Large-Scale Medical Crowdfunding Data Reveal Determinants and Preferences of Donation Behaviors

Mengning Wang, Mengsi Cai, Shuhui Guo, Mengjun Li, Xu Tan, Chaomin Ou, and Xin Lu

***Abstract*— The growing usage of online crowdfunding platforms has fundamentally changed the traditional modes of fundraising and donation. Previous studies have mainly focused on the performance and ethical issues of online crowdfunding. In contrast, there is a dearth of information about the complexity of online donation behaviors. To explore the characteristics of fundraising and donation in online crowdfunding campaigns, we conduct a comprehensive analysis of fundraising and donation behaviors based on 151 163 campaigns, with 188 955 849 donations created from 2016 to 2020 in one of the most popular medical crowdfunding (MCF) platforms called Easy Fundraising in China. We propose four indicators, namely, diversity, uncertainty, concentration, and consistency, to characterize the preferences of individual donors in choosing the donation amounts. Furthermore, we investigate the fundraising temporal dynamics and collective donation characteristics of crowdfunding campaigns using statistical methods. Results show that the first three days after the creation of a crowdfunding campaign is the most efficient fundraising period that largely determines the completion of the campaign. Donors who donate early are more generous than those who donate later. Individual donors prefer donation amounts in multiples of five, such as 5, 10, 20, and 50, and rarely change their donation amounts, which is irrelevant to the patients' locations. The empirical results obtained in this study provide valuable insights to improve crowdfunding management, public welfare systems' construction, and human donation behaviors' understanding.**

***Index Terms*— Donation behaviors, donation preference, Easy Fundraising, fundraising dynamics, medical crowdfunding (MCF).**

I. Introduction

CROWDFUNDING is becoming a popular method of generating a large number of small donations via Internet platforms, especially in the healthcare sector [1], [2]. It is reported that approximately 2000 global crowdfunding sites exist to give entrepreneurs and funders convenience as of 2016 [3], and the World Bank believes that crowdfunding could amass over $300 billion in cumulative transactions by 2025 [4]. In China, $503.17 million from 20 Chinese authoritative Internet-fundraising platforms was contributed to philanthropy in 2018, an increase of roughly 26.8% [5].

Medical crowdfunding (MCF) is known as the largest and fastest growing form of charitable crowdfunding, it involves using social media platforms to appeal for help in paying for medical care, and, as such, deserves much attention [6]. The total amount of global crowdfunding platform financing reportedly reached US $72.3 billion in 2017, and about half of this amount was estimated to have come from MCF [7]. An individual MCF campaign usually involves four types of parties: initiator, recipient, donor, and platform. In general, the recipient can be the individual running the campaign or, more commonly, a third party such as a friend or a relative of the initiator.

People use MCF to cover a variety of costs, such as surgical treatment, medical care, experimental therapies, diagnostic tests, and pharmaceuticals [8], [9]. However, it is reported that only 10% of MCF campaigns succeed in reaching their goal amounts [10], [11] and many fall far short of success. Health disparities in MCF usage and outcomes proportionately exist in many countries, including the US [1], [12], Canada [13], and China [14]. To investigate the performance of online crowdfunding, researchers have examined the relationships between MCF success and multiple factors, such as the characteristics of the patients (e.g., gender, race, age, and location) and the campaigns (e.g., type of treatment, text length, goal amount, duration length, photos, videos, and updates) [12], [13], [15], [16], illness narrative content [11], [17], [18], [19], and social networks [1], [20], [21], among others [22]. In addition, many ethical issues in MCF campaigns, such as disparity or fairness [23], privacy [14], identity [8], [24], credibility [25], [26], and fraud and misinformation [27], [28], have been widely discussed [29], [30].

However, with a few exceptions, empirical research on MCF campaigns have only been conducted in developed countries such as the US and some European countries [13]. There have been two studies conducted in China, and they only focused on the text analysis on the narrative contents of a very limited number of MCF campaigns [14], [20]. Despite the growing concerns in MCF regarding fundraising performance

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and ethical issues, there is a paucity of empirical research on donation behaviors from the perspective of donors, especially in China. Therefore, to fill the above research gap, based on the empirical data of 151 163 online crowdfunding campaigns from the popular MCF platform Easy Fundraising in China, this article investigates the static and dynamic characteristics of MCF campaigns, such as raised amount and fundraising completion. Furthermore, it analyzes the behaviors of donors, including individual donation behaviors and collective donation behaviors.

II. Related Work

A. MCF: Easy Fundraising

Since the first crowdfunding platform, Demohour, went online in 2011 [31], Internet philanthropy in China has rapidly grown. In 2016, China issued its first comprehensive legislation on philanthropy—the China Charity Law—and designated the Ministry of Civil Affairs as the main regulator of charitable activities. In 2022, there are 20 authoritative Internet crowdfunding platforms in China, contributing RMB1.8 billion and 5.26 billion times of donations for philanthropy in the first half of 2019. In addition, three MCF platforms (i.e., Easy Fundraising, Heart Fundraising, and ShuiDi Fundraising) have signed the "Self-discipline Pact on Internet Crowdfunding for Serious Personal Illness," which promotes the rapid and sound development of the MCF industry.

MCF sites seek public monetary support for health-related needs with a donation-based model that enables people to send monetary donations easily, quickly, and safely [11], as well as assist individuals in seeking funding for medical purposes. In China, Easy Fundraising is one of the most popular MCF platforms. It was developed in September 2014 and has since become an authoritative Internet crowdfunding platform approved by the Ministry of Civil Affairs. As of September 2018, 550 million users have registered in Easy Fundraising, contributing a total of RMB5.5 billion for over 2.53 million families. Easy Fundraising uses a direct donation model wherein the fundraisers get to keep all the donations even if the total does not reach the goal amount.

B. Charitable Donation Behavior

Several correlates of charitable donation behaviors have been identified in previous research, such as age, gender, income, social status, religiosity, participation in associations, moral identification, emotion, personality, and social networks [32], [33], [34], [35], [36], [37], [38]. In addition, some characteristics of the nonprofit organizations or charitable platforms can also affect the donors' donation intentions, such as the default donation amounts, campaign contents, website quality, trust, and donation outcomes [39], [40], [41], [42]. Other factors such as the tax price of giving, individuals' intrinsic motivations, and donation experiences can also influence the level of donations [43], [44].

However, most related studies have used surveys or sample data with a limited scale. Few efforts have focused on donation behavior analysis based on empirical data from online crowdfunding platforms. For example, Yang et al. [45] found that the donation process in massively multiplayer online role-playing games (MMORPGs) is non-Poissonian, based on about 100 000 donation actions. Sasaki investigated donors' conformity behaviors based on 9989 donations on JapanGiving by empirically examining the impacts of multiple earlier donations on the donation of a subsequent donor [46]. Another empirical study based on 558 067 individual donation transactions on GoFundMe found that donors gave significantly more to recipients who have the same last name as theirs, and women expressed significantly more empathy than men in the messages accompanying their donations [47].

MCF is premised on a donation-based model of giving wherein people financially contribute to various causes, and they are motivated by altruism and typically do not expect anything in return [48], [49]. Unlike the traditional donation model of charities and nonprofit organizations, MCF platforms have changed the way people donate and how quickly decisions to donate can be made. However, prior studies on MCF have mainly focused on the success of crowdfunding campaigns [13], [50]. Little is known about the characteristics of donors.

III. Data and Methods

A. Data Description

To conduct a systematic and comprehensive analysis of the fundraising process and donation behaviors in online crowdfunding in China, we collected large-scale individual MCF datasets from Easy Fundraising. To raise money for medical needs, individuals (i.e., the initiators) first create an MCF campaign at Easy Fundraising, providing the personal information of the patients, especially the disease information and the target amount for the fundraising. In most cases, the initiators are the patients themselves or their relatives. Then, they repost the crowdfunding information on their social media accounts to raise awareness and call for help.

1) Data Collection: In China, a highly effective way for initiators to spread information about their crowdfunding campaigns to obtain more donations is via Sina Weibo, the most popular Twitter-like social media platform in China with 530 million active users as of March 2021 [51]. Furthermore, Sina Weibo has accumulated 2.382 million discussions and 800 million views about the topic of Easy Fundraising as of May 24, 2021. Therefore, to collect information on individual MFC campaigns in Easy Fundraising, we started the data collection processes from Sina Weibo and developed two distinct web crawlers.

1) *Crawler 1*: This web crawler was used to collect the URLs of crowdfunding campaigns published in Easy Fundraising. First, the crawler searched crowdfunding-related posts on Sina Weibo from January 1, 2016, to December 31, 2020, using the keyword "Easy Fundraising," based on which we were able to extract 187 050 distinct URLs of crowdfunding campaigns created in Easy Fundraising.
2) *Crawler 2*: This web crawler was divided into *Crawler 2a* and *Crawler 2b* to collect the basic information and the donation details of the crowdfunding campaigns,

respectively. The crawlers first visited the Easy Fundraising server via the extracted Easy Fundraising campaign URLs (collected by *Crawler 1*) and then automatically visited the campaign pages and extracted related information. In detail, *Crawler 2a* extracted the basic information of the campaigns (i.e., campaign ID, initiator ID, campaign title, campaign description, category ID, target amount, raised amount, donation count, repost count, and confirmed count) and the publicly available personal information of the patients used in the pledge (i.e., age, location, disease type, and disease description). To obtain the donation details of the crowdfunding campaigns, *Crawler 2b* visited the donation list (who donated to the campaign), confirm list (who proved the realness of the campaign), and "Rank List" (top ten users who contributed the most to the campaign evaluated based on "kindness score") of each campaign. In the donation list, the campaign ID, donor ID, donation amount, and donation time of each donation record were extracted. In the confirmation list, the relationships between the donors and the patients were obtained. Finally, in the "Rank List," the top ten "kindness scores" of the donors were obtained. It is noteworthy that the "kindness scores" were calculated by the sum of their self-donated amount and other people's donation amount brought by their repost.

Combining the massive amount of data collected by the above crawlers, we constructed two datasets, namely, the campaign dataset and the donation dataset, comprising 187 050 crowdfunding campaigns and 239 246 033 donation records.

The data fields are listed in Table I. In the campaign dataset, the completion of a campaign can be calculated by the quotient of the target amount and the raised amount, while the support a campaign obtains can be reflected by the donation count, repost count, and confirmed count.

2) Data Preprocessing: While our study focused exclusively on individual MCF campaigns, it is worth noting that Easy Fundraising hosts various other types of campaigns, including tuition crowdfunding, poverty crowdfunding, and crowdfunding for animal aid and volunteer activities. To filter these non-MCF campaigns from the 187 050 collected campaigns, we adopted strict data preprocessing steps.

Step 1 (Time Filtering): Only the crowdfunding campaigns created between January 1, 2016, and December 31, 2020, were maintained, resulting in 186 508 campaigns for further processing.

Step 2 (Disease Information Filtering): We selected 138 172 campaigns whose disease descriptions or disease types were not empty, since they can be regarded as individual MCF campaigns. Then, Steps 3 and 4 were conducted on the remaining 48 336 campaigns whose disease descriptions and disease types were empty.

Step 3 (Campaign Category Filtering): After manually screening for the basic information of the remaining 48 336 crowdfunding campaigns, we fortunately discovered that the category IDs of most medical-related crowdfunding campaigns were marked as 3349 by Easy Fundraising. Therefore,

TABLE I
DATASET DESCRIPTION

Dataset	Data fields	Data type	Data size (before pre-processing)	Data size (after pre-processing)
Campaign dataset	Campaign ID	string	187,050 campaigns	151,163 campaigns
	Initiator ID	string		
	Campaign title	string		
	Campaign description	string		
	Category ID	int		
	Target amount	float (RMB)		
	Raised amount	float (RMB)		
	Donation count	int		
	Repost count	int		
	Confirmed count	int		
	Age	int		
	Location	string		
	Disease type	string		
	Disease description	string		
Donation dataset	Campaign ID	string	239,246,033 donation records	188,955,849 donation records
	Donor ID	string		
	Donation amount	float (RMB)		
	Donation time	datetime		
	Relationship	string		
	Kindness score	int		

we removed 17 159 crowdfunding campaigns whose category IDs were not 3349.

Step 4 (Keywords Filtering): We constructed a dictionary of various disease keywords by carefully searching the disease information from several medical knowledge websites such as https://www.zhzyw.com/jbdq.html, http://jb.qm120.com and http://www.a-hospital.com. Then we removed 12 249 crowdfunding campaigns whose campaign title and campaign descriptions did not contain any of the keywords in the dictionary.

Step 5 (Target Amount Filtering): To ensure the quality of the campaign data, we removed 4330 crowdfunding campaigns with target fundraising amounts that were less than RMB10 000 or more than RMB500 000.

Step 6 (Donation Count Filtering): We removed 1497 crowdfunding campaigns with no donations. Through manual inspection, most of the campaigns without donations are redundant, and they are often used by initiators to test the process of initiating campaigns.

Step 7 (Missing Data Filtering): We also removed 110 crowdfunding campaigns whose donation details were incomplete or missing.

After performing the above data preprocessing steps (Fig. 1), we finally obtained 151 163 individual MCF campaigns and 188 955 849 related donation records.

B. Fundraising Analysis

Fundraising is a multidimensional process, so we focused not only on how much funds were raised but also on how long the fundraising took. Therefore, taking both the donation

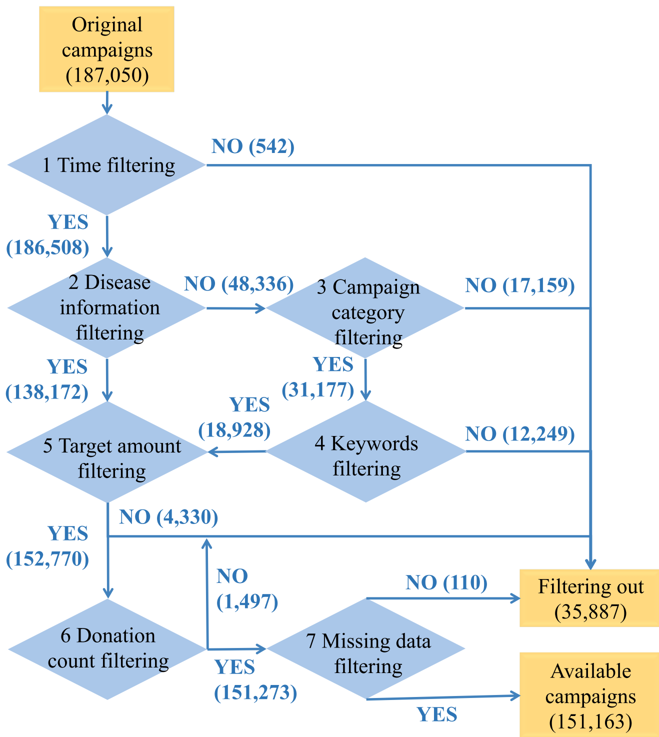

Fig. 1. Data preprocessing flowchart.

amount and the donation time into consideration, we calculated five indicators to describe the completion status and fundraising process of the campaigns: duration, inter-donation duration, completion ratio, donation amount per donor, and fundraising speed.

1) Duration: The duration (D) refers to the interval days between the initiation and the last donation in a campaign, indirectly reflecting the length of active time of the crowdfunding information spreading in social networks. Suppose a campaign is initiated at t_0 (in seconds), and it has n donation records, we let t_1 and t_n be the time (in seconds) of the first donation and the last donation, respectively. Then, we calculate the duration of the campaign in days as follows:

$$D = \frac{(t_n - t_0)}{60 \times 60 \times 24}. \tag{1}$$

2) Inter-Donation Duration: The inter-donation duration (IdD) refers to the interval hours between two consecutive donations in a particular campaign, calculated as follows:

$$\text{IdD} = \frac{(t_i - t_{i-1})}{60 \times 60}, i = 2, 3, \ldots, n. \tag{2}$$

3) Completion Ratio: The completion ratio (CR) measures the completion of a campaign in terms of money, which indicates the completion of the fundraising goal set by the initiator. We calculate the completion ratio by dividing the actual raised amount a_{raised} by the target amount a_{target} of fundraising as follows:

$$\text{CR} = \frac{a_{\text{raised}}}{a_{\text{target}}} \times 100\%. \tag{3}$$

4) Donation Amount Per Donor: The donation amount per donor (DA) is equal to the raised amount divided by the number of donors in a campaign. This ratio provides a quantitative measure of the average generosity of the donors in the campaign. For a campaign, the greater the DA, the more generous the donors in the campaign. Given a campaign that raised a_{raised} money from m donors, we calculate the donation amount per donor of the campaign as follows:

$$\text{DA} = \frac{a_{\text{raised}}}{m}. \tag{4}$$

5) Fundraising Speed: The fundraising speed (FS) is equal to the newly added fundraising amount in a unit hour. It provides an intuitive explanation for the efficiency and effectiveness of the fundraising process.

Based on the above definitions, we can divide the five indicators into two groups: the static indicators, which describe the completion status of campaigns, including duration, completion ratio, and donation amount per donor, and the dynamic indicators, which describe the fundraising process of campaigns, including inter-donation duration and fundraising speed.

C. Donation Behavior Analysis

Donors are free to choose a donation amount in a crowdfunding campaign. It is interesting to explore how donors determine the donation amount and the crowdfunding campaigns to donate. However, individual donation behaviors have been rarely investigated in previous studies. Herein, we proposed four indicators to characterize individual donation behaviors from the perspective of donation amount: diversity, uncertainty, concentration, and consistency. In addition, we calculated the Pearson correlation coefficient between the donation order and the donation amount to evaluate their correlation. We also examined the impact of patient' location on donors in terms of choosing crowdfunding campaigns based on the concept of entropy.

1) Diversity: Donors may contribute different amounts in each donation. Diversity is proposed to measure the differences in the number of unique donation amounts among the donors' donations. Given a donor that contributed k donation records, let S be the set of unique donation amounts of the donor, $|S| \leq k$. Considering that if a donor contributed more donation records, he/she is more likely to have a larger $|S|$, we define the donation amount diversity (DAD) of a donor as the quotient of the number of unique donation amounts and the number of donations as follows:

$$\text{DAD} = \frac{|S|}{k}. \tag{5}$$

2) Uncertainty: To further analyze how donors select the donation amounts to contribute, we use the concept of entropy to quantify the uncertainty associated with the chosen donation amounts. Given a donor with k donation records, S is the set of unique donation amounts selected by the donor. And $s_i \in S(i = 1, 2, \ldots, |S|)$ is selected c_i times, $\sum_{i=1}^{|S|} c_i = k$. We define the donation amount uncertainty (DAU) as the entropy of the donation amounts as follows:

$$\text{DAU} = -\sum_{i=1}^{|S|} P_i \log_2^{(P_i)} \tag{6}$$

TABLE II
BASIC STATISTICS OF THE 151 163 MCF CAMPAIGNS IN EASY FUNDRAISING

Information	Options	Frequency	Percentage (%)	Avg. Target amount	Avg. Raised amount	Avg. Raised count	Avg. Repost count	Success rate (%)[1]
Age	Infant (<2 yrs)	433	0.29	175,578	32,032	1,343	855	0.92
	Minor (2-18 yrs)	10,423	6.9	220,355	51,880	2,049	1,328	2.88
	Adult (>18 yrs)	107,698	71.25	186,235	35,967	1,109	507	5.33
	Unknown	32,609	21.57	164,609	46,509	1,460	203	14.48
Location	Eastern	48,451	32.05	196,622	43,208	1,487	663	5.27
	Central	44,546	29.47	188,086	35,719	1,021	521	5.43
	Western	24,663	16.32	176,783	29,597	935	524	4.42
	Unknown	33,503	22.16	165,139	45,675	1,442	215	14.07
Total		151,163	100	183,892	39,327	1,250	499	7.13

[1] The success rate is defined as the proportion of the campaigns that successfully achieved their target.

where P_i is the probability of donation in amount s_i, which is estimated by c_i/k.

3) Concentration: To identify whether a donor tends to select a fixed donation amount in each donation, we propose concentration to measure the proportion of the frequently used donation amount in all the donation amounts. Given a donor with k donation records, s_i is a unique donation amount selected c_i times. We define the donation amount concentration (DACn) of the donor as the probability of the donor selecting the most frequently used donation amount as follows:

$$\text{DACn} = \frac{\max(c_i)}{k}, \quad i = 1, 2, \ldots, |S|. \tag{7}$$

4) Consistency: Donation amount consistency measures the similarity of the donation amounts between every two consecutive donations at the micro level, reflecting the stability of the donation amount selection. Given a donor with k donation records, let the vector $T = [s_1, s_2, \ldots, s_k]$ be the time series of the donation amounts contributed by the donor. We define the donation amount consistency (DACy) as the proportion of the consecutive donations pairs with the same donation amounts as follows:

$$\text{DACy} = \frac{\sum_{i=1}^{k-1} \phi(s_i, s_{i+1})}{k-1} \tag{8}$$

where $\phi(s_i, s_{i+1})$ is equal to 1 when $s_i = s_{i+1}$; otherwise, it is 0. Therefore, a larger DACy indicates that the selection of donation amounts is more stable.

IV. FUNDRAISING ANALYSIS

A. Basic Description

The descriptive statistics of the collected 151 163 online MCF campaigns in Easy Fundraising are shown in Table II. In summary, 151 163 campaigns raised RMB5 944 784 884 and received 188 955 849 donations, 75 483 717 reposts in total. However, only 7.13% campaigns succeeded in achieving their target amounts. Most of the campaigns (71.25%) were initiated for adults, while only 0.29% of the campaigns were created for infants. Moreover, the minor group received the highest donation amount, donation count, and repost count, which indicates to a certain extent that people donate more generously and actively to minors than to infants and adults.

In addition, significant disparities in terms of location were observed in the crowdfunding campaigns. For example, there are noticeable differences in the number of campaigns initiated in different regions. Specifically, the number of campaigns initiated in the developed eastern regions was more than that in the less developed central regions and was about two times larger than that in the underdeveloped western regions. Moreover, the campaigns initiated in the eastern regions received the largest donation amount, donation count, and repost count compared with the campaigns initiated in central and western regions.

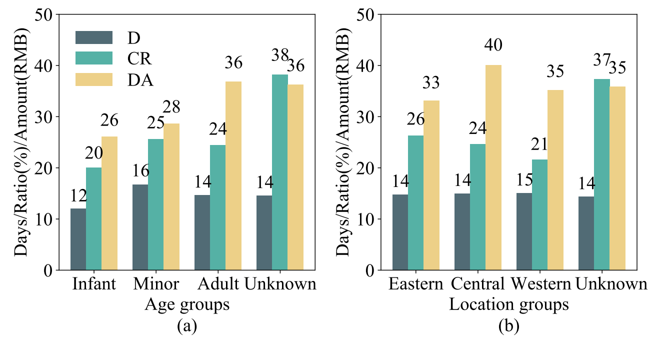

Fig. 2. Results of the static fundraising indicators for (a) different age groups and (b) location groups.

B. Static Fundraising Analysis

Fig. 2 illustrates the results of the proposed static fundraising indicators (i.e., D, CR, and DA) for the crowdfunding campaigns initiated for patients in different age and location groups. Fisher's exact testing was used to assess the statistical differences in completion ratios among these groups. The results show that the completion differed across the age groups [Fig. 2(a)]. For example, the campaigns for minors had the longest duration (16.73 days, $p<0.001$).

Significant differences were also noted across location groups in terms of CR [Fig. 2(b)]. Specifically, campaigns initiated in the eastern regions had the highest CR (26.35%, $p<0.001$). The finding is consistent with the statistics presented in Table II, which suggest that campaigns in the eastern regions received a significantly amount of money (RMB43 208, $p<0.001$) and donation count (1487, $p<0.001$) compared with the campaigns in other regions, particularly those in the western regions.

An interesting finding is that the campaigns targeting adults and the patients in central regions had the highest DA [Fig. 2(b)] and success rate (Table II). However, these

TABLE III
AVERAGE COMPLETION OF THE FIVE GROUPS OF CAMPAIGNS

Group	Campaigns count	Avg. Target amount	Avg. Raised amount	Avg. Donation count	Avg. Repost count	Avg. Donation amount per donor	Avg. Completion rate (%)	Avg. Success rate (%)
1	34,866	167,465	38,423	1,218	468	36.24	27.28	8.32
2	46,661	174,737	37,746	1,193	438	36.24	27.97	6.55
3	27,979	186,374	38,516	1,212	452	36.40	27.67	6.90
4	24,514	194,603	39,238	1,236	501	36.26	28.18	8.66
5	16,908	223,004	46,743	1,538	798	35.11	25.48	4.52

campaigns did not have the highest raised amount, donation count, repost count, or CR. Furthermore, we used the Pearson correlation coefficient to verify the correlation between the confirmed count and the completion status of the campaigns. Our analysis revealed that the confirmed count exhibited a weak positive correlation with the raised amount ($r = 0.65$, $p<0.001$).

C. Dynamic Fundraising Analysis

The durations of the 151 163 MCF campaigns varied widely, ranging from a few minutes to over 110 days, with an average of 14.76 days. Based on this phenomenon, we divided the crowdfunding campaigns into five categories according to the duration, ranging from one week to five weeks. We excluded campaigns that lasted more than five weeks, as they comprised only a negligible fraction (0.16%) of all the campaigns. The average completion of the campaigns in the different groups is shown in Table III. Notably, our findings suggest that the completion statuses of the campaigns with durations ranging from one week to four weeks were remarkably similar, indicating that the length of the active fundraising period is not significantly associated with the success of most (88.66%) campaigns.

Furthermore, we explored the time it took for the campaigns to reach the different stages of completion and examined the relationship between early fundraising and final campaign completion. After analyzing the data, we found that all the campaigns took an average of 1.95 days to obtain 50% of the final raised amount and an average of 2.04 days to get 50% of their final donation count. Furthermore, it took an average of 5.56 (5.71) days after campaign initiation to achieve 90% of the final raised amount (donation count). Therefore, the first six days are of great significance to crowdfunding campaigns. Thereafter, we, respectively computed the Pearson correlation coefficient between the raised amount on the first six days and the final raised amount. The final raised amount was weakly correlated ($r = 0.67$, $p<0.001$) to the cumulative raised amount of the first day but is strongly related to the later days ($r \geq 0.84$, $p<0.001$). These results highlight that the performance in the first six days following the commencement of a crowdfunding campaign plays a crucial role in determining its ultimate completion. A strong start during this early period can significantly enhance the chances of achieving the fundraising target.

Based on the above analysis, we further explored the fundraising growth on the first six days of the crowdfunding campaigns. In these experiments, we only analyzed the campaigns with durations longer than six days, which accounted for 83.07% of all the campaigns. From the average fundraising growth curve [Fig. 3(a)] and the average fundraising speed curve [Fig. 3(b)] of the campaigns, it is evident that the average fundraising speed periodicity dropped sharply on the first three days after the campaigns were initiated. Furthermore, we used an exponential model to fit the average raised amount on the first six days. The goodness of the fit was $r^2 = 0.996$, indicating that the fundraising speed had decreased exponentially.

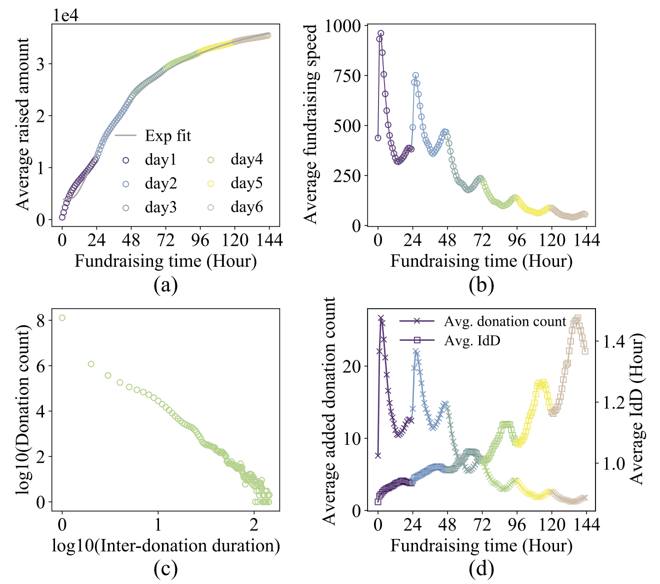

Fig. 3. General fundraising pattern. (a) Growth of raised amount. (b) Fundraising speed over time. (c) Distribution of the inter-donation duration and the donation count in a log–log scale. (d) Displays of the inter-donation duration and added donation count per hour over time.

Furthermore, the inter-donation duration follows a power-law distribution [Fig. 3(c)], which reveals that the campaigns experienced prolonged periods without receiving any donations, but also received intensive donations within a short period. Such a bursty pattern of donations often occurs in the early stages of fundraising, since the average inter-donation duration increased rapidly, which coincident with the sharp decline of the hourly added donation count [Fig. 3(d)].

D. Power-Law in Fundraising

Power-law distributions have been observed in various social phenomena, typically reflecting in the uneven

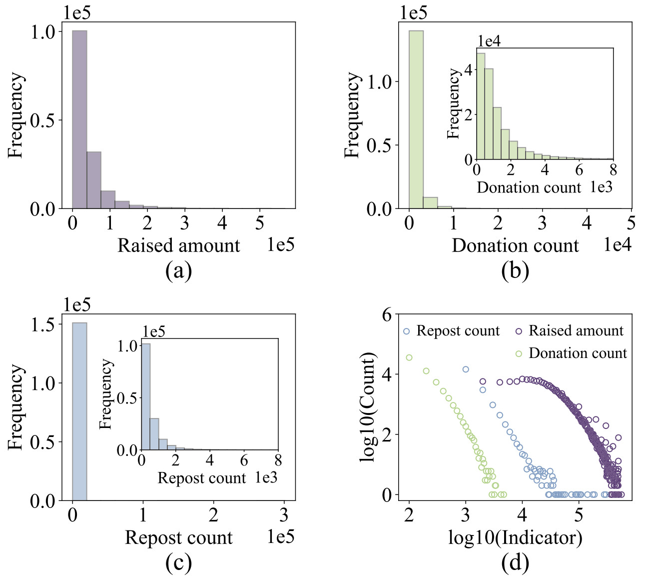

Fig. 4. Distribution of (a) raised amount, (b) donation count, and (c) repost count. (d) Distributions of the above indicators, and the values of the x-axis and the y-axis are $\log_{10}$ transformed.

distribution of personal wealth. For crowdfunding campaigns, power-law distributions are also found in the distributions of the raised amount, donation count, and repost count, as shown in Fig. 4. Specifically, among the crowdfunding campaigns we studied, the minimum raised amount was RMB1, while the maximum raised amount was as high as RMB566 797. Up to 76.28% and 92.28% of the campaigns raised less than RMB50 000 and RMB100 000, respectively [Fig. 4(a)]. This indicates that the raised amount was mainly concentrated on a relatively smaller amount. Similar to the raised amount, the minimum and maximum donation counts were 1 and 47 765, respectively. Most (83.21%) campaigns had less than 2000 donations, with 97.04% receiving less than 5000 donations [Fig. 4(b)]. In addition, some campaigns were not reposted at all, while some campaigns were reposted as many as 300 917 times. Most of the campaigns (87.09%) were reposted fewer than 1000 times [Fig. 4(c)]. When we performed logarithmic operations on the x-axis and y-axis values of the frequency distributions of the above indicators, we observed that the distributions were approximately linear [Fig. 4(d)], indicating that the above indicators followed a power-law distribution.

V. Individual Donation Behaviors

The study of individual donation behaviors is from a micro perspective. Based on the donation records of a large number of donors, we analyzed the donors' donation amount selecting patterns and their regional preferences in donation, and then explored whether the donation amount is affected by the order of donations.

A. Preference of Donation Amount

A total of 188 955 849 donations we collected were received from 104 643 631 unique donors. To gain a comprehensive understanding of individual donation patterns, it is necessary to have an adequate number of historical donation records for each donor. Therefore, we selected 16 494 donors who donated more than 50 times for further analysis. To access each donor's donation behavior, we calculated the proposed donation amount diversity, uncertainty, concentration, and consistency. Then we used the Hopkins statistic [52] to determine whether there were any meaningful clusters. The Hopkins statistic resulted in a score of 0.96, suggesting that clustering analysis was feasible. Thereafter, we applied the k-means algorithm to cluster the donors with similar preferences in choosing the donation amount. Afterward, we used the t-SNE [53] algorithm to achieve feature dimensionality reduction. The clustering results are shown in Fig. 5(a). The 16 494 donors were clustered into three different groups, each representing a different donation pattern. Fig. 5(b) displays the donation amounts of three randomly selected donors from each of the three patterns. It is notable that the donor in *Pattern 1* always donated fixed amount, while the donor in *Pattern 3* donated various amounts.

1) *Pattern 1 (Stable):* As depicted by the purple dots and lines in Fig. 5, these donors always donate a fixed amount. There are 6241 (37.84%) donors in *Pattern 1*, and they have the highest concentration (0.90) and consistency (0.83) but the lowest diversity (0.04) and uncertainty (0.52) in their donation amounts. The donors whose donation behaviors conform to *Pattern 1* tend to donate a small amount (RMB8.88 on average), and they donate most frequently (145 times on average).
2) *Pattern 2 (Ordinary):* As depicted by the green dots and lines in Fig. 5, the donation amounts preferred by these donors are also specific but not as concentrated as those in *Pattern 1*. There are 7709 (46.74%) donors in *Pattern 2*. The four indicators of *Pattern 2*, namely, diversity (0.09), uncertainty (1.72), concentration (0.54), and consistency (0.42), are moderate. The donors whose donation behaviors conform to *Pattern 2* donate an average of RMB19.76 and have donated 99 times on average.
3) *Pattern 3 (Irregular):* As depicted by the blue dots and lines in Fig. 5, it can be observed that the donors in this pattern donate varying amounts. There are only 2544 (15.42%) donors in *Pattern 3*, which is significantly fewer than donors in other two patterns. The diversity (0.23) and uncertainty (3.00) of the donors in *Pattern 3* are the highest, while the concentration (0.31) and consistency (0.21) of this pattern are the lowest. The donors whose donation behaviors conform to *Pattern 3* typically donate with a relatively large amount (RMB53.17 on average) and have donated 69 times on average.

The results show that most (84.58%) donors' donation amounts are relatively fixed over time. In detail, about 37.84% of the donors have an extremely stable preference for a constant donation amount. They usually choose their donation amount among three to four different amounts, with a 90.28% probability of selecting the amount they prefer most and an 83.49% probability of donating the same amount as the

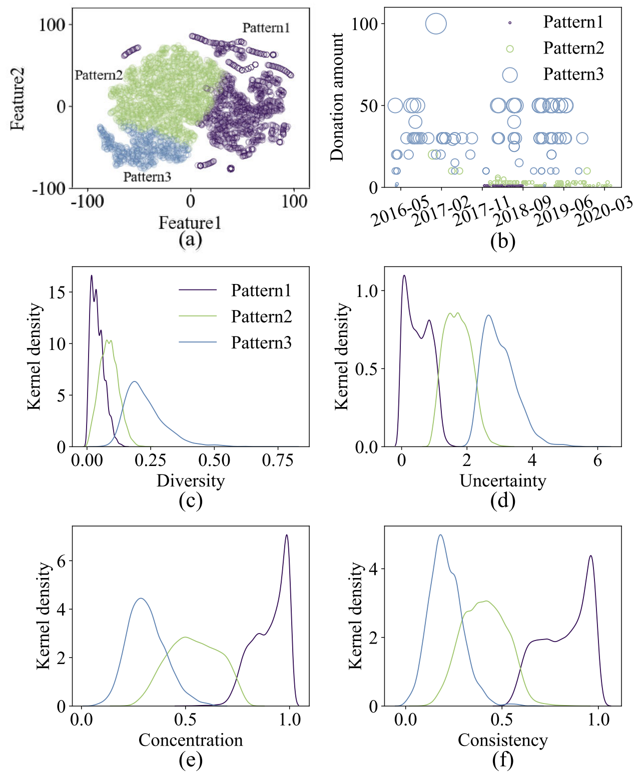

Fig. 5. Three patterns of donors in determining donation amount. (a) Result of k-means clustering; we used the t-SNE algorithm to reduce the high-dimensional feature space of each donation to 2-D. (b) Specific example of three random donors' donations in different patterns. (c)–(f) Results of, respectively, the diversity, uncertainty, concentration, and consistency measurement of donation amount of the three patterns.

last donation. The remaining 46.74% of donors have slightly more diverse options on the unique donation amounts. They typically donated with six to seven different amounts but are still likely to donate the fixed amount they prefer.

Since the k-means algorithm is sensitive to the initial placement of the cluster centers [54], we further tested the stability of our clustering results. Specifically, we repeated the experiment 1000 times, with a randomly selected set of initial cluster centers for each iteration. The results of our robustness analysis demonstrate indicate that the clustering results are quite stable. These donors are almost always (99.94%) divided into the same pattern.

B. Regional Preference

Based on the 16 494 donors who donated more than 50 times, we further extracted 6 935 donors who donated more than 50 times for the MCF campaigns with complete regional information. Afterward, we conducted an analysis and found that these donors donated to campaigns from 18 different provinces on average, with a minimum of one province and a maximum of 31 provinces. To gain a more quantitative understanding of the regional diversity of the campaigns donated to by the donors, we calculated the entropy of the corresponding provinces of each donor's donation campaigns. As shown in Fig. 6(a), the majority (71.58%) of the donors' donated campaigns covered more than 15 provinces, and the entropy was

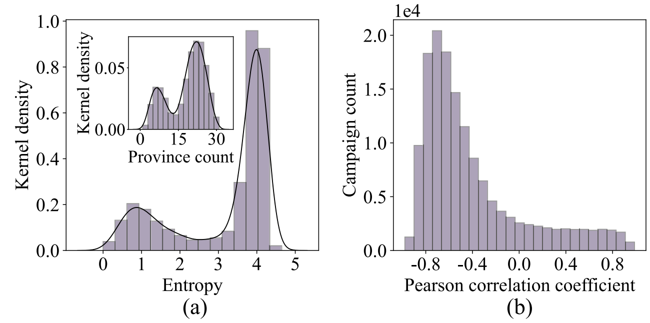

Fig. 6. Regional diversity of donor donations and impact of donation order. (a) Distribution of provinces count and entropy the donors donated. (b) Distribution of the Pearson correlation coefficient between the average donated amount and the donate order.

predominantly distributed in larger values. In addition, there was a strong positive correlation ($r = 0.94$, $p<0.001$) between the number of donation provinces and entropy, indicating that the higher the entropy, the more provincial patients the donors supported.

C. Impact of Donation Order

A study conducted in GoFundMe reveals that the average donation amount decreases as donations increase, which indicates that earlier donors tend to be more generous [18]. In this article, we also explored the trend of the average amount of donations over time in Easy Fundraising. To avoid the potential error caused by campaigns with too few donations, we removed the campaigns (3.27%) with less than 50 donations. For each remaining campaign, we calculated the average donation amounts corresponding to each donation. Then we calculated the Pearson correlation coefficient between the average donation amounts and the donation count for each campaign. As manifested in Fig. 6(b), the Pearson correlation coefficients follow a positively skewed distribution, with the majority of values clustered around the left tail of the distribution. In 57.45% of the campaigns, we found that the average donation amount decreases as the donation count increases, indicating the donor who donated early were significantly more generous ($r \leq$-0.5, $p<0.001$) than those who donated later.

D. Burstiness of Donation

Several studies have demonstrated that various human activities, such as communication, entertainment, and work, exhibit non-Poisson statistics [55], [56], [57], [58].

Many studies have demonstrated that various human activities, such as communication, entertainment, and work, exhibit [55], [56], [57], [58]. This type of behavior is characterized by bursts of rapidly occurring events, separated by long periods of inactivity. In this article, we quantitatively investigated whether non-Poisson statistics existed in the individual donation behaviors based on 1585 donors who had made at least 200 donations. To begin, we divided the donors into six groups according to their donation counts: 200–400 (66.56%), 400–600 (17.22%), 600–800 (7.44%), 800–1000 (2.91%),

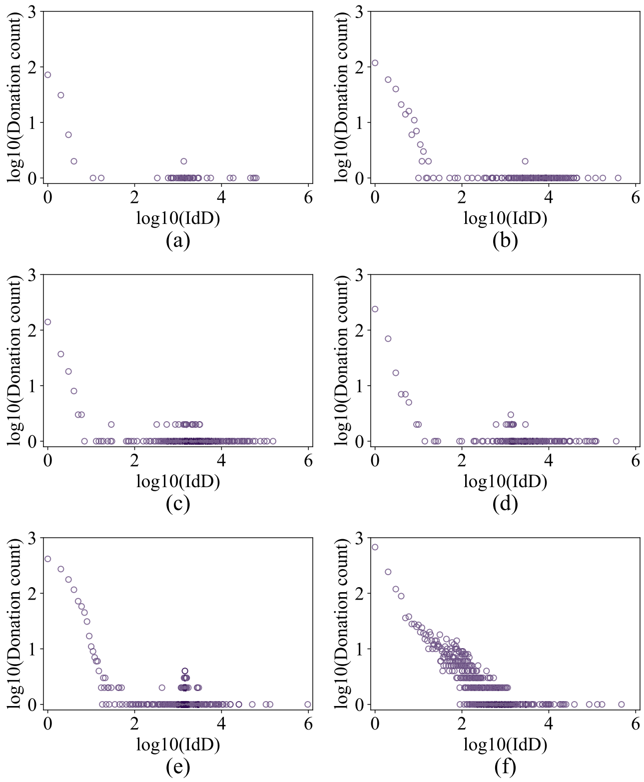

Fig. 7. Inter-donation duration distribution of six randomly selected individual donation from different groups. (a)–(f) Randomly selected donors with 214, 541, 757, 917, 1937, and 3272 donation records, respectively.

1000–2000 (4.61%), and 2000–7857 (1.26%). We then randomly selected six donors from each groups and calculated the time interval in minutes between two adjacent donations for their donations. The distributions of the time intervals of the six donors are shown in Fig. 7, all of which partly follow a power-low distribution. It indicates that most of their donations have short intervals, and the long intervals are very diverse. In summary, the donors' behaviors are heavy-tailed, allowing for very long periods of inactivity and separate bursts of intensive activity.

VI. Collective Donation Behaviors

The study of collective donation behaviors takes a macro perspective by analyzing the behavior of all the donors as a whole, with the aim of determining whether their donation behaviors exhibit preferences in terms of amount and time. In addition, we analyzed the contributions of different relationships in fundraising.

A. Donation Amount Preference

We counted the amount of 188 955 849 donations and listed the top ten frequently donated amounts, as shown in Table IV. The most prevalent donation amount was RMB10, accounting for 31.97% of the total donations. This amount was approximately 1.7 times more prevalent than the second most popular amount, which was RMB20 (18.80%). Following closely in third place was RMB5 (12.13%), and RMB50 (9.25%) secured fourth place. Notably, all these commonly donated amounts

TABLE IV

Distribution of the Top Ten Prevalent Donation Amounts

No.	Amount	Count	Ratio(%)
1	10	60,417,705	31.97
2	20	35,519,021	18.80
3	5	22,924,902	12.13
4	50	17,482,021	9.25
5	100	13,150,771	6.96
6	30	6,095,628	3.23
7	2	5,818,979	3.08
8	1	5,296,289	2.80
9	200	3,509,278	1.86
10	3	3,502,575	1.85

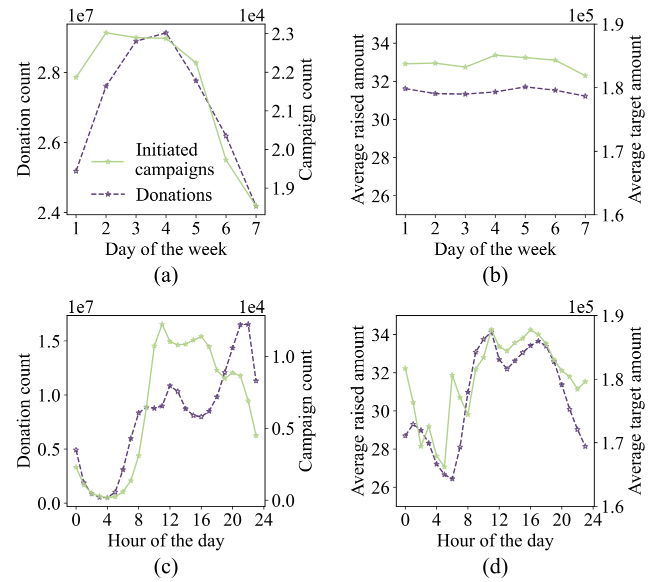

Fig. 8. Daily and weekly activity of donors and initiators. (a) and (b) Temporal variation in the donation count, the campaign count, the average donation amount, and the average target amount in a week. The value 1–7 on the x-axis represents Monday to Sunday, respectively. (c) and (d) Temporal variation in the above indicators in a day.

are all multiples of five. In the Easy Fundraising platform, the optional donation amounts are RMB10, 20, 50, 100, and customized, of which RMB10 is the default amount. Given that RMB10 is a moderate and default amount, the proportion of RMB10 in donations is significantly higher than that of other amounts.

B. Donation Time Preference

We conducted an analysis of time preferences among two groups of people: donors and initiators. The results reveal that during the course of a week, there was a noticeable disparity in the number of campaigns initiated on weekdays versus weekends [Fig. 8(a)]. However, the average donation amount (RMB31.71–32.22) and the average target amount of the campaigns (RMB181 885–185 119) fluctuated very little throughout the week, and both were at the lowest on Sundays [Fig. 8(b)]. Besides, both the initiated campaign count and the donation count were primarily influenced by the rule of people's surfing time in China [59] [Fig. 8(c)]. As for the average donation amount and the average target amount, they exhibited a similar fluctuation pattern in one day, with higher values during daytime and lower values at night [Fig. 8(d)].

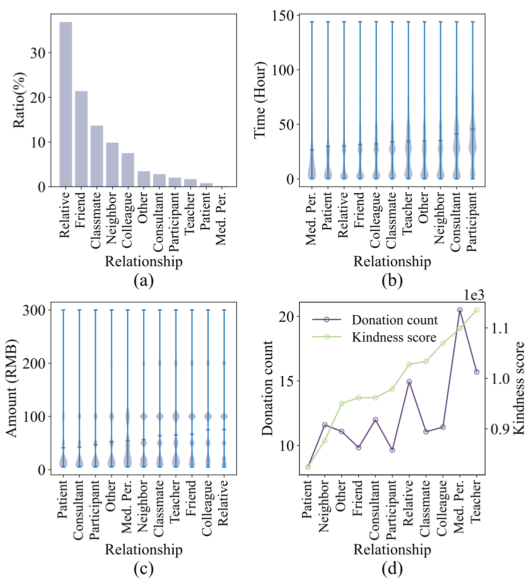

Fig. 9. Contribution of different relationships. (a) and (b) Count and the average reaction time of campaign confirmation of different relationships. (c) Average donation amounts of different relationships. (d) Friend count and "kindness score" of different groups.

C. Contributions of Different Relationships

When a campaign is released, the patient's relatives, friends, classmates, colleagues, neighbors, and so on can confirm it to augment the campaign's authenticity. Based on 5 891 481 confirmation records in the first six days of the campaigns, we statistically calculated the proportions, average reaction time (for confirmation), and average donation amounts of different relationships. Moreover, based on 49 703 campaigns with "kindness score" rankings, we combined the rankings and confirmation records to explore the contribution of different relationships. In addition, the ranking records provided only consist of the top 10 users who achieved the highest "kindness score."

As shown in Fig. 9(a), relatives (36.83%), friends (21.35%), classmates (13.68%), neighbors (9.87%), and colleagues (7.50%) were the main power behind campaign confirmations. After the campaigns had been initiated, medical personnel (26.62 h) were the first to confirm, followed by other patients (29.71 h) and relatives (30.22 h) [Fig. 9(b)]. On average, all the users took approximately 32.49 h to confirm the campaigns.

To provide a more general representation of the donation amounts among different relationships, we removed the data with amounts below the 5th quantile and above the 95th quantile. The results show that relatives (RMB75.25), colleagues (RMB74.70), and friends (RMB66.73) were the relatively more generous groups who donated more money [Fig. 9(c)]. Similarly, to avoid the influence from extreme values, we also conducted the same operation when evaluating the personal influence of different relationships. The results indicate that medical personnel (21), teachers (16), and relatives (15) called on more donations, and teachers (RMB1135.55), medical personnel (RMB1098.67), and colleagues (RMB1069.54) brought more donation amount to the campaigns [Fig. 9(d)].

VII. Discussion

A. General Fundraising Process

We first summarized a general fundraising process of the first six days after the crowdfunding campaigns' initiation. Then we comprehensively analyzed the distribution of inter-donation duration and the hourly added donation count over time. The fundraising speeds of the first six days drop exponentially, as well as the hourly added donations. The fundraising growth curve indicates that the first three days after the campaign initiation is the golden period for fundraising. That is, crowdfunding campaigns will receive intensive donations in the first three days, and as time goes on, people's attention to crowdfunding campaigns will substantially decline. Therefore, the initiators should hold on the initial stage of the campaign, actively publishing and reposting crowdfunding information on social media to stimulate others to donate.

B. Fundraising Completion Determinants

Combined with the results of basic description and static fundraising analysis, we find that minors are more likely to raise funds successfully than adults in Easy Fundraising, which is consistent with the findings in previous studies [60], [61] on Tencent GongYi, an alternative crowdfunding platform developed by Tencent in China. Moreover, there are spatial disparities of MCFs in China, and the donations tend to be concentrated in the more economically developed regions [60]. Furthermore, the confirmed count is positively correlated with the raised amount, since the perceived credibility of crowdfunding campaigns directly affects donors' donation intentions [62].

The distributions of raised amount, donation count, and repost count reveal that only a small number of campaigns will receive a large number of donations and reposts, while the majority of campaigns will receive only a few. Despite crowdfunding being a powerful tool for raising money, it is not a guarantee of success, and the support campaigns' initiators obtained from crowdfunding is usually limited.

MCF platforms facilitate interaction between the initiators and donors and indeed help patients to a certain extent. However, the completions of fundraising in different demographic groups are limited and uneven. It is recommended for charity institutions to funding the patients in poverty, especially patients from underdeveloped regions. In addition, the confirmed count is an intuitive proof of the credibility of a campaign, and a large confirmed count will encourage donors to donate more actively. Therefore, it is beneficial for the initiators to encourage their relatives and friends to confirm the authenticity of the MCFs.

C. Characteristics of Donation Behaviors

In this article, we have identified three distinct donation behavior patterns: stable, ordinary, and irregular patterns, based on four proposed donation behavior indicators. People with different donation behavior patterns show different preferences in donation amount selection. However, in general, most donor's donation amounts are relatively fixed and rarely change, and their donations are with a strong regularity and predictability. For example, donors tend to select a donation amount they prefer most and usually donate a similar amount with their last donation.

Through statistical analysis of the donation amounts, we found that RMB10 is the most prevalent donation amount. This is likely due to it being a moderate amount set as default in Easy Fundraising. According to the widely acknowledged default effect discussed in behavioral decision making [63], donors will be affected by the default donation amount when they determine their donation amounts. In particular, a moderate default amount will encourage people to donate, while a high default amount will backfire [64], [65]. Therefore, it is crucial for crowdfunding platforms to set a suitable default amount for promoting people to donate.

The order of donations will affect the amount donors donate. People who receive the MCF information early tend to have a closer relationship with the initiators, so they will donate more generously than those who are less familiar with the initiators. In addition, the cumulative raised amounts in the initial stage of the campaigns are relatively less, which can stimulate the donation intention of people.

No significant regional preference is found in most donors' donation behaviors. Donors donated patients from 18 different provinces on average. Before the advent of MCF platforms, people mostly obtain social support from others who are geographically close, but nowadays it is easy to raise money nationwide and even worldwide. It is notable that online crowdfunding platforms can break geographical barriers and strengthen connections between people in different locations.

VIII. Conclusion

Understanding the characteristics of people's donation behaviors is essential in managing MCF and promoting the high-quality development of public welfare undertakings. In our study, we first collated the large-scale crowdfunding campaigns between 2016 and 2020 in a well-known MCF platform called Easy Fundraising in China, and then we empirically analyzed the fundraising processes and human crowdfunding behaviors from multiple aspects.

In the fundraising analysis, we first carried out a comprehensive quantitative analysis of the completion of crowdfunding campaigns of different demographic groups. Significant differences were observed in groups of different ages and locations. Afterward, we analyzed the fundraising growth of a large number of crowdfunding campaigns and summarized a general rule from them. The results show that campaigns with longer duration do not manifest significant improvement in terms of completion. In fact, most of the raised funding is donated on the first three days. Furthermore, the inter-donation durations follow the power-law distribution, indicating the burstinesses of intensive donations at the early stage of fundraising.

Regarding the donation behaviors, we characterized the donation amount selection of individual donors with four indicators: diversity, uncertainty, concentration, and consistency, and cluster the donors into three groups. The results show that most donors' donation amounts are relatively fixed. Moreover, we found that the donation amount is rarely affected by the patient's location but is negatively correlated with the donation order. Furthermore, we found that donors tend to donate in the evening (19:00–23:00) and tend to opt for an amount that is a multiple of five. Notably, the most common donation amount is RMB10. In addition, the family is the leading group that proves the realness of a campaign, while the medical personnel group is the first group that provides confirmation after a campaign is initiated.

These results provide insights that will be useful in understanding human donation behaviors. We summarized the general laws of the fundraising process through big data analysis and explored human donation behaviors from multiple dimensions and aspects. However, we only analyzed the MCF campaigns of a single crowdfunding platform. In future work, we will expand the scope of data collection to encompass multiple crowdfunding platforms using multisource data to unveil more characteristics of human donation behaviors.

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