Title:

Identifying Emotions in Images and Their Effects on Donation Behavior in Online Crowdsourcing Platforms

Authors:

Elham Yazdani, Assistant Professor of Marketing, University of Georgia

Anindita Chakravarty, Associate Professor of Marketing, University of Georgia

Jeff Inman, Associate Dean for Research and Faculty, University of Pittsburgh

ABSTRACT

Although textual emotional appeals in a donation context have been studied in past research, there has been little work looking at facial emotions expressed in posted images. Drawing on a panel data of 25,321 crowdfunding projects from Gofundme, we investigate how facial emotions expressed in posted images might be strategically used to increase individual project effectiveness as measured by metrics relevant to the platform, i.e., donation amount per project. In this research, we focus on four emotions that can be inferred accurately from facial expressions in images using artificial intelligence methods; happy, sad, anger and surprise. Our empirical analysis shows that increasing the degree to which facial expressions in an image convey any of these four emotions has a positive impact on the contributed amount to a project, with sadness having the biggest effect, followed by anger, surprise, and happiness. We also use MTurk studies to explore the process behind these effects, finding that perceived justice is the most dominant mediator in all the conditions of surprise, angry, happy and sad images, while perceived empathy and emotion contagion are mediators only in the case of surprise and happy images. And finally in a follow-up controlled study, we provide strategic recommendations for platform revenue management.

Keywords: *Crowdfunding, Image Analysis, Facial Emotions, Perceived Justice, Perceived Empathy, Emotion Contagion, Endogeneity, Instrumental Variables, Multi-Method Research*

INTRODUCTION

Platform-based crowdfunding has experienced enormous growth in recent years. The crowdfunding volume in North America in 2019 was $17.2 Billion and is projected to grow to $39.8 Billion by 2026 (Shepherd 2020). A crowdfunding platform enables individuals or groups with monetary need to create projects that describe their need and their monetary goals. In turn, the platform enables potential donors to visit the platform, view, search, share and donate to projects of interest. In the process of facilitating pro-social behavior, the platform gains economically as well. Most platforms monetize by charging a percentage of the funds raised per project. For instance, personal fundraising platforms such as Gofundme.com and Fundly,com charge 2.9% and 4.9% of the donated amount as fees, respectively. Thus, it is in the platform's strategic interest to help project creators with advice about designing projects (i.e., choosing images and project descriptions) that increase the amount of money raised per project. In fact, Gofundme.com has a "dedicated team looking for great stories to amplify and share with the media and community" (https://www.gofundme.com/why-gofundme). As such then, crowdfunding platforms are interested in project design strategies that can influence potential donors, thereby improving a project's effectiveness at raising money.

In this research, we are interested in understanding whether facial emotions expressed in posted images might influence the amount raised by projects. Specifically, we employ a multi-method approach to investigate the impact of multiple types of facial emotions in images on the amount raised per project as well as the underlying psychological mechanisms by which different facial emotions influence donors. Whereas research has examined the impact of emotions on consumer purchase decisions and recommendations (see Kranzbuhler et al. 2020 for a meta-analysis), the literature on how emotions influence pro-social behavior (which mostly involves monetary donation without receiving any product/service in return) is relatively small (see Table 1). Moreover, in the domain of pro-social behavior, scholars have studied emotions expressed in advertisements and textual appeals for donation, but the literature on facial expression of emotions in donation contexts is scarce.

[Insert Table 1 about here]

Facial expressions of emotions in donation contexts are unique for several reasons. First, the same facial expression may be seen as expressing different types of emotion depending on the cultural context, i.e., eastern versus western (Matsumoto and Ekman 1989; Jack et al. 2012). Since crowdfunding sites are accessible to donors worldwide, we cannot apply traditional manipulations of emotions, which rely on subjective interpretations by small sets of individuals based within a homogenous setting such as the same institution or country. In recent years however, artificial intelligence methods are being used to detect facial expressions that are universally recognized to express a given emotion. The literature on facial expressions of emotion concludes that whereas artificial intelligence methods can reliably infer six basic emotions (happiness, sadness, anger, surprise[1], fear and disgust) from facial expressions, only four of these (happiness, sadness, anger and surprise) are accurately inferred irrespective of differences in cultural expressions of emotions (Jack et al. 2016). This is because the emotions of happiness, sadness, anger and surprise are conveyed by unique combinations of movements of different parts of a human face (e.g., Corneanu et al. 2016). Thus, study of facial expressions of emotions in the donation context could be improved by the use of artificial intelligence methods to detect the four universally recognized emotions.

[1] A type of facial expression with open mouth and wide-open eyes

Second, as emotions are interpreted via movements of different parts of a human face, an image of a human face may convey some degree of each emotion (Russell et al. 1986; Susskind et al. 2007) with typically a single dominant emotion. Study of facial expression of emotion must account not just for the dominant emotion but also for other emotions that are conveyed to lesser degrees. In other words, an empirical study of facial expression of emotions should study the impact of all four emotions simultaneously, which has so far not been studied in traditional experiment-based studies of emotions. Third, from a theoretical perspective, we want to assess our proposed mechanism through which facial expressions of emotions influence donation behavior of a potential donor. Whereas emotion contagion, perceived empathy and perceived justice have been shown to influence donation behavior in the literature (Small and Verrochi 2009, Hoffman 1990, Batson et al. 1995; Lee et al. 2014), it is not clear how emotions, particularly facial expressions of emotions in images, will impact such motivations.

We use the Microsoft Azure image processing API for facial emotion recognition. The Azure API can locate all the human faces in an image[2] and extract emotional scores using the latest deep learning algorithms and a massive training set of images[3]. There are other artificial intelligence tools for face detection and emotion recognition such as the Google Cloud API, and Amazon Rekognition. Although they all share a similar algorithm based on neural networks, a unique advantage of Azure API is its ability in facial detection with different head poses. Since some of the posted images in Gofundme.com are not captured from a near frontal view, we choose Azure API over other available tools, however there is a high correlation between the Azure API

[2] Up to 100 faces per image
[3] We provide some details about the deep learning algorithms in Web Appendix A.

scores and the emotional scores extracted using Google Cloud API, Amazon Rekognition and human subject pool[4].

Our research makes three primary contributions. First, our empirical analysis shows that the effect of emotions in images used for crowdfunding donation appeals follows a distinct rank order. Sadness has the largest positive effect on donation amount, followed by anger, surprise and happiness. This ordering emerges in our analysis of over 25,000 donation projects launched on Gofundme.com between 2010 and 2018 with more than 70,000 uploaded images, as well as in a follow-up experiment with random assignment to emotion condition. Second, we find that the effect of various emotions on donation amount is consistently mediated by perceived justice and somewhat by empathy and emotion contagion. Specifically, we find in Study 2 that perceived justice is a mediator across surprise, angry, happy and sad images, while perceived empathy and emotion contagion are mediators only in the case of surprise and happy images. Third, we demonstrate how a crowdfunding platform can utilize our findings to increase donations (and its revenue). Our findings in Study 3 reveal that donations can be increased by 6.4% by replacing a happy expression with a sad expression, which at the project level translates to over $240 additional donation dollars. Finally, our research illustrates the potential of a multi-method approach combining AI-powered analysis with causal experiments to analyze nuanced phenomena at scale and provide evidence of the underlying process.

To the best of our knowledge, this is the first research exploring how artificial intelligence tools (i.e., facial expressions of emotion interpreted by artificial intelligence) may be used to understand the mechanism behind users' engagement journey on an online crowdfunding donation platform. With our findings, we can provide strategic recommendations for platform managers in

[4] The correlation between Azure API scores averaged across all the four emotions and the corresponding scores from Google Cloud API, Amazon Rekognition and human subject pool is respectively 0.91, 0.82, and 0.95.

terms of improving one key performance metric, i.e., donation amount per project. If the platform is able to provide tools to users that help them achieve their project goals, the platform benefits monetarily as well since the platform fee is a percentage of the money raised. Thus, if the platform can recommend strategic use of facial expressions of emotions in images to users, both the project as well as the platform benefits.

In the following sections, we first review prior work on the relationships between emotions, AI applications in marketing and prosocial behavior, following which we provide our theoretical motivations about possible mediating mechanisms. We then outline our data and empirical analysis. Lastly, we present the mediation analysis and managerial implications.

BACKGROUND

Literature Review of the Influence of Emotions on Pro-Social Behavior

The literature on emotions in prosocial behavior is dominated by emotional framing of donation appeals. The donation appeals are primarily text messages and sometimes even appeals associated with verbal delivery of advertising messages (Hsieh and Yucel-Abat 2018, Shang et al. 2008). A variety of emotions have been examined including text and verbal messages framed in terms of sadness, guilt, nostalgia, fear, shame and inspiration (Bagozzi and Moore 1994, Hibbert et al., 2007, Marchand and Filiatrault 2002, Brennan and Binney 2010, Liang et al. 2016). While there is limited research on visual imagery such as Choi et al. (2016) and Parry et al. (2013), none study facial expressions of emotions, and instead experimentally study contextual background of images in extreme contexts that involve violence and extreme temperatures among others.

In terms of empirical studies, to our knowledge, there is one study that uses AI methods to extract positive and negative facial expressions of CEO images in order to assess their influence on firm performance as measured by initial coin offering underpricing (Momtaz 2020). However, this study does not provide granular comparisons of specific emotion expressions nor is the research context remotely similar to a pro-social behavior context where the donor typically does not receive anything in exchange for the donation. Turning to the specific context of pro-social behavior, there exists only one study in marketing that assesses happy versus sad and neutral facial expressions of images in an experimental charitable appeal context (Small and Verocchi 2009). Though this research provides valuable insights, interpretation of facial expressions of emotions in images is much more complex for multiple reasons.

Individuals using online donation platforms use a variety of images, not all of which convey only happiness or sadness. For example, among the projects created on Gofundme.com between 2010-2018, we used Azure API to find that though most of them convey either happiness (45%) or sadness (13%), about 8% of projects have images dominant in surprise and 4% of them are dominantly angry images. This is non-trivial evidence that individuals post images with a variety of facial expressions, and per se images cannot be neatly categorized as conveying only happiness or sadness. As such then, a study of the relevance of facial expressions of emotions in images in online donation platforms requires consideration of more than two emotions for face validity.

Consideration must also be given to the fact that online donation platforms are accessible to potential donors all over the world. It follows that any study on facial expressions of emotions in the context of online donation platforms should account for whether different cultures interpret facial emotion expressions similarly or not. For instance, research suggests that facial expressions that convey disgust and fear to western cultures do not convey the same to eastern cultures, though eastern and western cultures interpret facial expressions of anger, surprise, happy and sad consistently (Matsumoto & Ekman 1989; Jack et al. 2012, Jack et al. 2009). Thus, for a study to provide viable, practical strategies to online donation platforms, it must consider at least the four culturally universal facial expressions of emotions. Strategies based on these facial emotion expressions do not require customization of images based on the cultural context of the donor base. As such then, they represent largely costless strategies on the part of the platform as well as the individuals asking for donation.

Finally, consider that online donation platforms raise money for multiple contexts such as memorials, emergency relief, education and medical needs. They do not limit themselves to charitable organizations, which has been the focus of all emotion research in pro-social behavior. Thus, for a study to provide meaningful implications to online donation platforms, it should also be able to accommodate contexts other than charity. We do this and find that our results hold across five contexts: charity, memorials, emergency relief, education and medical needs. This provides evidence of the robustness of the effects.

To our knowledge, our research is the only study to both empirically and experimentally consider all of these factors. We collect large scale data from an online donation platform which reflects several donation contexts. We also use AI techniques to measure multiple facial expressions of emotions in images, especially anger, sadness, surprise and happy that are universally recognizable, and account for the effect of each facial expression of emotion in an image while controlling for other emotions that the image and associated text might convey. In the literature on AI applications in marketing, our research is unique in that we apply AI methods to emotions in a pro-social behavior context, in contrast to research that applies AI techniques in contexts unrelated to emotions or pro-social behavior, such as product line optimization

(Tsagarakis et al. 2013), bots for sales and customer service (Luo et al. 2019, Wilson-Nash et al. 2020, Kim et al. 2019), and social media listening platforms (Hayes et al. 2020).

Review of Potential Mediating Mechanisms

In the pro-social behavior literature, perceived empathy appears as the predominant mediator of the effect of emotional donation appeals on the pro-social behavior of the donor (Hoffman 2001). Perceived empathy refers to the degree to which the donor feels compassion toward the victim or the donation target. Multiple studies (e.g., Coke et al. 1978; Batson 1983; Lee et al. 2014) have reported that emotional text-based appeals are effective to the extent they can induce empathy for the donation target. More specifically, research shows that negative emotional appeals are likely than positive emotion appeals to induce more empathy in a pro-social context (e.g., Bagozzi & Moore, 1994, Fisher et al., 2008). In addition to perceived empathy, Small and Verocchi (2009) show that emotion contagion also mediates the effect of emotion appeals (in their case, happy and sad images) on donor's pro-social behavior in charity contexts. Emotion contagion is the extent to which the donor might feel the same emotion that is conveyed by the image of the donation target and/or description of the donation target's situation (e.g., Ekman et al. 1972). In summary, the literature suggests two mediators – perceived empathy and emotion contagion – that influence the donor through an affective route.

In contrast to the two mediators above, Liang et al. (2015) suggests a more cognitive route. They show that appraisals of emotional donation appeals can result in cognitive inferences about the donation target. Some scholars refer to such cognitive inferences as perceived justice, i.e., the donor's perceptions about the deservingness of the donation target to receive the donation. Specifically, people are less willing to provide support to those in need when recipients are judged as personally responsible for their problems (Barnes et al. 1979; Farwell and Weiner 2000; Henry et al. 2004; Skitka and Tetlock 1992; Weiner 1993). Using this logic, Lee et al. (2014) show that to the extent that charity recipients are perceived as personally responsible for their situation, donors may judge that providing a positive outcome (i.e., support from donors) to the recipients is unjust. As such, people develop perceptions of justice based on (1) the extent to which they feel that the descriptions or appeals for donation made by the donation target are sufficiently descriptive of the target's need for donation (e.g., Folger and Greenberg 1985), (2) the extent to which they feel that the description justifies the target's request for donation to help her/his situation (Adams 1963), and (3) the extent to which they feel that they are themselves being fair in understanding the donation target's plight and responding to it (Henry et al. 2004).

Whereas consumer behavior scholars have only considered the third dimension of perceived justice (e.g. Lee et al. 2014), the first two dimensions have frequently been used by organizational behavior scholars to understand how trust and perceptions of goodwill develop between managers of two transacting firms (Bies 1986; Shapiro et al. 1994; Folger and Konovsky 1989). Since donating to a victim or target requires some level of trust in the victim's situation, and goodwill that the victim will truly improve her/his situation upon receipt of donations (Leventhal 1976), we consider all three dimensions to underlie the theoretical construct of perceived justice.

In summary, the literature suggests three possible theoretical mediators: perceived empathy, emotion contagion and perceived justice. Thus, we investigate all three mediating effects for the relationship of each of the four facial emotion expressions on donor's pro-social behavior. We do this to understand multiple ways in which varying emotions expressed in images might influence donor behavior.

STUDY 1 (Gofundme Projects)

Data

Gofundme is one of the biggest online fundraising platforms, created in 2010 with contributions from more than 120 million donors. At the time of data collection, in 2019, Gofundme had a different format than the current version. It had a lower number of donation contexts, with the five most popular categories being charity, education, emergencies, medical and memorials. But with the start of pandemic, Gofundme experienced a huge surge in the number of donation projects for either individuals or businesses and consequently, more number of categories were added in response to the increased demand of crowdfunding initiatives. For example, before COVID-19, there was no category like “Wishes”, “Faith”, “Nonprofit”, “Coronavirus”, or “Animals”, and instead, there was a broad category “charity” that doesn’t exist anymore.

At the time of data collection, there were about 889,658 projects created in total among all different donation categories from 2010 till 2018 with charity, education, emergencies, medical and memorials comprising almost 60% of all projects[5]. We create our data sample as follows. First, we randomly selected 45,000 projects within the five most popular categories as mentioned above, which is about 5% of all the created projects on Gofundme.com. Then, similar to Mollick (2014) and Raab et al. (2020), we excluded 2,215 outlier projects with a monetary goal of less than $100 or more than $1,000,000. Also, we excluded 3,540 projects that lasted less than 5 days because it can be a signal of low effort in fund raising from the project creator (Raab et al.2020). Then, we eliminated 5,120 projects without any posted image of a human face, e.g. the projects with images of only objects or animal faces. Next, we excluded 5,230 projects with images that were either too

[5] The other 40% of projects belong to either of the categories “Business”, “Community”, “Creative”, “Event”, “Sports”, and “Travel”.

blurry that Azure API couldn't recognize any faces or only part of the face is shown or the face is covered. And finally, we had to exclude 3,574 projects that didn't receive any donation.

Our final dataset includes 25,321 projects across all the five most popular categories of charity, education, emergencies, medical and memorials that were launched between 2010 and 2018. To create a weekly panel of donations for the 25,321 projects, we track changes in each project and all the raised donations over each week after their launch date, resulting in 423,895 observations in total at the project-week level. Our unit of analysis is project-week and the dependent variable is the total dollar amount of donations contributed each week per project.

Measurement

For each donation project, we collect data on project description, uploaded images, the project's monetary goal, and all the contributed donations at each week after the project launch, along with the project creator's donation activity and all the comments written for the project. There are more than 70,000 uploaded images across all the projects in our data set, and for each image we perform facial detection and emotion recognition in addition to extracting other image attributes such as image blurriness and brightness, which is a combined measure of hue, saturation and lightness. We list these image attributes in detail later in this section.

The standard way of measuring facial emotion is based on the Facial Action Coding System (FACS) (Ekman and Friesen 1978). FACS categorizes the physical expression of emotions based on facial muscular movements called action units. For example, happiness is characterized by the two action units of "cheek raiser" and "lip corner puller". Identifying action units by manual coders has been shown to underperform the computer-based tools (Bartlett et al. 1999). Considering the potential for human error given the scale of this study, we use an artificial intelligence (AI) tool, similar to previous researchers (e.g. Liu et al. 2018; Teixeira et al. 2012; Li and Xie 2020; Raab et al. 2020). One of the advantages of using an AI tool is the access to pre-trained models on large image data sets. More importantly, AI methods allow large scale extraction of a variety of emotions as expressed by the faces of individuals in the images. Measuring all the four universal facial expressions of emotions on continuous scales in order to obtain the degree of expressed emotion (instead of only the presence or absence) in thousands of images requires us to use an AI method.

There are different artificial intelligence tools for face detection and emotion recognition such as Microsoft Azure API, Google Cloud API, and Amazon Rekognition. The other available option is IBM Watson Cloud but it can only detect faces, age and gender, not emotion expression of faces. Although all these tools have a similar face detection algorithm based on neural networks, an important advantage of Azure API is its ability in facial detection with different head poses. Not all the images in our dataset are captured from a near frontal view, which is we choose Azure API over other available tools. Also, Azure API generates normalized, continuous scores for emotions, which makes it easier for relative comparison of emotion expressions[6]. Microsoft Azure API can detect the number of faces in an image and generate for each face in the image data about the individual's age, and a score between 0 and 1 indicating the proportion to which the facial expression in an image conveys each of the four emotions of happiness, sadness, anger and surprise. The details of how it works follows.

The algorithm to find the location of human faces in an image is part of object detection. All human faces share some common universal characteristics, for example the eyes region is darker than its neighboring pixels and the nose area is brighter than the eye region. Detection of eyes, nose etc. is supplemented with the help of edge detection, line and center detection. Azure API then specifies faceRectangle, which is the pixel coordinates for each face in an image

[6] The emotion scores from Google Cloud API and Amazon Rekognition are between 0-5 and 0-100 respectively.

indicating the location of the face. The faceRectangles in an image are the points of our interest in an image. For each faceRectangle, Azure identifies 27 face landmarks (key facial structures) that are helpful in extracting face attributes[7]. Figure 1 shows the face landmarks that Azure API uses. The algorithm to recognize facial emotions is based on the Facial Action Coding System (FACS) (Ekman and Friesen 1978) categories, called action units such as "Jaw Drop" and "Mouth Stretch". The different combinations of action units can reveal the type of emotion expression and its degree of intensity.

For each face in an image, Azure API generates a score for a list of emotions that sum to one. A normalized score for all the emotions translates to accounting for the simultaneous occurrences of different emotions, which enables us to capture the emotion expression in a continuous manner and not just a binary dominant emotion. As mentioned earlier, we use Microsoft Azure image processing API for every face of each uploaded image in our dataset to generate the scores of anger, happiness, sadness and surprise along with number of faces and age of people in each uploaded image. Figure 2 shows the facial features of a sample image extracted by Azure API.

[Figures 1-3 about here]

In addition to facial features, we measure image attributes such as blurriness and brightness to control for image quality and its color system (Li and Xie 2020). The algorithm for blurriness score is the variance of Laplacian method, which is based on detecting edges in an image. The objects in a non-blurry image have clear edges, which is why detecting objects in a non-blurry image is much easier than a blurry image with unclear edges. The outcome of the variance of Laplacian method indicates intensity changes between edge like and non-edge like regions of an

[7] https://docs.microsoft.com/en-us/azure/cognitive-services/face/concepts/face-detection

image. A high variance translates to clear edges and a normal image, and a low variance is an indicator of a blurry image[8] (Bansal et al. 2016). We use 100 as a threshold to determine the image blurriness, an image is considered a normal one if its variance of Laplacian is above 100 and otherwise is a blurry image[9]. Figure 3 shows examples of a non-blurry vs. a blurry image.

We also extract the color combination of an image. HSL (hue, saturation, lightness) and HSV (hue, saturation, value) were developed in the 1970s by computer graphics to describe colors (Hunt 2005). We use an algorithm based on HSL and HSV to capture the image brightness, which is a representation of an image three-color system (Ford and Roberts 1998; Bezryadin et al. 2007). Similar to Bezryadin et al. (2007), we use the length of the color vectors of red, green and blue to generate the brightness score using the formula in Equation 1[10]:

$$Image\ Brightness = \sqrt{.299 * Red^2 + .587 * Green^2 + .114 * Blue^2} \tag{1}$$

Thus, overall, by using Azure API along with other image processing techniques, we are able to generate measures of all four universal facial expressions of emotions and other image attributes in our empirical setup.

The independent variables of interest are the Azure average scores of anger, sadness, surprise and happiness[11] for all uploaded images at the project level. As one project can have multiple uploaded images and the Azure scores of emotions are extracted for each face in every image, we first convert these scores to the image level by taking their average across all the recognized faces in an image. We then aggregate those numbers to the project level by averaging across all the posted images of a project.

---

[8] https://github.com/indyka/blur-detection
[9] https://www.pyimagesearch.com/2015/09/07/blur-detection-with-opencv/
[10] http://alienryderflex.com/hsp.html
[11] Since Azure API over-represents the happiness scores, we re-scaled this variable in our empirical analysis, as described subsequently.

We also extract measures of the number of faces, age of people in the image and other image attributes such as brightness and blurriness of each uploaded image. The next step is to aggregate these scores, which are extracted for each image, to the project level since our data is a weekly-project panel. For all of these measures except blurriness, we use their average scores across all the uploaded images of a project in our empirical analysis. For the blurriness measure, we use the proportion of images for a project that are blurry, in other words we divide the number of blurry images by the total number of uploaded images for a project. In addition to image covariates, we include other control variables such as number of uploaded images, project's monetary goal, project creator's donation activity[12], which is total number of donations (s)he has made before creating the focal project, project's age since the launch date, and number of donors' comments associated with a project through week t.

To account for projects' textual differences, we control for both emotional and analytical appeals in project description. We measure both the volume of emotional content and the net valence, in addition to the proportion of analytical to emotional words in the project description. Linguistic Inquiry and Word Count (LIWC) is one of the popular text analysis tools used in the marketing literature (Li and Xie 2020; Ludwig et al. 2013). LIWC (Pennebaker et al. 2007) has a dictionary of words for different linguistic and psychological categories such as affect, analytic, and social, based on which it generates the proportion of words in a sample matching the list of words in a category. "Affect" measures the percentage of words in a sample containing either positive (e.g. happy, excited) or negative (e.g. angry, sad, anxious) emotions. We extract the "Affect" measure for each project description, representing the volume of emotions or the percentage of words in project description expressing any type of emotion.

[12] As a robustness check, our results stay consistent by adding project creator fixed effects to the model.

To get the net valence of emotions, we subtract the proportion of negative emotions from the proportion of positive emotions in a project description. Also to control for the project description structure being more analytical or emotional, we divide the proportion of extracted analytical words by the proportion of extracted affective words in the project description. For more details about the variables, Table 2 lists descriptive statistics and the pairwise correlations are in Web Appendix B.

[Insert Table 2 about here]

Our empirical estimation is based on a log-log model in Equation 2, with the dependent variable being total amount of donation contributed to project i at week t since the project launch. In our model, the project age and number of comments are updated at the end of each week after the launch date. To account for differences based on the time of donation, we include both year and month fixed effects in addition to project age:

$$\begin{aligned}\log(Weekly\_Donation\_Amount_{it}) \\ &= \beta_0 + \beta_1 \log(Project\_Age_{it}) \\ &+ \beta_2 \log(Project\_Comments_{it}) + \beta_3 \log(Project\_Goal_i) \\ &+ \beta_4 \log(Creator\_Activity_i) + \beta_5 \log(Av\_Anger\_Score_i) \\ &+ \beta_6 \log(Av\_Happy\_Score_i) + \beta_7 \log(Av\_Sad\_Score_i) \\ &+ \beta_8 \log(Av\_Surprise\_Score_i) + \beta_9 \log(Num\_Images_i) \\ &+ \beta_{10} \log(Num\_Faces_i) + \beta_{11} \log(Av\_Age\_Faces_i) \\ &+ \beta_{12} \log(Av\_Brightness_i) + \beta_{13} \log(Av\_Bluriness_i) \\ &+ \beta_{14} \log(Proj\_Descrp\_Volume\_Affect_i) \\ &+ \beta_{15} \log(Proj\_Descrp\_NetValence\_Affect_i) \\ &+ \beta_{16} \log(Proj\_Descrp\_Affect\_Analytic\_Ratio_i) + \tau_t + \varepsilon_{it}\end{aligned} \tag{2}$$

Endogeneity

Although accounting for project category and time fixed effects can control for some of the time invariant factors, there can be unobserved differences among project creators that explain why they select images with specific facial expressions of emotions, which can be a source of endogeneity. If so, our key measures of interest (Av_Anger_Score, Av_Happy_Score, Av_Sad_Score, and Av_Surprise_Score) may be endogenous, which might result in a correlation between the regressors and the error structure, biasing OLS estimates. We use the instrument variable (IV) method for endogeneity correction.[13] The intuition behind any choice of instruments is to have variables that are correlated with the facial emotion expression in the image but uncorrelated with the unobservable (ε_{it}) in Equation 2. As the instrument for each of the average emotion scores, we use the average score for the corresponding emotion used in the previously launched projects in the same donation context. The logic is that project creators are likely to browse past projects in the same category and be influenced by the facial expressions of emotions in the uploaded images of such past projects. The identifying assumption is that, conditional on project characteristics, donation context, etc., covariation between the current project's facial emotional expression and the previous ones is due to heterogeneity of project creators in exploring images of previous projects and not due to unobserved factors that might affect the donors' donation amounts of the current project.

Selection Bias

We observe that in our data, a majority of projects (45%) have images that are dominantly happy. Thus, it seems that a majority of project creators prefer happy images potentially leading to a selection bias, i.e., due to the over representation of happy emotion compared to other types of emotions in our sample, we need to prevent the effects of happy emotion from being over-estimated or the effects of other emotions to be under-estimated. We use a Heckman correction procedure (Heckman 1979) to control for the potential selection bias, i.e., we estimate the inverse

[13] We also try an alternate endogeneity correction using the control function approach. Our results remain consistent.

Mills ratio from a first stage probit that includes a binary dependent variable (1 if the project has images expressing happy emotion dominantly and 0 otherwise). We include the inverse Mills ratio in Equation 2. The details of the selection correction procedure and results of the first stage probit are described in Web Appendix C.

Results

In each of the four first stage equations of our 2SLS model, the dependent variable is the endogenous variable (average Azure score of one emotion type) and we have all the four instrument variables and exogenous variables from Equation 2 in the right-hand side of the equation. Before we estimate the first stage equations with instrumental variables and exogenous variables, we estimate the F-values of each of the first stage regressions with only the corresponding instrumental variables as independent variables. Each of the four F values are above 10. Next, we use both instrumental variables and exogenous variables as independent variables as shown in Table 3. We find that most of our instruments are statistically significant at the 95% confidence interval. Thus, we do not have a weak instrument problem.

[Insert Table 3 about here]

The second-stage estimation results (after using the predicted values of average emotion scores from the first stage) are presented in the first column of Table 4. The first key finding is that increasing the degree to which facial expressions in an image covey any of the four emotions has significant positive impact on donation amount per week, with sadness ($b = 2.425$, $p < .05$) having the biggest impact followed by anger ($b = .248$, $p < .01$), surprise ($b = .191$, $p < .05$) and happiness ($b =.112$, $p < .05$). Thus, we establish a rank order of multiple facial expressions of emotions such that happy facial expressions are not the only alternative to sad facial expressions. Instead, our results suggest that project creators may also use angry or surprised facial expressions in uploaded images than happy facial expressions in order to increase the dollar amounts raised. Given that project creators mostly tend to select images with happy expressions (about 45% of projects approximately), this finding suggests that the platform should advise future project creators against the use of only happy images. The second column of Table 4 shows the results of our model after accounting for both endogeneity and self-selection correction. We see consistent results for all the parameters across the two columns.

The control variables show expected results. For example, the older a project, the lesser donation it will get ($b = -.921$, $p < .01$), or projects with bigger monetary goals receive higher donations per week ($b = .28$, $p < .01$). Also, a project with an active creator who has contributed to other donation projects ($b = .082$, $p < .01$) or a popular project with a lot of comments has a high potential of receiving high donation amounts per week ($b = .311$, $p < .01$). Although neither number of uploaded images nor their brightness impacts donation amount, the average estimated age of the individuals in the project's image has a positive effect on donation amount per week ($b = .379$, $p < .01$). Also clarity of images matters, projects with blurry images receive less amounts of donation per week ($b = -.009$, $p < .01$). Further, among all three affect related variables of the project description (volume of affect words, net valence of affect words and ratio of analytic to affective words), we find that only net valence expressed in the project description matters, i.e., increase in positive relative to negative affect words used in project description leads to higher donation amount per week ($b = .042$, $p < .01$).

[Insert Table 4 about here]

Robustness Check - Does Alignment of Facial Emotion Expression in Image and Net Valence of Project Description Matter?

Given that in our estimation, we find significant effects of net valence of the project description on donation amount, it is possible that potential donors may consider the similarity between the specific emotion expressed in an image and the overall net emotion expressed in the project description. For example, a potential donor may be persuaded by a project that conveys a sad facial expression in the image and a sad project description more than a sad expression in the image and a happy or perhaps optimistic tone of the project description. In order to test for this, we interact each of the four average emotion scores of the images of a project with the net valence of the text or project description. We include the four interactions in Equation 2 and estimate the new model. We find that the direction and statistical significance of the four emotion expressions in images remains unchanged, and none of the interactions are statistically significant at the 95% confidence interval. This result suggests that potential donors are influenced by the facial emotion expressions in images independent of its relation to the emotion content of the project description.

Although empirical analysis helps us estimate the impact of facial emotion expressions in images on donation behavior after controlling for other variables, it does not assess the psychological mechanisms underlying the influence of facial expressions of emotions in images on donors. In the next section, we explain our experimental setup based on MTurk studies to understand the psychological process underlying donor behavior. This process also helps us validate the causal effects of the four facial expressions of emotions as well as their rank order of impact on donation amounts of projects.

STUDY 2 (Experiment to Test Process)

The aim of Study 2 is to test the causal relationship between facial emotion expressions in images (sadness, anger, surprise and happiness) and donation amount, and to examine whether this relationship is mediated by perceived empathy, perceived justice, and emotion contagion. To begin, we conducted a pre-test study to assess the reliability of our measures of the psychological constructs (perceived empathy, perceived justice, emotion contagion). Following the pre-test, we designed our main experiment using real images from gofundme.com. We first describe our pre-test followed by the main experiment.

Pretest

In the pre-test, we create four conditions or projects such that the projects differ only in the facial emotion expression in the image and not the project description. Thus, we conduct the pre-test in a controlled fashion and use the images of one person posed with different emotion expressions. To do a robust manipulation check of facial emotion expressions, we add a neutral condition in addition to the four conditions of happy, sad, angry and surprise. We ensured that the Azure score extracted for each image was dominant in one specific emotion (i.e., happy image has a Azure score of at least .5 for happiness, sad image has Azure score of at least .5 for sadness, angry image a score of at least .5 for angry, surprise image has Azure score of at least .5 for surprise). Azure also provides scores for neutral emotions, thus the neutral image has an Azure score of at least .5 for neutral emotion).

We created our own project text to describe the situation and why the victim needs donation, which was neutral in emotion (i.e., did not contain any emotion word). The same project description was used with every image. Figure 4 shows the stimuli used for each of the five conditions in the pre-test.

[Insert Figure 4 about here]

A sample of 91 participants (M_{age} = 31.4 years, 49.1% female) from Amazon Mechanical Turk (out of an initial 120) who passed attention checks participated in the survey for payment. Participants were randomly assigned to see one of five images dominant in either happiness, sadness, anger, surprise, or neutral, followed by a text describing the situation.

Perceived empathy. The first section of the survey measured participants' perceived empathy after they viewed the image and read the descriptions. There is consistent agreement among researchers about perceived empathy measures. Coke et al. (1978) used eight measures of sympathetic, empathic, concerned, moved, compassionate, warm, softhearted, and tender to measure empathy. Similarly, Batson (1983) and Lee et al. (2014) used six measures of sympathetic, moved, compassionate, warm, softhearted, and tender. We borrow all the eight items used by Coke et al. (1978) in our survey; each participant reported the degree to which they felt the six feelings toward the donation target (1="Not at all" and 7="Extremely"). Factor analysis reveals that five of the items (sympathetic, empathic, concerned, compassionate, and softhearted) load highly on one factor (.77 or higher), and Cronbach's alpha for these five items is .89. Thus, we used these five items for our empathy scale[14].

Perceived justice. In the second section of the survey, participants were asked about measures of perceived justice. We use a total of eight measures, two of which are adapted from the consumer behavior literature (e.g., Chen et al. 2014) and represent the potential donor's or respondent's perceptions about themselves being fair and just in understanding the donation target's situation. The remaining six items are adapted from the organizational behavior literature on inter-firm trust and goodwill. Two of these items represent the extent to which the explanations for donation request in project description are reasonable, thorough, fair and appropriate explanations of the individual's need for donation (Bies 1986, Shapiro et al. 1994, Maxham et al. 2002, Leventhal 1976). The remaining two items represent the extent to which the potential donor or respondent believes that the individual requesting donation will benefit from the donation (Folger and Konovsky 1989, Leventhal 1976).

[14] As a robustness check, we got similar results in Study 2 by using all eight items for the empathy scale.

Eight items were used to measure perceived justice, rated the items on a 7 point scale (1 = *Strongly Disagree*; 7 = *Strongly Agree*). The items include (1) "I support donating to this individual to be fair", (2) "I support donating to this individual to be just", (3) "Has the individual's condition begin described thoroughly?", (4) "Is the explanation regarding donation request reasonable?", (5) "Given the description of the individual, I think it is appropriate to ask for donations", (6) "Given the inconvenience suffered by the individual, request for donations is fair", (7) "Given the hassle suffered by the individual, I should respond fairly and quickly", and (8) "Although the individual is in a difficult state right now, I think donations will result in a very positive outcome for the individual".

Factor analysis reveals that four of the items (fair, just, thorough explanation of the situation, and need of a fair and quick reaction to the situation) load highly on one factor (.73 or higher), and Cronbach's alpha for these four items is .87. Thus, our final measure of perceived justice includes these four items.

Emotion contagion. In the third section of our pre-test, we measure the impact of facial emotion expression on participant's own feelings. Similar to Small and Verrochi (2009), we use the three items of sad, upset, and depressed to measure sadness contagion and we use happy, excited, and enthusiastic to measure happiness contagion. We use angry, furious, and resentful for anger, and surprised, unexpected, and amazed for surprise. Each participant reported their feelings after looking at the donation target (1="Not at all" and 7="Extremely"). Factor analysis shows that the three items for each emotion load highly on one factor (.82 or above), and Cronbach's alpha for happy, sad, angry and surprise items are .90, .92, .89, and .81, respectively.

Main Study Procedure

In this study, we explore if perceived empathy, perceived justice, or emotion contagion mediate the effect of facial emotion expression on the amount of donation that the project receives. In this study, we use images that are uploaded on the Gofundme website. We choose a random sample of 100 images that are dominant in either happiness, sadness, anger, surprise or neutral from our Godundme image database. As in the pretest, an image is dominant in either happiness, sadness, anger, surprise or neutral if the Azure score for the corresponding emotion is greater than 0.5. Then, we design five conditions of happy, sad, angry, surprise and neutral using an image dominant in the emotion and its corresponding project description from Gofundme.com narrating the situation and why the victim needs donation. A sample of the five conditions is described in figure 5.

[Insert Figure 5 about here]

A sample of 901 participants (M_{age} = 33.2 years, 42.8% female) from Amazon Mechanical Turk (out of an initial 1,170) who passed attention checks participated in the survey for payment. In this between-subject study, participants were randomly assigned to see two images in one of the five conditions of happy, sad, angry, surprise or neutral (Neutral is control vs. Happy vs. Sad vs. Angry vs. Surprise). They were asked to look at the image, read its description and then answer five sets of questions: (1) the amount willing to donate, followed by (2) perceived empathy measures, (3) perceived justice measures, (4) perceived emotions, and (5) emotion contagion measures.

The first part of the questionnaire asked participants how much they would donate (1=$0, 7= More than $200[15]). In the second part, participants reported their perceived empathy toward the donation target (1=”Not at all” and 7=”Extremely”) based on the five items from the reliability

[15] 1=$0, 2=Less than $10, 3= $11-$34, 4=$35-$59, 5=$60-$89, 6=$90-$199, 7= More than $200

test in the pre-test (sympathetic, empathic, concerned, compassionate, and softhearted). Subsequently, participants indicated their perceived justice for the donation target (1 = *Strongly Disagree*; 7 = *Strongly Agree*) based on the four items from the pre-test (fair, just, thorough explanation of the situation, and need of a fair and quick reaction to the situation). Next, we measure emotion contagion or participants' emotions after looking at the donation target (1="Not at all" and 7="Extremely"), for which we use all three items for each emotion that we used in the pre-test. At the end, respondents reported their perception of the facial emotion expression in the image. These latter questions serve as a manipulation check that the respondent's perception of the facial emotion in the image matched the target emotion condition (e.g., how much the image looks happy, sad, angry, or surprised (1="Not at all" and 7="Extremely")).

Results

Perceived emotions manipulation check. Although we use the emotional scores from Azure API for the analysis, we ask participants about what emotion the face in the image conveys as a manipulation check. The results indicate that the perceived happiness level of a happy image (M_{Happy} = 5.39, SD = 1.43) is more than a sad (M_{Sad} = 3.14, SD = 2.01, p <.001), an angry (M_{Angry} = 3.09, SD = 1.97, p <.001), a surprise ($M_{Surprise}$ = 4.87, SD = 1.57, p <.05) and a neutral ($M_{Neutral}$ = 3.16, SD = 1.73, p <.001) image. Analogously, the perceived sadness level of the sad image (M_{Sad} = 5.29, SD = 1.61) is more than of a happy (M_{Happy} = 3.25, SD = 1.99, p <.001), an angry (M_{Angry} = 4.52, SD = 1.68, p <.001), a surprise ($M_{Surprise}$ = 3.77, SD = 1.92, p <.001) and a neutral image ($M_{Neutral}$ = 3.98, SD = 1.67, p <.001). Similarly, the perceived surprise level of a surprised image ($M_{Surprise}$ = 5.06, SD = 1.64) is greater than of a happy (M_{Happy} = 3.43, SD = 2.00, p <.001), a sad (M_{Sad} = 3.43, SD = 1.97, p <.001), an angry (M_{Angry} = 3.06, SD = 1.98, p <.001) and a neutral image ($M_{Neutral}$ = 3.01, SD = 1.83, p <.001). Finally, the perceived angry levels of an angry image

(M_{Angry} = 5.19, SD = 1.97) is greater than of a happy (M_{Happy} = 3.13, SD = 2.03, p <.001), a sad (M_{Sad} = 3.28, SD = 1.97, p <.001), a surprise ($M_{Surprise}$ = 3.55, SD = 2.01, p <.001) and a neutral image ($M_{Neutral}$ = 3.26, SD = 1.94, p <.001).

Donation amount. First, we need to see if emotion of any type can result in a greater donation intention compared to a neutral condition. Results of a one-way ANOVA (Neutral: control vs. Happy vs. Sad vs. Angry vs. Surprise) confirm that the four conditions with any facial emotion expression have higher donation intentions than the neutral condition ($F(4,1800)=6.02$, p <.001). Looking at donation amount, participants in the sadness condition contribute larger donations (M_{Sad} = 3.83, SD = 1.59), followed by angry (M_{Angry} = 3.17, SD = 1.71, p <.001), surprise ($M_{Surprise}$ = 2.92, SD = 1.69, p <.001), happy (M_{Happy} = 2.52, SD = 1.64, p <.001) and neutral ($M_{Neutral}$ = 1.86, SD = 1.61, p <.001). Note that this is the same ordering that we find in our Gofundme analysis in Study 1.

Mediation analysis. We test whether perceived empathy, perceived justice or emotion contagion mediate the effects of facial emotion expression on donation amount. Since our dependent variable, donation amount, is a discrete count variable that can take values of zero, we use zero-inflated negative binomial regression for the mediation analysis[16]. We present direct, indirect and total effects in Table 5. We find that perceived justice significantly mediates the effects of all four facial emotion expressions, while perceived empathy and emotion contagion significantly mediate only two facial emotion expressions: surprise and happy.

Looking at the mediation paths for each facial emotion condition, we find that all four emotions have a positive significant impact on perceived justice ($b_{Happy\ vs.\ Neutral}$= .073, SD= .021, p <.01; $b_{Sad\ vs.\ Neutral}$= .236, SD= .007, p <.01; $b_{Surprise\ vs.\ Neutral}$= .202, SD= .042, p <.01;

[16] The results of our parallel mediation analysis are robust using PROCESS Model 4 (Hayes 2017).

$b_{Angry\ vs.\ Neutral}$= .241, SD= .009, p <.01), perceived empathy ($b_{Happy\ vs.\ Neutral}$= .182, SD= .053, p <.01; $b_{Sad\ vs.\ Neutral}$= .259, SD= .065, p <.01; $b_{Surprise\ vs.\ Neutral}$= .318, SD= .009, p <.01; $b_{Angry\ vs.\ Neutral}$= .306, SD= .011, p <.01), and emotion contagion ($b_{Happy\ vs.\ Neutral}$= .364, SD= .054, p <.01; $b_{Sad\ vs.\ Neutral}$= .481, SD= .008, p <.01; $b_{Surprise\ vs.\ Neutral}$= .296, SD= .073, p <.01; $b_{Angry\ vs.\ Neutral}$= .388, SD= .086, p <.01). Perceived justice has a significant positive path to donation amount in all the four conditions ($b_{Happy\ vs.\ Neutral}$= .204, SD= .009, p <.01; $b_{Sad\ vs.\ Neutral}$= .483, SD= .063, p <.01; $b_{Surprise\ vs.\ Neutral}$= .144, SD= .019, p <.01; $b_{Angry\ vs.\ Neutral}$= .133, SD= .020, p <.01). However, perceived empathy has a significant effect on donation amount only in the happy and surprise conditions ($b_{Happy\ vs.\ Neutral}$= .045, SD= .028, p = .054; $b_{Sad\ vs.\ Neutral}$= -.02, SD= .035 p = .284; $b_{Surprise\ vs.\ Neutral}$= .066, SD= .009, p <.01; $b_{Angry\ vs.\ Neutral}$= .013, SD= .129, p = .450), as does emotion contagion ($b_{Happy\ vs.\ Neutral}$= .011, SD= .003, p <.01; $b_{Sad\ vs.\ Neutral}$= -.008, SD= .012, p = .253; $b_{Surprise\ vs.\ Neutral}$= .027, SD= .005, p <.01; $b_{Angry\ vs.\ Neutral}$= .057, SD= .157, p = .358). We also did an omnibus mediation analysis replicating this analysis (see Web Appendix D).

[Insert Table 5 about here]

Validation for rank order of effects. The results for empirical analysis Study 1, reported in Table 4 and experimental Study 2 reported in Table 5 exhibit the same rank ordering for the impact of facial emotion expressions on donation amount. Table 4 shows that sadness emotion expressed in the image has the biggest impact on donation amount ($b_{Sad\ vs.\ Neutral}$ = 2.425, p < .05), followed by angry ($b_{Angry\ vs.\ Neutral}$= .248, p < .01), surprise ($b_{Surprise\ vs.\ Neutral}$ = .191, p < .05) and happy ($b_{Happy\ vs.\ Neutral}$ = .112, p < .05) emotions. Table 5 shows the total impact of facial emotion expression on donation amount, which is the summation of direct and indirect effects of facial emotion expression on the dependent variable. We find the biggest effect in the case of sad images ($b_{Sad\ vs.\ Neutral}$ = .069, p < .01), followed by angry ($b_{Angry\ vs.\ Neutral}$ = .037, p < .01), surprise ($b_{Surprise\ vs.\ Neutral}$ = .010, p < .01) and happy ($b_{Happy\ vs.\ Neutral}$ = .008, p < .01) images. Thus, in both our empirical and experimental studies, we find that sadness has the highest impact on donation amount whereas happiness has the lowest impact on donation amount.

In the next study, we create a completely controlled setting such that both images and project descriptions are created by us instead of using real images and project descriptions from Gofundme.com. We seek to replicate not only the rank order of effects of facial emotion expressions but also to quantify the gain in donation amount if a facial emotion expression lower in the rank order is replaced by a facial emotion expression higher in the rank order. With quantifiable outcomes, we seek to provide actionable implications for managers of online donation platforms.

STUDY 3 (Follow-up Experiment)

Procedure

The purpose of this study is to see how much the donation amount will change by replacing one type of facial emotion expression with another. To answer this question, we run the study in a more controlled fashion than before so that surveys include the images from the same person and differ only in the expressed emotion in the image and all other attributes are the same. Unlike Study 2, where we chose a sample of images from our Gofundme database, in this study we choose four images of happy, sad, angry, and surprise from the same person[17]. So, the four conditions of happy, sad, angry and surprise are only different in the facial emotion expressed in the images. In

[17] Our results are robust when either selecting images from a female or a male person.

order to control for other possible differences between the four conditions, we use images from the same person with the same image attributes (except the expressed emotion), the same project description, and also we ask participants about their donation willingness given a specific amount instead of an open-ended question. All the selected images show dominance in either happiness, sadness, anger, or surprise based on their Azure score.

A sample of 280 participants (M_{age} = 33.6 years, 51.3% female) from Amazon Mechanical Turk (out of an initial 310) who passed attention checks participated in the survey for payment. Participants were randomly assigned to see one of four images dominant in either happiness, sadness, anger, or surprise followed by a text describing the project. Figure 6 shows a sample of the images used in Study 3.

[Insert Figure 6 about here]

Participants were asked to look at the image, read the description and then answer the question "If you are given $200 to donate to this situation, how much will you donate?" To measure how much they would donate, we used a slider ranging from 0 to 200[18].

Results

To investigate the changes in donation amount if we replace one type of facial expression with another, we look at differences in donation amount between any two combinations of conditions. For example, participants in the sad condition are willing to donate 6.4% (SD= 2.11, p <.01) more than the participants in the happy condition. In other words, replacing a project with happy dominant images with sad images will lead to an average of 6.4% greater donation from each donor.

[18] As a robustness check, we got similar results using categorical measures (1= $0, 2= Less than $25, 3= $26-$50, 4= $51-$75, 5= $76-$100, 6= $101-$125, 7= $126-$150, 8= $151-$175, 9= $176-$200).

To make meaningful interpretations at the platform (Gofundme) level, we use some insightful numbers from our empirical dataset. A project with dominantly happy images has on average 41 donors and each donor contributes an average of $91.6, or in total $3,755.6. The results from Study 3 shows that if we replace a happy image with a sad one, each donor will contribute on average $97.46 ($91.6 + %6.4) and the total donation amount to the project will be about $3,996 which is $240.4 more than before replacement (we assume number of donors to remain the same before and after the replacement[19]). To translate this calculation to the platform level, we need to multiply it by the number of projects with happy-dominant images (11,571 out of 25,321 projects in our sample). Considering the platform fee of 2.9% of transaction value, Gofundme's revenue will increase by $80,668.4 after replacing all the happy-dominant images with sad ones.

We did similar calculations for other replacement conditions of surprise with sad, angry with sad, surprise with angry, happy with angry and happy with surprise in Table 6. We also repeated the study using the Prolific participant pool (see Web Appendix E).

[Insert Table 6 about here]

GENERAL DISCUSSION

Crowdfunding platforms are a popular way of fundraising for individuals and entrepreneurs with financial need. Exploring the factors that contribute to the amount raised is important not only for campaign creators but also for platform managers since platform revenue is dependent on the contributed donation amount. Since prior research has focused on campaigns' textual characteristics, mainly emotional appeals, we know little about the impact of image attributes, especially facial emotion expressions on campaign's success. Using a multi-method approach, we

[19] To confirm this assumption, the results from experiments show similar percentage of participants who choose not to donate (5% in either happy, sad or surprise and 6.3% in angry condition).

offer insights into the interplay between facial emotion expression in images and contributed donations in a crowdfunding platform. In our empirical Study 1, after controlling for both time-varying and project-varying variables, we find that increasing the degree to which facial expressions in an image convey any of the four facial expressions of emotions (i.e., sad, anger, surprise and happy) has a positive impact on the weekly donation amount per project compared to a neutral image. Also, the effect of emotions follows a distinct rank order such that sadness has the largest positive effect on donation amount, followed by anger, surprise and happiness respectively. Our results hold across the five most popular categories used by Gofundme.

To assess the underlying process, experimental Study 2 uses a random sample of real projects and their associated images extracted from Gofundme to see if perceived empathy, perceived justice, and emotion contagion mediate the impact of facial emotion expression on donation amount. Building on prior studies that show that facial emotion expressions influence donors via emotion contagion and perceived empathy (e.g., Small and Verocchi 2009), we find that perceived justice is the most dominant mediator in all four emotion conditions of surprise, angry, happy and sad images, while perceived empathy and emotion contagion are mediators only in the case of surprise and happy images. This finding is important because it suggests that independent of the emotions they trigger, images do influence the way donors consider the person's situation as worthy of a donation. Thus, there is a cognitive dimension to the psychological mechanisms through which facial emotion expressions in images influence donor behavior.

Finally, a crowdfunding platform could benefit from the rank order established in the first and second studies if we are able to indicate the dollar amount increase in donation amount per donor when a specific facial emotion expression in a posted image is replaced by a different facial emotion expression. For this purpose, we run a third study controlling for possible differences among donation projects except the facial emotion expressions in images, which we manipulate. Among other results, we find that replacing a happy expression with a sad expression increases the donation amount per donor by 6.4%, which at the project level aggregates to approximately $240 additional donation dollars. These gains in donation amounts could increase platform revenue by $80,667 because crowdfunding platforms are monetized by charging a percentage of the total amount raised by a project as the platform fee. We also find that replacing a happy expression with an angry expression generates 5.76% additional dollars per donor, which at the platform level aggregates to approximately $72,580.94 additional revenue.

Managerial Implications

Our findings offer various practical implications both for campaign/project creators and donation platform managers. First, project creators should bear in mind that prospective donors go through the posted images and are responsive to the emotions expressed in those images. Second, project creators should be aware that their campaign's success depends on the type of facial emotion shown in the images. Images dominant in sadness lead to highest donated contributions followed by angry, surprise and happy emotions. Thus, the main suggestion for project creators is that all the posted images are not considered the same in the eyes of a potential donor and being selective in the type of expressed facial emotions can help the campaign's success.

Finally, understanding the relative importance of facial emotion expressions in images can help donation platform providers manage their revenue more strategically. In our third study, we show the magnitude of changes in platform revenue in different scenarios. The two scenarios with the biggest change in the platform revenue are replacing happy images with sad or angry images. Given the current dominance of happy facial expressions in images uploaded in donation platforms such as Gofundme.com and Fundly.com, replacing those images with facial emotion expressions of sadness or even anger can strategically make a large change in the platform revenue. Also, platform managers can provide such tips to campaign creators to increase their campaign prosperity overall.

Limitations and Future Research

In conclusion, this study provides an initial step toward understanding the effects of imagery facial emotion expressions on consumer decision-making in a crowdfunding context with the use of an AI algorithm. While our study provides several contributions to research and practice, we acknowledge limitations, which are also avenues for future research. First, our dataset includes donation history for only five campaign types (charity, education, memorial, medical and emergencies). However, there are a variety of other kinds of fundraising domains related to animals, business, sports and COVID currently. Future work could examine similar effects in these significant donation domains. Second, we do not have data on donor heterogeneity in our empirical setup in terms of their demographics, background, and closeness to the campaign creator. Future research may benefit from exploring how the impact of facial emotion expressions in images on donation behavior varies across different strata of donors. Another approach for future studies would be to consider the heterogeneity among campaign creators based on the size or the privacy settings of their social network.

Table 1: Summary of Research works regarding the Role of Emotion Expression in Prosocial Behavior

Article	Emotion Expression in Text	Emotions in Facial Expressions	Number of emotions	Crowd Funding Platform	Heterogeneity of Effects	Findings
Bagozzi and Moore 1994	✓	NA	Sadness	NA	NA	Negative emotions in public ads can stimulate empathic reactions leading to more donations.
Marchand and Filiatrault 2002	✓	NA	Fear	NA	NA	Fear-based messages are more effective than other message strategies in AIDS prevention intentions
Vitaglione and Barnett 2003	✓	NA	Anger	NA	NA	Empathic anger has positive effect on helping the victim.
Hibbert *et al.*, 2007	✓	NA	Guilt appeals	NA	NA	Guilt arousal is positively related to donation intention.
Fisher et al. 2008	✓	NA	Positive versus negative	NA	NA	Valence of emotional appeals, either positive or negative, as expressed in verbal dialogue or text impacts funding for public television charity ads
Lwin and Phau 2014	✓	NA	Existential Guilt	NA	NA	Existential guilt (result of a comparison btw one's well-being and others') results in more donation to a charity.
Cockrill and Parsonage 2016	✓	NA	Neutral, positive and shocking ads	NA	NA	Using strong negative emotional appeals in charity ads is much less effective than using positive emotions of interest and surprise.
Liang et al. 2016	✓	NA	Positive emotion of strength	NA	NA	Using positive strength along with sadness persuades people to donate more than using only either of these emotions.
Majumdar and Bose 2018	✓	NA	Negative appeals	NA	NA	Rational characteristics of charity requests are more persuasive than emotional content in making people send a pizza online to someone who needs it.
Small and Verrochi 2009	NA	✓	Happy, sad and neutral faces	NA	NA	Sadness becomes contagious to donors when seeing sad children's faces than happy or neutral faces, persuading them to sympathize more with the victim and making more donations.
Our Study	✓ (Control)	✓	Four universally recognized emotions in facial expressions	✓	✓	All the four emotions of happy, sad, anger and surprise impact donation behavior through different mechanisms.

Table 2: Descriptive Statistics

Variable	Definition	Mean	St. Dev.
$Weekly\ Donation\ Amount_{it}$	Donation amount of project i in week t	\$808.9	5,211.2
$Project\ Age_{it}$	Number of weeks since project i was launched till week t	16.4	25.6
$Project\ Comments_{it}$	Number of comments for project i in week t	1.2	.473
$Project\ Goal_{i}$	Monetary goal of project i	\$28,319.3	48,495.5
$Creater.Activity_{i}$	Total number of previous donations of project i's creator	1.8	10.14
$Av.Anger\ Score_{i}$	Average Azure anger score for all posted images of project i	.19	.23
$Av.Happy\ Score_{i}$	Average Azure happiness score for all posted images of project i	.57	.4
$Av.Sad\ Score_{i}$	Average Azure sadness score for all posted images of project i	.29	.16
$Av.Surprise\ Score_{i}$	Average Azure surprise score for all posted images of project i	.23	.27
$Num.Images_{i}$	Number of posted images of project i	2.7	6.03
$Num.Faces_{i}$	Number of faces in all the posted images of project i	1.93	1.44
$Av.Age.Faces_{i}$	Average age of people in all the posted images of project i	30.9	14.7
$Av.Brightness_{i}$	Average brightness of all the posted images of project i	115.6	25.5
$Av.Bluriness_{i}$	Average percentage of blurriness for all the posted images of project i	.19	.32
$Proj.Descrp.Volume.Affect_{i}$	Percentage of affective words in description of project i	5.6	2.5
$Proj.Descrp.NetValence.Affect_{i}$	Sentiment of affective words in description of project i	2.6	2.5
$Proj.Descrp.Affect.Analytic.Ratio_{i}$	Ratio of analytic to affective words in description of project i	17.01	14.4

Table 3: First-Stage Instrument Variable Analysis

DV= Endogenous Variable	Avg. Angry Score	Avg. Happy Score	Avg. Sad Score	Avg. Surprise Score
Angry_ Instrument. Variable	.179 *** (.0242)	-.041 (.067)	.077 ** (.028)	-.017 (.038)
Happy_ Instrument. Variable	-.011 (.0137)	.539 *** (.038)	-.037 * (.021)	.019 (.022)
Sad_ Instrument. Variable	.005 (.009)	.013 (.026)	.145 *** (.015)	-.054 *** (.015)
Surprise_ Instrument. Variable	.139 *** (.015)	-.066 (.055)	-.132 *** (.024)	.384 *** (.024)
Exogenous Variables	Yes	Yes	Yes	Yes
Project Category Fixed Effect	Yes	Yes	Yes	Yes
Year and month Fixed Effect	Yes	Yes	Yes	Yes
R-Squared	.1258	.1586	.1152	.0966
Number of Observations	423,895	423,895	423,895	423,895

*** p<0.01; ** p<0.05; * p<0.1, Standard errors in parentheses

Table 4: Results with Endogeneity/Self-selection Correction

DV= Log(Weekly Donation Amount)	Endogeneity Correction	Endogeneity and Selection Correction
Avg. Anger Score	.248 *** (.014)	.282 ** (.123)
Avg. Happy Score	.112 ** (.047)	.101 ** (.140)
Avg. Sad Score	2.425 ** (.085)	2.401 *** (.085)
Avg. Surprise Score	.191 ** (.085)	.177 ** (.085)
Project_ Age	-.921 *** (.005)	-.922 *** (.005)
Project_ Goal	.280 *** (.004)	.252 *** (.006)
Creator_ Activity	.082 *** (.007)	.087 *** (.007)
Project_ Comments	.311 *** (.101)	.317 *** (.101)
Num_ Images	-.089 (.099)	-.085 (.091)
Avg. Age Faces	.379 *** (.021)	.377 *** (.021)
Num_ Faces	.079 ** (.031)	.085 ** (.041)
Avg. Brightness	.047 (.062)	.061 (.066)
Avg. Blurriness	-.009 *** (.002)	-.009 *** (.003)
Proj_Descrp_Volume_Affect	.014 (.013)	.010 (.013)
Proj_Descrp_NetValence_Affect	.042 *** (.008)	.042 *** (.008)
Proj_Descrp_Affect_Analytic_Ratio	.010 (.009)	.009 (.009)
Inverse Mills Ratio		2.637 *** (.433)
Project Category Fixed Effect	Yes	Yes
Year and month Fixed Effect	Yes	Yes
R-Squared	.4535	.4535
Number of Observations	423,895	423,895

*** $p<0.01$; ** $p<0.05$; * $p<0.1$, Standard errors in parentheses

Table 5: Mediation Results

Mediation Analysis of Azure score on Donation Amount	**Angry**	**Surprise**	**Sad**	**Happy**
Direct effect of X on Y	-.013 (.024)	-.049*** (.021)	-.036*** (.017)	-.022*** (.007)
Indirect effect of X on Y through perceived empathy	.004 (.004)	.021*** (.072)	-.005 (.023)	.008*** (.003)
Indirect effect of X on Y through perceived justice	.032*** (.005)	.029*** (.009)	.114*** (.044)	.015*** (.006)
Indirect effect of X on Y through emotion contagion	.022 (.041)	.008*** (.003)	-.004 (.052)	.004*** (.001)
Total effect of X on Y	.037*** (.009)	.010*** (.003)	.069*** (.022)	.008** (.005)

*** p<0.01; ** p<0.05; * p<0.1, Standard errors in parentheses

Table 6: Platform Revenue Change for Different Image Replacement Scenarios

Replacement Scenarios	Percentage Change in Average Donation Amount per Donor	Approximate Change in Platform Revenue ($)
Replacing Happy with Sad	6.40 *** (2.11)	80,668.4
Replacing Surprise with Sad	1.97 *** (.52)	5,473.01
Replacing Angry with Sad	0.60 (1.41)	703.13
Replacing Surprise with Angry	1.36 *** (.23)	3,771.32
Replacing Happy with Angry	5.76 *** (2.59)	72,580.94
Replacing Happy with Surprise	4.34 *** (1.93)	54,726.03

*** p<0.01; ** p<0.05; * p<0.1, Standard errors in parentheses

Figure 1: Face Landmarks used by Microsoft Azure Emotion Recognition API

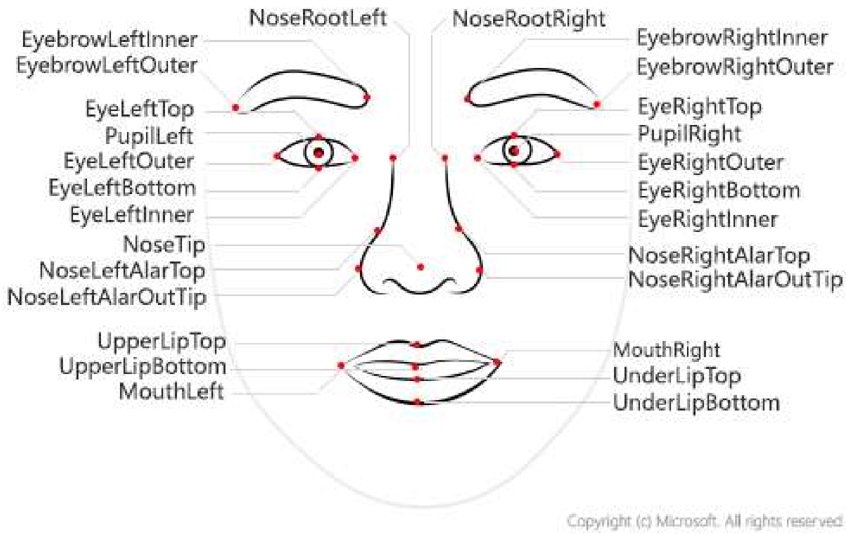
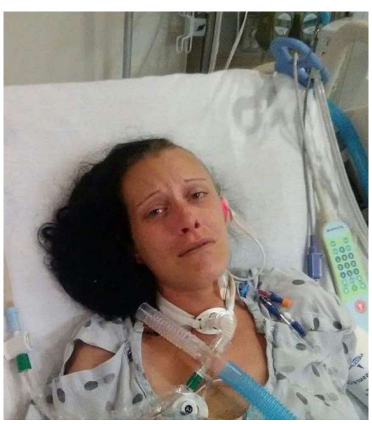


Figure 2: An Example of Azure API Scores for Facial Emotion Expressions



Number of faces: 1

Age: 33

Happy: 0.004

Sad: 0.845

Anger: 0

Surprise: 0

Neutral: 0.146

Figure 3: Examples of a Non-Blurry and a Blurry Image
(https://www.pyimagesearch.com/2015/09/07/blur-detection-with-opencv/)

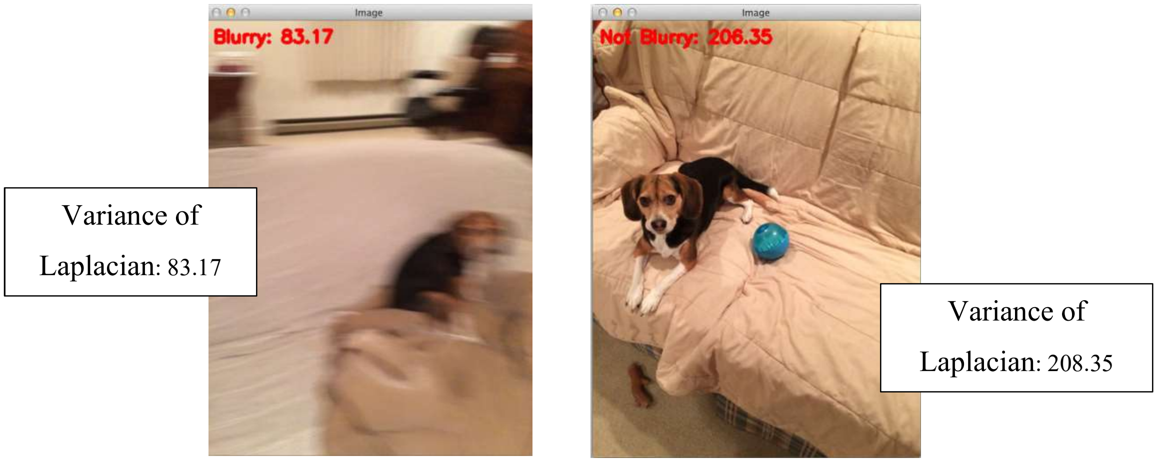


Figure 4: Stimuli used in the pre-test for happy, sad, angry, surprise and neutral conditions

Each pre-test condition includes the below description with only one of the following images

"Tania's Brain Cancer Fight"

Tania was diagnosed with Brain Cancer few months ago. Tania is currently unemployed and struggling to make ends meet. Please help us raise money to assist with her expenses during this time.

Figure 5: A Sample from *Gofundme* of Five Conditions for the Mediation Analysis

Happy Condition

Noah Smith Jr. Memorial
We lost Noah at a very young age. Noah was my brother-in-law, a close friend, and very close to his family. He touched the lives of so many people. I've started this donation to help support his family and the funeral costs. Please keep the all of Noah’s loved ones in your prayers. Thank you for any help.

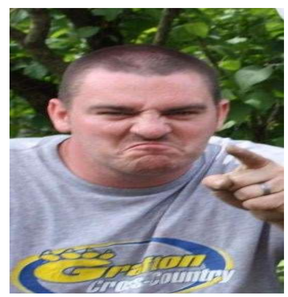
Sad Condition

In Loving Memory of Emma Miller
For we know that when this Earthly tent we live in is taking down, we will have a house in heaven, and internal body made for us by God himself and not by human hands. My mom, Emma left us just few days ago. We want to thank you all for the love and prayers. We also appreciate any donation toward her funeral expenses.

Surprise Condition

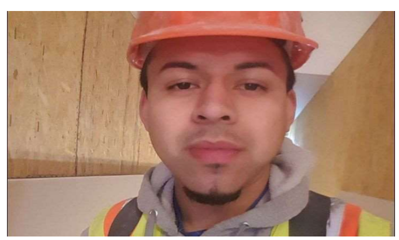
In Loving Memory of Ben
My best friend, Ben passed away just few days ago. Ben was a great son, brother, cousin and friend with a spirit. We would like to have a memorial service surrounded by family and friends who loved him. With this event that none of us would have ever thought we are for donations. Any amount is truly appreciated.

Angry Condition



James Brown Memorial Fund
Today we suddenly lost a family member. James Brown, 38, went to be with the Lord this morning. We lost our heart today. James was a nurturer to his family who meant the absolute world to him. We hope he rests in peace. We would like to help the family defray as much of the cost as possible when they lay him to rest. Every little bit counts, Thanks for your support.

Neutral Condition



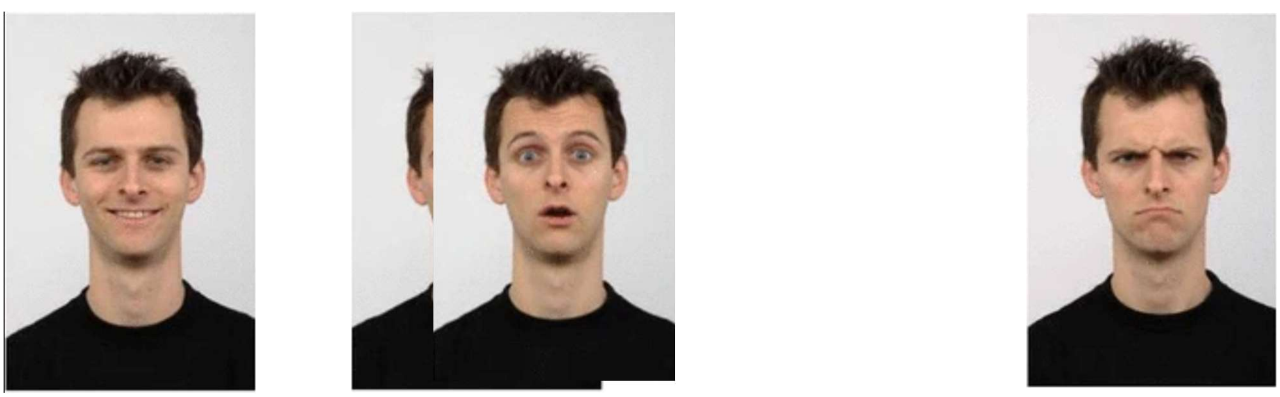
Carlo’s Funeral Expenses
We lost a great son, brother, cousin and friend. We would like to have a memorial service surrounded by family and friends who knew and loved him. With this event that none of us would have ever thought we are asking anyone who feels prompted in donating to make this possible. Any amount is truly appreciated, no donation is too small.

Figure 6: Stimuli used in Study 3 for happy, sad, angry, and surprised conditions

Each condition includes the description below with only one of the following images

"Help for Jake Harper's Funeral and Family"

Last week we received a phone call that no one wants to receive. Our brother, Jake Harper, was taken from this Earth unexpectedly in a car accident. Jake was the primary support of his family finances. He worked hard to give the family what he could provide. Jake was always the first one to step up to help anyone in need. Jake is without life insurance, and at this time we need help gathering funds for his funeral. We ask for donations to give him the memorial he deserves, to honor his memory, and to say our goodbyes. Please consider donating any amount, as any amount will help our family during this difficult time. Any raised amount left after paying the funeral cost will go to Jake's wife and his two young children. Jake cared for his children's education. The least we can do is helping his wife with their children's long-term education expenses.



REFERENCES

Adams, J. Stacy (1963), "Towards an Understanding of Inequity," *Journal of Abnormal and Social Psychology*, 67 (5), 422-436.

Bagozzi, Richard P., and David J. Moore (1994), "Public Service Advertisements: Emotions and Empathy guide Prosocial Behavior," *Journal of Marketing*, 58 (1), 56-70.

Bansal, Raghav, Gaurav Raj, and Tanupriya Choudhury (2016), "Blur Image Detection using Laplacian operator and Open-CV." *International Conference System Modeling & Advancement in Research Trends (SMART*), IEEE.

Bartlett, M. S., Hager, J. C., Ekman, P., & Sejnowski, T. J. (1999), "Measuring Facial Expressions by Computer Image Analysis." *Psychophysiology*, 36(2), 253-263.

Batson, C. D., O'Quin, K., Fultz, J., Vanderplas, M., & Isen, A. M. (1983). Influence of Self-Reported Distress and Empathy on Egoistic versus Altruistic Motivation to help. *Journal of Personality and Social Psychology*, 45(3), 706.

Batson, Daniel C., Tricia Klein, Lori Highberger & Laura L. Shaw (1995), "Immorality from Empathy-induced Altruism: When Compassion and Justice Conflict," *Journal of Personality and Social Psychology*, 68(6), 1042.

Barnes, Richard D., William Ickes, and Robert F. Kidd (1979), "Effects of the Perceived Intentionality and Stability of another's Dependency on Helping Behavior," *Personality and Social Psychology Bulletin*, 5 (3), 367-372.

Bezryadin, Sergey, Pavel Bourov, and Dmitry Ilinih (2007), "Brightness Calculation in Digital Image Processing," *International Symposium on Technologies for Digital Photo Fulfillment*, 2007 (1), 10-15, Society for Imaging Science and Technology.

Bies, Robert J. (1986), "Interactional Justice: Communication Criteria of Fairness," *Research on Negotiation in Organizations*, 1, 43-55.

Brennan, Linda, and Wayne Binney (2010), "Fear, Guilt, and Shame Appeals in Social Marketing," *Journal of Business Research*, 63 (2), 140-146.

Chen, Hong, and Yang-Hua Jin (2014), "The Effects of Organizational Justice on Organizational Citizenship Behavior in the Chinese Context: The Mediating Effects of Social Exchange Relationship," *Public Personnel Management*, 43 (3), 301-313.

Choi, Jungsil, Priyamvadha Rangan, and Surendra N. Singh (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.

Cockrill, Antje, and Isobel Parsonage (2016), "Shocking People into Action: Does it Still Work?: An Empirical Analysis of Emotional Appeals in Charity Advertising," *Journal of Advertising Research*, 56 (4), 401-413.

Coke, Jay S., C. Daniel Batson, and Katherine McDavis (1978), "Empathic Mediation of Helping: a Two-stage Model," *Journal of Personality and Social Psychology*, 36 (7), 752.

Corneanu, Ciprian A. Marc O. Simon, Jeffrey F. Cohn, and Sergio Escalera Guerrero (2016), "Survey on RGB, 3D, Thermal, and Multimodal Approaches for Facial Expression Recognition: History, Trends, and Affect-related Applications," *IEEE Transations on Pattern Analysis and Machine Intelligence,* 38 (8), 1548–1568.

Ekman, Paul, and Wallace V. Friesen (1972), "Hand Movements," *Journal of Communication*, 22 (4), 353-374.

Ekman, Paul, and Wallace V. Friesen (1978), "Facial Action Coding Systems," *Consulting Psychologists Press*.

Farley, Patrick, et al (2019), "Face Detection and Attributes," accessed on January 12, 2021 at https://docs.microsoft.com/en-us/azure/cognitive-services/face/concepts/face-detection.

Farwell, Lisa, and Bernard Weiner (2000), "Bleeding Hearts and the Heartless: Popular Perceptions of Liberal and Conservative Ideologies," *Personality and Social Psychology Bulletin*, 26 (7), 845-852.

Feather, Norman T (1999), "Judgments of Deservingness: Studies in the Psychology of Justice and Achievement," *Personality and Social Psychology Review*, 3 (2), 86-107.

Finley, Darel Rex (2006), "HSP Color Model — Alternative to HSV (HSB) and HSL," accessed on January 12, 2021 at http://alienryderflex.com/hsp.html.

Fisher, Robert J., Mark Vandenbosch, and Kersi D. Antia (2008), "An Empathy-helping Perspective on Consumers' Responses to Fund-raising Appeals," *Journal of Consumer Research*, 35 (3), 519-531.

Folger, Robert, and Mary A. Konovsky (1985), "Effects of Procedural and Distributive Justice on Reactions to Pay Raise Decisions," *Academy of Management Journal* 32 (1), 115-130.

Folger, Robert, and Jerald Greenberg (1985), "Procedural Justice: An Interpretive Analysis of Personnel Systems," *Research in Personnel and Human Resources Management*, 3 (1), 141-183.

Ford, Adrian, and Alan Roberts (1998), "Colour Space Conversions," *Westminster University, London 1998*, 1-31.

Hayes, Andrew F. (2017), “Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-based Approach,” *Guilford Publications.*

Hayes, Jameson L., Brian Britt, William Evans, Stephen Rush, Nathan Towery, & Allison Adamson (2020), “Can Social Media Listening Platforms’ Artificial Intelligence Be Trusted? Examining the Accuracy of Crimson Hexagon’s (Now Brandwatch Consumer Research’s) AI-Driven Analyses,” *Journal of Advertising*, 1-11.

Heckman, James J. (1979), “Sample Selection Bias as a Specification Error,” *Econometrica: Journal of the Econometric Society*, 153-161.

Henry, P. J., Christine Reyna, and Bernard Weiner (2004), "Hate Welfare But Help the Poor: How the Attributional Content of Stereotypes Explains the Paradox of Reactions to the Destitute in America 1," *Journal of Applied Social Psychology*, 34 (1), 34-58.

Hibbert, S., Smith, A., Davies, A., & Ireland, F. (2007), “Guilt Appeals: Persuasion Knowledge and Charitable Giving,” *Psychology & Marketing*, *24*(8), 723-742.

Hoffman, Martin L (1990), "Empathy and Justice Motivation," *Motivation and Emotion* 14 (2), 151-172.

Hoffman, Martin L (2001), “Empathy and Moral Development: Implications for Caring and Justice,” *Cambridge University Press*.

Hsieh, Meng-Hua, and Ozge Yucel-Aybat (2018), "Persuasive Charity Appeals for less and more Controllable Health Causes: The Roles of Implicit Mindsets and Benefit Frames," *Journal of Advertising*, 47 (2), 112-126.

Hunt, Robert William Gainer (2005), “The Reproduction of Colour,” *John Wiley & Sons.*

Indyka (2018), “Blur Detection with Opencv-python,” accessed on January 12, 2021 at https://github.com/indyka/blur-detection.

Jack, Rachael E., Oliver G. B. Garrod, Hui Yu, Roberto Caldara, and Philippe G. Schyns (2012), "Facial Expressions of Emotion are not Culturally Universal," *Proceedings of the National Academy of Sciences*, 109 (19), 7241-7244.

Jack, Rachael E., Wei Sun, Ioannis Delis, Oliver Garrod, & Phillip Schyns (2016), “Four not Six: Revealing Culturally Common Facial Expressions of Emotion,” *Journal of Experimental Psychology: General*, *145*(6), 708.

Jack, R. E., Blais, C., Scheepers, C., Schyns, P. G., & Caldara, R. (2009). “Cultural confusions show that facial expressions are not universal”, *Current biology, 19(18), 1543-1548.*

Kranzbühler, Anne-Madeleine, Zerres, A., Kleijnen, M. H., & Verlegh, P. W. (2020), "Beyond Valence: A Meta-analysis of Discrete Emotions in Firm-Customer Encounters," *Journal of the Academy of Marketing Science*, 1-21.

Kim, Soomin, Joonhwan Lee, and Gahgene Gweon (2019), "Comparing Data from Chatbot and Web Surveys: Effects of Platform and Conversational Style on Survey Response Quality," *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*.

Lee, Saerom, Karen Page Winterich, and William T. Ross Jr (2014), "I'm Moral, but I won't Help You: The Distinct Roles of Empathy and Justice in Donations," *Journal of Consumer Research*, 41 (3), 678-696.

Leventhal, Gerald S. (1976), "Fairness in Social Relationships," *Morristown, NJ: General Learning Pre*ss.

Li, Yiyi, and Ying Xie (2020), "Is a Picture Worth a Thousand Words? An Empirical Study of Image Content and Social Media Engagement," *Journal of Marketing Research*, 57 (1), 1-19.

Liang, Jianping, Zengxiang Chen, and Jing Lei (2016), "Inspire Me to Donate: The Use of Strength Emotion in Donation Appeals," *Journal of Consumer Psychology*, 26 (2), 283-288.

Liu, X., Shi, S. W., Teixeira, T., & Wedel, M. (2018), "Video Content Marketing: The Making of Clips," *Journal of Marketing*, *82*(4), 86-101.

Ludwig, S., De Ruyter, K., Friedman, M., Brüggen, E. C., Wetzels, M., & Pfann, G. (2013), "More than Words: The Influence of Affective Content and Linguistic Style Matches in Online Reviews on Conversion Rates," *Journal of Marketing*, *77*(1), 87-103.

Luo, X., Tong, S., Fang, Z., & Qu, Z. (2019), "Frontiers: Machines vs. Humans: The Impact of Artificial Intelligence Chatbot Disclosure on Customer Purchases," *Marketing Science*, *38*(6), 937-947.

Lwin, Michael, and Ian Phau (2014), "An Exploratory Study of Existential Guilt Appeals in Charitable Advertisements," *Journal of Marketing Management*, 30 (13-14), 1467-1485.

Majumdar, Adrija, and Indranil Bose (2018), "My Words for your Pizza: An Analysis of Persuasive Narratives in Online Crowdfunding," *Information & Management*, 55 (6), 781-794.

Marchand, June, and Pierre Filiatrault (2002), "AIDS Prevention Advertising: Different Message Strategies for Different Communication Objectives," *International Journal of Nonprofit and Voluntary Sector Marketing*, 7 (3), 271-287.

Matsumoto, David, and Paul Ekman (1989), "American-Japanese Cultural Differences in Intensity Ratings of Facial Expressions of Emotion," *Motivation and Emotion*, 13 (2), 143-157.

Maxham III, James G., and Richard G. Netemeyer, (2002), "Modeling Customer Perceptions of Complaint Handling over Time: The Effects of Perceived Justice on Satisfaction and Intent," *Journal of Retailing*, 78 (4), 239-252.

Mollick, Ethan (2014), "The Dynamics of Crowdfunding: An exploratory study," *Journal of Business Venturing*, 29 (1), 1-16.

Momtaz, Paul P. (2020), "Initial coin offerings." *PLoS ONE,* 15.5: e0233018.

Parry, S., Jones, R., Stern, P., & Robinson, M. (2013), "'Shockvertising': An Exploratory Investigation into Attitudinal Variations and Emotional Reactions to Shock Advertising," *Journal of Consumer Behaviour*, *12*(2), 112-121.

Pennebaker, James W., and Cindy K. Chung (2007), "Expressive Writing, Emotional Upheavals, and Health," *Foundations of Health Psychology*, 263-284.

Raab, M., Schlauderer, S., Overhage, S., & Friedrich, T. (2020), "More than a Feeling: Investigating the Contagious Effect of Facial Emotional Expressions on Investment Decisions in Reward-based Crowdfunding," *Decision Support Systems*, 113326.

Rosebrock, Adrian (2015), "Blur detection with OpenCV," accessed on January 12, 2021 at https://www.pyimagesearch.com/2015/09/07/blur-detection-with-opencv/.

Russell, James A., and Merry Bullock (1986), "On the Dimensions Preschoolers use to Interpret Facial Expressions of Emotion," *Developmental Psychology*, 22 (1), 97.

Shang, Jen, Americus Reed, and Rachel Croson (2008), "Identity Congruency Effects on Donations," *Journal of Marketing Research*, 45 (3), 351-361.

Shapiro, Debra L., E. Holly Buttner, and Bruce Barry (1994), "Explanations: What Factors enhance their Perceived Adequacy?," *Organizational Behavior and Human Decision Processes*, 58, 346-346.

Shepherd, Maddie (2020), "Crowdfunding Statistics (2021): Market Size and Growth," accessed on January 7, 2021 at https://www.fundera.com/resources/crowdfunding-statistics.

Skitka, Linda J., and Philip E. Tetlock (1992), "Allocating Scarce Resources: A Contingency Model of Distributive Justice," *Journal of Experimental Social Psychology*, 28 (6), 491-522.

Small, Deborah A., and Nicole M. Verrochi (2009), "The Face of Need: Facial Emotion Expression on Charity Advertisements," *Journal of Marketing Research*, 46 (6), 777-787.

Susskind, J. M., Littlewort, G., Bartlett, M. S., Movellan, J., & Anderson, A. K. (2007), “Human and Computer Recognition of Facial Expressions of Emotion,” *Neuropsychologia*, *45*(1), 152-162.

Teixeira, Thales, Michel Wedel, and Rik Pieters (2012), "Emotion-induced Engagement in Internet Video Advertisements," *Journal of Marketing Research*, 49 (2), 144-159.

Tsagarakis, N. G., Morfey, S., Cerda, G. M., Zhibin, L., & Caldwell, D. G. (2013, May). Compliant humanoid coman: Optimal joint stiffness tuning for modal frequency control. In *2013 IEEE International Conference on Robotics and Automation* (pp. 673-678). IEEE.

Vitaglione, Guy D., and Mark A. Barnett (2003), "Assessing a New Dimension of Empathy: Empathic Anger as a Predictor of Helping and Punishing Desires," *Motivation and Emotion*, 27 (4), 301-325.

Weiner, Bernard (1993), "On Sin versus Sickness: A Theory of Perceived Responsibility and Social Motivation," *American Psychologist*, 48 (9), 957.

Wilson-Nash, Carolyn, Amy Goode, and Alice Currie (2020), "Introducing the Socialbot: A Novel Touchpoint along the Young Adult Customer Journey,” *European Journal of Marketing*.

WEB APPENDIX A – Overview of Convolutional Neural Network

A Convolutional Neural Network, or CNN, is a type of artificial neural network that allows the user to assign relative importance, or weights, to objects or components within a specific image or matrix input and successfully differentiates between those characteristics by producing a probability breakdown between 0 and 1. A CNN effectively functions as a filter to scan through large and complex images to stipulate unique characteristics. Convolutional Neural Networks are made up of various layers, including convolutional layers and pooling layers. A CNN algorithm functions to reduce images into a digestible format to process while still maintaining defining characteristics. Some real world applications of the Convolutional Neural Network are programming in virtual assistants, electromyography recognition, and image classification and object detection.[20]

For humans, image classification or recognition is a skill that comes easily without much effort on our part. We see an image of a dog and can recognize that the subject of the image is, in fact, a dog. Machines are not as in tune to image assessment and categorization as we are, and the Convolutional Neural Network provides the ability for machines to filter images as an array of numbers, such as pixel intensity or color, and classify inputs in this manner. Ultimately, the goal of a CNN is to teach a machine or computer how to differentiate between subjects, such as what might make images of a dog a dog and what might make images of a dog not a cat. This process occurs subconsciously for humans but through this Deep Learning algorithm, it can be done through the layers of a CNN.[21]

---

[20] Tondak, A. (2020, September 23). https://k21academy.com/microsoft-azure/convolutional-neural-network/
[21] Deshpande, A. (2016, July 20). https://adeshpande3.github.io/A-Beginner%27s-Guide-To-Understanding-Convolutional-Neural-Networks/

The convolutional layer is the very first layer of the algorithm to assess the features from a provided image. It is considered to be a core component of a CNN. Within the convolutional layer, specific regions of the image, distributed as an array of pixel values, are scanned by a filter or kernel, or "a two-dimensional array of weights.[22]" The kernel shifts, or convolves, across different parts of the image array and performs matrix multiplication operation between the kernel and the region of the image it is being applied to. The stride value describes the number of pixels that the kernel shifts over the input matrix. The kernel will continue to move systematically through the image per the stride value until the entire image has been assessed, first to the right and then down by the same stride value to repeat the process.

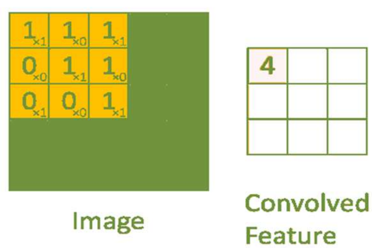


Figure A1: Convoluting a 5x5x1 image with a 3x3x1 kernel to get a 3x3x1 convolved feature[23]

It is important to recognize that the kernel interprets and detects features within small squares of data at a time and that the mathematical operation involved in this layer multiplies the filter matrix by the image pixel matrix to output a two-dimensional volume dimension array that is called the activation or feature map. The convolutional layer also preserves the spatial relationship between pixels. The objective of the convolutional operation is to learn, identify, and extract features from the input image. These features can be characteristics such as edge detection,

---

[22] Brownlee, J. (2020, April 17). https://machinelearningmastery.com/convolutional-layers-for-deep-learning-neural-networks/

[23] Saha, S. (2018, December 15). https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53

gradient orientation and adjustments such as blurring and sharpening. Additionally, in many operations, there are more than one convolutional layer. Added convolutional layers provides the opportunity to capture high-level features to provide a more holistic understanding of the image and its components. Additionally, the more filters we have, the better the convolutional neural network becomes at recognizing characteristics and patterns within images.

A supplemental process to the convolutional operation is the ReLU function. ReLU, or the Rectified Linear Unit, serves to increase the non-linearity of the image. This is utilized because most images or other real-world input data are naturally non-linear, such as the progression of pixels in an image.[24]

Next, the pooling layer involves spatial pooling, also called downsampling or subsampling. Within this layer, dimensionality, width and height, are reduced from each feature map, while still preserving the most important information. This pooling layer allows for some of the detected features to become more defined. Dimension reduction of the convolved feature also aids in decreasing the computational power needed to process the data. There are different types of spatial pooling, such as max pooling, average pooling and sum pooling. Max pooling involves designating a spatial window of the activation map, such as a 2x2 portion, and identifying the largest element within that window. Furthermore, average pooling inputs the average of all the values within the specific spatial window and sum pooling inputs the sum of all the values within the specific spatial window.

[24] Saha, S. (2018, December 15). https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53

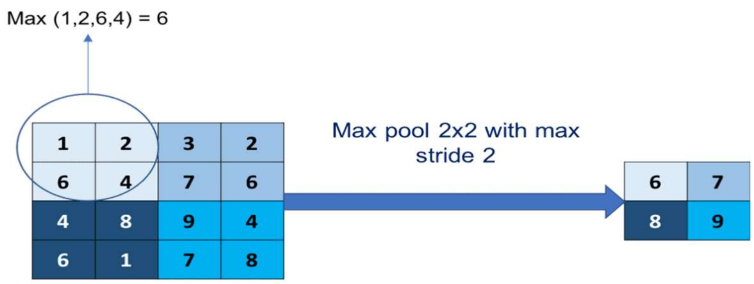
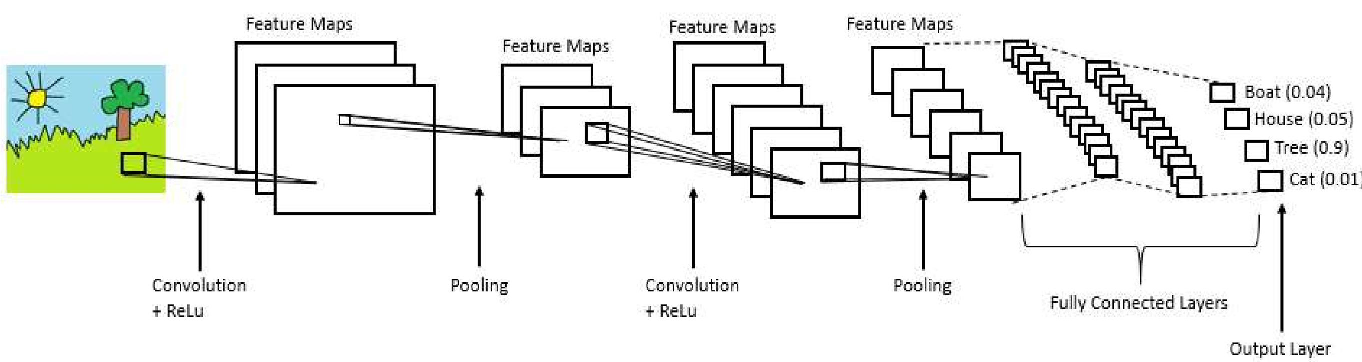


Figure A2: Max pooling technique within the pooling layer [25]

The fully connected layer, or FC layer, is the final layer that aids the convolutional neural network in the high-level reasoning and classification of images. The purpose of the FC layer is to take the high-level features that were determined in the convolutional and pooling layers and use them to classify the input image into various class characteristics. In detail, the output of the previous layer is flattened in order to create a new vector output. The dimensions of this vector output depends on the number of class characteristics there are to differentiate between. For example, if the program were classifying by digits (1-9), there would be 10 dimensions in the vector output. The FC layer applies weights to which high level features most strongly correlate with a class characteristic and from those weights, probabilities of each characteristic are derived in the final output layer.



[25] Tondak, A. (2020, September 23). https://k21academy.com/microsoft-azure/convolutional-neural-network/

Figure A3: The complete CNN process[26]

When understanding convolutional neural networks and their components, it is necessary to acknowledge the deep learning algorithm's applications in image classification and object detection. Image classification is the "process of segmenting images into different categories based on their features."[27] Features of images include characteristics such as the edges of a subject in an image and pixel values and intensity. Pixels are defined as the smallest particles that make up an image and the variance in their strength is what is referred to as pixel intensity. Further, the pixel value is made up of three different values that correspond to the RGB channels (used to produce any visible color imaginable). It is difficult to detect patterns across different images based on pixel value or intensity alone, as the background or colors of an image and even clothing on the subject may vary, so advanced techniques like CNN are utilized to learn the distinct features that make up an image and differentiate between those characteristics regardless of the input image.

CNN Applications to Facial Emotion Detection:

Facial emotion detection involves the process of discerning specific human emotions from facial expressions. The technology to increase a machine's ability to excel at facial emotion recognition is continuously improving and includes the convolutional neural network algorithm. Intelligence such as CNN works to learn what each facial expression means and how it is displayed on human faces and applying that knowledge to new procedures or information. By inputting various images of an array of human expressions, it is possible to teach a CNN what features on

---

[26] Prabhu. (2018, March 4). https://medium.com/@RaghavPrabhu/understanding-of-convolutional-neural-network-cnn-deep-learning-99760835f148
[27] Das, A. (2020, August 20). https://towardsdatascience.com/convolution-neural-network-for-image-processing-using-keras-dc3429056306

the face are most prominent and expressive in certain emotions. This results in a more accurate output of determining what expression the input image is likely conveying. As mentioned previously, emotional recognition software has widespread demand across many industries and fields, such as business and medicine. The goals of applying deep learning algorithms like the CNN to facial recognition objectives are to extract facial features and characteristics from images and classify the extracted data into various emotions. While the field of facial detection software is growing and more and more research is being conducted, there is still a necessity to improve and continue exploring the role of algorithms like CNN in this software. Recognition rates of certain emotions vary across research projects as different researchers develop the deep learning algorithm differently. However, by building off what is known about the procedures involved with convolutional neural networks, knowledge on facial emotion detection in machines can become more defined and more accurate.

There are a few established approaches to extract the necessary facial features to describe an image. Geometry-based extraction focuses on geometric features, such as the shapes of the eyes, eyebrows, nose, mouth, and chin, while the appearance-based method derives information from features "representing facial texture, including wrinkles, bulges, and furrows" (Zeng et al. 2008). Combining both geometric-based and appearance-based methods may provide a more holistic assessment of the image by automatic machines. Further, in the area of facial detection, facial landmarks are used by certain interfaces, such as Microsoft Azure API, to pinpoint certain pivotal areas of the human face and return these points as units of pixels within the algorithm. Face landmarks include a default of 27 landmark points, including loci such as the tip of the nose, the inner corner of the left eye and the top of the upper lip.[28] The purpose of utilizing techniques such as geometry or appearance-based extraction and face landmarks are to improve deep learning algorithms, like the convolutional neural network, in their ability to determine the most defining and important features of the face and of expressions and use that knowledge to classify emotions.

When assessing intelligence that is used to evaluate emotional displays, it is important to recognize the role of FACS. The Facial Action Coding System (FACS) is a system that analyzes the facial muscle movements that correspond to an exhibited emotion.[29] FACS allows researchers to analyze facial expressions and subsequent emotions in real-time, which has proved to be immensely noteworthy in the furthering of research in facial emotion detection within machines. Almost every possible facial expression can be coded using the FACS system as it breaks apart components of emotions based on the facial muscle involved and the specific action unit (AU), or the "contraction or relaxation of one or more muscles."[30] Intensities can be assigned to action unit numbers in FACS with letters A-E; A represents the weakest trace of muscle movement while E represents the maximum intensity.[12] Action units can be categorized as main action units, action units involving the movement of the head and action units involving the movement of the eyes. These action units can be combined to create specific emotions. For example, AU6 represents the raising of cheeks, or the orbicularis oculi and pars orbitalis muscles, and AU12 represents the pulling of the corners of the lips, or the zygomatic major muscle. The combination of these two AUs, 6 + 12, provides emotions that most closely resemble happiness or joy.[11] FACS is particularly useful in providing the possibility of determining how strong an individual felt and how that

[28] Malik, S. (2018, May/June). https://www.codemag.com/Article/1805031/Identify-Faces-with-Microsoft-Cognitive-Services
[29] Farnsworth, B. (2019, August 18). https://imotions.com/blog/facial-action-coding-system/
[30] Facial Action Coding System. (2020, December 7). https://en.wikipedia.org/w/index.php?title=Facial_Action_Coding_System&oldid=992895192

emotion manifested itself in response to a specific stimulus. Similar to CNN, FACS allows researchers to forgo the extensive effort required in evaluating emotions frame by frame to teach a machine. Instead, systems can conduct this analysis on its own and use it to detect accurate facial emotions.

There are obstacles that can be faced when applying the convolutional neural network to facial emotion detection situations. It is necessary to feed a large variety of input data into the model for it to accurately learn emotions and discern between them.[31] No two humans express sadness or fear, for example, in the same way so it is imperative that the algorithm have a large dataset to train with to cover many possible expressions. Accuracy is important in facial emotion recognition and this can only come with repeated and consistent training of the algorithm itself. The more varied photos and expressions are trained with a CNN, the more successful and accurate results the program can produce and the more likely the CNN is to become paralleled to the human brain and facial emotion detection by a human.

[31] Li, C., & Zhao, L. (2019). https://docs.lib.purdue.edu/purc/2019/Posters/63

WEB APPENDIX B

Table B1: Correlation Table

Variable	Weekly Donation Amount	Avg. Happy Score	Avg. Sad Score	Avg. Anger Score	Avg. Surprise Score	Avg. Age Faces	Number of Faces	Avg. Brightness	Avg. Blurriness	Descr. Volume. Affect	Descr. NetVal. Affect	Descr. Affect. Anltc.Ratio
Weekly Donation Amount	1											
Avg. Happy Score	-.004	1										
Avg. Sad Score	.016	-.105 ***	1									
Avg. Anger Score	.043 ***	.073	.164 ***	1								
Avg. Surprise Score	.051 ***	.003	.004 ***	.191 ***	1							
Avg. Age Faces	.056 ***	.069 ***	-.175 ***	.018 ***	-.167 ***	1						
Number of Faces	.063 ***	.145 ***	-.015 ***	.028 ***	.011 ***	.078 ***	1					
Avg. Brightness	-.011 ***	.008	.032 ***	.003	.005 *	-.070 ***	-.033 ***	1				
Avg. Blurriness	.003	-.039	-.005	-.023 ***	.007	-.046 ***	-.183 ***	-.048 ***	1			
Descr. Volume.Affect	.008 **	.045 ***	-.018 ***	-.003	-.016 ***	.035 ***	.027 ***	-.008 **	.008 **	1		
Descr. NetVal.Affect	.019 ***	.046 ***	-.035 ***	.019 ***	-.008	.028 ***	.032 ***	.004	-.025 ***	.447 ***	1	
Descr. Affect.Anltc.Ratio	-.044 ***	-.029 ***	.027 ***	.021 ***	.041 ***	-.047 ***	-.013 ***	.025 ***	-.027 ***	-.153 ***	-.129 ***	1

WEB APPENDIX C – Selection Bias

Our empirical results may be influenced by selection bias from project creators by uploading more happy images when creating a donation campaign. To address this potential bias, we use a binary Probit model in the first stage to estimate the probability that project creator i will create donation project j that is happy dominant.

$$\Pr\left(Happy_{Dominant_{ij}} = 1\right) = \Phi(\mathrm{Z}'\ \delta) \tag{B1}$$

Where,

$Happy_{Dominant_{ij}}$ is a binary variable that equals 1 if project creator i creates donation project j as a happy dominant project (The project has an avg. happy score larger than 0.5)

Z includes the explanatory variables describing the creator's decision to launch a happy-dominant project. These variables are explained later in this section.

$\Phi(.)$ is cumulative distribution function of the standard normal distribution

Following the Heckman method (Heckman 1979) and using the estimated parameters from equation B1, we construct the inverse mills ratio ($\hat{\lambda_{ij}}$) in equation B2 and include it in the final model outlined in equation 2.

$$\hat{\lambda_{ij}} = \frac{\phi(Z'\ \delta)}{\Phi(Z'\ \delta)} \tag{B2}$$

Where,
$\phi(.)$ is standard normal density function

A project creator's decision to whether launch a happy-dominant project or launch a project with other types of emotional dominance can depend on monetary goal of the project, creator's previous donation activities such as number of donations (s)he has made before, and average emotion expressions in uploaded images of previous projects in the same donation context. To capture the impact of previous projects' facial emotions, we measure the average score for the happy (Avg. Happy Score), sad (Avg. Sad Score), angry (Avg. Angry Score), and surprise (Avg. Surprise Score) emotion expressions used in the previously launched projects in the same donation context. These variables are all included in Z and the estimated δ are shown in table B1.

Table C1: Factors Impacting a Project Creator to Launch a Happy Dominant Project

	DV = 1 if a Project is Happy-Dominant
Avg. Angry Score	-.120 * (.071)
Avg. Happy Score	.098 ** (.043)
Avg. Sad Score	-.349 *** (.117)
Avg. Surprise Score	-.310 *** (.081)
Project_ Goal	-.020 *** (.004)
Creator_ Activity	.004 (.006)
Project Category Fixed Effect	Yes
Year and month Fixed Effect	Yes
R-Squared	.4535
Number of Observations	423,895

*** p<0.01; ** p<0.05; * p<0.1, Standard errors in parentheses

WEB APPENDIX D – Omnibus Mediation Analysis

Table D1: Omnibus Mediation Analysis Including Neutral, Happy, Sad, Angry and Surprise Conditions

Omnibus Mediation Analysis of Azure score on Donation Amount	**Angry**	**Surprise**	**Sad**	**Happy**
Direct effect of X on Y	-.026*** (.077)	-.074 (.080)	-.018*** (.087)	-.034*** (.078)
Indirect effect of X on Y through perceived empathy	-.0005 (.001)	.013*** (.001)	.003 (.004)	.002*** (.0002)
Indirect effect of X on Y through perceived justice	.069*** (.035)	.019*** (.016)	.059*** (.034)	.027*** (.004)
Indirect effect of X on Y through emotion contagion	.015 (.449)	.012*** (.003)	-.023 (.666)	.009*** (.023)
Total effect of X on Y	.045*** (.019)	.040*** (.013)	.043*** (.019)	.004** (.0003)

*** p<0.01; ** p<0.05; * p<0.1, Standard errors in parentheses

WEB APPENDIX E – Study 3 Robustness Check

Table E1: Platform Revenue Change for Different Replacement Conditions_ Based on Prolific Surveys

Replacement Scenarios	Percentage Change in Average Donation Amount per Donor	Change in Platform Revenue ($)
Replacing Happy with Sad	2.96 *** (1.04)	37,341.2
Replacing Surprise with Sad	2.77 *** (1.12)	7,686.71
Replacing Angry with Sad	1.75 *** (.65)	2,037.97
Replacing Surprise with Angry	1.00 (1.28)	2,771.99
Replacing Happy with Angry	1.18 *** (.59)	14,900.99
Replacing Happy with Surprise	0.18 ** (.11)	2,300.71

*** p<0.01; ** p<0.05; * p<0.1, Standard errors in parentheses

References

Brownlee, J. (2020, April 17). How Do Convolutional Layers Work in Deep Learning Neural Networks?. Machine Learning Mastery. Accessed on January 7, 2021 at https://machinelearningmastery.com/convolutional-layers-for-deep-learning-neural-networks/

Das, A. (2020, August 20). Convolution Neural Network for Image Processing — Using Keras. Towards Data Science. Accessed on January 7, 2021 at https://towardsdatascience.com/convolution-neural-network-for-image-processing-using-keras-dc3429056306

Deshpande, A. (2016, July 20). A Beginner's Guide To Understanding Convolutional Neural Networks. Github. Accessed on January 7, 2021 at https://adeshpande3.github.io/A-Beginner%27s-Guide-To-Understanding-Convolutional-Neural-Networks/

Facial Action Coding System. (2020, December 7). In *Wikipedia.* Accessed on January 7, 2021 at https://en.wikipedia.org/w/index.php?title=Facial_Action_Coding_System&oldid=992895192

Farnsworth, B. (2019, August 18). Facial Action Coding System (FACS) - A Visual Guidebook. iMotions. Accessed on January 7, 2021 at https://imotions.com/blog/facial-action-coding-system/

Heckman, James J. (1979) "Sample Selection Bias as a Specification Error," *Econometrica: Journal of the Econometric Society*, 153-161.

Li, C., & Zhao, L. (2019). Emotion Recognition using Convolutional Neural Networks [Poster Presentation]. Purdue Undergraduate Research Conference. Accessed on January 7, 2021 at https://docs.lib.purdue.edu/purc/2019/Posters/63

Malik, S. (2018, May/June). Identify Faces with Microsoft Cognitive Services. CODE Magazine. Accessed on January 7, 2021 at https://www.codemag.com/Article/1805031/Identify-Faces-with-Microsoft-Cognitive-Services

Prabhu. (2018, March 4). Understanding of Convolutional Neural Network (CNN) — Deep Learning. Medium. Accessed on January 7, 2021 at https://medium.com/@RaghavPrabhu/understanding-of-convolutional-neural-network-cnn-deep-learning-99760835f148

Saha, S. (2018, December 15). A Comprehensive Guide to Convolutional Neural Networks — the ELI5 Way. Towards Data Science. Accessed on January 7, 2021 at https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53

SuperDataScience. (2018, August 17). Convolutional Neural Networks (CNN): Step 1(b) - ReLU Layer. Accessed on January 7, 2021 at https://www.superdatascience.com/blogs/convolutional-neural-networks-cnn-step-1b-relu-layer/

Tondak, A. (2020, September 23). Convolutional Neural Network (CNN) | Azure Machine Learning. K21Academy. Accessed on January 7, 2021 at https://k21academy.com/microsoft-azure/convolutional-neural-network/

Zeng, Z., Pantic, M., Roisman, G. I., & Huang, T. S. (2008), "A Survey of Affect Recognition Methods: Audio, Visual, and Spontaneous Expressions. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *31*(1), 39-58.