

How to Make Successful Campaigns in Donation-based Crowdfunding: The Role of Facial Expression and Content

Dong-Hoon Shin* and Hyo-Jung Kim

Graduate School of Information, Yonsei University, Republic of Korea

*Corresponding Author: *dh_shin@yonsei.ac.kr*

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Abstract

Online donation has grown the most among the various fundraising tools in recent years. In particular, donation-based crowdfunding, which is a way for charitable organizations to raise funds efficiently and minimize efforts to separately recruit donors, is growing rapidly. This donation-based crowdfunding can be evaluated as having a very high value in that the operating cost is considerably reduced compared to the existing offline charities, providing greater benefits to project organizers. As such, the popularity of donation-based crowdfunding is increasing, and at the same time, there are many charitable projects that are not able to achieve their fundraising goals within a certain period, although their value is also quite high. Therefore, the purpose of this study is to identify factors that influence the success of donation-based crowdfunding projects based on text and image analysis included in the project. Through this study, it is expected that it will be able to propose elements necessary for the success of donation-based crowdfunding, 'GoFundMe', and contribute to raising the rate of achievement of funding goals. First, in the case of images, AZURE, an image recognition API(Application Programming Interface) provided by Microsoft, was used to check whether the face was revealed, and elements for facial expressions were extracted, and in the case of contents, various features were extracted using natural language processing and machine learning. Regression analysis is performed using variables extracted from photos and contents and basic campaign information, and through this, the influence of image and content variables on the fundraising amount is to be grasped.

Keywords: Donation-based crowdfunding, text analysis, facial expression, face recognition, emotion score, empirical analysis

1. Introduction

Charitable activities have developed greatly as philanthropy activities utilizing digital platforms due to the recent growth of the Internet. In parallel with this trend, online donation has grown the most among various fundraising tools in recent years (Cox et al., 2018; Lee & Park, 2020; Li et al., 2018), in particular, donation-based crowdfunding, which is a way for charitable organizations to raise funds efficiently and minimize efforts to separately recruit donors, is growing rapidly (Mollick, 2014).

This donation-based crowdfunding can be evaluated as having a very high value in that the operating cost is considerably reduced compared to the existing offline charities, providing greater benefits to project organizers. According to the Charity Navigator Report, a world-renowned accreditation body for charity, even charities with the highest ratings in terms of financial operations, on average, spend more than 25% of their total income on labor and other operating expenses. On the other hand, 'GoFundMe', a representative donation-based crowdfunding company, only receives a fee of 1.9%. As such, it can be seen as remarkable in that it increases the actual beneficiary rate through a donation-based crowdfunding platform.

As such, the popularity of donation-based crowdfunding is increasing, and at the same time, there are many charitable projects that are not able to achieve their fundraising goals within a certain period, although their value is also quite high. According to a report by Fundly, a crowdfunding platform, about 50% of crowdfunding projects did not meet their goals. Therefore, in order to achieve the success of donation-based crowdfunding, it is necessary to analyze the factors that significantly affect the donation behavior of potential donors, and to draw implications that can effectively recruit donors and induce continuous participation.

The purpose of this study is to identify the factors that affect the success of donation-based crowdfunding projects based on the text and image analysis included in the project. Through this study, it is expected that it will be able to propose elements necessary for the success of donation-based crowdfunding and contribute to raising the rate of achievement of funding goals.

2. Conceptual Background

2.1 Literature Review

Crowdfunding can be divided into four main types: reward-based, lending-based, equity-based, and donation-based (Silvio, 2019). In the donation-

based crowdfunding context, the investors in the crowdfunding activities differ from those in the other three types of crowdfunding. Philanthropy has been framed from three competing perspectives: altruism, self-interest, and reciprocity (Barmann, 2017). Altruism refers to behaviors that mainly consider the needs of others rather than one's own. Self-interest is defined as an unusual economic exchange behavior. Reciprocity views the giving as a social exchange act. The backers donate their money and time in the crowdfunding because of altruistic factors instead of a desire for rewards. In recent years, rapid development of donation-based crowdfunding has gradually become an effective way for an individual recipient or a non-profit organization to raise donations.

However, most studies have been conducted to explore the determinants of campaign success on the reward-based crowdfunding platform (Kwak & Lee, 2014). So, it is difficult to apply directly to donation-based crowdfunding. They have been found that interactions with the project explanation and pictures (Greenberg et al., 2013), project types (Mitra & Gilbert 2014), writing style (Parhankangas & Renko, 2017), the amount of goal (Miller et al., 2013) have a significant impact on the success of reward-based crowdfunding projects. It has been discovered the key factors of reward-based crowdfunding, and it is necessary to discover the factors of donation-based crowdfunding.

In some donation-based crowdfunding studies, survey-based studies have been conducted. It was found that variables such as attitude, subject norms, and trust had an effect on the success of donation-based crowdfunding (Yuangao et al., 2019). Also, it was possible to find out that the target amount, resource type, and partnership affect the amount of donation-type crowdfunding (Park & Shin, 2016). However, there is a limit in that the subjective evaluation result of the person who made the donation was evaluated for the factors with not much data.

Several researchers have attempted to predict reward-based crowdfunding success using various machine learning techniques. A research was developed that the decision tree classifier predicted the crowdfunding success with an accuracy of 68% (Greenberg et al., 2013). Another research has been proposed a semantic text analytic approach to predicting crowdfunding success, and they found that topic models mined from topic descriptions are useful for prediction (Yuan et al., 2016). A study has been conducted an empirical analysis to examine the relationship between facial expression and crowdfunding success. They found out the inclusion of a smiling face is associated with 5% increase in the funding amount (Kim & Park, 2017). However, it was difficult to find analysis studies using these machine learning techniques in donation-based crowdfunding studies. Therefore, by analyzing the text and images uploaded by the project

organizer using a machine learning method, we intend to find the success factors of the donation-based crowdfunding projects.

2.2 Social Presence Theory

Social presence describes how the use of the media is influenced by the social environment (Short et al., 1976). Adding features that evoke a sense of social presence on a website may increase donation intention by increasing a funder's trust. A study on individual donation behavior found that trust is related to donation intention and that it will increase the intention to donate (Liu et al., 2018). Therefore, one of the main factors influencing the intention to donate is trust, which is expected to have a positive effect on the intention to donate. One study defined a social being as "personal, warm, intimate, sociable, or sensitive sense of social interaction in a virtual context." (Animesh et al., 2011) Therefore, in this paper, we define the social existence of a website as "the degree to which a website allows its users to psychologically experience others." (Heijden et al., 2004) Thus, social beings play a leading role in the user's attitude toward donation decisions. (Gefen et al., 2003).

2.3 Theory of Planned Behavior

Theory of Planned Behavior (TPB) is that intentions are determined based on the evaluation of a specific object and lead to behavior. The most direct factor in determining behavior is intention, which is governed by positive or negative emotions toward the object being evaluated. This theory is used to explain behaviors such as purchase intention or entrepreneurial intention (Lorenz et al., 2015; Wu et al., 2015). TPB represents a positive or negative assessment of an individual's behavior. This is a kind of psychological emotion generated by consumer evaluation, and if it is positive, the behavioral intention tends to be more positive (Chen et al., 2014). Perceived behavioral control, indicated as performing an action, is simple or complex for the following reasons: It combines past donations related to disability and predictable disability (Ajzen et al., 1991; Paul et al., 2016). Webb et. al. is the first application of TPB in the field of charitable donations.

3. Research Methodology

3.1 Research Procedure

The data used in this study was collected from 10,443 cases by web crawling project posting data from October 27, 2019 to October 30, 2020 on the Gofundme platform. Posts include the type of project, the amount of money raised, the number of times the organizer updated the post, the number of times donors shared it on social media, and the post and photo data containing project-related content.

After completing the data collection and pre-processing process, theoretically based variables

were extracted from text and images included in individual projects. First, LIWC-based variable extraction was performed for text. LIWC (Linguistic Inquiry & Word Count), a text analysis program, was used to extract linguistic features from text data (Pennebaker., 2001). LIWC is a vocabulary database that provides word sets related to various psycholinguistic categories and is frequently used

for feature extraction in social media text analysis studies (Desai, 2015, Guntuku et al., 2019). And AZURE, an image recognition API provided by Microsoft, was used for images. After extracting the variables, empirical analysis was performed to find meaningful variables that influence the project fundraising amount. (Refer to Figure 1)

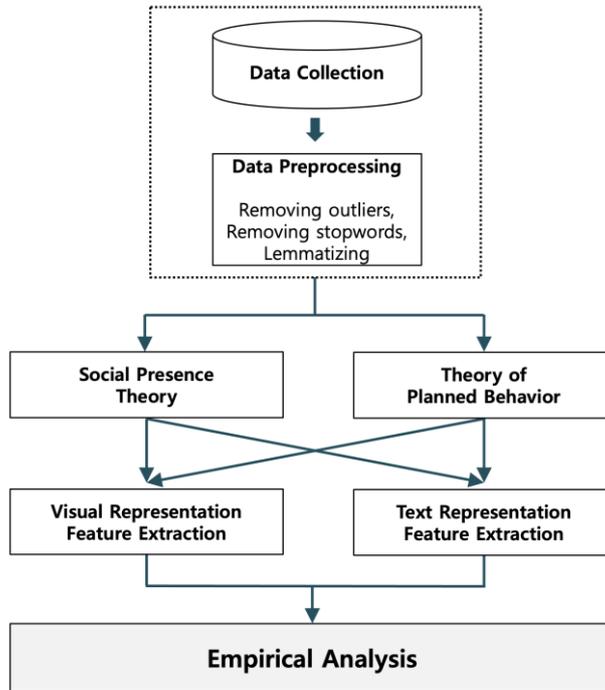


Figure 1: Research Procedure

3.2 Feature Extraction

For this study, data were crawled on GoFundme, and a total of 10,443 project posts were collected. The posts included the type of project,

the amount raised, the number of times the organizer updated the posts, the number of times donors shared them on social media, and the text and photo data containing project-related content. (Refer to Figure 2)

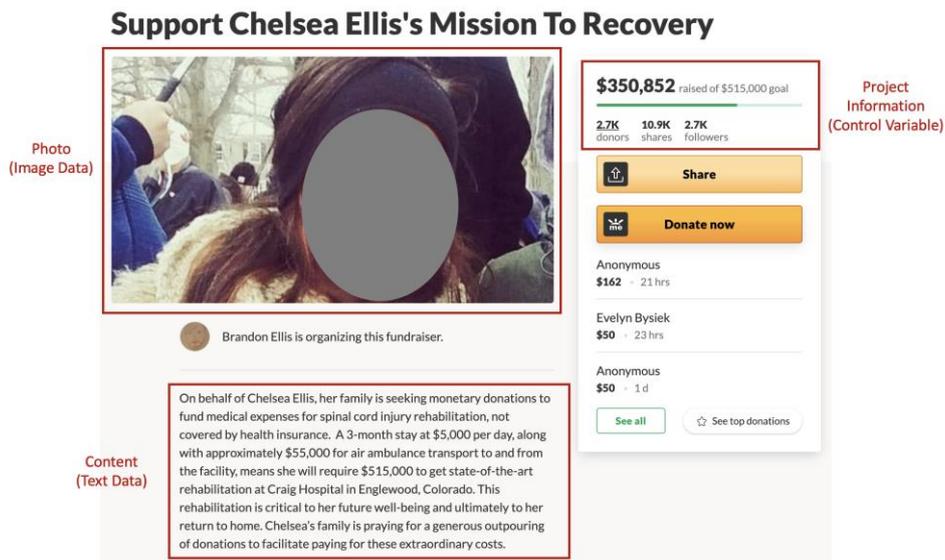


Figure 2: A Campaign Sample on GoFundMe.com (recognizable faces are masked to preserve privacy)

Table 1: Definitions of Features Extracted from Text & Image Data

Type	Var.	Definition	Example
Text	Length	The length of content	
	Analytical thinking	Percentages of words in a text that match up with 'Analytical thinking' categories	determined algorithmically using correlated words based on a dictionary of terms associated with underlying meanings
	Informality	Percentages of words in a text that match up with informal words	Swear words (e.g., f**k, damn, shit), Netspeak (e.g., lol, thx), Assent (e.g., OK, yes), Nonfluencies (e.g., er, hm, umm),
	Authenticity	Percentages of words in a text that match up with 'Authentic' categories	I-words(I, my, me, mine), present-tense verbs(have, know), relativity words(old, far, here)
	Mention of money	Frequency of words in a text that mention anything related to money	audit, cash, owe
	Positive emotion	Score for positive vocabulary mention	good, nice, happy, pretty
	Negative emotion	Score for positive vocabulary mention	hate, worthless, enemy
	SNS_Disclosure	Whether to be exposed to the SNS account	@*****rn4\nFacebook
Image	Face_Disclosure	Whether the face is exposed on the photo	"faceId": "1d3738b9-6f23-4c09-ac31-0bdc5bb37f18",
	Face_Sadness	Score for facial expressions	"happiness": 0.004,
	Face_Happiness		"neutral": 0.932,
	Face_Neutral		"sadness": 0.055

In this study, the positive, negative level of posts and the frequency of direct mention of money, analytical thinking (the degree to which the post reflects the formal and logical characteristics of the post), informality (the degree to which informal words such as slang), and authenticity (the degree to which information is revealed) was extracted from contents by using LIWC. In addition, the disclosure of SNS was extracted from the content that the organizer posted his social media information on the posting.

Microsoft Azure Face, which detects, identifies, and analyzes faces in images, was used to extract scores for facial expressions and facial expressions from image data. Azure Face has been

used in various studies that analyzed emotions based on human image data (Alfarrarjeh et al., 2017, Feine et al., 2019). For use in this study, the presence or absence of a person in the photo and three emotional scores were extracted: happiness, sadness, and neutral. The definition and examples of extracted variable from text and image data are shown in Table 1. Descriptive statistics of features extracted from text and image data are shown in Table 2. Also, the correlation between variables to be used in the study is shown in Table 3. If there is multicollinearity between variables, bias or errors may occur in estimation, but the possibility of multicollinearity as a whole seems to be low.

Table 2: Descriptive Statistics

Var.	Mean	Std	Min	Max
Num of Shares	1328.18	4456.44	0.00	131500.00
Num of Updates	1.57	3.18	0.00	20.00
Raised money (\$)	41686.11	464782.20	11.00	44453500.00
Length	275.45	255.56	2.00	6203.00
Analytical thinking	76.48	18.04	1.00	99.00
Informality	0.30	0.72	0.00	28.57
Authenticity	23.38	23.08	1.00	99.00
Mention of money	2.38	1.99	0.00	50.00
Positive emotion	4.81	2.52	0.00	60.00
Negative emotion	1.21	1.27	0.00	12.50
SNS_Disclosure	0.10	0.30	0.00	1.00
Face_Disclosure	0.43	0.49	0.00	1.00
Face_Sadness	0.00	0.04	0.00	0.99
Face_Happiness	0.33	0.46	0.00	1.00
Face_Neutral	0.09	0.26	0.00	1.00

Table 3: Variable Correlations

Var.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Num of Shares	1														
2. Num of Updates	0.12	1													
3. Raised money	0.27	0.02	1												
4. Length	0.06	0.10	0.06	1											
5. Analytical thinking	0.03	0.01	0.02	0.07	1										
6. Informality	-0.02	-0.01	-0.01	-0.04	-0.05	1									
7. Authenticity	-0.09	-0.05	-0.03	0.02	-0.09	0.01	1								
8. Mention of money	-0.03	-0.03	0.00	-0.14	0.08	0.00	-0.02	1							
9. Positive emotion	-0.04	-0.07	-0.01	-0.17	-0.13	0.05	-0.13	-0.03	1						
10. Negative emotion	0.13	0.06	0.03	0.00	-0.06	-0.04	-0.11	-0.08	-0.06	1					
11. SNS_Disclosure	0.00	0.03	0.00	0.19	0.08	0.10	0.00	0.01	-0.07	-0.03	1				
12. Face_Disclosure	-0.03	-0.08	-0.02	-0.09	-0.01	0.00	-0.02	0.01	0.07	-0.03	-0.02	1			
13. Face_Sadness	0.00	-0.01	0.00	-0.01	0.02	0.02	0.00	0.00	0.02	0.01	0.01	0.11	1		
14. Face_Happiness	-0.03	-0.07	-0.02	-0.08	-0.02	0.00	-0.01	0.01	0.06	-0.03	-0.02	0.53	-0.04	1	
15. Face_Neutral	-0.01	-0.02	-0.01	-0.04	0.00	0.00	-0.02	0.00	0.02	-0.01	-0.01	0.40	0.12	-0.16	1

Figure 3 shows the schematic results of reflecting variables in each theory based on Social Presence Theory and Theory of Planned Behavior, which are the basic theories of this study. Variables derived from Social Presence theory are ‘SNS Disclosure’, ‘Face Disclosure’, and ‘Authenticity’.

Variables derived from Planned Behavior theory are composed of 6 variables including ‘Length’, ‘Analytical Thinking’, and ‘Informality’. In addition, the control variables consist of ‘Num of Shares’ and ‘Num of Updates’, and the dependent variable is ‘Raised Money’.

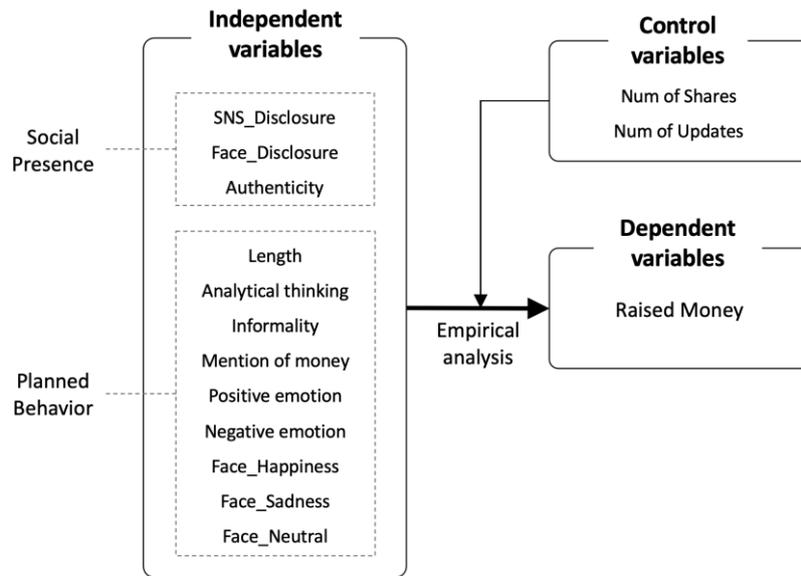


Figure 3: Empirical Research Model

We will estimate the following empirical model. Y_i is the logarithm of the amount of raised money, Z_i is a set of control variables, ϵ_i is a random error for a project i , and all independent variables reported in Figure 3 are included in the analyses. In independent variables, Length, Analytical thinking and Authenticity are log-transformed to correct skewness.

$$Y_i = \alpha + Z_i\gamma + \beta_1 SNS_Disclosure_i + \beta_2 Face_Disclosure_i + \beta_3 Authenticity_i + \beta_4 Length_i + \beta_5 Analytical_thinking_i + \beta_6 Informality_i + \beta_7 Mention_of_money_i + \beta_8 Positive_emotion_i$$

$$+ \beta_9 Negative_emotion_i + \beta_{10} Face_Happiness_i + \beta_{11} Face_Sadness_i + \beta_{12} Face_Neutral_i + \epsilon_i$$

4. Expected Contributions and Future Plan

As a next step, this paper will focus on empirical analysis. In the case of empirical analysis, the purpose is to identify the factors that influence the success of donation-based crowdfunding projects. In addition to the currently features extracted from text variables and image variables, additional variables will be found and regression analysis will be performed. In addition, in terms of image analysis, we intend to add 'arousal', which means image immersion, which is a remarkable variable in terms of

theoretical basis and utilization of various studies. In addition to the main text of the project, the vocabulary used in materials and comments, interrelationships such as geographic and cultural distance between the recipient and the funder, the interest of the funder, and the impact of a wide range of variables such as the timing of donation are also explored.

Expected academic contributions include research into donation-based crowdfunding to uncover the success factors of the project. In particular, after extracting key variables based on a large amount of image and text data preprocessed with machine learning technology, we intend to conduct an empirical analysis to explore variables that have a significant influence on the success of the campaign. The expected practical contribution is that, based on the meaningful variables identified through empirical analysis, the company plans to proceed with the proposal of a success plan by utilizing the factors necessary for the success of donation-based cloud funding.

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About Authors

Dong-Hoon Shin, Graduate Student, Graduate School of Information, Yonsei University, Seoul, Korea, Email: dh_shin@yonsei.ac.kr

Hyo-Jung Kim, Graduate Student, Graduate School of Information, Yonsei University, Seoul, Korea, Email: libertygood9@yonsei.ac.kr

