which makes it difficult to capture and measure the characteristics and emotions of individual works of art in an empirical study. This study proposes and applies a novel approach to identify objective emotion measurements, which shows the value of machine learning in processing unstructured data such as images (Shin et al., 2020). In the empirical research, we develop a deep neural network-based image emotion classifier to transform subjective measures to objective ones, which not only serves our particular purpose but also shows the implication and value of deep learning techniques for emotion- and fundraising-related research.

To investigate whether and what image attributes can explain the variance of emotions in project images, we extract image attributes defined in the existing literature (Wang et al., 2013; Zhang et al., 2021) to measure the aesthetic features of project images from Kickstarter.com. The results show significant evidence that some image attributes can explain the variance of emotions, which is consistent with literature arguing that there are emotional responses to any type of artwork including photographs and paintings (Barry, 2006; Carroll, 2003; Mendelson & Papacharissi, 2007; Silvia, 2005).

As the role of project images in charitable crowdfunding is insufficiently explored, our study will contribute to the charitable crowdfunding theory and practice. Our empirical analyses based on the data from Kickstarter.com support that emotions in project images play a critical role in crowdfunding performance in terms of the number of backers, amount raised and percentage of fundraising goal achieved. The results indicate that image emotions, such as sadness and contentment are significant drivers of the potential backers' donation to public benefit crowdfunding projects. When emotions in both project images and text descriptions are considered, we show that multiple image emotions have a significant impact on project performance while only sadness emotion in text descriptions is significant. Furthermore, we show that this role of image emotions varies with the budget and category of the charity fundraising projects, that is, only the contentment emotion significantly affects project performance for high-budget projects, or community or environment projects; while for high-budget or education type of projects, sadness emotion of project images are significant and powerful in driving the success of the crowdfunding project.

Our research contributes to the IS literature by offering insights for possible improvement in charity fundraising in this unique service, crowdfunding. Information systems can be helpful in supporting charity, for example, Tan et al. (2021) showed that the platform and users on Twitter can be critical to creating and sharing charitable content. Crowdfunding is an innovative service that utilizes online platforms to reach out to the general public and collect funds for charity purpose. And the small contribution of each individual in a crowd will make the proposal come true. Although crowdfunding platform provides the opportunities to fundraisers, different from traditional charity fundraising, these projects also face competition while all similar projects are listed together and are competing for backers' resources. The paper is one of the first studies that demonstrate the function of project images in drawing attentions and trigger emotions in charity crowdfunding campaigns and offers practical suggestions on how to attract backers and motivating donation from the project image design perspective.

These findings greatly enrich the results of the role of emotions on traditional charity donations in the literature. That is, we expand the research setting to crowdfunding platforms, extend the study of emotions beyond sadness, and consider both positive and negative empathy. Moreover, we apply the S-O-R framework to study the complete research question including both how the design factors stimulate each emotion in addition to the performance impact of emotions on charitable crowdfunding projects.

5.2 Practical Implications

The results of this research provide practical and actionable insights for crowdfunding seekers and platforms to improve the performance and outcome of charitable fundraising projects. First, this study provides practical guidance on how to gauge emotions, understand the impact of image emotions, and to design project images to create emotions to those who are interested in improving the performance of charity crowdfunding projects.

This study demonstrates how to implement new deep learning algorithms to classify intangible emotions conveyed by images and to further discover the roles of emotions in charity fundraising. Applying machine learning on unstructured data to extract useful features for further data analysis can avoid possible response biases and noises that may arise in traditional Human Intelligence Tasks (HITs) such as surveys.

The findings of this study suggest that seekers or crowdfunding platforms should pay attention to designing project images with more contentment and sadness emotions and less fear to incentivize backers to participate in the charity fundraising projects and donate more. The results also suggest that seekers should vary the design of emotions according to the budget and category of the charitable crowdfunding projects. Based on our findings, sadness is a powerful emotion in charity fundraising that can prompt people to contribute, but only for low-budget and education type of charity fundraising campaigns. To increase the sadness emotion in project image, we recommend adopting lower saturation, warm hue, and contrast of brightness, which are, among many image attributes, negatively related to sadness with statistical significance. The results also suggest showing human face in the project images can significantly arouse sadness emotion. In other words, controlling these attributes in the project images can potentially increase the viewers' sadness, which might benefit the charitable crowdfunding performance in practice.

Another key finding is that the positive contentment emotion also significantly affects charity crowdfunding performance since people who donate are more contented, but only for high-budget, and community and environment types of charity fundraising campaigns. According to our results, images with higher contrast of brightness, including animals or human face increase contentment, while images with text, and diagonal dominance all have a negative relationship with contentment. Thus, practitioners can follow these results to control the image attributes to improve the contentment emotion in their project images and to further improve project performance.

Our results also suggest to practitioners that the emotions of competing projects reduce the number of backers and donation amounts of their charity projects. Thus, a seeker should strengthen the emotional effects of their own project images and avoid competing with other charity fundraising projects with strong emotions to mitigate the negative effects.

6. CONCLUSION

We perform empirical and experimental analyses on how the emotions evoked by project images, which are influenced by image design factors, affect the performance of charitable crowdfunding projects. This research contributes to the existing streams of literature on charity fundraising and crowdfunding with new findings. This study demonstrates an application of advanced machine learning techniques in studying performance issues in crowdfunding. As crowdfunding is increasingly adopted to charity fundraising, this study provides actionable and practical guidance for fundraisers to design the project images according to project budget and category in order to attract backers and evoke their emotions to arouse positive and/or negative empathies which motivate their donation behaviors.

There are a few limitations to the present research. First, our deep learning algorithm is built upon the emotion set from the emotion-learning paper Machajdik and Hanbury (2010), which is also used by You et al. (2016). It is the most frequently used and best-developed emotion set for research on image emotions to date. Using the same emotion set allows us to compare our algorithm with those in other studies. However, it is possible that other emotion sets may offer an even better way of categorizing emotions. Second, image emotion is detected by our trained deep neural network model. Seeking better emotion classifiers is also one planned venue for our future research. Third, this study focuses on crowdfunding projects in the public benefit category on Kickstarter.com, and the variables and models in this research are based on the existing literature in the domain of charity fundraising. The findings may be subject to change and may not be able directly applied in a different scenario. However, our research framework and methodologies are likely to be applied to other domains and contexts.

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REFERENCES

Ahlers, G. K. C., Cumming, D., Günther, C., & Schweizer, D. (2015). Signaling in Equity Crowdfunding. *Entrepreneurship Theory and Practice*, *39*(4), 955–980. https://doi.org/10.1111/etap.12157

Ali, A. (2019). *Study: Google's AI is the best when it comes to image recognition accuracy*. https://www.digitalinformationworld.com/2019/08/amazon-google-or-ibm-microsoft-which-company-does-the-best-job-at-image-recognition.html

Allison, T. H., Davis, B. C., Short, J. C., & Webb, J. W. (2015). Crowdfunding in a Prosocial Microlending Environment: Examining the Role of Intrinsic versus Extrinsic Cues. *Entrepreneurship Theory and Practice*, *39*(1), 53–73. https://doi.org/10.1111/etap.12108

Andreoni, J. (1989). Giving with Impure Altruism: Applications to Charity and Ricardian Equivalence. *Journal of Political Economy*, *97*(6), 1447–1458. https://doi.org/10.1086/261662

Andreoni, J. (1990). Impure Altruism and Donations to Public Goods: A Theory of Warm-Glow Giving. *Economic Journal*, *100*, 464–477. https://doi.org/10.2307/2234133

Andreoni, J., Rao, J. M., & Trachtman, H. (2017). Avoiding the Ask: A Field Experiment on Altruism, Empathy, and Charitable Giving. *Journal of Political Economy*, *125*(3), 625–653. https://doi.org/10.1086/691703

Andreychik, M. R., & Migliaccio, N. (2015). Empathizing with others' pain versus empathizing with others' joy: Examining the separability of positive and negative empathy and their relation to different types of social behaviors and social emotions. *Basic and Applied Social Psychology*, *37*(5), 274–291. https://doi.org/10.1080/01973533.2015.1071256

Animesh, A., Pinsonneault, A., Yang, S.-B., & Oh, W. (2011). An Odyssey into Virtual Worlds: Exploring the Impacts of Technological and Spatial Environments. *MIS Quarterly*, *35*(3), 789–810. https://doi.org/10.2307/23042809

Aslam, M. M. (2006). Are You Selling the Right Colour? A Cross-cultural Review of Colour as a Marketing Cue. *Journal of Marketing Communications*, *12*(1), 15–30. https://doi.org/10.1080/13527260500247827

Bagozzi, R. P., & Moore, D. J. (1994). Public service advertisements: Emotions and empathy guide prosocial behavior. *Journal of Marketing*, *58*(1), 56–70. https://doi.org/10.2307/1252251

Barry, A. M. (2006). Perceptual Aesthetics: Transcendent Emotion, Neurological Image. *Visual Communication Quarterly*, *13*(3), 134–151. https://doi.org/10.1207/s15551407vcq1303_2

Batson, C. D., & Shaw, L. L. (1991). Evidence for Altruism: Toward a Pluralism of Prosocial Motives. *Psychological Inquiry*, *2*(2), 107–122. https://doi.org/10.1207/s15327965pli0202_1

Blackbaud Institute. (2020). *Charitable Giving Report*. Blackbaud Institute. https://institute.blackbaud.com/charitable-giving-report

Bland, E. M., Black, G. S., & Lawrimore, K. (2007). Risk-Reducing and Risk-Enhancing Factors Impacting Online Auction Outcomes: Empirical Evidence from Ebay Auctions. *Journal of Electronic Commerce Research*, *8*(4), 236–243.

Boulding, K. E. (1962). Notes on a Theory of Philanthropy. In *Philanthropy and Public Policy* (pp. 57–72). NBER.

Braun, C. C., Sansing, L., & Silver, N. C. (1994). The Interaction of Signal Word and Color on Warning Labels: Differences in Perceived Hazard. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *38*(14), 831–835. https://doi.org/10.1177/154193129403801407

Burt, C., & Strongman, K. (2005). Use of images in charity advertising: Improving donations and compliance rates. *International Journal of Organisational Behaviour*, *8*, 571–580.

Burtch, G., Ghose, A., & Wattal, S. (2013). An Empirical Examination of the Antecedents and Consequences of Contribution Patterns in Crowd-Funded Markets. *Information Systems Research*, *24*(3), 499–519. https://doi.org/10.1287/isre.1120.0468

Carroll, N. (2003). Art and Mood: Preliminary Notes and Conjectures. *The Monist*, *86*(4), 521–555. https://doi.org/10.5840/monist200386426

Casas, A., & Williams, N. W. (2019). Images that Matter: Online Protests and the Mobilizing Role of Pictures. *Political Research Quarterly*, 72(2), 360–375. https://doi.org/10.1177/1065912918786805

Chang, C.-T., & Lee, Y.-K. (2009). Framing Charity Advertising: Influences of Message Framing, Image Valence, and Temporal Framing on a Charitable Appeal. *Journal of Applied Social Psychology*, *39*(12), 2910–2935. https://doi.org/10.1111/j.1559-1816.2009.00555.x

Choi, J. (David), Rangan, P., & Singh, S. N. (2016). Do Cold Images Cause Cold-Heartedness? The Impact of Visual Stimuli on the Effectiveness of Negative Emotional Charity Appeals. *Journal of Advertising*, *45*(4), 417–426. https://doi.org/10.1080/00913367.2016.1185982

Chung, S. H., Goswami, A., Lee, H., & Hu, J. (2012). The impact of images on user clicks in product search. *Proceedings of the Twelfth International Workshop on Multimedia Data Mining*, 25–33. https://doi.org/10.1145/2343862.2343866

Cialdini, R. B., Schaller, M., Houlihan, D., Arps, K., Fultz, J., & Beaman, A. L. (1987). Empathy-based helping: Is it selflessly or selfishly motivated? *Journal of Personality and Social Psychology*, *52*(4), 749–758. https://doi.org/10.1037//0022-3514.52.4.749

Crumpler, H., & Grossman, P. J. (2008). An experimental test of warm glow giving. *Journal of Public Economics*, *92*(5), 1011–1021. https://doi.org/10.1016/j.jpubeco.2007.12.014

Di, W., Sundaresan, N., Piramuthu, R., & Bhardwaj, A. (2014). *Is a picture really worth a thousand words? - On the role of images in e-commerce*. 633–642. https://doi.org/10.1145/2556195.2556226

Drollinger, T. (2010). A Theoretical Examination of Giving and Volunteering Utilizing Resource Exchange Theory. *Journal of Nonprofit & Public Sector Marketing*, *22*, 55–66. https://doi.org/10.1080/10495140903190416

Dunn, E. W., Aknin, L. B., & Norton, M. I. (2008). Spending Money on Others Promotes Happiness. *Science*, 319(5870), 1687–1688. https://doi.org/10.1126/science.1150952

Dupré, D., Krumhuber, E. G., Küster, D., & McKeown, G. J. (2020). A performance comparison of eight commercially available automatic classifiers for facial affect recognition. *PLOS ONE*, 15(4), e0231968. https://doi.org/10.1371/journal.pone.0231968

Ekman, P., Friesen, W. V., O'Sullivan, M., Chan, A., Diacoyanni-Tarlatzis, I., Heider, K., Krause, R., LeCompte, W. A., Pitcairn, T., & Ricci-Bitti, P. E. (1987). Universals and cultural differences in the judgments of facial expressions of emotion. *Journal of Personality and Social Psychology*, *53*(4), 712–717. https://doi.org/10.1037//0022-3514.53.4.712

Enge, E. (2019). *Image Recognition Accuracy Study*. https://www.perficient.com/insights/research-hub/image-recognition-accuracy-study

Ettis, S. A. (2017). Examining the relationships between online store atmospheric color, flow experience and consumer behavior. *Journal of Retailing and Consumer Services*, *37*(C), 43–55. https://doi.org/10.1016/j.jretconser.2017.03.007

Ferguson, E., Taylor, M., Keatley, D., Flynn, N., & Lawrence, C. (2012). Blood donors' helping behavior is driven by warm glow: More evidence for the blood donor benevolence hypothesis. *Transfusion*, *52*(10), 2189–2200. https://doi.org/10.1111/j.1537-2995.2011.03557.x

Fisher, R. J., Vandenbosch, M., & Antia, K. D. (2008). An Empathy-Helping Perspective on Consumers' Responses to Fund-Raising Appeals. *Journal of Consumer Research*, *35*(3), 519–531. https://doi.org/10.1086/586909

France, C. R., & France, J. L. (2018). Fear of donation-related stimuli is reported across different levels of donation experience. *Transfusion*, *58*(1), 113–120. https://doi.org/10.1111/trf.14382

Freeman, M. (2007). *The Photographer's Eye: Composition and Design for Better Digital Photos*. (1st ed.). Routledge.

Gao, X.-P., Xin, J. H., Sato, T., Hansuebsai, A., Scalzo, M., Kajiwara, K., Guan, S.-S., Valldeperas, J., Lis, M. J., & Billger, M. (2007). Analysis of cross-cultural color emotion. *Color Research & Application*, *32*(3), 223–229. https://doi.org/10.1002/col.20321

Garimella, A., Fan, M., Kotha, S., & You, W. (2017). *Launch on a High Note: How Prefunding Affects Crowdfunding Outcomes* (SSRN Scholarly Paper ID 3049768). Social Science Research Network. https://doi.org/10.2139/ssrn.3049768

Giving USA. (2021). *2021 Annual Report*. Giving USA. https://store.givingusa.org/products/2021-annual-report

Goswami, A., Chittar, N., & Sung, C. H. (2011). A study on the impact of product images on user clicks for online shopping. *Proceedings of the 20th International Conference Companion on World Wide Web*, 45–46. https://doi.org/10.1145/1963192.1963216

Hanada, M. (2018). Correspondence analysis of color–emotion associations. *Color Research & Application*, *43*(2), 224–237. https://doi.org/10.1002/col.22171

Hayes, A. F. (2017). *Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach*. (2nd ed.). Guilford.

Hemphill, M. (1996). A note on adults' color–emotion associations. *The Journal of Genetic Psychology: Research and Theory on Human Development*, *157*(3), 275–280. https://doi.org/10.1080/00221325.1996.9914865

Hobbs, J., Grigore, G., & Molesworth, M. (2016). Success in the management of crowdfunding projects in the creative industries. *Internet Research*, *26*(1), 146–166. https://doi.org/10.1108/IntR-08-2014-0202

Hong, Y., Hu, Y., & Burtch, G. (2018). Embeddedness, prosociality, and social influence: Evidence from online crowdfunding. *MIS Quarterly*, *42*(4), 1211–1224. https://doi.org/10.25300/MISQ/2018/14105

Hsiao, R.-L. (2003). Technology fears: Distrust and cultural persistence in electronic marketplace adoption. *The Journal of Strategic Information Systems*, *12*(3), 169–199. https://doi.org/10.1016/S0963-8687(03)00034-9
Jacobs, L., Keown, C., Worthley, R., & Ghymn, K. (1991). Cross-cultural Colour Comparisons: Global Marketers Beware! *International Marketing Review*, *8*(3), 21-30. https://doi.org/10.1108/02651339110137279
Kang, L., Jiang, Q., & Tan, C.-H. (2017). Remarkable advocates: An investigation of geographic distance and social capital for crowdfunding. *Information & Management*, *54*(3), 336–348. https://doi.org/10.1016/j.im.2016.09.001
Kaya, N., & Epps, H. H. (2004). Relationship between color and emotion: A study of college students. *College Student Journal*, *38*(3), 396–405.
Kelly, K. J., Slater, M. D., & Karan, D. (2002). Image Advertisements' Influence on Adolescents' Perceptions of the Desirability of Beer and Cigarettes. *Journal of Public Policy & Marketing*, *21*(2), 295–304. http://doi.org/10.1509/jppm.21.2.295.17585
Kickstarter. (2021). *Telling your story*. https://www.kickstarter.com/help/handbook/your_story
Kickstarter Stats. (2021). *Kickstarter Stats*. https://www.kickstarter.com/help/stats.
Kurt, S., & Osueke, K. K. (2014). The Effects of Color on the Moods of College Students. *SAGE Open*, *4*(1), 1-12. https://doi.org/10.1177/2158244014525423
Landis, J. R., & Koch, G. G. (1977). The Measurement of Observer Agreement for Categorical Data. *Biometrics*, *33*(1), 159–174.
Lang, P. J., Greenwald, M. K., Bradley, M. M., & Hamm, A. O. (1993). Looking at pictures: Affective, facial, visceral, and behavioral reactions. *Psychophysiology*, *30*(3), 261–273.
Liang, J., Chen, Z., & Lei, J. (2016). Inspire me to donate: The use of strength emotion in donation appeals. *Journal of Consumer Psychology*, *26*(2), 283–288. https://doi.org/10.1016/j.jcps.2015.09.001
Light, S. N., Moran, Z. D., Zahn-Waxler, C., & Davidson, R. J. (2019). The Measurement of Positive Valence Forms of Empathy and Their Relation to Anhedonia and Other Depressive Symptomatology. *Frontiers in Psychology,* (10), Article 815.
Lin, M., & Viswanathan, S. (2016). Home Bias in Online Investments: An Empirical Study of an Online Crowdfunding Market. *Management Science*, *62*(5), 1393–1414. https://doi.org/10.1287/mnsc.2015.2206
Liu, B. (2018, November 21). *Which is Better—Kickstarter or Indiegogo?* https://zendure.com/blogs/news/which-is-better-kickstarter-or-indiegogo
Liu, L., Dzyabura, D., & Mizik, N. (2020). Visual Listening In: Extracting Brand Image Portrayed on Social Media. *Marketing Science*, *39*(4), 669–686. https://doi.org/10.1287/mksc.2020.1226
Luqman, A., Cao, X., Ali, A., Masood, A., & Yu, L. (2017). Empirical investigation of Facebook discontinues usage intentions based on SOR paradigm. *Computers in Human Behavior*, *70*, 544–555. https://doi.org/10.1016/j.chb.2017.01.020
Machajdik, J., & Hanbury, A. (2010). Affective image classification using features inspired by psychology and art theory. *Proceedings of the 18th ACM International Conference on Multimedia*, 83–92. https://doi.org/10.1145/1873951.1873965
Manav, B. (2007). Color-emotion associations and color preferences: A case study for residences. *Color Research & Application*, *32*, 144–150. https://doi.org/10.1002/col.20294
Mehrabian, A., & Russell, J. A. (1974). *An Approach to Environmental Psychology*. MIT Press.

Mendelson, A. L., & Papacharissi, Z. (2007). Reality vs. Fiction How Defined Realness Affects Cognitive & Emotional Responses to Photographs. *Visual Communication Quarterly*, *14*(4), 231–243. https://doi.org/10.1080/15551390701730224

Mikels, J. A., Fredrickson, B. L., Larkin, G. R., Lindberg, C. M., Maglio, S. J., & Reuter-Lorenz, P. A. (2005). Emotional category data on images from the international affective picture system. *Behavior Research Methods*, *37*(4), 626–630. https://doi.org/10.3758/BF03192732

Minguillon, J., Lopez-Gordo, M. A., Renedo-Criado, D. A., Sanchez-Carrion, M. J., & Pelayo, F. (2017). Blue lighting accelerates post-stress relaxation: Results of a preliminary study. *PLoS ONE*, *12*(10), e0186399. https://doi.org/10.1371/journal.pone.0186399

Mollick, E. (2014). The dynamics of crowdfunding: An exploratory study. *Journal of Business Venturing*, *29*(1), 1–16. https://doi.org/10.1016/j.jbusvent.2013.06.005

Morelli, S. A., Lieberman, M. D., & Zaki, J. (2015). The Emerging Study of Positive Empathy. *Social and Personality Psychology Compass*, *9*(2), 57–68. https://doi.org/10.1111/spc3.12157

Nezlek, J., Feist, G., Wilson, F. C., & Plesko, R. (2001). Day-to-Day Variability in Empathy as a Function of Daily Events and Mood. *Journal of Research in Personality*, *35*, 401–423. https://doi.org/10.1006/jrpe.2001.2332

Ordanini, A., Miceli, L., Pizzetti, M., & Parasuraman, A. (2011). Crowd-funding: Transforming customers into investors through innovative service platforms. *Journal of Service Management*, *22*(4), 443–470. https://doi.org/10.1108/09564231111155079

Peck, J., & Childers, T. L. (2003). To have and to Hold: The Influence of Haptic Information on Product Judgments. *Journal of Marketing*, *67*(2), 35–48. https://doi.org/10.1509/jmkg.67.2.35.18612

Peng, C., & Kim, Y. G. (2014). Application of the Stimuli-Organism-Response (S-O-R) Framework to Online Shopping Behavior. *Journal of Internet Commerce*, *13*(3–4), 159–176. https://doi.org/10.1080/15332861.2014.944437

Rao, T., Li, X., Zhang, H., & Xu, M. (2019). Multi-level region-based Convolutional Neural Network for image emotion classification. *Neurocomputing*, *333*, 429–439. https://doi.org/10.1016/j.neucom.2018.12.053

Reece, W. S. (1979). Charitable Contributions: New Evidence on Household Behavior. *The American Economic Review*, *69*(1), 142–151.

Sallquist, J., Eisenberg, N., Spinrad, T. L., Eggum, N. D., & Gaertner, B. M. (2009). Assessment of preschoolers' positive empathy: Concurrent and longitudinal relations with positive emotion, social competence, and sympathy. *The Journal of Positive Psychology*, *4*(3), 223–233. https://doi.org/10.1080/17439760902819444

Sargeant, A. (1999). Charitable Giving: Towards a Model of Donor Behaviour. *Journal of Marketing Management*, *15*(4), 215–238. https://doi.org/10.1362/026725799784870351

Shin, D., He, S., Lee, G., Whinston, A., Cetintas, S., & Lee, K. (2020). Enhancing Social Media Analysis with Visual Data Analytics: A Deep Learning Approach. *MIS Quarterly*, *44*(4), 1459–1492. https://doi.org/10.25300/MISQ/2020/14870

Silvia, P. J. (2005). Emotional Responses to Art: From Collation and Arousal to Cognition and Emotion. *Review of General Psychology*, *9*(4), 342–357. https://doi.org/10.1037/1089-2680.9.4.342

Singh, P., Katiyar, N., & Verma, G. (2014a). Retail Shoppability: The Impact Of Store Atmospherics & Store Layout On Consumer Buying Patterns. *International Journal of Scientific & Technology Research*, *3*(8), 9.

Small, D. A., & Verrochi, N. M. (2009). The Face of Need: Facial Emotion Expression on Charity Advertisements. *Journal of Marketing Research*, *46*(6), 777–787. https://doi.org/10.1509/jmkr.46.6.777_JMR6F
Sugden, R. (1982). On the economics of philanthropy. *Economic Journal*, (92), 341-345.
Tan, X., Lu, YD., and Tan, Y. (2021). The Impact of Subscription Reciprocity on Charitable Content Creation and Sharing: Evidence from Twitter on Giving Tuesday. *MIS Quarterly*, 45(2), 535-562. https://doi.org/10.25300/MISQ/2021/14676
Trope, Y., & Liberman, N. (2010). Construal-Level Theory of Psychological Distance. *Psychological Review*, *117*(2), 440–463. https://doi.org/10.1037/a0018963
Valdez, P., & Mehrabian, A. (1994). Effects of color on emotions. *Journal of Experimental Psychology: General*, *123*(4), 394–409. https://doi.org/10.1037/0096-3445.123.4.394
Videras, J.R. & Owen, A.L. (2006). Public Good Provision and Well-Being: Empirical Evidence Consistent with the Warm Glow Theory. *The B.E. Journal of Economic Analysis & Policy*, *5*(1), Article 9. https://doi.org/10.1515/1538-0645.1531
Vieira, V. A. (2013). Stimuli–organism-response framework: A meta-analytic review in the store environment. *Journal of Business Research*, *66*(9), 1420–1426. https://doi.org/10.1016/j.jbusres.2012.05.009
Wang, X., Jia, J., Yin, J., & Cai, L. (2013). Interpretable aesthetic features for affective image classification. *2013 IEEE International Conference on Image Processing*, 3230–3234. https://doi.org/10.1109/ICIP.2013.6738665
Whitley, C. T., Kalof, L., & Flach, T. (2020). Using Animal Portraiture to Activate Emotional Affect. *Environment and Behavior*, *53*(8), 837–863. https://doi.org/10.1177/0013916520928429
Wilms, L., & Oberfeld, D. (2018). Color and emotion: Effects of hue, saturation, and brightness. *Psychological Research*, *82*(5), 896–914. https://doi.org/10.1007/s00426-017-0880-8
Yang, C., Zhang, L., Lu, H., Ruan, X., & Yang, M.-H. (2013). Saliency Detection via Graph-Based Manifold Ranking. *2013 IEEE Conference on Computer Vision and Pattern Recognition*, 3166–3173. https://doi.org/10.1109/CVPR.2013.407
Yin, D., Bond, S. D., & Zhang, H. (2014). Anxious or Angry? Effects of Discrete Emotions on the Perceived Helpfulness of Online Reviews. *MIS Quarterly*, *38*(2), 539–560. https://doi.org/10.25300/MISQ/2014/38.2.10
You, Q., Luo, J., Jin, H., & Yang, J. (2016). Building a Large Scale Dataset for Image Emotion Recognition: The Fine Print and The Benchmark. *ArXiv:1605.02677 [Cs]*. http://arxiv.org/abs/1605.02677
Yuan, H., Lau, R. Y. K., & Xu, W. (2016). The determinants of crowdfunding success: A semantic text analytics approach. *Decision Support Systems*, *91*, 67–76. https://doi.org/10.1016/j.dss.2016.08.001
Zhang, S., Lee, D., Singh, P. V., & Srinivasan, K. (2021). What Makes a Good Image? Airbnb Demand Analytics Leveraging Interpretable Image Features. Forthcoming at *Management Science*. https://doi.org/10.1287/mnsc.2021.4175
Zheng, H., Li, D., Wu, J., & Xu, Y. (2014). The role of multidimensional social capital in crowdfunding: A comparative study in China and US. *Information & Management*, *51*(4), 488–496. https://doi.org/10.1016/j.im.2014.03.003

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Appendix A. Summary and Comparison of Extant Literature

Table A1. Comparison with Extant Literature					
Articles	**Image Attributes (If no image, source of emotional appeals)**	**Considera-tion of Emotions**	**Considera-tion of Empathy**	**Context**	**Findings**
Carroll (2003)	—	Negative & positive	No	General artworks	Artworks can arouse or induce moods by generating emotional spillover and/or arousing somatic feeling states.
Machajdik and Hanbury (2010)	Color (HSV, contrast, etc.), Texture, Composition, Content (faces and skin)	Negative & positive	No	Affective image classification	Developed an image emotion classification algorithm with low-level features.
Wang et al. (2013)	Color (HSV), Composition, Figure-ground relationship, Shape	Negative & positive	No	Affective image classification	Proposed visual features and used them to classify and interpret affective images.
Kelly et al. (2002)	—	No	No	Retail	Ads with image-oriented visuals produce more positive attitude toward the ad, the brand, and the product category evaluations.
Peck and Childers (2003)	—	No	No	Retail	When touch is unavailable, for less haptically motivated consumers, providing a product image will increase consumer confidence in judgment.
Bland et al. (2007)	—	No	No	Ecommerce	Displaying stock or actual pictures of the product increases the final bid in eBay auction.
Goswami et al. (2011)	Color (RGB), Brightness, Contrast, Ratio of background and foreground	No	No	Ecommerce	Product image features have a significant correlation with click-through rate on a product search engine.
Chung et al. (2012)	Color (HSV), Texture, Shape, Contrast, Aspect ratio, Range, Background features	No	No	Ecommerce	Image features are more prominent in the prediction of user clicks on product search results than other factors like price and shipping cost.
Di et al. (2014)	Not explicitly measured, but mentioned for image quality (e.g., Brightness, Clarity, Contrast)	No	No	Ecommerce	Image quantity and quality have significant impact on buyers' "watching" the product page for certain categories.
Zhang et al. (2021)	Color (HSV, contrast, clarity) Composition, Figure-ground relationship	No	No	Ecommerce	Airbnb properties have higher demand after acquisition of professionally taken images.
Batson and Shaw (1991)	—	No	Negative& positive	Prosocial motives	The experimental results supported the empathy-altruism hypothesis, which explains people helping others in terms of altruism evoked by *empathy*.
Bagozzi and Moore (1994)	(Emotions manipulated by public service TV ads)	Negative	Negative	Public services	Public service ads designed to reduce child abuse stimulate *negative emotions*; in turn, lead to empathic reactions and the decision to help.
Burt and Strongman (2005)	Image emotions evoked by the human content and their facial expressions	Negative & positive	No	Philanthropic Fundraising	Images showing *negative emotions* generated significantly larger donations.

Articles	Image Attributes (If no image, source of emotional appeals)	Considera-tion of Emotions	Considera-tion of Empathy	Context	Findings
Fisher et al. (2008)	(Emotions evoked by Televised fundraising drives)	Negative & positive	Negative& positive	Philanthropic Fundraising	The most effective fundraising appeals communicate the benefits to others rather than to the self and evoke *negative* rather than *positive emotions*.
Chang and Lee (2009)	Image emotions evoked by the human content	Negative & positive	No	Philanthropic Fundraising	Image valence enhances framing effects on advertising effectiveness of a charitable appeal when the image is congruent with the framed message, especially when the image and the message are presented *negatively*.
Small and Verrochi (2009)	Image emotions evoked by the human's facial expressions	Negative & positive	Negative& positive	Philanthropic Fundraising	The expression of emotion on a victim's face is contagious to viewers, who are particularly sympathetic and likely to donate when they see *sad expressions* versus happy or neutral expressions.
Sallquist et al. (2009)	(Children's videotaped emotions & mothers' reports)	Positive & negative	Positive & negative	Psychology	There were numerous positive relations between *positive empathy* and social competence and between positive empathy and empathy/sympathy with negative emotions.
Morelli et al. (2015)	(Participants' self-reported emotions)	Positive	Positive	Psychology	*Positive empathy* correlates with increased prosocial behavior, social closeness, and well-being.
Liang et al. (2016)	(Emotions manipulated from text contents in ads)	Positive & negative	No	Philanthropic Fundraising	Combining the positive emotion of strength and the negative emotion of sadness is more effective as a means of persuading people to donate.
Our study	Color (HSV, saturation, brightness, warm hue), Content (animal, human)	Negative & positive	Negative& positive	Philanthropic Fundraising & crowdfunding	Image attributes of charity fundraising projects evoke *positive* or *negative emotions*, which cause *empathy* or *sympathy* of the donors, and drive their donation behaviors. Sadness only significantly motivates donation behaviors in low-budget or educational type of campaigns, while contentment significantly enhances the outcomes of high-budget or community and environmental types of campaigns.

Appendix B. Preliminary Study of Project Images on a Crowdfunding Platform

One feature of crowdfunding that distinguishes it from other fundraising methods (e.g., door-to-door, direct mail, special events, online fundraising pages) is that it allows multiple competing fundraising projects to appear on the same webpage simultaneously. Given the high failure rate in crowdfunding, it is critical to know what attracts a potential donor's attention on a crowdfunding page. We conduct a preliminary analysis to explore this critical element.

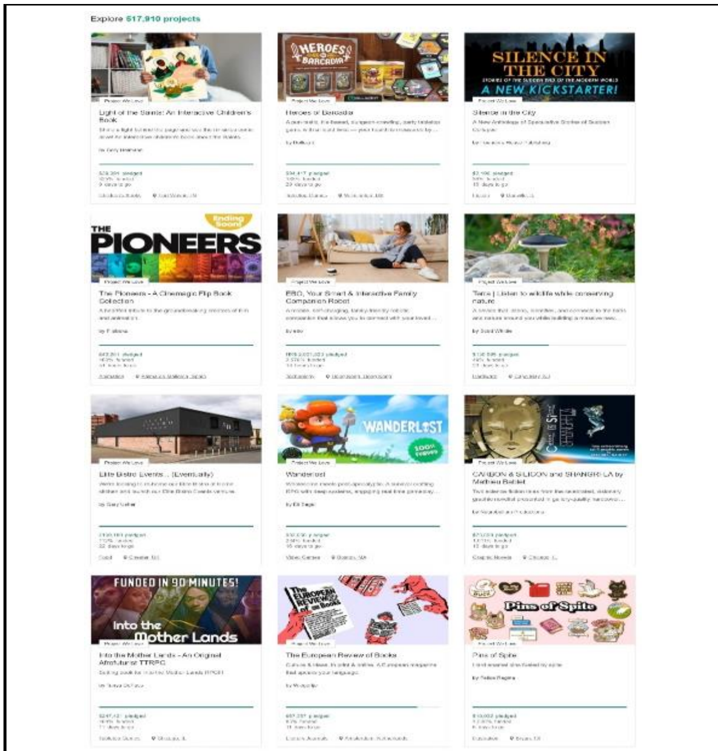

Figure B1. A Screenshot of a Crowdfunding Website

Figure B2. Example for One Project

Design

We first ask all the participants to browse a real crowdfunding webpage for at least 15 seconds. Then they are required to fill out a simple survey that contains two questions. The first question asks participants "Assume you are looking for a project to support. When browsing this page, which area catches your attention the most? Please click on one area on the following screenshot:" Then we provide a screenshot (Figure B1) captured from the real crowdfunding platform. There are 12 competing charity campaigns showing on the webpage. Participants can select one area on the screenshot.

The second question asks "Assume you decide to support this project. When browsing this project, which area catches your attention the most? Please click on one area on the following screenshot:" Similar to the second question, but this one focuses on one single project (Figure B2).

Data and Results

We distribute the survey on Amazon Mechanical Turks. Participants need to meet the criteria of 95% completion rate and their location need to be in the US. We collected 143 samples with the demographic data summarized in Table B1.

Table B1. Demographic for the Preliminary Experiment (N = 143)

	Pooled Data Distribution		Pooled Data Distribution

Education	Less than high school degree	0.7%	Income	Less than $10,000	4.9%
	High school graduate	7.7%		$10,000 to $19,999	7%
	Some college but no degree	9.1%		$20,000 to $29,999	7%
	Associate degree in college	4.2%		$30,000 to $39,999	10.5%
	Bachelor's degree in college	56.6%		$40,000 to $49,999	11.2%
	Master's degree	21.7%		$50,000 to $59,999	20.3%
	Doctoral degree	0%		$60,000 to $69,999	9.8%
	Professional degree (JD, MD)	0%		$70,000 to $79,999	7%
Gender	Male	58.0%		$80,000 to $89,999	6.3%
	Female	42.0%		$90,000 to $99,999	2.1%
Age (Years)	Mean (S.D.)	41.161		$100,000 to $149,999	10.5%
		(11.956)		$150,000 or more	2.1%

When displaying a screenshot of a crowdfunding browsing page, we ask participants to select one area that attracts their attention the most. Based on the area they clicked, we create a heatmap (Figure B3) to show the area that catches more attention in a darker color. Figure B3 demonstrates that participants pay more attention to the image areas, which highlights the importance of images in a crowdfunding platform.

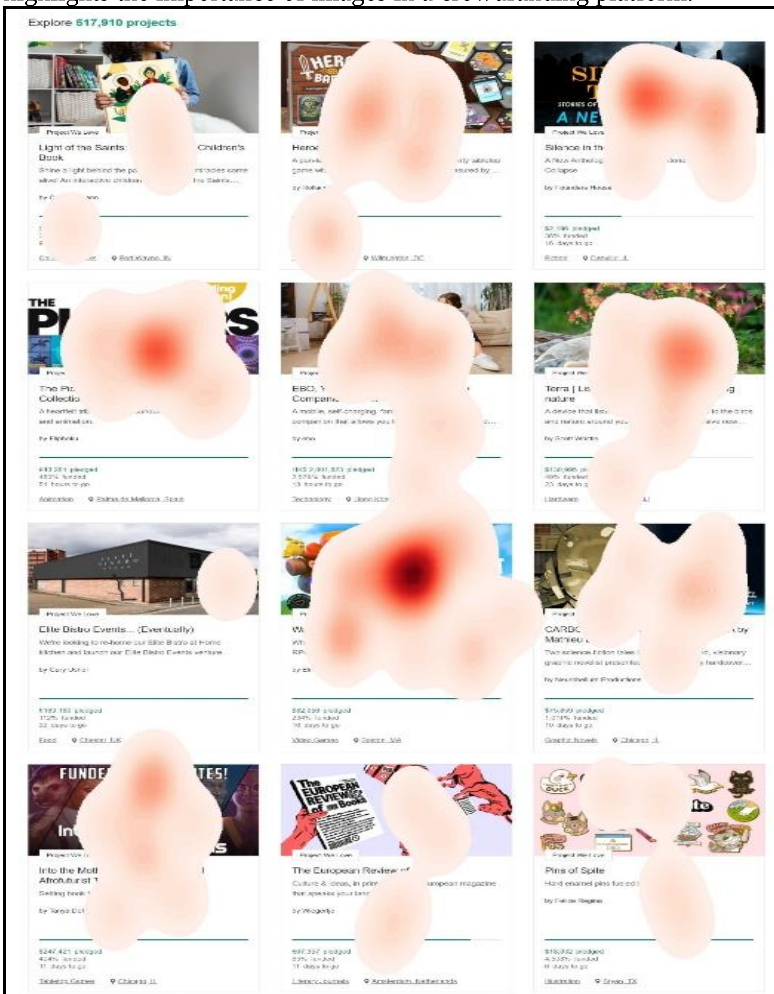

Figure B3. Heatmap based on the First Question

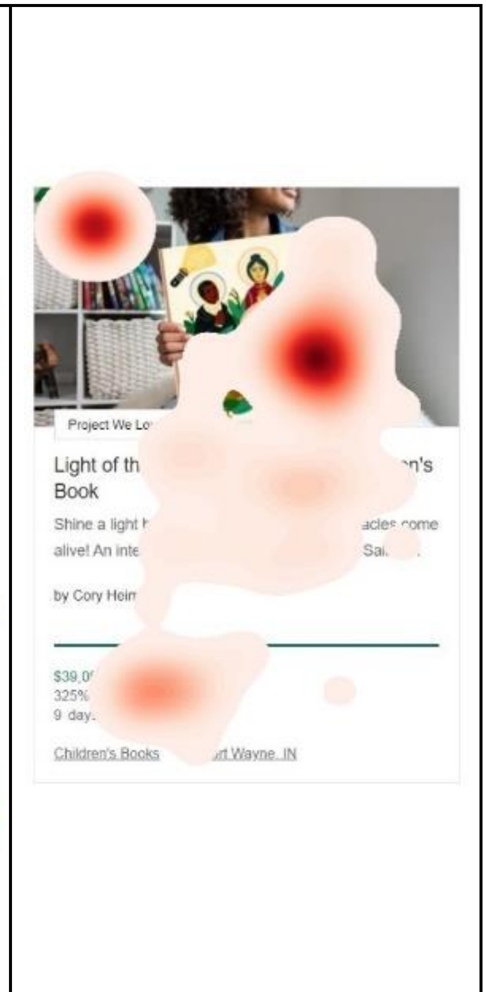

Figure B4. Heatmap based on the Second Question

For the second question, we conducted a similar heatmap analysis (Figure B4) on one single project instead of several projects together. The result is consistent that people still focus on the image area. Therefore, the above results conclude that images are attention-catching elements among the other web elements about a crowdfunding project. Thus, we focus on images in this study.

Appendix C. Emotion Detection via a Deep Learning Framework

1. Training Image Data

Our training data is a set of human-labeled images compiled by You et al. (2016), with 23,185 images from 8 emotion categories (amusement, anger, awe, contentment, disgust, excitement, fear and sadness). The descriptive statistics of this training data are shown in Table C1.

Table C1. Statistics of the Training Image Dataset

Emotion	Number of images
Amusement	4,923
Anger	1,255
Awe	3,133
Contentment	5,356
Disgust	1,657
Excitement	2,914
Fear	1,046
Sadness	2,901
Total	23,185

We show several examples of the training images with their emotion labels in Figure C1.

Figure C1. Examples of Training Images with Emotion Labels

2. Methods

Features: We build a supervised multi-class classification model to predict the emotions of project images. The features we mainly focus on are: (1) instead of purely relying on low-level features (e.g., pixel-level values in the RGB space) that are commonly used in most image classification tasks, we use both mid-level and low-level features. Specifically, we extract the adjective noun pairs (ANPs) from images, because we believe that ANPs are more easily linked to human stimuli and they are close to human emotions. ANPs (adjective-noun pairs) are from the image. Borth et al. (2013) applied the psychological theory, Plutchik's Wheel of Emotions, as the guiding principle to construct a large-scale visual sentiment ontology (VSO) that consists of more than 3,000 semantic concepts (called ANPs). Building upon the VSO they implemented SentiBank[3], a linear SVM-based classifier of trained concept detectors. In our study, we use their provided code (concept detector) to identify top 1,200 ANP concepts released by SentiBank. (2) The objects embedded in images are another important feature that tend to

[3] https://www.ee.columbia.edu/ln/dvmm/vso/download/sentibank.html

affect users' emotional responses. For example, a spider in a picture is likely to lead to a fear emotion. We use Google Vision API to extract top 10 objects for each image. Google Vision API offers object detection service that automatically assigns objects to images based on a model trained on millions of images. We believe that objects provided by Google Vision API service may supplement ANPs and enhance our predictive performance. Each of these features is converted into a vector representation. For example, Python package CV2 is applied to extract image low-level pixel values. TF-IDF[4] is used to transform ANPs and objects into vector representation. We do not use any advanced text representation-based methods (e.g., embedding) because our texts do not have any contextual information (no orders among words in ANPs and objects).

Model: Deep neural networks have achieved great successes in analyzing unstructured data and rapidly developed in many domains, in particular image classification tasks. We expect that they, together with mid-level features, will outperform commonly used traditional machine learning approaches that have been demonstrating good performance in many industry applications, such as ensemble tree methods Random Forest and XGBoost. They are considered as the best baselines, especially among traditional machine learning models, and they also offer easy implementation, less parameter tuning, and low computational cost. We also compared with a cutting-edge deep learning based model (Rao et al., 2019). This model first builds a multi-level region-based Convolutional Neural Network (CNN) framework to discover the sentimental response of local regions. It employs Feature Pyramid Network (FPN) to extract multi-level deep representations. Then, an emotional region proposal method is used to generate proper local regions and remove excessive non-emotional regions for image emotion classification. The idea is very similar to our model where different levels (lower-level pixels, higher-level ANPs and objects) of representations are captured to learn image emotions. To improve the performance, we designed a mixed deep neural networks-based model (see the architecture in Figure C2) via multi-sources of data fusion, including image representation via Xception from raw pixel-level values in the RGB space, text representation from ANPs and tags. Xception can be replaced by other pre-trained models, such as VGG16 and NASLarge. Our model further learns implicit relationships between the obtained representation of text and image via a fully connected feedforward network with one hidden layer of 128 neuron units, the activation function of *ReLU*, a dropout rate of 0.8 (for the purpose of avoiding overfitting), and a *softmax* layer as the output. It is implemented using the *Python Keras* package. We release the code of our model for the ease of reproducibility[5]. Note that these hyper-parameters are tuned through a simple grid search approach[6].

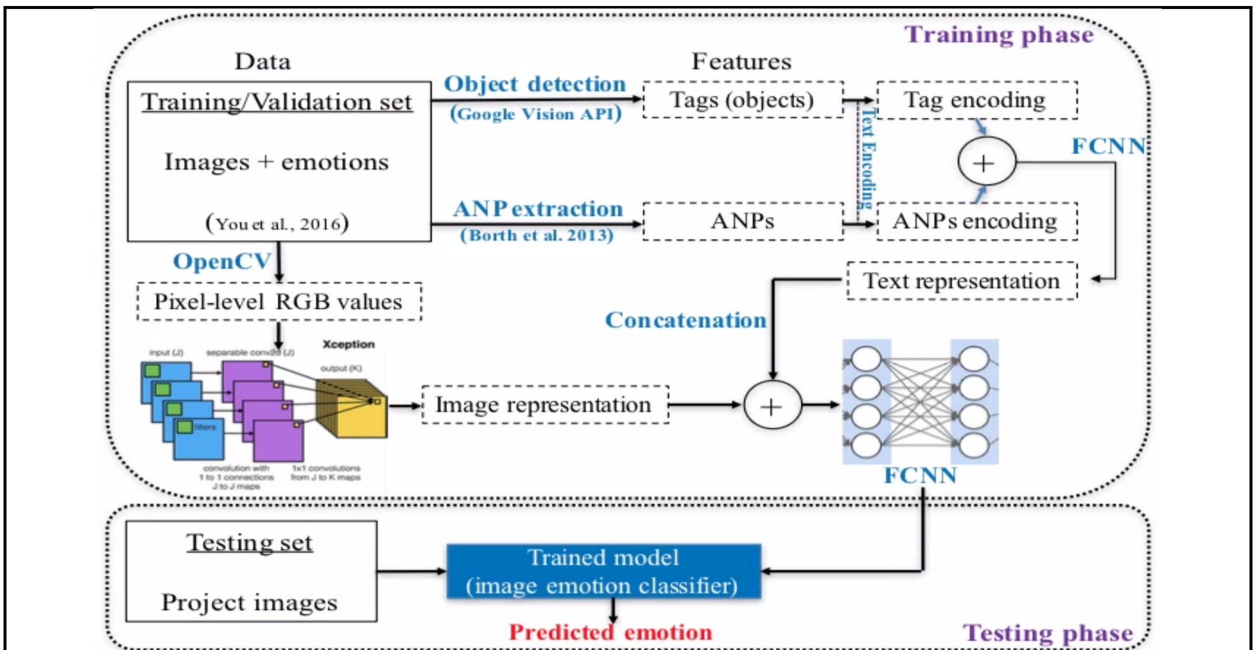

Figure C2. The Architecture of Image Emotion Classifier

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[4] https://en.wikipedia.org/wiki/Tf-idf

[5] https://github.com/kpzhang/ImageEmotionDetection

[6] https://scikit-learn.org/stable/modules/grid_search.html

3. Results

To evaluate the performance, we use 10-fold cross validation. The overall performance (shown in Table C2) is good. The numbers in Table C2 are classification accuracies. The accuracy is the ratio of number of correct predictions to the total number of images in the testing set. Each image is classified to the corresponding emotion with the highest predicted score. From Table C2, we have several interesting observations. First, the Random Forest model demonstrates an overall accuracy of 26.88% for an eight-emotion classification task. This suggests that it only works better than random guess (12.5%), but far from satisfaction. Second, the deep learning models outperform traditional machine learning models, which proves that the image representation learning via deep neural network is useful to understand image emotions. Third, adding the mid-level features (ANPs and Tags) into the model can significantly improve the performance, which is consistent with the findings in the S-O-R model that human emotions can be affected and stimulated by visual objects. Meanwhile, the Tags feature does not lift the performance that much as compared to ANPs. The Tags feature increases the performance by 2.07%, 0.13%, 6.37%, 7.32%, 5.00%, and 13.71% for Random Forest, XGBoost, Rao's, VGG16, NASLarge and our model, respectively, as compared to 3.79%, 25.85%, 17.87%, 19.38%, 21.69%, and 17.96 for ANPs. This can be explained by that most objects in Tags are probably already included in ANPs (the Noun (N) component). Finally, our model performs better than the Rao's model at a slight margin. One plausible explanation is that the higher-level representations used in our method are from powerful models pre-trained by Google and Deep SentiBank. But our model is efficient, where the training of our model is much faster than Rao's model (about 3.5 vs. 7.5 hours).

Table C2. Performance Comparison of Different Models (Accuracy in %)

Features	Models					
	Random Forest	XGBoost	Rao's	VGG16	NASLarge	**Our model**
Image Pixel	21.02	30.92	42.56	41.85	43.23	39.39
Image Pixel + ANPs	24.81	56.77	60.43	61.23	64.92	57.35
Image Pixel + ANPs + Tags	26.88	56.90	66.80	68.55	69.92	**71.06**

Since our training and validation are conducted on a dataset that is different from our target dataset – Kickstarter project images, even the dataset consists of various types of images and viewed as a representative one, we still have a risk of domain shifting issue. To address this, we further evaluate our model using Kickstarter project images. Specifically, we randomly picked 20 images from each of predicted emotion categories (resulting in 160 images in total). Each image has one predicted emotion label by our algorithm trained on the dataset created by You et al (2016). We asked 10 different workers on Amazon Mechanical Turk to label the emotion for each image and take the majority vote as the final "true" emotion. To avoid any biases from human labelers, we only allow each worker to work on three images (e.g., based on their AMT ID and login IP address). See the interface (Figure C3) we created for this AMT survey. Note that we also collected some of users' personal information and their working time duration for the quality control. For example, we excluded 4 users who spent much longer time (more than 350s) to work on one task – labelling three images (i.e., the average time is 64.4753s).

The overall accuracy (correctly classified) is 73.125%, which is consistent with the performance obtained via our 10-fold cross validation. Figure C4 shows the confusion matrix for these 160 images. The row is the label from AMT while the column is the emotion label by our algorithm. However, some might be concerned about the relatively low precision for the category of Amusement and Excitement (i.e., about 60%), in particular significantly affecting the subsequent analyses upon which image emotions are predicted. To demonstrate the effectiveness and the robustness of emotion prediction from our model, we conduct an additional 'simulation'-like study.

Given that the misclassification for the Amusement and the Excitement is primarily from Disgust images (6 out of 29) and from Anger images (7 out of 27), respectively, we decide to manually switch the predicted emotions for some images and re-run some empirical analysis. Specifically, in each iteration we randomly select 20.7% (i.e., 6/29) images from Amusement and change their labels to Disgust, which involves 22 (i.e., 20.7%*108) images. Similarly, we change emotion labels for 33 (i.e., 7/27*126) images from Excitement to Anger. We then fit this new dataset into our empirical regression model for the subsequent analysis. We repeat this 100 times and report the frequency of significant results for the effect of four relevant image emotions (i.e., Amusement, Disgust, Excitement, and Anger) on three major dependent variables (i.e., Baker #, Amount (K$), and % of goal achieved). The results shown in Table C3 indicate the consistency between the original and this 'simulated' studies.

Table C3. The comparison between the original and the 'simulated' studies. Note that the numbers X/Y indicate the number of significant/non-significant results for the 100 iterations.

DV. in Table 6		**Image Emotions**

		Amusement	Disgust	Excitement	Anger
Backer #	Original study	Non-sig			Not in the model
	Simulated study	0/100	3/97	0/100	
Amount (K$)	Original study	Non-sig			
	Simulated study	0/100	0/100	0/100	
% of goal achieved	Original study	Non-sig			
	Simulated study	0/100	0/100	0/100	

4. Implementation

We apply the derived image emotion classifier to our crowdfunding project image dataset to predict their emotions. The images in the training and test datasets share similar attributes in that they are both art designs that reflect a theme but not as portrait-dominant as most other emotion-related image databases. Figure C4 presents a few examples of predicted emotions and Table C4 shows a summary of the descriptive statistics.

Table C4. Descriptive Statistics of the Emotion Metrics of the Project Images (N = 840)

Emotions	Min	Max	Mean	Std.
Amusement	0.022	85.822	11.930	15.584
Anger	0.038	94.500	24.293	22.353
Awe	0.015	98.117	7.362	17.821
Contentment	0.030	91.264	6.914	11.456
Disgust	0.023	98.181	11.802	18.192
Excitement	0.048	95.099	16.182	17.792
Fear	0.187	68.037	11.332	11.015
Sadness	0.046	83.381	10.185	11.583

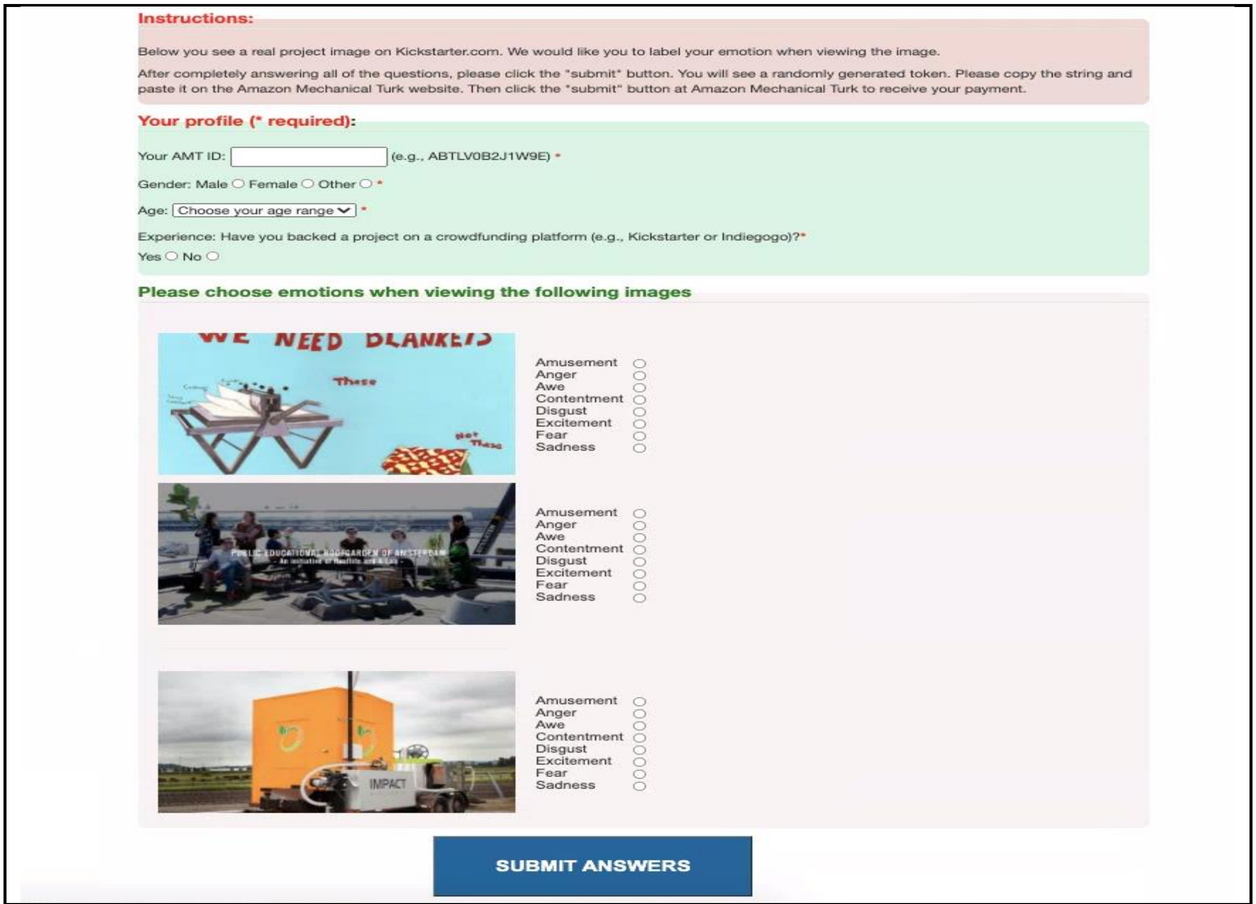


Figure C3. Screenshot for our AMT study

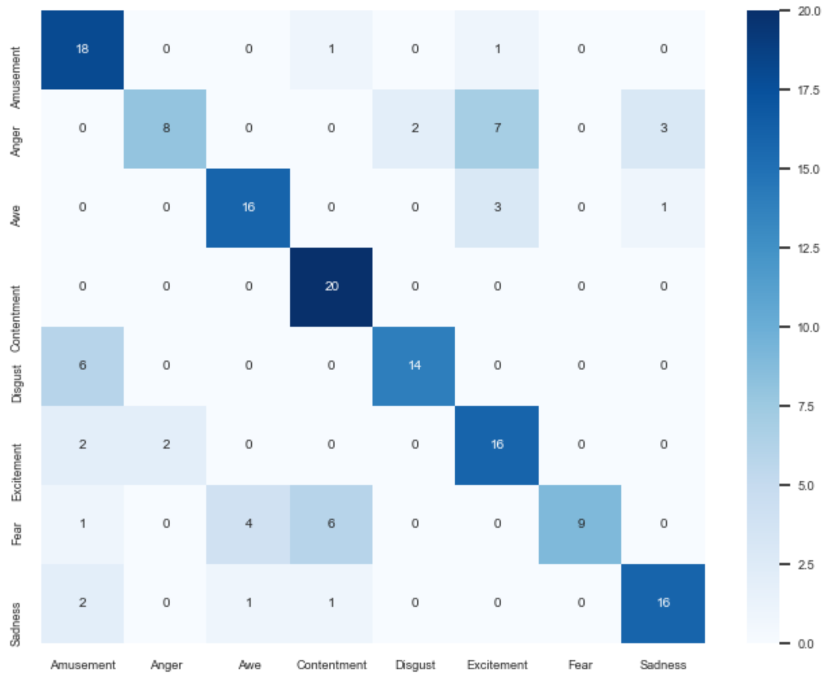


Figure C4. Confusion Matrix of Emotion Prediction for 160 Images (The row emotions are labeled by AMT while the column emotions are predicted by our algorithm)

References

Freeman, M. (2007). The Photographer's Eye: Composition and Design for Better Digital Photos. Focal Press.

Borth, D., Ji, R., Chen, T., Breuel, T., and Chang, S. (2013). Large-scale visual sentiment ontology and detectors using adjective noun pairs. *In Proceedings of the 21st ACM international conference on Multimedia (MM '13)*. New York, NY, USA.

Appendix D. Image Design Attributes – Composition and Main Element-background Relationship

Composition

Organizing the graphic elements into an effective and compelling composition is essential for a strong image. Thus, image composition can convey visual stimuli for feelings and emotions. A number of established guidelines about image composition include diagonal dominance, symmetry, visual balance color and rule of thirds, which are laid out in the professional photography book of Freeman (2007) and adopted in Zhang et al. (2021). We will next discuss each of those metrics and their operationalization. Since most of them are defined based on arranging the main elements within the image frame, we first employ the saliency algorithm (Yang et al. 2013) to identify the main element of each project image.

Diagonal dominance — Rule of thirds

Figure D1. Examples of Image Attributes: Composition

Diagonal dominance: Leading lines in a photo can guide a viewer's focal point, and the two diagonal lines are the longest leading lines in a photo (Figure D1). If we position the main elements of a photo along the two diagonal lines, it will lead the viewer's focal points through the whole photo and create a feeling of spaciousness. To operationally define the diagonal dominance, we calculate the shortest distance between the main element and the two diagonal lines. A shorter distance represents better diagonal dominance since the main figure is placed close to a diagonal line. We take the additive inverse of that distance score as a measure of diagonal dominance to make it positively related to diagonal dominance, for easy interpretation. **Symmetry:** Symmetric distribution of the main elements across the vertical central line of the photo can give rise to a feeling of order and provide aesthetic pleasure. To operationally define "symmetry", we calculate the distribution of the main element across the vertical central line, and subtract the smaller portion from the larger portion to make it positively related to symmetry.

Visual balance color: Like the symmetry attribute, balanced color across the vertical central line can also provide a feeling of order and aesthetic pleasure. To operationally define visual balance color, we calculate the mean of the Euclidean color distance for each mirrored pixel pair across the central vertical line. For easy interpretation, we take the additive inverse of it as the measurement.

Rule of thirds: As illustrated in Figure D1, we can divide any photo into a three-by-three grid with nine even portions by two vertical lines and two horizontal lines. Photographers believe that if we place main element on the four intersections or on the lines, the photo will be aesthetically pleasing by using an unbalanced composition to move the viewer's focal point. Compared with the symmetry attribute, the rule of thirds uses an unbalanced composition to present the feeling of something unusual. We operationally measure rule of thirds by calculating distance between the main element and the four intersections and then taking the additive inverse for easy interpretation.

Main element-background relationship

The difference between the main element and the background will make the main element more stand out, which is measured by the size, color and texture differences in this research.

Size Difference: We first employ the saliency algorithm (Yang et al., 2013) to find the main element for each project image. Then we compute the proportion of the main element in each photo. A higher score of size difference suggests a larger proportion that the main body occupies in the project image.

Color difference: Again, the main element of each project image is detected by the saliency algorithm (Yang et al., 2013). Euclidean distance is calculated by the average color of the main body and the average color of the background. A higher score of color difference represents a greater color difference between the main body and the background.

Texture difference: To calculate texture difference, we first employ edge detection algorithm on the main body and on the background of the project images, respectively. Then we compute the density of edge for the main body and for the background to define the different texture, and we further subtract the edge density of the main body from that of the background to be the texture difference score. A higher texture difference score indicates a higher texture difference between the main body and the background.

Web Appendix E. Standardized Results of Empirical Tests

Table E1. Results of Using Image Attributes to Explain the Variance of Image Emotions (N = 840 Standardized)

	Amuse-ment	Awe	Content-ment	Anger	Disgust	Excite-ment	Fear	Sadness
Warm hue	0.004	-0.040	-0.064*	0.085***	-0.043	0.107***	-0.066*	-0.079**
Saturation	0.070*	0.010	0.024	-0.012	0.072*	0.070*	-0.140***	-0.198***
Brightness	-0.017	-0.073**	0.051	0.088**	0.084**	-0.016	-0.146***	-0.053
HumanFace in image	-0.159***	-0.092**	0.159***	0.088**	-0.068*	0.072*	-0.067*	0.087**
Animal in image	-0.101***	-0.052	0.272***	0.042	-0.045	-0.073**	0.013	0.036
Human in image	0.013	-0.103**	-0.063	0.085**	-0.175***	0.292***	-0.054	-0.084**
Contrast of brightness	-0.011	0.097**	-0.011	0.007	-0.085*	0.033	0.038	-0.089**
Text in image	-0.133***	-0.184***	-0.126***	0.376***	-0.054	-0.024	0.030	-0.046
Diagonal dominance	-0.003	0.049	-0.099***	-0.013	0.004	-0.003	0.027	0.022
Symmetry	0.009	0.017	-0.010	0.041	0.011	0.015	-0.090*	-0.062
Color balance	-0.060	0.154***	0.040	-0.011	-0.170***	0.002	0.085*	0.007
Rule of thirds	0.054	-0.072*	0.058	0.012	0.027	-0.017	-0.062	-0.002
Size difference	-0.020	-0.052	0.053	0.041	0.027	-0.019	-0.071*	0.029
Color difference	-0.082**	-0.095**	-0.025	0.154***	0.003	-0.038	0.016	0.025
Texture difference	0.018	-0.042	0.028	-0.035	-0.023	0.034	0.061*	0.007
R^2	7.4%	10.9%	12.8%	22.7%	7.9%	15.0%	5.3%	5.0%
Adj. R^2	5.6%	9.2%	11.1%	21.2%	6.1%	13.3%	3.5%	3.2%

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table E2. Image Emotions on Campaign Performance (N = 840 Standardized)

	Backer #	Amount (K$)	% of goal achieved	Backer #	Amount (K$)	% of goal achieved
Amusement	0.012	0.001	0.010			
Awe	-0.040	0.014	-0.006			
Contentment	**0.068****	**0.055***	**0.091****			
Disgust	-0.035	-0.021	-0.011			
Excitement	-0.034	-0.033	-0.008			
Fear	**-0.088****	-0.056	-0.062			
Sadness	**0.122*****	**0.072****	0.034			
#Competing projects	-0.026	-0.058*	-0.091**			
Competing Amusement	**-0.067***	-0.032	0.014			
Competing Awe	-0.032	-0.053	-0.011			
Competing Contentment	**-0.096*****	-0.042	**-0.088****			
Competing Disgust	-0.008	-0.015	0.053			
Competing Excitement	-0.018	0.025	0.031			
Competing Fear	**-0.079****	-0.036	**-0.066***			
Competing Sadness	-0.019	**-0.059***	-0.038			
Anxiety in text description	0.004	0.006	-0.005	0.004	0.008	0.001
Anger in text description	0.016	0.000	-0.010	0.015	0.002	-0.006
Sadness in text description	0.046	0.003	0.025	0.055*	0.013	0.033
Preset Goal	0.271***	0.369***	-0.273***	0.280***	0.371***	-0.263***
Project popularity	0.047	0.009	0.021	0.043	0.007	0.013
Length of text description	0.140***	0.060*	0.073*	0.130***	0.061*	0.072*
No. of Images	0.090**	0.145***	0.149***	0.090**	0.149***	0.152***
No. of Videos	0.159***	0.175***	0.099***	0.178***	0.185***	0.119***
Duration	-0.021	-0.010	-0.007	-0.027	-0.023	-0.019
R^2	26.0%	30.8%	13.0%	21.6%	28.4%	9.5%
Adj. R^2	23.8%	28.7%	10.4%	20.8%	27.6%	8.6%

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table E3. Effects of Image Emotions on Crowdfunding Performance by Budget (standardized)						
	High Budget			**Low Budget**		
	Backer #	**Amount (K$)**	**% of goal achieved**	**Backer #**	**Amount (K$)**	**% of goal achieved**
Amusement	-0.001	-0.005	0.070	0.016	0.006	-0.048
Awe	-0.042	0.067	0.039	-0.037	-0.035	-0.041
Contentment	**0.182*** **	**0.142*** **	**0.156*** **	-0.034	-0.019	0.017
Disgust	-0.037	0.023	0.045	-0.029	-0.050	-0.049
Excitement	-0.053	-0.039	-0.005	-0.041	-0.039	-0.012
Fear	-0.036	-0.027	-0.024	**-0.130*** **	-0.069	**-0.093* **
Sadness	0.009	0.019	0.015	**0.200*** **	**0.103** **	0.045
#Competing proj.	-0.032	-0.070	-0.090	-0.011	-0.048	**-0.137*** **
Competing Amusement	**-0.120** **	-0.077	-0.069	-0.023	-0.008	**0.110** **
Competing Awe	0.040	-0.015	0.019	-0.056	-0.057	-0.018
Competing Contentment	**-0.192*** **	**-0.117** **	**-0.179*** **	-0.040	0.005	-0.029
Competing Disgust	0.092	0.056	0.106	-0.052	-0.052	0.009
Competing Excitement	0.011	0.058	0.036	-0.017	-0.001	0.029
Competing Fear	-0.050	-0.049	-0.051	**-0.085* **	-0.030	**-0.089* **
Competing Sadness	-0.014	-0.050	-0.059	-0.028	**-0.086* **	-0.043
Anxiety in text description	0.013	0.015	-0.019	0.016	0.014	0.030
Anger in text description	0.005	0.009	-0.017	0.042	0.004	-0.012
Sadness in text description	0.080	-0.009	-0.024	0.003	0.005	0.070
Preset Goal	**0.236*** **	**0.331*** **	**-0.251*** **	**0.279*** **	**0.391**	**-0.304*** **
Project popularity	0.030	-0.027	-0.044	0.041	0.023	**0.078* **
Length of text description	0.044	0.049	0.049	0.194***	0.055	**0.095* **
No. of Images	**0.138** **	**0.133** **	**0.138** **	0.081	**0.175*** **	**0.156*** **
No. of Videos	**0.227*** **	**0.254*** **	**0.093* **	**0.104** **	**0.106** **	**0.132*** **
Duration	0.031	0.004	-0.018	-0.033	-0.008	0.029
N	348	348	348	492	492	492
R^2	32.7%	36.1%	14.7%	27.6%	30.7%	18.5%
Adj. R^2	27.7%	31.3%	8.3%	23.8%	27.1%	14.3%

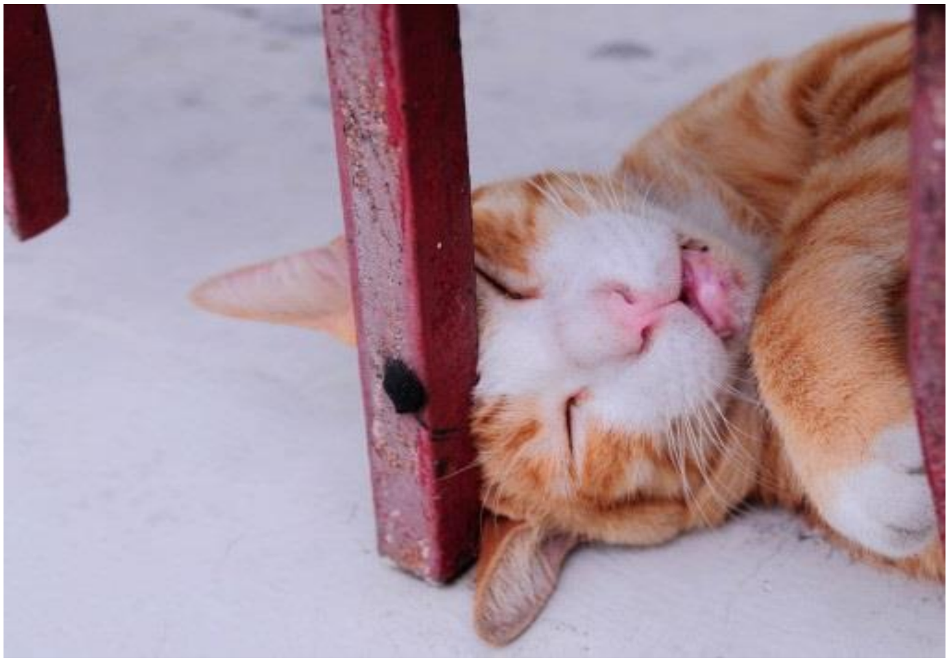
Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table E4. Effects of Image Emotions on Crowdfunding Performance by Project Type (Standardized)									
	Community			**Environment**			**Education**		
	Backer #	**Amount (K$)**	**% of goal achieved**	**Backer #**	**Amount (K$)**	**% of goal achieved**	**Backer #**	**Amount (K$)**	**% of goal achieved**
Amusement	0.057	0.044	**0.158***	0.061	-0.032	0.124	-0.030	-0.013	**-0.113***
Awe	-0.035	-0.040	-0.011	0.039	0.002	0.003	-0.054	-0.024	-0.084
Contentment	**0.139****	**0.270*****	0.006	**0.343*****	**0.287*****	**0.238****	-0.089	-0.071	0.002
Disgust	-0.046	-0.021	-0.023	0.060	-0.011	0.004	-0.040	0.009	-0.038
Excitement	0.021	-0.006	-0.050	0.051	0.066	-0.040	-0.077	-0.051	0.073
Fear	-0.073	-0.042	-0.038	0.023	0.037	-0.090	-0.109	-0.095	-0.020
Sadness	0.008	-0.023	-0.012	0.076	0.009	0.022	**0.272*****	**0.262*****	0.046
#Competing proj.	-0.025	-0.094	-0.096	0.040	0.040	-0.004	0.044	0.008	0.083
Competing Amusement	-0.061	-0.087	-0.037	**-0.190***	**-0.218****	-0.149	0.045	0.044	0.073
Competing Awe	-0.033	-0.079	-0.016	-0.044	-0.033	-0.006	-0.008	-0.009	**0.142****
Competing Contentment	**-0.182*****	-0.084	-0.024	**-0.239****	**-0.174****	**-0.217****	-0.027	0.007	**0.157****
Competing Disgust	**-0.204****	**-0.252*****	-0.117	-0.007	-0.059	0.071	0.041	0.015	**0.239*****
Competing Excitement	**-0.249****	**-0.204****	-0.090	-0.070	-0.079	0.016	0.014	0.027	**0.179****
Competing Fear	**-0.171****	**-0.138***	-0.117	-0.014	-0.078	-0.023	-0.094	-0.080	0.096
Competing Sadness	0.016	-0.125	-0.080	-0.149	**-0.149***	-0.136	0.089	0.053	**0.159****
Anxiety in text description	0.001	0.013	-0.018	0.034	0.056	-0.032	0.019	0.006	-0.003
Anger in text description	-0.006	0.026	0.021	-0.038	-0.048	-0.003	0.032	0.017	-0.048
Sadness in text description	**0.210*****	0.004	0.004	0.049	0.089	0.017	0.007	0.008	0.075
Preset Goal	**0.447*****	**0.573*****	**-0.329*****	**0.169***	**0.373*****	**-0.218****	**0.334*****	**0.435*****	**-0.333*****
Project popularity	0.069	-0.049	0.018	-0.019	-0.045	-0.041	0.056	0.023	0.027
Length of text description	0.075	0.023	0.010	**0.185****	**0.200****	0.131	**0.133***	0.087	0.114
No. of Images	-0.038	-0.016	0.128	0.157	0.049	0.115	0.026	0.088	-0.037
No. of Videos	**0.224*****	**0.240*****	0.082	**0.235*****	**0.285*****	0.134	0.059	0.094	**0.218*****
Duration	-0.064	-0.071	0.025	-0.106	-0.102	-0.054	-0.082	-0.083	-0.076
N	206	206	206	134	134	134	254	254	254
R^2	43.6%	50.1%	16.5%	40.2%	51.3%	24.4%	30.1%	38.0%	23.7%
Adj. R^2	36.1%	43.5%	5.5%	27.0%	40.5%	7.7%	22.8%	31.6%	15.7%

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Appendix F. Experiment: Charity Fundraising Project for the Experiment

Background



TNR- Trap, Neuter, and Return
by CatVille

On the street of Donhou, there are numerous cats live here. Cats bring energy and vitality to this town. However, they are also a huge burden for Donhou. The residents in Donhou do love cats, but their homes and belongings are damaged by cats and their excreta time after time. Especially, the noise and aggressive action brought by cats' courtship. Although people love cats, the impact of cats still needs to be addressed. Therefore, this crowdfunding campaign is launched to protect both cats' and residents' wellbeing.

Traditionally, government officers would catch stray cats and take them to shelter. If nobody adopts these cats, after 14 days in shelter, mercy killing will be the destination of these cats. Due to the dangerous environment, stray cats usually have a life span between 2 to 3 years. Since they only have such a short life span, it would be cruel to just take their life away. Thus, we launched this campaign to do birth control for these stray cats.

The TNR (Trap, Neuter, and Return) program will catch stray cats and release them back to the street after sterilizing. Sterilizing could reduce the aggressive action for courtship, which makes sterilized stray cats healthier, and their life span can be longer (~10 years) than usual ones (~2 years). Sterilized cats will be marked and will not be caught by government officers anymore. Moreover, the life quality of residents will also be improved thanks to no more courting noise and urine spraying.

Most animal hospitals are willing to provide low-cost sterilized surgery to stray cats. But due to the great number of stray cats, the cost of the TNR program still cannot be fully covered. Although you might never meet any cats in Donhou, you can still help them with your donation. Your help means a lot to both us and the stray cats in Donhou.

Demographics of Participants

Table F1. Demographic for Main Experiment		Pooled Data (N = 177)	Warm Hue High (N = 37)	Warm Hue Low (N = 48)	Saturation High (N = 39)	Saturation Low (N = 53)
		Distribution	Distribution			
Education	Less than high school degree	0.6%	0%	2.1%	0%	0%
	High school graduate	4.5%	5.4%	4.2%	5.1%	3.8%
	Some college but no degree	15.3%	8.1%	22.9%	20.5%	9.4%
	Associate degree in college	7.3%	8.1%	2.1%	10.3%	9.4%
	Bachelor's degree in college	51.4%	56.8%	45.8%	46.2%	56.6%
	Master's degree	19.2%	16.2%	22.9%	17.9%	18.9%
	Doctoral degree	0%	0%	0%	0%	0%
	Professional degree (JD, MD)	1.7%	5.4%	0%	0%	1.9%
Income	Less than $10,000	4%	5.4%	0%	5.1%	5.7%
	$10,000 to $19,999	4.5%	0%	8.3%	5.1%	3.8%
	$20,000 to $29,999	11.3%	18.9%	8.3%	2.6%	15.1%
	$30,000 to $39,999	10.2%	5.4%	12.5%	10.3%	11.3%
	$40,000 to $49,999	5.6%	2.7%	10.4%	7.7%	1.9%
	$50,000 to $59,999	16.4%	13.5%	16.7%	20.5%	15.1%
	$60,000 to $69,999	9%	0%	12.5%	10.3%	11.3%
	$70,000 to $79,999	10.2%	5.4%	8.3%	7.7%	17%
	$80,000 to $89,999	8.5%	21.6%	8.3%	5.1%	1.9%
	$90,000 to $99,999	6.8%	10.8%	4.2%	5.1%	7.5%
	$100,000 to $149,999	9.6%	13.5%	4.2%	15.4%	7.5%
	$150,000 or more	4%	2.7%	6.3%	5.1%	1.9%
Gender	Male	62.7%	54.1%	64.6%	71.8%	60.4%
	Female	37.3%	45.9%	35.4%	28.2%	39.6%
		Mean (S.D.)	Mean (S.D.)			
Age (Years)		38.650 (10.593)	39.510 (10.519)	39.98 (11.157)	36.15 (10.051)	38.68 (10.488)

Positive and Negative Empathy Measurements

Adapting from the literature (Light et al., 2019; Andreychik & Migliaccio, 2015), we develop our scale to measure positive and negative empathy by the items listed in Table F2. Cronbach α and factor loading (varimax) are reported as well.

Table F2. Measurements of Positive and Negative Empathy

Construct	Items	Factor Loading	α	References
Positive Empathy	I very much enjoy and feel uplifted by caring stray cats.	0.744	0.933	Light et al. (2019)
	I can't stop myself from smiling when the stray cats are cared.	0.757		
	I also feel good when stray cats are cared.	0.847		
	I enjoy hearing about stray cats' better life.	0.869		
	It often makes me feel good to see stray cats are helped.	0.837		
Negative Empathy	I get upset at stray cats' short life.	0.787	0.930	Andreychik and Migliaccio (2015)
	It makes me sad to know that stray cats may live a short life.	0.637		
	I often become upset when receiving upsetting news about stray cats.	0.843		
	Stray cats' misfortunes often disturb me a great deal.	0.838		
	When knowing stray cats live a sad life, I become sad.	0.749		
	I cannot continue to feel OK if I learn stray cats probably pass away soon.	0.833		

Discriminant validity test is used to verify if our measurements can show positive empathy and negative empathy are two separated concepts. In the following table, the values in diagonal line represent the square root of AVE

(Average Variance Extracted), which represent how well each measurement is related to the respective concepts. The value 0.738 is the correlation between positive empathy and negative empathy. Since 0.819 and 0.784 are both bigger than 0.738, the results indicate that our measurements are more related to its own concepts than to those of other concepts (Fornell & Larcker, 1981). The results support discriminant validity (Table F3).

Table F3. Discriminant Validity

	Positive Empathy	Negative Empathy
Positive Empathy	0.819	-
Negative Empathy	0.738	0.784

Additional Reference

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, 18(1), 39–50.

Appendix G. Additional Studies

The experiment study in Section 4 validates that manipulating image attributes can change the subject's emotional reactions, which lead to positive or negative empathy and pledge intention. Those findings are obtained from a particular category of charity crowdfunding—animal related projects. To check the generalizability of our findings to other categories of charity crowdfunding projects, we consider multiple projects from different charity categories.

Since it is challenging to manipulate image attributes with many uncontrollable factors related to project contents, characteristics, etc., we focus on verifying the Hypotheses H2a, H2b, H2c, and H2d in the extended research model with multiple projects from more diverse charity categories.

Design

We selected three projects from Kickstarter.com, with their descriptive information and original project images are provided in Table G1.

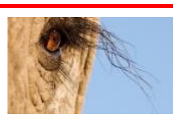
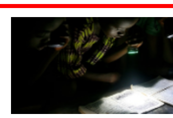
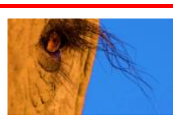
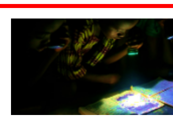
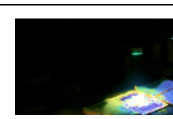
Table G1. Projects Included in This Study

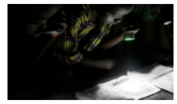
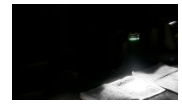
ID	Projects Description	Images	Category
1	Remembering Elephants: A fund-raising hardback book of elephant photos by some of the world's top wildlife photographers including Art Wolfe & Michael Poliza.		Animal Art & Culture Education
2	SafariSeat: Open source wheelchair for developing countries.: We've designed a low cost, all terrain wheelchair for rural communities. Join us, let's make as many as possible!		Medical
3	Life Without Lights: 1.4 billion people live without electricity. This project reveals the impact of global Energy Poverty while questioning energy's future		Environment

Full Image Variation in the Additional Study

The original project images are picked from the public benefit category of Kickstarter.com, displayed in row 1 and columns 1 to 3 of Table G2. We vary the color and content attributes of the project images by removing the human(s) and changing color, resulting in a total of 20 variations in Table G2. Removing a subject such as a human from images considerably changes all the 4 major components of image attributes: color, composition, content, and main element-background relationship. We randomly assign one of the images in Table G1 to each participant.

Table G2. Original Images and Their Different Variations via Manipulation

	1	2	3	2_NoHuman	3_NoHuman
Original					
Color 2					

Color 3		 	 
Color 4		 	 

The study is established on the well-known survey platform, QuestionPro. This survey link is released to MTurk to recruit participants. To obtain high-quality responses, we screen participants via a set of criteria, such as residing in the US, and having previously completed at least 500 Human Intelligence Tasks (HITs) with an approval rate of at least 95%. After each subject being presented with a variation of the project image, we conduct survey to measure the emotions, positive empathy, negative empathy, and donation intention. During this survey, we require subjects to report their demographic data.

Findings

We collected 467 samples from MTurk in January 2022. Like in the previous experiment study, we removed those subjects who do not have previous experiences with crowdfunding and end up with 255 samples. The descriptive statistics are given below.

Table H3. Descriptive Statistics in the Full Sample (N = 255)

Variable	Min	Max	Mean	Std. dev.
Pledge Intention	0	1	0.760	0.430
Positive Empathy (Average)	1	7	5.560	1.019
Negative Empathy (Average)	1	7	5.231	1.150
Amusement	1	7	3.250	2.193
Awe	1	7	4.100	2.013
Anger	1	7	4.450	1.837
Contentment	1	7	3.910	1.965
Disgust	1	7	3.820	2.057
Excitement	1	7	3.800	2.020
Fear	1	7	4.020	2.058
Sadness	1	7	5.130	1.565
Age	19	63	39.369	9.937
Education	1	8	4.700	1.248
Income	1	12	6.350	3.043
Gender	1	2	1.460	0.499

We first study the relationships between the effect of positive and negative emotions on positive and negative empathies (Models 3 and 4), respectively. Similar to the experimental results in Section 4, negative emotions disgust and sadness are both positively related to negative empathy, and positive emotions awe and contentment are positively related to positive empathy, while amusement negatively affects positively empathy. Thus, H2a and H2b is partially supported.

Table G4. Effects of Image Emotions on Empathy (N = 255)

		Positive Empathy	Negative Empathy
Positive Emotions	Amusement	**-0.098****	
	Awe	**0.175*****	
	Contentment	**0.126****	
	Excitement	0.013	
Negative Emotions	Anger		-0.066
	Disgust		**0.152*****
	Fear		0.045
	Sadness		**0.047*****
	Constant	4.561***	3.373***

	R^2	15.1%	27.3%
	Adj. R^2	13.8%	26.1%

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

We then test the effects of positive and negative empathies on the intention to pledge (Model 5). The results in Table G5 show that both positive and negative empathies significantly lead to intention to pledge. Thus, H2c and H2d are supported.

Table G5. Effect of Image Empathy on the Pledge Intention (N = 255)

Variables		Pledge Intention
Empathy	Positive Empathy	**0.345***
	Negative Empathy	**0.407****
Control Variable	Income	**-0.131****
	Education	0.082
	Age	-0.005
	Gender	-0.093
	Elephant_Dummy	**1.332****
	Wheelchair_Dummy	0.361
Constant		-3.437**
Cox and Snell R^2		0.169

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Therefore, the conclusions we draw from the previous experiment still hold with charity fundraising campaigns in more general categories.