ESSAYS ON ONLINE BEHAVIOR IN MEDICAL CROWDFUNDING

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by

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"Ask, and it shall be given you; seek, and ye shall find;

knock, and it shall be opened unto you."

- Matthew 7:7

DEDICATION

I dedicate this work to my parents, Tak Hur and Mi Ryang Kim,

and the Lord, who made all of this possible.

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SUMMARY

In the context of medical crowdfunding, this dissertation investigates how individual reactions are diversified as they encounter certain events online. Specifically, this dissertation focuses on the two types of events: the social endorsement cue and the varying physical attractiveness of patients in medical crowdfunding cases.

In the second chapter, we examine how the impact of social influence changes in the presence of non-social cues of various strengths in affecting a user's likelihood to donate. We conduct a large-scale randomized field experiment to find that the impact of social influence depends on its relational informational value in the presence or the absence of alternative credible information sources. The findings of this study suggest that informational social influence dominates normative social influence in this context, contributing to both the literature and the managerial insights by uncovering user behavior in medical crowdfunding and related fields.

In the third chapter, we examine the differential impact of physical attractiveness on the two types of prosocial behavior: sharing and donation. Based on the large-scale randomized field experiment, we discover that the impact of physical attractiveness depends on whether the online behavior is private or public, as people behave less restricted in private and behave to manage image in public. The findings of this study contribute to understanding the controversies in the existing research and provide a guideline in building online business strategies.

CHAPTER 1. INTRODUCTION

This dissertation investigates online behavior in medical crowdfunding. Medical crowdfunding refers to the practice of raising small amounts of donations from strangers online to manage expenses related to healthcare (Young and Scheinberg 2017). As increasing healthcare costs is becoming a significant worldwide problem (Deloitte 2017), medical crowdfunding is creating a new channel for patients and their families to raise the funds needed for their medical treatment. On the other hand, the success rates of crowdfunding campaigns are not the same for all cases. Studies show that only less than 10 percent of campaigns in the top crowdfunding platform meet their fundraising goal (Berliner and Kenworthy 2017), leaving 90 percent of cases unable to receive the support they need from medical crowdfunding.

An emerging stream of studies is starting to explore the factors that lead to such heterogeneity in medical crowdfunding outcomes. For example, Koch and Siering (2015) investigate the influence of project description, related images and videos as well as the question of whether the founder has previously backed other projects in funding success. Cordova et al. (2015) list the project funding goal amount and the project duration as critical factors in project success. The majority of these findings, however, are limited to reward-based crowdfunding. Even though donation crowdfunding projects consist of a major part of all crowdfunding projects, with medical crowdfunding alone constituting almost half of the total sum raised on major U.S. crowdfunding platforms (Valle 2017), no research has yet investigated the success factors of medical crowdfunding. Since contribution to medical crowdfunding does not involve neither tangible nor financial return, it is likely that a different set of factors play larger roles in making favorable decisions to medical crowdfunding cases.

The following chapters examine the roles of social influence and physical attractiveness. Specifically, the chapter two examines the heterogeneous impact of social influence in the presence, or the absence of alternative credible information sources, and discovers the dominance of the informational social influence over the normative social influence in medical crowdfunding. The chapter three acknowledges the controversies in the impact of physical attractiveness in charitable behavior and suggests that people's reactions to physical attractiveness can be inconsistent based on the type of behavior they conduct. The findings not only contribute to the literature on medical crowdfunding, but they also bridge the gap in the existing research on social influence and physical attractiveness to provide deeper understanding about individual behavior in online platforms.

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CHAPTER 2: SYMPATHY TO THE SEEMINGLY NEEDY: INTERACTIONS OF SOCIAL AND NON-SOCIAL CUES IN MEDICAL CROWDFUNDING

2.1 Introduction

In an increasingly inter-connected world, users' behaviors are influenced by the actions of others both online and offline (Turner 1991). Previous studies have examined whether social influence exists and how its strength varies in different conditions (Aral and Walker 2011, Bapna and Umyarov 2015, Huang et al. 2020, Zhang et al. 2018). However, no research has systematically studied how social influence interacts with alternative information sources in influencing user behavior. This paper aims to fill this research gap. Using a large-scale randomized field experiment in the medical crowdfunding context, we evaluate how social and non-social cues interact to influence users' donation behaviors and examine the mechanisms that may explain such interaction effects.

Medical crowdfunding is a prominent type of donation-based crowdfunding, where fundraisers seek financial help from donors to cover medical expenses (Young and Scheinberg 2017). It has grown rapidly in scale and popularity in recent years; for example, GoFundMe has raised a total of $650 million in contributions to medical crowdfunding cases on its platform (Cerullo 2019). However, not all fundraisers find themselves equally successful in convincing potential donors to offer help. Often, large disparities exist in the attention and support different cases receive (Kim et al. 2016). A major difference between medical crowdfunding and traditional crowdfunding is that fundraisers are raising funds for an identifiable patient, instead of a general group of recipients. To present a compelling case to donors, fundraisers need to understand how different case attributes (such as patient age, medical condition, and gender) affect users' willingness to donate and whether social influence interacts with this effect. Without such an understanding, a blanket implementation of social cues can reduce social cue's effectiveness and even cause negative impacts in practice (Burtch et al. 2013, Zhang and Liu 2012). Therefore, it is of both theoretical and practical importance to understand how social influence and other information sources interact and how they influence donation decisions.

We conduct a large-scale donor-level randomized field experiment involving more than one million donors on a leading medical crowdfunding platform in China. The platform sets up the medical crowdfunding cases and handles the donations, but the case information is disseminated entirely by users sharing case links with their social connections. Thus, donors can only access a case page by clicking the case link shared with them and not through searching or browsing. This feature of the medical crowdfunding platform makes it an ideal context for studying the impact of social influence and how it interacts with other case information present. During the experiment period, we randomly assign users into treatment and control groups the first time they click to view the details of a case page. This assignment is fixed for a given donor across all subsequent case page visits, for the duration of the experiment. For the control group, the case page displays the case title, target funding amount, and a text description; for the treatment group, the case page displays the same information as that for the control group, except for an additional social cue, showing the donations contributed by the friend from whom the focal donor receives the case link.

To identify the prominent case attributes (referred to as the non-social cues) in this context, we perform a word frequency analysis using the text descriptions. Thus, we establish the relative strength of these non-social cues in persuading users to donate, based on theory and empirical analyses. Young patient age and cancer-related medical condition are identified as two strong non-social cues and female patient gender is identified as a weak non-social cue. Based on the strength of the non-social cues present in each case, we compare users' likelihood to donate across the treatment and control groups for the following four subsamples respectively: (i) cases with adult non-cancer patients (where no strong non-social cues exist), (ii) cases with young cancer patients (where two strong non-social cues exist), (iii) cases with adult cancer patients (where one strong non-social cue exists), and (iv) cases with young non-cancer patients (where one strong non-social cue exists).

Our results show that the strength of social influence differs greatly, depending on the presence of various non-social cues. For cases without strong non-social cues, both social cue and weak non-social cue (female gender) increase the likelihood to donate, and social cue mitigates the impact of the weak non-social cue. In contrast, for cases involving two strong non-social cues (young age and cancer condition), neither social cue nor weak non-social cue significantly increases the likelihood to donate. For cases with a single strong non-social cue (either young age or cancer condition), social cue still significantly increases donation likelihood, while weak non-social cue does not. These findings suggest that the impact of social influence is dependent on the relative informational role of social cue compared with non-social cues. According to the Elaboration Likelihood Model (ELM), this indicates that informational social influence dominates normative social influence in this context, since we observe that users mostly engage in the central route of processing and cognitively compare the quality of informational cues available, rather than inducing affective responses to conform with friends' donations.

By systematically studying how social and non-social cues interact in driving donation decisions, we provide important insights for medical crowdfunding platforms and fundraisers to understand the conditions under which social cue can increase donations. We demonstrate that social cue helps funnel attention and funding, particularly for cases that do not have strong non-social cues to help them stand out from other cases. In addition, the findings of this paper can generalize to other contexts, such as peer-to-peer platforms and prosocial campaigns, where it social influence and other types of information are both present.

The rest of the paper is organized as follows. Section 2 reviews the related literature and highlights the contributions of this study. Section 3 describes the experiment design and the empirical analysis framework. Section 4 presents our main results. Section 5 reports additional analysis for underlying mechanism and robustness checks. Finally, Section 6 discusses the contributions and managerial implications.

In this section, we review four streams of related literature: 1) medical crowdfunding, 2) social influence and the ELM framework, 3) non-social cues and their relative strength in informational value, and 4) interactions of social and non-social cues. Based on the literature review, we discuss the theoretical foundations of this study and our contributions to the existing literature.

2.2 Related Literature and Theoretical Foundation

In this section, we review four streams of related literature: 1) medical crowdfunding, 2) social influence and the ELM framework, 3) non-social cues and their relative strength in informational value, and 4) interactions of social and non-social cues. Based on the literature review, we discuss the theoretical foundations of this study and our contributions to the existing literature.

2.2.1 Medical Crowdfunding and Charitable Giving

Medical crowdfunding, i.e., raising donations from the crowd for healthcare-related purposes, provides an alternative solution to alleviating financial shocks from unexpected medical conditions and associated expenses (Young and Scheinberg 2017). Through making donations to medical crowdfunding cases, donors provide financial support towards cases they find compelling. Existing studies in this literature stream either focus on the impact of medical crowdfunding on individual bankruptcy filings (Burtch and Chan 2019), or use observational data to analyze factors that influence the credibility of medical crowdfunding campaigns (Kim et al. 2016). Despite the increasing popularity of medical crowdfunding, few studies have explored the patterns in donation behaviors or factors that influence donors' willingness to donate.

Medical crowdfunding differs significantly from traditional charitable giving in that detailed information about each case is accessible to users and donations are made to a specific fundraiser (patient) rather than a charity or group. On one hand, this works in favor of fundraisers since previous studies have found that people tend to experience more sympathy and therefore display more generous behavior towards identifiable victims than towards statistical victims (Small et al. 2007). On the other hand, this introduces a new dimension of influencing factors, namely the attributes of each fundraiser and social cues for each case (Dovidio et al. 2017). Most of the existing studies on charitable giving focus on how donor-side factors affect outcomes (Andreoni and Vesterlund 2001, Einolf 2011) and how certain manipulations, such as compassion mediation and cost of prosocial behavior, moderate such differences in outcomes (Ashar et al. 2016, Kessler and Milkman 2018). Other studies investigate how external factors such as advertising content and designs of the campaign influence donors' likelihood to contribute to charitable campaigns (Karlan and List 2007, Sudhir et al. 2016). Overall, prior studies on charitable giving mostly treat fundraisers as a homogenous group and do not examine how various fundraiser attributes may change donors' likelihood to donate. In contrast, medical crowdfunding provides great variations on the fundraiser side such that we can explore how fundraiser attributes can influence donations. Overall, by using a randomized field experiment and detailed donor-level data, our study extends this literature stream and provides a systematic understanding of how different case attributes influence donation likelihood and how the impact of social cues varies for different case attributes.

While existing studies have examined the informational cues for social influence in the reward-based crowdfunding context, few studies have examined the interactions of social cue with other informational attributes (Bapna 2019, Zhang and Liu 2012). Given the substantial differences between the two types of crowdfunding, it is important to understand the role of social influence in medical crowdfunding donation decisions. Our study fills this gap by applying the ELM framework to examine how users process information in medical crowdfunding, conducting a large-scale randomized field experiment and analyzing how social influence and case-level attributes interact in affecting users' likelihood to donate. Medical crowdfunding is also distinctive from reward-based crowdfunding, in both the information problems in the decision-making process and the motivations to contribute. First, in reward-based crowdfunding, the information asymmetry problem originates from investors not fully knowing the founders' quality or the chances of project success; while in medical crowdfunding, the information problem comes from the difficulty for fundraisers to convince users that the patient's need is genuine, such as the severity of the condition is not exaggerated and the fundraisers do not have alternative resources to finance the medical treatments for the patients (Kim et al. 2016). While the medical crowdfunding platforms exert substantial efforts in evaluating each case and some even have peer-monitoring mechanisms in place as another resort to verify the credibility of the case descriptions, the negative publicity from the few fraudulent cases could still dampen the motivation for donors to contribute. In addition, donors' lack of expertise on the specific medical conditions of the patients is another main reason preventing them from fully perceiving the need for help and being persuaded to donate. Sine medical crowdfunding mainly relies on the information presented in a case to motivate donors to make donations, fundraisers need to understand how different information sources influence the prosocial behaviors of the donors.

Second, the motivations to contribute to reward-based crowdfunding and donation-based crowdfunding are different. The investment decisions in reward-based crowdfunding are mainly driven by motivations to reduce risks and maximize expected rewards from investment (either pecuniary or non-pecuniary). Consequently, investors process the information for different projects and check for cues that indicate project success, such as innovative project ideas and solid founder teams. In contrast, for medical crowdfunding, it would be very challenging, if not impossible, to find a uniform measure to evaluate which cases are more deserving of help. In this context, the fundraiser's goal is to persuade users to donate, based on the perceived need of the case and attitude towards providing help. In fact, previous studies have shown that the perceived need of help is a stronger stimulus of prosocial behavior, than the actual need of those who seek help (Bekkers and Wiepking, 2011). The focus of this study is therefore, to understand the information processing mechanism on how donors perceive the need for help from different cases and are persuaded to make donations, rather than making normative claims on whether users are donating to the cases most in need of help. In this sense, medical crowdfunding presents a clearer context to examine how social influence and the inherent case attributes influence donors' decisions, which is not confounded by the actual "quality" of the cases.

2.2.2 Social Influence and the ELM Framework

Previous literature establishes that people's behaviors are affected by others' behaviors, an effect referred to as social influence (Aral and Walker 2011, Bapna and Umyarov 2015, Zhang et al. 2018). There are two types of social influence, informational social influence and normative social influence. Through informational social influence, people infer information from others' behavior to reduce uncertainty, referring to social cue as a source of information (Cohen and Golden 1972, Iyengar et al. 2011). Through normative social influence, people conform their behavior to the expectations from other people (Deutsch and Gerard 1955). While some existing literature has used the Elaboration Likelihood Model (ELM) to examine the impact of social influence in technology adoption, to our knowledge, no study has applied the theory to examine the information processing in the medical crowdfunding context, or the interactions between social influence and the inherent non-social cues in general.

The Elaboration Likelihood Model (ELM) proposes two different routes of processing information: the central route and the peripheral route (Petty and Cacioppo 1984). In the central route, information is processed through critical thinking to evaluate the merits of the arguments presented, which demands a higher level of cognitive efforts. In contrast, in the peripheral route, people rely on the heuristic cues rather than the quality of the arguments in making decisions, which requires less cognitive efforts. The extent to which people lean towards one route or another is referred to as elaboration likelihood and it is influenced by factors such as personal ability and motivation. In the medical crowdfunding context, donors process the available information, including both the case attributes and the social cues from friends, and decide whether they are persuaded to make donations. In this context, social influence could have different impacts on the decision process, depending on which information processing route is engaged. The interactions of social influence with the non-social case attributes likely also differ across the two routes.

Informational social influence provides external information to enhance preferences for cognitive evaluation, which is associated with the central route processing (Lee et al. 2006, Li 2013). For example, Burtch et al. (2013) find that social influence informs the crowd on the attainable marginal utility upon donation decision, presenting substitution effect as the result of informational social influence. In the medical crowdfunding context, friends' donations can serve as an informational social cue, since friends who donated to a case likely possess private information, such as relevant medical knowledge about the medial condition or personal connections with the patient, to validate the need of the case.

If donors tend to engage in the central route of processing, then informational social influence dominates, and donors tend to evaluate the informational value of social cues in comparison with other available information. This suggests that the impact of the social cue varies, depending on the presence of alternative credible information sources.

Normative social influence, or the tendency to conform with the expectations of others, does not require such high levels of cognitive efforts to discern the quality of arguments and it associated with the peripheral route of processing (Bhattacherjee and Sanford 2006, Li 2013). Various studies show normative social influence leading to conforming behaviors in the group, in various contexts ranging from new product adoption, product purchases, to investment decisions (Hong et al. 2018, Iyengar et al. 2015, Thies et al. 2016). If normative social influence dominates, people are likely to incur affective responses to this peripheral cue and attempt to follow the behaviors of their friends, rather than engaging in cognitive thinking to process the quality of the information (Li 2013). In this case, social cue would have a significant impact on user behaviors regardless of the presence of alternative information sources.

Since social influence increases donation likelihood under both routes of processing, we cannot distinguish whether users largely refer to the informational, or the normative value of peer endorsement by studying its main effect alone. We next discuss the informational value of the non-social attributes for the medical crowdfunding cases and how the impact of social influence and its interaction with non-social attributes differ across the two informational processing routes. This would allow us to distinguish which type of social influence dominates in affecting donation behaviors and explore whether the impact of social influence varies depending on the presence of other strong informational cues.

2.2.3 Non-Social Cues and Their Relative Strength in Informational Value

According to the ELM theory, in the central route of processing, users evaluate the strength of the arguments presented, which then induces altitude changes. Here, the strength of the arguments (or informational cues) is empirically determined. Arguments that tend to enhance one's beliefs would be considered as "strong arguments", while those that leave the beliefs unchanged are considered as "weak arguments" (Petty and Cacioppo 1984). In the medical crowdfunding context, potential donors likely use case attributes as informational cues for the perceived need of the case and decide whether to donate. We identify the prominent case attributes (i.e. the non-social cues), from a word frequency analysis using the case title and full text description, as reported in detail in Section 3.3.1. We find three prominent non-social cues: patient age, types of disease, and patient gender. The theoretical arguments on the relative strength of the non-social cues in influencing donation decisions are included in this section and the empirical findings to corroborate these arguments are reported in Section 3.3.2. Previous studies demonstrate that the respective strength of the non-social cues is reflected in the correlation between patient attribute and the neediness (Connelly et al. 2011), therefore, we focus on evaluating whether there is consensus on how donors perceive the neediness for help associated with each attribute from the theoretical perspective.

First, we argue that young patient age is a strong non-social cue, since there is a consensus on young age being a strong indicator or need of help across various fields of study. Relating to the medical context, children are widely considered as a vulnerable population in need of care and help (Landrigan 2004). Moreover, medical treatment of children is one of the most preferred causes of charity (Dimitrova 2012). From a biological viewpoint, it is shown that adults tend to respond more positively to the call of help from offsprings of younger ages (Emlen 1970, Trivers 1974). From a psychological viewpoint, young people are generally perceived as immature and dependent, incentivizing adults to comply with the call for help from the young (James and Prout 1997, Waksler 2003). Studies also show that people are typically more generous in contributing to campaigns for children rather than those for adults (Ren et al. 2020). Since a person's age is closely linked to his or her medical condition and financial situation, young patient age is likely regarded as a strong argument for the need for help. Due to the general consent in existing studies on how adults react to call for help from the young, young patient age should be a strong non-social cue to persuade users to donate to the case.

Second, we argue that cancer-related condition is a strong non-social cue. Cancer-related conditions are the most common patient condition in the dataset, amounting to 21.89% of cases.[1] Compared with other medical conditions, such as broken bones, burns, bleeding, brain conditions and cardiac conditions, we focus on cancer-related diseases, because the public is generally aware of the severity and the mortality rates of cancer conditions (Kolata 2011, McGivney 2019). In addition, it is also documented that the early detection and treatment for cancer effectively leads to decline in global cancer mortality rate (Chatenoud et al. 2014, Hashim et al. 2016). Therefore, donors are more likely persuaded to help patients with cancer-conditions, when they anticipate a chance for

[1] The second largest category, cardiac conditions, accounts for 4.36% of cases

making a difference with their efforts. Overall, we expect cancer-related conditions to serve as a strong informational cue for donors.

Last, we consider the female gender as a weak non-social cue, since existing studies show mixed findings on whether females are perceived as more in need of help than males. On the one hand, studies indicate disparities in access to healthcare for women (Manuel 2018, Rosen and Schneider 2004). On the other hand, studies also indicate that women often have better health outcomes than men despite their lower likelihood of receiving treatments (Regitz-Zagrosek et al. 2010) and, in general, show greater longevity and less risk of suffering from fatal conditions (i.e., cardiovascular diseases) compared with men (National Vital Statistics Report 2019, Harvard Men's Health Watch 2019). Therefore, we expect the female gender to have a weaker impact on the perceived neediness of the case from donors and consider female patient gender as a weak non-social cue.

2.2.4 Interactions of Social Influence and Non-Social Cues

While previous studies have examined factors that moderate the impact of social influence, no studies have systematically examined how social influence interacts with other sources of information in influencing user behavior. Existing studies mostly focus on exploring how certain context-specific factors moderate the role of social influence. Huang et al. (2020) report product characteristics as the moderator of social influence, as status goods rely more on normative social influence and experience goods rely more on informational social influence. Iyengar et al. (2015) find that informational social influence dominates in trial stages to reduce risk (product adoption), whereas normative social influence exerts stronger influence in repeated behavior to increase conformity, showing that the different stages in decision making moderate the impact of social influence. Sun et al. (2020) find that variations in peer-to-peer message content can influence recipients' purchase and referral behaviors. To the extent of our knowledge, no studies have examined how the non-relational factors, aside from decision stages and product characteristics, moderate the impact of social influence. We aim to fill in this research gap, using ELM as the theoretical foundation, to explore the interaction of social and non-social cue influence the decision-making process, in the medical crowdfunding context.

We argue that how social influence interacts with inherent non-social case attributes depends on the information processing route users engage in. In the central route, users will cognitively evaluate the strength of informational social influence, along with the strength of the non-social cues. Previous literature on information literacy shows that signals can have different levels of strength depending on their levels of saliency (Gulati and Higgins 2003, Ramaswami et al. 2010). It is possible for two signals to complement each other when both signals provide relevant information on the same issue through different facets, and the information contained in one signal does not fully encompass the information in the other signal (Steigenberger and Wilhelm 2018). However, when multiple signals are present, users could potentially discount or disregard low-priority information in the presence of a superior information source (Milgram 1970). Based on these studies, we argue that when users engage in the central route of processing, the impact of informational social influence is expected to differ based on the relative strength of non-social cues. When compelling, strong non-social cues are present, social influence likely has a smaller impact; in contrast, when only relatively weak non-social cues are present, social influence likely has a larger impact on users' donation decisions and could mitigate the impact of the weak cues.

In contrast, if users mostly employ the peripheral route of processing, where the normative social influence serves as a heuristic cue to prompt donors to conform with their friends' donation behaviors, we expect to see the impact of social influence to be similar, regardless of the presence of the strong or weak non-social cues. In this scenario, users are not engaged in cognitive assessment of the relative strength of the information cues. Therefore, it is unlikely that the impact of social influence changes when strong non-social cues are present, compared with when only relatively weak cues are present. To empirically examine which route users mostly employ for the medical crowdfunding donations, we divide our sample into four subsets based on the strength of the non-social cues to examine if the impact of social influence differs in the presence of alternative credible information sources.

2.3 Methodology

2.3.1 Research Content and Experiment Design

We collaborate with a leading medical crowdfunding platform in China to conduct a large-scale randomized field experiment. The platform does not collect fees, and the entire sum of donations collected are sent to fundraisers. Adopting the "keep-it-all" rather than the "all-or-nothing" model, the platform allows fundraisers to receive the amount of donations raised even when the fundraising goal is not fully met. As an additional measure to prevent fraud, there is a seven-day grace period after the campaign completes, which allows the platform to investigate potential reports on the qualifications of the case before the funds are transferred to fundraisers. In the year 2019, the platform has funneled a total of 13 billion RMB (around 2 billion USD) in donations, which is of a similar scale as the existing philanthropic organizations[2]. Recent estimates show that the platform has over 400 million active users who click to view and potentially donate to cases launched through the platform (i.e. the platform's user base covers about 50% of all the internet users in China). The large number of donors and high volumes of donations on the platform make it a representative context for the purpose of this study.

To gain access to potential donors and receive donations on this platform, the fundraiser (the patient himself or family/friends acting on the patient's behalf) must first submit relevant case information to the platform. Fundraisers have to follow strict guidelines to pass the review process. Documentations, including medical certificates, pictures of the patient, and proofs from the hospital(s) treating the patient, are usually required. The platform's employees would review each case and the supporting documentations extensively to evaluate the validity of the case. Once the case passes the review, a case detail page with all supporting information becomes active and a unique link to the case page is generated, to be distributed to potential donors. While the platform does not stipulate a limit on the length of time a campaign can stay active, the majority of cases remain open for about six weeks, and then conclude the campaign to draw the funds.

The platform employs a unique design to disseminate case information, relying almost exclusively on users sharing the information through their social networks on a third party social media platform. Unlike most donations and crowdfunding websites, where visitors have access to all open cases, this platform only allows access to a case through its distinct

[2] The total revenue for the American National Red Cross amounted to 2.8 billion USD in 2019.

case link. This link is created when the case is published and then disseminated as the fundraisers share this link through posting on social media or direct messaging their friends or families, who in turn can distribute the link further through their own social networks. Therefore, someone not directly connected to the fundraiser can only view the case if its link is shared by friends either through direct messaging or posting, but not through other means such as browsing or searching. This design helps improve the chances that potential donors see cases relevant to them, involving patients they are connected to, and also reduces the chance of wide distribution of fraudulent campaigns. This unique design of the crowdfunding platform also makes it a highly suitable context to examine the impact of social influence on donations without confounding factors such as search ranking and content promotions.

Our randomized experiment is carried out over the course of four days, from December 7th, 2017, to December 10th, 2017.[3] This sample period did not overlap with public holidays or special events to confound the findings. All active cases during the period are included in the experiment. The randomization is performed on the donor-level. Users (potential donors) are randomly assigned to the treatment or the control group the first time they click the link to view the details on any of the cases' information page during the experiment, and this assignment is fixed for the user throughout the duration of the experiment. When the page is loaded, donors in the control group see the details about the case. Donors in the treatment group see details about the case, exactly the same as the

[3] We verify that during our experiment period, no other advertising campaigns or promotion events were taking place at the same time. In addition, we confirm from the previous year's observations that this particular time window is not associated with particular user behavior, such as spikes in donations associated with seasonal factors.

control group, with the exception of one additional sentence, “person X donated Y amount,” displayed underneath the case’s fundraising goal. The friend displayed here is the person who sent or shared the link with the focal donor. All other aspects of the case information page are identical for the treatment and control groups. A total of 1.9 million observations (page views) occurred during the experiment. Snapshots of the case details page for a sample case across the two groups are shown in Figure 2-1.

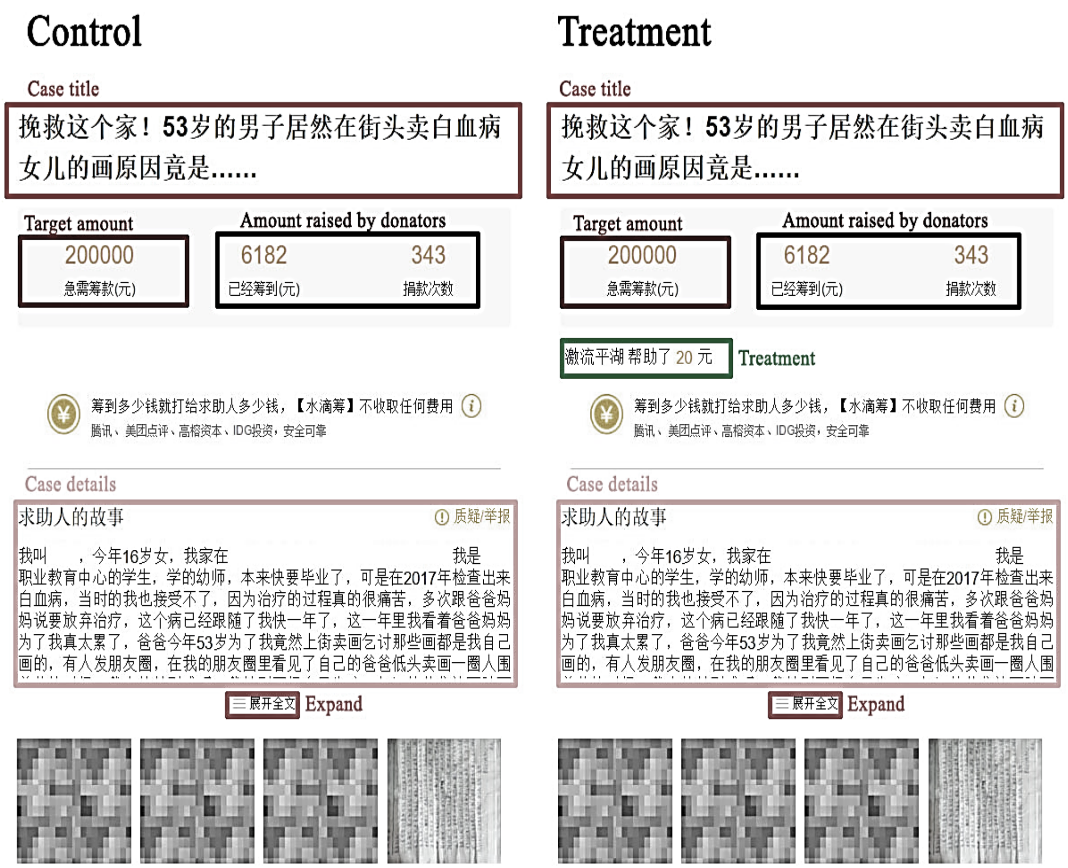

Figure 2-1. Screen Snapshots of the Experiment Design

2.3.2 Data and Measures

We aggregate the data to the donor-case-level, to account for donors clicking to see the same case page multiple times before making donations. We aggregate the data to reflect whether the donor eventually donated to the case and the total amount of money donated. This ensures that multiple visits to the same case from the same donor does not inflate the data, resulting in a higher weight to these donors. Initial assignment to the treatment or the control group stays the same throughout the experiment for each donor, to ensure the validity of our experience.

We also obtain a comprehensive list of case-level and donor-level control variables. The case-level controls include the age, gender, disease type, enrollment in commercial insurance status of the patient, target donation amount, word count for the case descriptions text, number of pictures uploaded, fundraiser identity (whether the fundraiser is the patient him/herself) and the length of time elapsed since case creation (the length of time in days the case has been active, measured at the time of the donor's visit). The donor-level data include the access channel (direct message or posts), percentage of donation fulfilled (at the time the user accesses the case), whether the user is visiting the platform for the first time, time since first visit (the length of time measured in days since the donor's first visit to the platform; 0 for new donors), previous donation indicator (whether the user has previously donated to the platform), same geographic location (whether the user is from the same geographic area as the patient). For the channel of access, 94.91% of visits come from two main channels, friends' SNS feeds (also referred to as WeChat Moments, which is similar to Facebook posts) and WeChat direct messages (which is similar to Facebook direct message).[4] We exclude observations involving gender-specific diseases, such as prostate cancer and cervical cancer. This allows for a more generalizable analysis on how patient gender and disease type impact donors' likelihood to donate. We also removed 11 cases with less than 23 in word count (the average length of a sentence) in their case descriptions as potential outliers. Our finalized dataset contains approximately 1.04 million user-case level observations. Summary statistics of the variables are reported in Table 2-1.

Table 2-1. Summary Statistics

Variables	**Mean (Std.)**	**Min**	**Max**
Female Patient (0/1)	0.404 (0.491)	0	1
Young Patient (0/1)	0.183 (0.387)	0	1
Cancer Related Diseases (0/1)	0.222 (0.416)	0	1
Patient Age	36.579 (18.012)	1	91
Patient Has Commercial Insurance (0/1)	0.040 (0.196)	0	1
Target Donation Amount (RMB)	232,525.6 (150,465.7)	500	1,000,000
Word Count for Case Description	435.453 (269.625)	23	2,364
Number of Pictures Uploaded	5.123 (2.140)	0	16
Fundraiser Identity (0/1)	0.461 (0.498)	0	1
Time since Case Creation	4.840 (13.128)	0.000	203.244
User Access Channel (0/1)	0.188 (0.390)	0	1
Percentage of Donation Fulfilled (%)	9.320 (13.737)	0	854.590

[4] In some instances, the medical crowdfunding platform also reached out to a few donors who have shown prior interest in similar cases and invited page views and these are observations are removed from our sample. The majority of visits still come from viewing the case link through their social networks.

Table 2-1 (continued)

First-time Visit (0/1)	0.431 (0.495)	0	1
Time since First Visit	31.150 (39.089)	0	149.999
Donated Previously (0/1)	0.185 (0.388)	0	1
Same Geographic Location (0/1)	0.084 (0.277)	0	1
Total Observations 1,041,691			

To verify that users are randomly assigned to the treatment and control groups, we perform a balance check and examine whether there exist significant mean differences in the case- and donor-level measures. Table 2-2 confirms that mean values for all the variables are statistically similar across the two groups, with target donation amount as the exception. At the same time, we note that the mean difference of target donation amount is of small magnitude, comparable in scale to the statistically insignificant mean differences of other variables. Thus, this one significant *t*-test result is most likely due to the very large sample size (over one million observations) and unlikely to cause significant biases or influence the results (Lin and Lucas 2013). As an additional robustness check, we perform within-case propensity score matching on the donor-level variables to verify that our results are consistent on a matched sample where all the control variables are perfectly balanced for the control and treatment groups.

Table 2-2. Balance Check for the Control and Treatment Groups

Variable	**Control Group Mean**	**Treatment Group Mean**	**Mean Difference** $(\frac{\mu_C-\mu_T}{\mu_T})$
Female Patient (0/1)	0.404	0.404	0.002
Young Patient (0/1)	0.184	0.182	0.007
Cancer Related Diseases (0/1)	0.221	0.222	-0.004
Patient Age	36.572	36.609	-0.001

Table 2-2 (continued)

Patient Has Commercial Insurance (0/1)	0.040	0.040	0.003
Target Donation Amount (RMB)	232,911.3	232,167.4	0.003**
Word Count for Case Description	435.558	435.038	0.001
Number of Pictures Uploaded	5.119	5.125	-0.001
Time since Case Creation	5.260	5.254	0.001
User Access Channel (0/1)	0.187	0.187	-0.005
Percentage of Donation Fulfilled (%)	9.336	9.306	0.003
First-time Visit (0/1)	0.432	0.431	0.003
Time since First Visit	31.104	31.194	-0.003
Donated Previously (0/1)	0.184	0.185	-0.003
Same Geographic Location (0/1)	0.056	0.057	-0.009
Total (n)	501,694	539,997	

Notes: *p<0.1; **p<0.05; ***p<0.01.

2.3.3 Empirical Analysis on Non-Social Cues

2.3.3.1 Identifying the Main Non-Social Cues

To determine the most salient case attributes in medical crowdfunding, we start with examining the complete list of information required from the fundraisers by the platform for screening. First, fundraisers need to provide the demographics information, including the patient's name, patient's medical condition, and the relationship between the fundraiser and the patient[5]. The platform fully reviews and verifies this information in the screening process before the case is published. Second, fundraisers are required to provide additional information on alternative financing resources, such the insurance status and the properties owned (e.g., balances in bank accounts, real estate properties, cars owned), as shown in

[5] Note that fundraisers submit demographic information such as age and gender of the patient to the platform. When such information is presented to the donors, it is not displayed in a table format (e.g., Gender: Female), but incorporated in the case descriptions. Still, such information is very easy for users to extract. For example, for a case description that starts with "my 11-year-old son is sick", it is straightforward to understand that the patient is of male gender and 11 years of age.

Figure 2-2. For this additional list of information, the platform does not have the resources to verify every case and it is only brought under scrutiny if users report the case for potentially fraudulent claims. Overall, the full set of case information groups into five main categories of attributes: Age, Medical Condition, Gender, Financial Status, and Insurance Status.

From the full set of attributes, we next establish how frequently they appear in prominent positions on the case pages, to identify the list of prominent non-social cues to focus on for our subsequent empirical analysis. The first 25 Chinese characters of the case title and the first sentences (up to 60 Chinese characters) of the case description are considered as prominent positions in the case page, since all donors can see this information, without the extra step of clicking to expand and view the full case description. It is reasonable to assume that fundraisers would display the information they consider as most relevant and most likely to attract the attention of users in the most prominent positions in the case description. Also, from the donors' perspective, it is reasonable to assume that due to the limited time and attention span of potential donors, they tend to focus on reading the case title and the first sentences to grasp the information they need to know about the case.

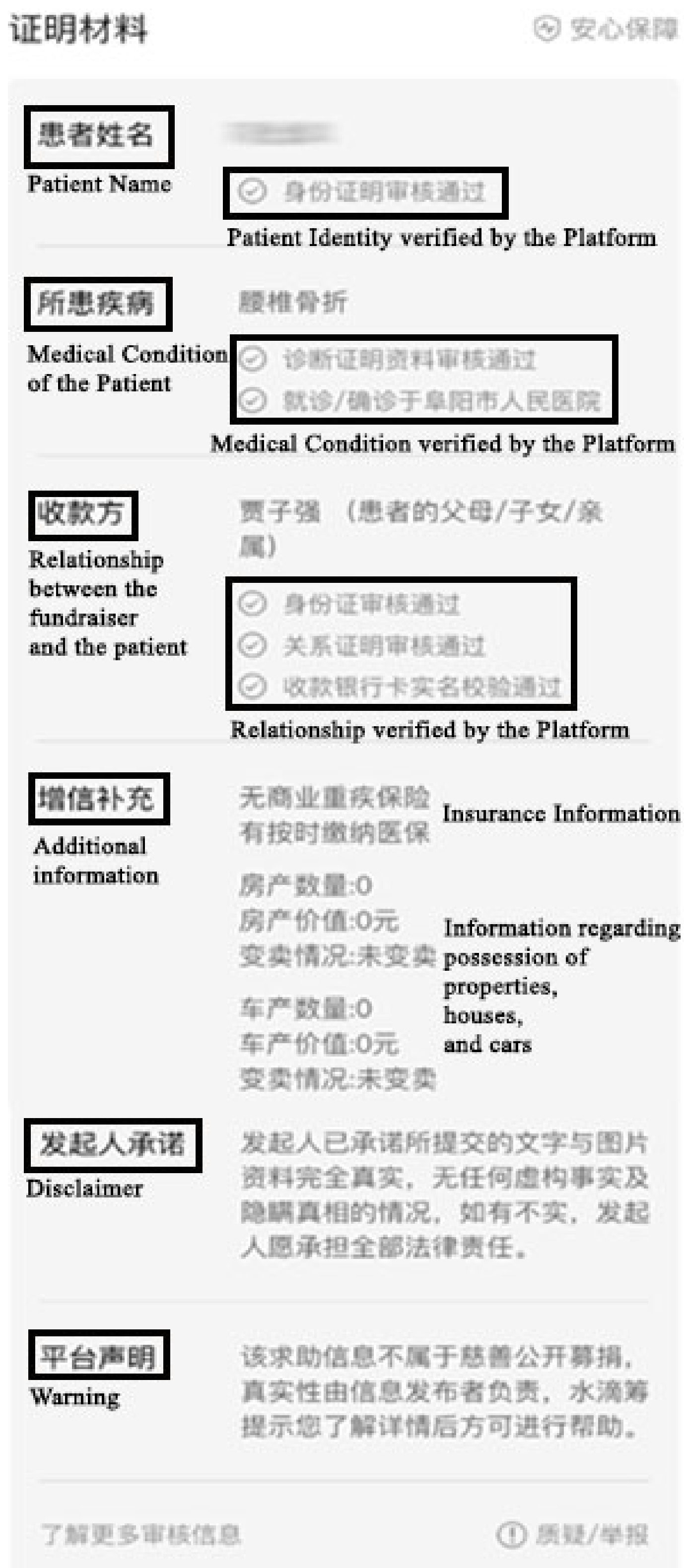

Figure 2-2. Screen Snapshot of the Summary

Table 2-3 reports the lexicon we use to define each case attribute, the proportion of cases displaying each attribute in prominent places and the TF-IDF weight. These five categories of case attributes cover the full set of information the platform collects about the case from the fundraisers. The normalized term frequency weights (TF-IDF) are calculated by taking the natural logarithm of the frequencies of the words belonging to the lexicon of each attribute appearing in the prominent position in the case page, divided by their frequencies in the entire title and the full case description. The weights, in this case, signify the saliency of the attributes in prominent positions, while accounting for their general prevalence in the full corpus.

Table 2-3. Text Frequency Analysis for Non-Social Cues

Case Attributes	Lexicon	Proportion of Cases Showing the Case Attribute in Prominent Positions	Term Frequency Weights (TF-IDF)
Age	Numbers between 1 and 110 “years old”, variants of adjectives describing “young”, “old”, “child”, “adult”	60.66%	0.173
Medical Condition	20 most frequently mentioned types of medical conditions (i.e. cancer, heart disease), various expressions for “suffering” and “sick”	55.04%	0.068
Gender	“man”, “woman”, “he”, “she”	14.63%	0.053
Financial Status	“real estate”, “property”, “house”, “car”, “money”, “income”	1.46%	0.003
Insurance Status	“commercial insurance”, “medical insurance”, “insurance”	0.04%	0.000

The results of the text analysis show that the top three prominent case attributes include: 1) patient age (with 60.66% of the 13,921 cases showing this information in the title and the first sentence), 2) the medical condition of the patient (55.04% of all cases highlighting this attribute) and 3) patient gender (14.63% of all cases highlighting this attribute). Among the various medical-conditions, cancer is the most frequently observed condition, accounting for 22.2% of all cases. The TF-IDF weights show consistent ranking of the most prominent case attributes displayed, after accounting for their baseline prevalence. In addition, since there is a large contrast between the top three categories of case attributes from the bottom two (financial status and insurance status), we focus on patient age, patient medical condition, and patient gender as the three primary non-social cues for this context. The results show an average weight of 0.173 for the age-indicative words, 0.068 for the medical condition-indicative words, and 0.053 for the gender-indicative words. Among the three salient non-social cues we identify from the text analysis, we then evaluate the relative signal strength in the medical crowdfunding context, based on theory and empirical analysis on the different impacts of the three non-social cues on the users' likelihood to donate.

2.3.3.2 Relative Strength of the Non-Social Cues

From the theory perspective, we argued in Section 2.2.3 that among the three primary non-social cues, young patient age and cancer-related medical condition are relatively strong non-social cues and patient gender is a relatively weak non-social cue. In this section, we empirically compare the impact of the non-social cues on donors' likelihood to donate. For this purpose, we only use the control group, where no social influence information is displayed. We employ a logistic regression framework with robust clustered standard errors, as shown in Equation (1), relating the natural log of the odds ratio for whether the donor donates to the case ($Donation_i$), to the main variables of interest, including young patient indicator, cancer condition indicator and patient gender indicator, while controlling for all the other case- and donor-level control variables available (as discussed in Section 2.3.2).

$$log\left(\frac{Pr(Donation_i = 1)}{1 - Pr(Donation_i = 1)}\right)$$
$$= \beta_0 + \beta_1 Young_i + \beta_2 Cancer_i + \beta_3 Female_i + \beta_4 Controls_i + \varepsilon_i \quad (1)$$

Results in Table 2-4 show that the coefficient for the Young Patient indicator variable is 0.216 and statistically significant. This suggests that all else equal, users are 24.1% (i.e., $e^{0.216}$-1) more likely to donate to cases involving young patients than those involving adults. Similarly, holding other factors equal, users are 5.0% (i.e., $e^{0.049}$-1) more likely to donate to cancer cases than non-cancer cases, and 3.9% (i.e., $e^{0.038}$-1) more likely to donate to cases involving female patients than male patients. We also note that among all the other case attributes, cases with more detailed information, such as richer text descriptions or more photos uploaded as supporting evidence, see increase in donation likelihood. In contrast, other case attributes, such as whether the patient has commercial insurance or the target goal amount, do not significantly influence donation likelihood. These findings confirm that patient age, disease type, and gender are the main non-social cues that influence users' donation decisions and that the three non-social cues have different strength in their informational value to users. The young age (ages 1-18) exerts the strongest impact in improving donation likelihood, followed by the cancer and the female gender.[6] Therefore, in the following analysis, we refer to "young patient" and "cancer condition" as strong non-social cues and "female patient" as a weak non-social cue.

Table 2-4. Non-social Cues and Donation Likelihood

	Sample	Control Group
	Dependent Variable	Donation (0/1)
	Model	Logit
Case-level variables	Young	0.216^{***}
		(0.049)
	Cancer	0.049^{**}
		(0.023)
	Female	0.038^{*}
		(0.022)
	Patient Age	-0.002^{**}
		(0.001)
	Patient Has Commercial Insurance	-0.055
		(0.051)
	Standardized (Target Donation Amount (RMB))	0.015
		(0.011)
	Standardized (Word Count for Case Description)	0.029^{*}
		(0.016)
	Number of Pictures Uploaded	0.011^{**}
		(0.005)
	Fundraiser Identity	0.014
		(0.023)
	Time since Case Creation	-0.079^{***}
		(0.005)
Donor-level variables	Donated Previously	1.260^{***}
		(0.019)
	Percentage of Donation Fulfilled	-0.002^{*}
		(0.001)
	Same Geographic Location	0.468^{***}
		(0.018)
	First Time Visit	0.611^{***}
		(0.016)
	User Access Channel	0.257^{***}
		(0.017)
	Time since First Visit	0.003^{***}
		(0.000)

[6] Since the three non-social cues, Young, Cancer and Female are all binary variables, we compare the scale of the coefficient estimates for these three variables directly, for their relative strength in persuading donors to donate. We have also repeated the analysis using the standardized values of these three variables and verify that their relative effect sizes remain consistent.

Table 2-4 (continued)

Constant	-2.669***
	(0.065)
Observations	501,694

Notes: i. This table shows results with the control group only
ii. Robust standard errors, clustered by cases, are reported in parentheses
iii. *p<0.1; **p<0.05; ***p<0.01

2.3.4 Framework for Main Analysis

To examine how social cue interacts with these three non-social cues, we partition the donor-case-level data into four segments based on the presence of the two relatively strong inherent non-social cues in each case, "young patient" and "cancer condition", as illustrated in Table 2-5. Segment 1 is composed of all donor-case observations for cases involving adult non-cancer patients, with neither of the two strong non-social cues. Segment 4 is composed of observations for cases involving young cancer patients, with both the two strong non-social cues, "young patient" and "cancer condition". Segments 2 and 3 consist of observations for cases with only one strong non-social cue each: adult cancer patients for Segments 2 and young, non-cancer patients for Segment 3.

Table 2-5. Four Subsets based on the Presence of the Two Strong Non-Social Cues[7]

		Cancer	
		0	1
Young	0	(1) Adult, Non-Cancer	(2) Adult, Cancer
	1	(3) Young, Non-Cancer	(4) Young, Cancer

[7] We conduct our analysis on the four subsets based on the stronger cues instead of the whole combined dataset. Conducting analysis on the whole dataset is likely to complicate the interpretation of the coefficients, since our model would then incorporate 4-way interactions (3 non-social cues and 1 social cue). Moreover, the non-social cues are unlikely to be independent from each other; there is a high chance of correlations among them.

We explore how social cue interacts with non-social cues, by examining how the effect of social cues varies, depending on whether strong or weak non-social cues are present. Equation (2) outlines the regression framework for our main analysis, using a logistic model to relate the likelihood of donation, to the treatment indicator, patient gender indicator, and their interaction term. The full list of control variables reported in Table 2-1 and their interaction terms with the treatment variable are also included. Equation (2) is estimated on each of the four segments to compare the coefficients. Specifically, β_1 reflects the impact of social influence on the likelihood to donate, and comparing the estimates of β_1 across segments can inform us whether the impact of social influence differs in the presence of different non-social cues. We examine the scale of the estimates for β_2 to see if the weak patient gender cue increases donation likelihood and if so, the estimates of β_3 indicate how the effect of social cue interacts with patient gender in affecting donation likelihood.

$$log\left(\frac{Pr(Donation_i = 1)}{1 - Pr(Donation_i = 1)}\right) = \beta_0 + \beta_1 Presence\ of\ Social\ Cue_i$$

$$+\beta_2 Female_i + \beta_3 Presence\ of\ Social\ Cue_i \times Female_i$$

$$+\beta_4 Controls_i + \beta_5 Presence\ of\ Social\ Cue_i \times Controls_i$$

$$+ \varepsilon_i \qquad (2)$$

The validity of this subsample analysis is ensured since the randomization of our experiment is performed on the donor-level, and the randomized assignment of control and treatment groups also holds for any subsample of cases. This allows us to clearly examine the impact of the treatment condition (whether social cue is introduced), the female patient gender variable, and their interactions on the likelihood for the donor to donate to the case.

If we relied on the full interaction terms for this analysis on the full sample instead, the treatment indicator and the three non-social cues yield a total of 15 terms, making interpretation of the findings highly challenging. Still, we verified that our findings are consistent with the full sample, complete interactions specification. We also verify (not shown here due to space limitations) that our findings are consistent with and without the inclusion of additional control variables, as is expected from the nature of the randomized experiment. In addition, while our main analysis focuses on the likelihood to donate, we verify that the findings are consistent, using the amount donated as the dependent variable in the robustness check section.

2.4 Results

We estimate Equation (2) on each of the four data segments, as defined in Table 2-5, and report the results in this section, exploring the impact of social cue on the likelihood to donate and how the impact changes in the presence of other strong or weak non-social cues.

2.4.1 Social Influence and Gender Cue for Cases Involving Adult Non-Cancer Patients

First, we examine the segment of user-case level observations for cases involving adult non-cancer patients. Neither of the two strong non-social cues from the inherent case attributes is available for these cases to persuade donors to donate. We report the estimations based on Equation (2) for this segment in Table 2-6. The first observation is that for these cases, donors refer to the weak non-social cue, female patient gender, in their decisions on whether to donate in the absence of the two strong non-social cues. The coefficient for the *Female* variable for the control group is 0.060 (column 1 of Table 2-6), which suggests that donors are 6.2% (i.e., $e^{0.060}$-1) more likely to donate to cases involving female patients than cases involving male patients.

Interestingly, we observe that the impact of patient gender on donation likelihood decreases and becomes insignificant as the social cue is introduced (column 2). When donors are presented with information on their friends' donations, their donation likelihood increases by 26.9% (i.e., $e^{0.238}$-1) in the absence of the two strong non-social cues (column 3). At the same time, social cue reduces the impact of patient gender by 3.7% (i.e., $e^{0.036}$-1). We observe that users tend to refer to patient gender and social cue in the absence of the two strong non-social cues. This suggests that in the absence of strong informational cues, such as patient age or disease type, donors refer to the informational value of social influence, as they engage the central route information processing to enable more in-depth evaluation of a case and also reduces the reliance on the weak non-social cues.

Table 2-6. Social Influence and Gender Cue for Cases Involving Adult Non-Cancer Patients

	(1)	(2)	(3)
Sample	Control Group	Treatment Group	Control and Treatment Groups
Dependent Variable	Donation (0/1)	Donation (0/1)	Donation (0/1)
Model	Logit	Logit	Logit
Female	0.060^{**} (0.030)	0.024 (0.028)	0.060^{**} (0.030)
Presence of Social Cue			0.238^{***} (0.050)
Female × Presence of Social Cue			-0.036^{**} (0.017)

Table 2-6 (continued)

Control variables	Patient commercial insurance status, target donation amount, word count for case description, number of pictures uploaded, fundraiser identity, time since case creation, usage of age/ medical condition / gender/ financial status – indicative words in the prominent position, a user's previous donation, percentage of donation fulfilled, same geographic location, user type, access channel, and time since first visit; We exclude insurance-indicative words in the prominent position (0/1) as our control variable since it sometimes predicts failure perfectly		
Constant	-1.874*** (0.084)	-1.773*** (0.080)	-1.874*** (0.084)
Observations	304,433	327,738	632,171

Notes: i. Reporting results on the sample of cases involving adult, non-cancer patients;
ii. Robust clustered standard errors clustered by cases reported in parentheses, *p<0.1; **p<0.05; ***p<0.01.

2.4.2 Social Influence and Gender Cue for Cases Involving Young Cancer Patients

Next, we examine the segment with the largest contrast to the first segment, observations for cases involving young cancer patients. These cases have the two strong non-social cues, the young patient age and cancer condition, that donors can refer to in assessing the validity of the case. We explore whether social influence and the weak non-social cue still have significant impact on the likelihood to donate in the presence of the two strong non-social cues. Results in Table 2-7 indicate that the weak non-social cue, patient gender, does not influence the likelihood to donate for either the control or the treatment group (columns 1 and 2). In addition, social influence does not affect the likelihood to donate either (column 3), and the interaction between social influence and patient gender is also insignificant. This suggests that with multiple inherent strong non-social cues, both the social cue and the relatively weak non-social cue become redundant.

Overall, the results in Table 2-7 indicate that for cases with the two strong non-social cues (young age and cancer disease), neither patient gender nor social influence contributes to higher likelihood to donate.

The contrast in the results here, compared with Table 2-6, shows that the impact of social influence changes, depending on whether strong non-social cues are present. This indicates that donors tend to use the central route of processing more and cognitively evaluate the quality of different non-social cues to decide whether to make donations and the informational social influence is the dominant type of social influence in this context.

Table 2-7. Social Influence and Gender Cue for Cases Involving Young Cancer Patients

	(1)	(2)	(3)
Sample	Control Group	Treatment Group	Control and Treatment Groups
Dependent Variable	Donation (0/1)	Donation (0/1)	Donation (0/1)
Model	Logit	Logit	Logit
Female	0.007 (0.175)	0.081 (0.203)	0.007 (0.175)
Presence of Social Cue			-0.095 (0.269)
Female × Presence of Social Cue			0.074 (0.108)
Control variables	Yes	Yes	Yes
Constant	-1.399^{***} (0.240)	-1.636^{***} (0.297)	-1.399^{***} (0.240)
Observations	5,939	6,294	12,233

Notes: i. Reporting results on the sample of cases involving young, cancer patients;
ii. Control variables include the full set of case-level controls, the full set of donor-level controls and their interactions with the treatment variable;
iii. Robust clustered standard errors clustered by cases reported in parentheses, *p<0.1; **p<0.05; ***p<0.01.

2.4.3 Social Influence and Gender Cue for Cases Involving Adult Cancer Patients

Next, we examine the segment of observations for cases involving adult patients with cancer diseases, where the presence of disease type serves as a strong non-social cue. The results in Table 2-8 show that the coefficient estimates for the *Female* variable are statistically insignificant for both the control group (column 1) and the treatment group (column 2), confirming that in the presence of a single strong non-social cue, a weak non-social cues does not significantly influence users' likelihood to donate. In the pooled estimation in column 3, the results show that *Presence of Social Cue* increases the likelihood to donate overall by 24.9% ($e^{0.222}$-1), indicating that the social cue can increase the donation likelihood despite the presence of a single strong non-social cue (cancer disease). The results also reveal that social cue exerts a stronger informational value than patient gender cue and that social influence still has a significant informational role in the presence of a single strong inherent non-social cue. At the same time, the results show that social cue does not increase or decrease the effect of patient gender cue in this case.

Table 2-8. Social Influence and Gender Cue for Cases Involving Adult Cancer Patients

	(1)	(2)	(3)
Sample	Control Group	Treatment Group	Control and Treatment Groups
Dependent Variable Model	Donation (0/1) Logit	Donation (0/1) Logit	Donation (0/1) Logit
Female	0.024 (0.039)	0.054 (0.040)	0.024 (0.039)
Presence of Social Cue			0.222^{***} (0.082)
Female × Presence of Social Cue			0.030 (0.026)
Control variables	Yes	Yes	Yes
Constant	-1.857^{***} (0.107)	-1.607^{***} (0. 109)	-1.857^{***} (0.107)
Observations	105,325	113,882	219,207

Notes: i. Reporting results on the sample of cases involving adult cancer patients;
ii. Control variables include the full set of case-level controls, the full set of donor-level controls and their interactions with the treatment variable;
iii. Robust clustered standard errors clustered by cases reported in parentheses, $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

2.4.4 *Social Influence and Gender Cue for Cases Involving Young Non-Cancer Patients*

For the segment of observations for cases involving young patients with non-cancer diseases, where the presence of young age serves as a strong non-social cue, results are reported in Table 2-9, which are largely similar as the results in Table 2-8. We note that the coefficient estimates for the *Female* variable are not statistically significant across the control group (column 1) and the treatment group (column 2). However, the presence of social cue still increases the likelihood to donate overall by 19% ($e^{0.174}$-1, as indicated in column 3), suggesting that the presence of a single strong inherent non-social cue does not provide sufficient information on a patient's neediness for help and social cues can still add marginal informational value in this context. Furthermore, the interaction term for female and the treatment is insignificant, suggesting that in the presence of a strong non-social cue, the social cue neither significantly enhances nor reduces the impact of the weak non-social cue.

Table 2-9. Social Influence and Gender Cue for Cases Involving Young Non-Cancer Patients

	(1)	(2)	(3)
Sample	Control Group	Treatment Group	Control and Treatment Groups
Dependent Variable	Donation (0/1)	Donation (0/1)	Donation (0/1)
Model	Logit	Logit	Logit
Female	-0.004 (0.048)	-0.008 (0.051)	-0.004 (0.048)
Presence of Social Cue			0.174** (0.081)
Female × Presence of Social Cue			-0.004 (0.028)
Control variables	Yes	Yes	Yes

Table 2-9 (continued)

Constant	-1.668*** (0.095)	-1.524*** (0.089)	-1.668*** (0.095)
Observations	85,997	92,083	178,080

Notes: i. Reporting results on the sample of cases involving young, non-cancer patients;
ii. Control variables include the full set of case-level controls, the full set of donor-level controls and their interactions with the treatment variable;
iii. Robust clustered standard errors clustered by cases reported in parentheses, *p<0.1; **p<0.05; ***p<0.01.

Overall, the results across the four segments consistently show that the impact of social influence on the likelihood to donate varies, depending on the strength of the non-social cues present. This suggests that in the medical crowdfunding context, informational social influence dominates normative social influence. These findings indicate that in the medical crowdfunding context, donation behaviors are to a larger extent, the result of cognitive assessment of the strength of persuasion in informational social influence together with non-social cues through the central route, rather than the result of affective responses to normative social influence through the peripheral route.

2.5 Additional Results

2.5.1. Evidence for Underlying Mechanism by Varying the Elaboration Likelihood

In the first robustness check, we use the donor access channel as a variable that influences the elaboration likelihood (i.e., the tendency to employ the central route or the peripheral route), to verify the mechanisms of our findings according to the ELM framework. Donor access channel specifies whether a donor accessed a case by clicking the case link sent via a direct message from a friend or posted on the friend's SNS feed (WeChat Moments), which is visible to everyone in their social networks.

When the donors access a case through friends' SNS feeds, which are not specifically referred by their friends, their decisions to click to visit the case demonstrate their interest in the case and willingness to learn more about it. This suggests a higher level of motivation to spend cognitive effort in evaluating the case. According to the ELM, higher personal motivation increases the use of the central route, while a lower level of motivation suggests that users are more likely to process information through the peripheral route (Petty and Cacioppo 1984). Therefore, we expect to see that users accessing the case through links shared on friends' SNS are more discerning on the relative strength of the social and non-social cues, since they are more likely to use the central route of information processing.

To verify the mechanism of our results using the difference in elaboration likelihood indicated in user access channel, we segment the sample in Table 2-6 (observations for cases involving adult, non-cancer patients; where neither of the two strong non-social cues is present) by the two different donor access channels, and repeat the analysis. Table 2-10 reports the results. We observe that donors who accessed through friends' shared links (column 1) are not significantly influenced by the patient gender cue in their donation decisions. This supports our argument that highly motivated users are more likely to employ the central route of information processing and are more discerning on the quality of the information presented for the case. In contrast, donors accessing through links shared directly by friends are significantly influenced by the patient gender cue and that this effect is mitigated by the presence of the social cue (column 2). These donors have lower motivation to exert cognitive effort to evaluate the case and thus are more likely under the peripheral route. Therefore, the weak informational cues still have some impact, but this is mitigated by the presence of the relatively stronger social cue. When we compare the coefficients for the social cue across the two columns, while the effect appears to be larger in the high motivation case (column 2), the difference is not statistically significant (t-value = 0.71). This is also consistent with our findings, that the strength of the social cue is stronger than the female patient gender cue, but not as strong as the young patient age cue and the cancer disease cue together. Therefore, when users use the central route more, the impact of this informational cue does not necessarily increase. This robustness is consistent with the interpretation of our findings under the ELM framework, that informational social influence is the dominant type of social influence in this context and that donors evaluate the strength of social and non-social cues through the central processing route as they make donation decisions.

Table 2-10. Social Influence and Gender Cue Depending on Channel of Access for Cases Involving Adult Non-Cancer Patients

Sample	(1) SNS Feed Channel of Access	(2) Direct Message Channel of Access
Dependent Variable	Donation (0/1)	Donation (0/1)
Model	Logit	Logit
Female	0.050	0.094^{***}
	(0.035)	(0.036)
Presence of Social Cue	0.244^{***}	0.230^{**}
	(0.057)	(0.107)
Female × Presence of Social Cue	-0.020	-0.090^{**}
	(0.020)	(0.036)
Controls	Yes	Yes
Constant	-1.824^{***}	-1.827^{***}
	(0.094)	(0.104)

Table 2-10 (continued)

Observations	515,310	116,861

Notes: i. Reporting results on the sample of cases involving adult, non-cancer patients;
ii. Control variables include the full set of case-level controls, the full set of donor-level controls and their interactions with the treatment variable;
iii. Robust clustered standard errors clustered by cases reported in parentheses, *p<0.1; **p<0.05; ***p<0.01.

2.5.2. Robustness Checks on the Data and Measures

We verify that the results in Section 4 are consistent with different sample specifications and robust to our choice of the dependent variable, with the following robustness checks: 1) using a matched sample from within-case propensity score matching and 2) using logged values of the amount donated for each visit as the dependent variable and estimating a Tobit model to account for the observations without donations, showing 0s as the amount donated. We run these additional analyses to replicate the results in Table 2-4, to verify that the relative strength of the non-social cues from the empirical estimations are robust. We also replicate results in Tables 2-6 to 2-9 to verify our main findings under these alternative specifications.

The within-sample propensity score matching is motivated by what we observed in the balance checks in Table 2-2. One of the case-level variables, target donation amount, has statistically significant mean differences, although small in scale, across the control and treatment groups. To verify that such mean differences do not have a major influence on our results, we conduct within-case propensity score matching and estimate our models on the matched sample. For each case, we matched donors in the control and treatment conditions by the donor-level control variables, including access channel, user type, geographic location, and previous donation indicator. Within-case propensity score matching gives us a subsample of donors whose characteristics are statistically similar across the control and treatment assignments within each case. On this matched sample, the mean differences for all control variables are insignificant for the control and treatment groups. By repeating our analysis on this subsample of donors, we address the potential concern of unobserved case-level heterogeneities, such as different social networks of patients, and confirm that our findings remain consistent.

In addition to the likelihood to donate, we also verify that our results are consistent when using the amount of money each user donated. Since the donation amount are marked as zeros for case page views that did not lead to donations, we estimate a Tobit model for the latent true amount of donations donors intend to donate, where the observed donation amount is left-censored at 0, as specified in Equation (3):

$$y_i^* = \beta_0 + \beta_1 Young_i + \beta_2 Female_i + \beta_3 Cancer_i + \beta_4 Controls_i + \varepsilon_i \qquad (3)$$

where $\varepsilon_i \sim N(0, \sigma^2)$ and the donation amount actually observed, y_i, is specified as:

$$y_i = \begin{cases} y_i^* & if\ y_i^* > 0 \\ 0 & o\ therwise \end{cases}$$

In Table 2-11, we reproduce the results from Table 4 to column 1 here for easier comparison. Using this matched sample from propensity score matching, column 2 in Table 2-11 confirms that non-social cues including young patient age, cancer-related conditions, and female patient gender influence the likelihood to donate. The relative scales of the coefficient estimates in these robustness checks are also consistent with before. Similarly, we find that users likely donate larger amounts of money to cases involving young patients, cancer patients, and female patients (column 3, Table 2-11) and consistent scale of the estimates with our observations earlier: young patient and cancer condition are the two strong non-social cues and patient gender is the weak non-social cue.

Table 2-11. Non-Social Cues and Donation Likelihood, Different Specifications

Label	(1) Main Result	(2) Within Case Matching	(3) Donation Amount
Sample	Control Group	Control Group	Control Group
Dependent Variable	Donation (0/1)	Donation (0/1)	log(Donation Amount+1)
Model	Logit	Logit	Tobit
Young	0.216^{***}	0.194^{***}	0.538^{***}
	(0.049)	(0.052)	(0.130)
Cancer	0.049^{**}	0.053^{**}	0.122^{**}
	(0.023)	(0.024)	(0.060)
Female	0.038^{*}	0.040^{*}	0.102^{*}
	(0.022)	(0.025)	(0.058)
Control Variables	Yes	Yes	Yes
Constant	-2.669^{***}	-2.473^{***}	-5.610^{***}
	(0.065)	(0.057)	(0.178)
Observations	501,694	473,735	501,694
Censored (at 0)			447,978
Uncensored			53,716

Notes: i. Reporting results using control group only;
ii. Column 1 replicates the main findings in Table 4 for easier comparison, column 2 uses within-case matching to balance control variables on the control and treatment groups column 3 uses a Tobit model, with logged amount donated as the dependent variable.
iii. Control variables include all case level controls, all user level controls and their interactions with the treatment variable, except for insurance-indicative words in the prominent position (0/1) since it sometimes predicts failure perfectly
iv. Robust clustered standard errors clustered by cases reported in parentheses,
$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table 2-12 reports the results from a similar set of robustness checks on the interaction of the social cue with patient gender, on the sample of views for cases involving adult, non-cancer patients, with similar specifications as Equation (2). Column 1 of Table 2-12 reproduces the results in column 3 of Table 2-6 for easier comparison. Column 2 shows consistent results using the balanced sample from propensity score matching. For this segment of cases with neither of the stronger inherent non-social cues, users are more likely to donate to cases involving female patients (persuaded by the informational value of the patient gender cue). However, the presence of the social cue not only increases the likelihood to donate overall, but also reduces the impact of the weak non-social cue.

Column 3 reports results using the Tobit model, with the logged values of donation amount as the dependent variable and shows that social cue also increases the amount of money donated, while mitigating the impact of the patient gender attribute. Overall, our findings are robust across these alternative specifications.[8]

Table 2-12. Robustness Check Results for Non-Cancer Adult Patients

Label	(1) Main Result	(2) Within Case Matching	(3) Donation Amount
Sample	Control and Treatment	Control and Treatment	Control and Treatment
Dependent Variable	Donation (0/1)	Donation (0/1)	log(Donation Amount+1)
Model	Logit	Logit	Tobit
Female	0.060**	0.062**	0.163**
	(0.030)	(0.012)	(0.079)
Presence of Social Cue	0.238***	0.184***	0.691***
	(0.050)	(0.045)	(0.129)
Female × Presence of	-0.036**	-0.032**	-0.077*
Social Cue	(0.017)	(0.017)	(0.046)
Control Variables	Yes	Yes	Yes
Constant	-1.874***	-1.844***	-5.910***
	(0.084)	(0.070)	(0.233)
Observations	632,171	602,973	632,171
Censored (at 0)			565,102
Uncensored			67,069

Notes:

i. Reporting results using the sample of observations for cases involving adult, non-cancer patients;
ii. Column 1 replicates the main findings in Table 6 for easier comparison, column 2 uses within-case matching to balance control variables on the control and treatment groups column 3 uses a Tobit model, with logged amount donated as the dependent variable.
iii. Control variables include all case level controls, all user level controls and their interactions with the treatment variable, except for insurance-indicative words in the prominent position (0/1) since it sometimes predicts failure perfectly
iv. Robust clustered standard errors clustered by cases reported in parentheses,
*p<0.1; **p<0.05; ***p<0.01.

2.6 Discussion and Conclusion

[8] We also found consistent results for other segments of cases, as the findings in Tables 6, 7 and 8, which are not reported here.

2.6.1. Summary of Findings

This paper is one of the very first study to systematically examine the role of social influence in medical crowdfunding and how it interacts with other sources of information, such as inherent non-social attributes. Based on the ELM, we explore the mechanism of how social influence impacts donation decisions, to evaluate whether donors mostly employ the central route of information processing, where informational social influence dominates, or mostly employ the peripheral route of information processing, where normative social influence dominates. Based on the large-scale randomized field experiment involving over one million users, we first identify the prevalent non-social cues and their relative strength in persuading users to donate. Based on theoretical arguments and empirical evidence, we decide to focus on young patient age, cancer-related condition, and female patient gender as the three prominent non-social cues, with young patient age and cancer disease as the strong cues, and female patient gender as the weak cue. Then, we examine the impact of social influence on the likelihood to donate, using different subsamples of observations, according to the presence or absence of the strong non-social cues.

We find that the impact of social influence differs greatly, depending on whether the non-social attributes are strong or weak informational cues to persuade users to donate. Specifically, for cases that lack strong non-social cues (i.e., involving adult patients with non-cancer conditions), social cue significantly increases donation likelihood, and reduces the impact of the weak non-social cue (female patient gender). In contrast, for cases with both strong non-social cues present (i.e., involving young, cancer patients), the impacts of social cue and the weak non-social cue on the willingness to donate become insignificant.

For cases with only one strong non-social cue, the presence of social cue still increases the likelihood to donate while female patient gender does not. Our results consistently show that donors tend to evaluate the quality of the information in the social cue, in comparison with other non-social cues to decide whether to donate and the impact of social cue is more salient in the absence of strong non-social cues. These findings are consistent with the central route of information processing, where informational social influence dominates normative social influence, and donors make their donation decisions based on cognitive evaluation of the strength of the cues present.

2.6.2. Theoretical Contributions and Future Research

This study makes the following areas of theoretical contributions. First, we contribute to the literature on medical crowdfunding (Burtch and Chan 2019, Kim et al. 2016, Young and Scheinberg 2017), using a large-scale randomized field experiment to examine the factors that influence users' willingness to donate. While existing studies mostly focus on how the donors' attributes influence donations, we focus on how the recipient attributes and social influence interact in influence donations. The field experiment presents a clean setting to evaluate how the impact of social influence on donations varies, depending on the presence of the non-social cues and provide new insights on the conditions under which social influence has strong impact on donations. Second, we contribute to the stream of literature on social influence (Aral and Walker 2011, Bapna and Umyarov 2015, Huang et al. 2020, Zhang et al. 2018), evaluating the mechanisms for how donors evaluate the information in social and non-social cues in their decision-making process. Based on the ELM framework, we reveal from the findings that informational social influence dominates normative social influence in this context, as donors more likely use the central route of information processing, cognitively evaluating the quality of different sources of information. Third, this study contributes to the literature stream on ELM (Bhattacherjee and Sanford 2006, Li 2013), extending the applications of ELM from technology adoption, product purchase and investment decisions, to explaining how users are persuaded to engage in prosocial behaviors such as donations.

There are some limitations of our study due to data availability that future research can further expand upon. First, our data does not include detailed information on the identity of the friends or their social connections. The attributes of the influencer likely have an impact on how users process social cues. Previous studies show that social influence exerts heterogeneous impacts based on different conditions, such as influencer identity (Aral and Walker 2012, Chaiken 1979, Eagly and Chaiken 1993, Strodtbeck et al. 1957), recipient identity (Falomir and Invernizzi 1999), and relationships between the influencer and the recipient (Aral and Walker 2014, Haslam et al. 2004). However, due to the limitations of our data, we do not focus on the differential impact of social influence depending on the characteristics of the influencer in this study. While our study focuses on establishing how social and non-social cues interact in influencing donation decisions, future studies can explore how such interaction effect is moderated by the attributes of the friends' social networks. For example, future studies can examine whether the focal user is more likely to employ the peripheral route of processing when observing friends with strong ties or more connections in their social networks. Second, detailed user demographics information is not available in our data, as the platform does not mandate such data collection from potential donors. Future extensions can potentially investigate further whether donors of different gender, age groups, and previous experiences exhibit different donation behaviors in response to patient attributes and the presence of social cues. For example, studies could examine whether donors with more expertise are more likely to engage in the central route of processing, where informational social influence plays a larger role in their decisions. In addition, existing work has shown that user anonymity has an impact on herding behavior in donations (Jiang et al. 2020). In our context, donor anonymity is somewhat ambiguous, since donors' screennames are displayed in the case pages, which are easily recognizable by their friends, but would be considered anonymous for people outside their social networks. Future studies can also extend from here to examine whether anonymity influences how donors process social and non-social cues in their donation decisions.

2.6.3 Managerial Implications and Generalizability of the Findings

The managerial insights from this study are in the following areas. First, our findings provide a potential solution to those in need of help from medical crowdfunding, whose cases do not have eye-catching information to stand out from other cases. Social influence has a strong impact on increasing donations to these cases that lack strong non-social cues. These fundraisers can leverage social networks and present social cues as persuasive information for their need of help, to increase the attention and donations from potential donors. At the same time, for cases with distinctive characteristics that serve as strong informational cues of need already, we show that social cue does not reduce their chance to get support. Overall, medical-crowdfunding platforms can promote the use of social cues to promote equal chances for patients in need to get the financial support they seek. Second, we demonstrate that even in the medical crowdfunding context (where we may expect donors to engage in the peripheral route and respond to peripheral cues more), the impact of normative social influence is still dominated by informational social influence. Potential donors cognitively evaluate the informational value of social and non-social cues to make donation decisions. This suggests that social influence is not a universal solution to all types of problems that require persuading users to take certain actions. Instead, a more detailed examination into the quality of the information available in the specific context is required, to evaluate whether social influence has a positive impact. Third, through the additional analysis on the elaboration likelihood, we show that encouraging donors to spontaneously seek information (for example, clicking the links shared by friends, compared with when they passively receive the links from friends) likely promotes central route of processing and prompts donors to pay more attention to the quality of information relevant to the issue. This suggests that fundraisers should focus more on presenting quality evidence for their cases, especially when potential donors engage the central route to process all information rationally.

While we are not making normative claims in this study on how potential donors should compare the neediness of one case against another or on the efficiency of the donations allocated across cases, our findings provide some insights on alleviating the inequality in chances of funding success (Berliner and Kenworthy 2017, Young and Scheinberg 2017). We find that the impact of social influence is most salient for cases without inherent strong non-social cues. In other words, social cue could have a larger impact for cases lacking the inherent attributes that draw potential donors' attention (young patient or easily recognizable severe disease types). To further verify the impact of social cues on improving equal chances of funding success across cases, we compute the concentration of donations across different cases for the control group and the treatment group, respectively. We find that the entropy measure is 27.9 for the control group and 23.9 for the treatment group (a reduction of 14%), suggesting that in the presence of social cues, donations are more evenly spread out across cases. This further verifies that social cue enhances the chances for crowdfunding cases to get successfully funded overall, instead of having a few cases receiving over-the-cap donation amounts while other cases fail to reach their fundraising goals.

Furthermore, the findings of this study have broader implications to a more general context of studies, across other types of platforms where users are exposed to multiple sources of information, including the actions of other users (social cues) and the non-social information. We find that in the context of medical crowdfunding, potential donors refer to the informational value of social influence instead of conforming to the decisions made by the others. Such behaviors of users in medical crowdfunding potentially replicate in other similar contexts, such as prosocial campaigns and petitions, which suggest less reliance on influencer marketing for the platforms in similar contexts. Insights from this study are also relevant for a broad range of contexts, including e-commerce, online content promotions, and peer to peer exchange platforms, in guiding businesses to best combine social influence with other sources of information to generate intended user behaviors.

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CHAPTER 3. THE IMPACT OF PHYSICAL ATTRACTIVENESS ON DONATION AND SHARING IN MEDICAL CROWDFUNDING: A LARGE-SCALE RANDOMIZED FIELD EXPERIMENT

3.1 Introduction

As inferable from the popular stereotype that "what is beautiful is good," attractive people are associated with many positive traits, such as expertise, trustworthiness, and persuasive power (Eagly et al. 1991, Patzer 1985). Given the advantages attributed to attractive people, advertisers have actively incorporated physically attractive spokespeople and endorsers in conventional advertising, aiming to transfer the fondness from the models to the products. Existing studies report findings that support the decisions of the advertisers. Physical attractiveness of a person shown in an advertisement is found to increase a customer's willingness to purchase (Petroshius and Crocker 1989) as well as actual purchases (Caballero and Solomon 1984).

However, utilizing physical attractiveness might not always work to the best of the advertisers' interests. Studies report several incidences in which the sales of a product are not affected, or even negatively associated with physical attractiveness of the model (Baker and Churchill 1977, Caballero and Solomon 1984, Bower 2001). The advantages of using physically attractive model seem to be strongly impacted by many factors, including the negative affect generated from comparing of oneself with the models (Bower 2001) and not being distinguished from other advertisements (Caballero and Solomon 1984). For example, Baker and Churchill (1977) find that physical attractiveness of a female model shown in an ad negatively affects purchase intentions of males when the advertised product does not have a romantic overtones. While the sex and physical attractiveness of an advertisement model do influence the audience's attitude toward the aesthetics of the advertisement and therefore, overall liking of the ad, these two variables are rather unrelated to the audience's cognitive acceptance of the advertised message (Baker and Churchill 1977, Petroshius and Crocker 1989). Considering the prevalence of physically attractive models in product argument, much discrepancies remain in the existing works.

Cultivating a more profound understanding regarding the role of physical attractiveness becomes a more important task with the advent of online platforms. Content creation platforms (i.e., YouTube, TikTok) and Peer-to-Peer marketplaces (i.e., P2P lending market, crowdfunding market) have actively expanded over the last decades and expect to grow further (Allied Market Research 2020, InsightSlice 2020). Not only has more content become available on the Internet, but a good share of ordinary people create content, pitch for a variety of products, and generate financial resources through the actions they have taken online. It is critical for the active participants of online platforms to make their arguments credible, since they are easily the only ones in charge to promote their own campaigns (Luca 2017). In an attempt to enhance source credibility, many content creators and individuals on P2P marketplaces are encouraged to disclose their identities (Forman et al. 2008, Burtch et al. 2015, Kim et al. 2017), of which one critical component is physical attractiveness. By examining the role of physical attractiveness in online contexts, content creators and active participants of online platforms would be able to construct more efficient survival strategies.

In this study, we examine the impact of physical attractiveness of patients in medical crowdfunding posts on the likelihood to donate to the case and the likelihood to share the post on social media. Medical crowdfunding is a type of donation-based crowdfunding that seeks to raise funds for addressing healthcare-related expenses (Young and Scheinberg 2017). As in other contexts, the existing research on the impact of physical attractiveness in charitable giving returns contradictory findings. Beautiful donation recipients are found to be preferred (Mims et al. 1975; West and Brown 1975), as well as neglected (Fisher and Ma 2014) by donors in comparison to less attractive recipients. Few studies have attempted to bridge the gap in the findings (Cryder et al. 2017; Park et al. 2019), yet to the extent of our knowledge, no study has attempted to explore whether the donors' reactions to physical attractiveness stay consistent based on the publicity of the actions taken by the donors.

Based on Schlenker's impression management theory (1980), we conjecture that visitors show different behaviors online depending on the type of their behaviors. If a visitor considers his/her online behavior as public, the visitor is likely motivated to make a good impression and behave in manners conforming with social norms. On the other hand, as a visitor perceives his/her online behavior as private, the visitor likely expresses genuine minds more, unrestrained by social expectations. We conduct a large-scale randomized field experiment with one of the largest medical crowdfunding platforms in China. In the experiment, we manipulate the photo uploading guidelines given to fundraisers as they compose their campaigns. Both the control and the treatment groups receive the same standard photo uploading guidelines, except that directly above the photo uploading tool, the treatment group sees a specific recommendation for picking a physically attractive photo as the cover photo, while the control group sees a general recommendation that does not concern physical attractiveness. The experiment was conducted for a total duration of five days, involving a total of 670 medical crowdfunding cases, and 3,625,307 number of unique visitors.

We find that visitors exhibit different reactions to physical attractiveness depending on the type of online behavior they conduct. Overall, physical attractiveness of a patient decreases the likelihood for a visitor to donate to the case, but increases the likelihood to share it on social media. The negative impact on donations is mostly driven by cases involving female patients, while the positive impact on sharing is mostly driven by cases involving male patients. Furthermore, examining the genders of the patients and the donors jointly, we find that physical attractiveness only reduces female visitors' likelihood to donate to female patients, whereas it increases the likelihood for both male and female donors to share a case involving male patients.

Such contrasting impact could be explained by the different mechanisms in play when a visitor's action is private or public. The donation behavior happens in a private environment (for example, the decision to not donate will not be publicly broadcasted) and visitors have less concern for image management. Therefore, the potential jealousy towards physically attractive individuals may be more clearly exhibited. In contrast, sharing takes place in a public online environment (the post shared is publicly observed by a visitor's social ties) and is more likely influenced by visitors' concerns to manage impression. Visitors are more likely to share contents that conform with social conventions, for example, where the physical appearance conforms with social standards for beauty. At the same time, visitors may suppress their potential jealousy towards physically attractive individuals, driven by the need to maintain their own self-image and reputation in a public online environment. Using two moderators, visitor identity disclosure and social network size, we affirm that impression management is more salient when there is a larger audience who observe the behavior (i.e. having a larger network of friends on the platform) and more consistent with the expression of true intentions in a more private setting (e.g. anonymity without personal information disclosure). We find that visitors who disclosed identity are less hostile toward physically attractive female patients in donation behavior than those who did not; we also find that those with a larger social network size are more likely to share the cases of physically attractive male patient than those with a smaller social network size.

This study juxtaposes the behaviors of the visitors in a medical crowdfunding context to examine if a medical crowdfunding post should display more physically attractive pictures depending on the composition of a patient's social network. Findings from this study are relevant in improving chances of funding success for medical crowdfunding fundraisers. Our findings also yield important managerial insights, providing guidelines in image content design for online marketing strategies (i.e., in a prosocial/charity campaigns, utilization of a physically attractive male model can be helpful in spreading the advertisement image). Moreover, we demonstrate that visitors react differently to physical attractiveness based on the type of online behavior they conduct. Such finding implies that the amount of buzz generated to contents with physically attractive people might not always lead to intended consumption of the contents. The alteration in visitor behaviors based on the publicity (or privacy) of the online behavior potentially replicates in other contexts as well, providing a deeper understanding regarding people's behaviors taken online.

This study makes several contributions to the literature. First, our study contributes to the literature on physical attractiveness as one of the few studies that provides explanation for the heterogeneous impact of physical attractiveness. Despite the heavy volume of literature on physical attractiveness, most of the existing literature either report positive, or negative impact of physical attractiveness without providing explanations for the inconsistencies in the findings. The work of Cryder et al. (2017) suggests that the inconsistent reactions to physically attractive charity recipients originates from the battle between the donors' intuitive willingness to donate to the more attractive recipients and the cognitive effort to donate to the needier, less attractive recipients. While the work provides an important insight, the degree of deliberation in donors' minds leaves little room for managerial utilization. Park et al. (2019) finds that a donor's gender interacts with the charity recipient's gender in understanding the impact of physical attractiveness. In this paper, we also interact the genders of visitors and patients to find that the impact of physical attractiveness differs based on the genders of the visitors and the patients, and that it can be further differentiated based on the publicity (or privacy) of the responses. Second, extending the literature on impression management, this study is among the first to theorize online behavior from the public vs. private behavior perspective. If individuals react differently to physical attractiveness based on the publicity, or the privacy of their online behaviors, then the individuals might also react differently to other types of information based on the types of their online behaviors. Several studies report findings consistent to our theory development (Chen and Hwang 2020; Guillory and Hancock 2012; Hancock et al. 2004), but no previous paper has formally connected the impression management theory to explain how a person might show different responses to the same information based on the type of the response. Lastly, this study adds to the growing literature on medical crowdfunding.

The rest of the paper is organized as follows: section 2 reviews the relevant literature streams; section 3 describes the methodology (experiment design and the empirical analysis framework); section 4 reports our main results; section 5 reports additional results, and section 6 summarizes our findings and discusses the managerial implications.

3.2 Literature Review

In this section, we review three streams of literature relevant to our study: 1) physical attractiveness, 2) Impression management theory and online behavior, and 3) medical crowdfunding.

3.2.1 Physical Attractiveness

3.2.1.1 Physical Attractiveness and Charitable Behavior

A long history of literature on physical attractiveness exhibits robust association between physical attractiveness and a list of positive traits, including but not limited to social skills, mental health, intelligence, expertise, trustworthiness, and persuasive power (Dion et al. 1972, Eagly et al. 1991, Feingold 1992, Patzer 1985, Wilson and Eckel 2006). Several studies report the presence of "beauty premium" in peer-to-peer donation. The works of Landry et al. (2006) and Park et al. (2019) find that physical attractiveness helps female fundraisers secure more donations in peer-to-peer fundraising, driven by the encouraged donations from male donors. Comparably, the works of Ravina (2012) and Jenq et al. (2015) report lender preferences for both physically attractive female and male borrowers in online charitable microfinance lending. While these studies support the positive connection between physical attractiveness and charitable giving, they have been conducted with a small sample size from a restricted age range (Landry et al. 2006) and archival datasets (Ravina 2012, Jenq et al. 2015) with subsequent laboratory experiments (Park et al. 2019). In this study, we conduct a large-scale field experiment to examine whether the physical attractiveness of patients lead to favorable charitable decisions. We also assess both the sharing and the donation behavior to discover if the type of charitable behavior differentiates a visitor's reactions to physical attractiveness.

Despite the findings on the positive impact of physical attractiveness on charitable giving, existing studies report contrasting findings as well. Fisher and Ma (2014) conduct four series of studies to report that the physical attractiveness of children in need inversely affects the empathy and helping responses of the potential donors. The authors explain their findings in terms of the advantageous status given to physically attractive people (Webster and Driskell 1983), which penalizes physically attractive recipients in charitable giving context by making them seem less needy. The work of Cryder et al. (2017) confirms the presence of the internal battle between the donors' innate preferences for the more physically attractive recipients and the donors' cognitive belief that the less attractive recipients must be needier and thereby deserve to be helped more. Such perspective regarding the perceived neediness of the recipients could be one factor that drives the decisions of the potential donors as they make charitable decisions. If the physical attractiveness penalty for physically attractive patients originates from the perceived lack of neediness and the limited donor resources to provide financial help with, we assume that the physical attractiveness penalty would not exist in charitable actions that do not require financial support, such as sharing of medical crowdfunding posts.

Furthermore, Park et al. (2019) claim that a charitable response to physical attractiveness would depend on the genders of the recipient and the donor. Likewise, in this study, we examine whether the genders of the patient and the visitor interact with the impact of the patient's physical attractiveness on the behaviors (donation and sharing) of the visitors. Park et al. (2019) find female donors are less inclined to donate to more physically attractive female patients in the context of medical crowdfunding, nominating the perceived lack of neediness as a potential cause. We expect to observe similar results in the findings of our study for the female-female patient/visitor interactions for charitable donations. Park et al. (2010) find male donors prefer to donate to physically attractive female patients over physically unattractive female patients; such the preference, however, reports marginal significance with limited control variables (i.e., donor age and income), and the findings of our study would contribute to deepen the understanding of female-male patient/visitor interactions for charitable donations.

3.2.1.2 Physical Attractiveness in Online Platforms

Despite the vast volume of literature that examines the role of physical attractiveness in various settings, ranging from one-on-one interpersonal interactions (Chaiken 1979) to different types of advertising (Caballero and Solomon 1984, Kamins 1990), only a few studies have currently examined the impact of physical attractiveness in online platforms. These studies, however, suggest that the examination of physical attractiveness in online contexts leads to significant insights.

For example, certain responses to physical attractiveness in a more traditional context might not be replicated in the online context. Chan and Wang (2018) show that since the online environments hold innate differences to the traditional offline environments, online responses to physical attractiveness can differ from the responses in the conventional contexts. Unlike the prevalent hiring biases against physically attractive female applicants in the traditional labor market (Ruffle and Shtudiner 2015), Chan and Wang (2018) find hiring biases for female applicants in online labor market due to female applicants' higher level of physical attractiveness. Interestingly, both the hiring biases against physically attractive female applicants in the traditional labor market (Ruffle and Shtudiner 2015) and the hiring preferences for physically attractive female applicants in the online labor market (Chan and Wang 2018) are driven by female employers. The work of Chan and Wang (2018) indicates the differences between the online and the offline labor markets as causing the contrasting findings, suggesting the importance of conducting studies specific to online environments.

Furthermore, the unique features of online platforms enable different interpretations of the existing findings with contrasting findings. In response to the contrasting reactions to physical attractiveness in the existing works, Peng et al. (2020) suggests a different take. While the existing studies find both the attractiveness premium and the attractiveness penalty in product sales, Peng et al. (2020) suggests a U-shaped relationship between facial attractiveness and product sales in customer-to-customer e-commerce platforms, finding both the attractiveness premium and the ugliness premium in product sales over displaying plain-looking profile pictures. The majority of existing works on physical attractiveness and product sales have largely focused on the physical attractiveness of the models featured in product advertisements and its impact on the product sales. Since the majority of the models featured in conventional product advertisements tends to be physically attractive, the generic comparison group tends to be either unattractive, or plain-looking models. However, since the sellers in e-commerce platforms are often ordinary individuals who advertise their own products, Peng et al. (2020) refer to profile pictures of ordinary users and examine product sales in relation to different levels of physical attractiveness. Peng et al. (2020)'s approach to physical attractiveness as a continuous variable provides a potential explanation for the controversial findings in the existing literature, raising awareness for the unique contributions of the works examining physical attractiveness in the context of online.

In this paper, we aim to examine the impact of physical attractiveness on the two types of helping behaviors: donation and sharing. Most of the existing studies on physical attractiveness and charitable giving focus only on the direct action of making donations, as the donation is often the only form of participation in the traditional charitable giving context. Likewise, most of the studies conducted in online charitable giving platforms focus only on the direct act of making donations or lending as well (Kuwabara and Thébaud 2017, Park et al. 2019, Ravina 2012). By investigating the two different types of helping behaviors in the medical crowdfunding context, we seek to provide potential explanations for the inconsistencies in the existing works.

3.2.2 Impression Management Theory and Online Behavior

Impression management refers to "the goal-directed activity of controlling or regulating information in order to influence the impressions formed by an audience"

(Schlenker 1980). Most often, the impressions seek to establish positive qualities to a person of interest (Wayne and Liden 1995). Since impression management is relevant for publicly observed behaviors, we expect Internet users to adjust their actions to maintain positive impressions when their action is seen by others (e.g. when posting content, sharing information on social media). On the other hand, in a private online environment where anonymity is granted, users are expected to show unrestricted behavior, free from social norms and expectations to meet (Suler 2004).

Although no prior research has formally theorized user online behavior from the public vs. private behavior perspective, there are several studies reporting patterns in user actions in line with our theory development. For example, Chen and Hwang (2020)'s paper on investor behavior finds that positive articles are shared more often, referring to the general public's tendency to dislike the sources of negativity. The authors also find that investors tend to keep the articles with informational values to themselves; such a portrayal of self-centered action corresponds to our expectations of online behavior in a private environment. Hancock et al. (2004) find that emails contain the least lies, compared to face-to-face interactions and telephone calls, as emails leave written traces that could be investigated afterward. Concurrently, Guillory and Hancock (2012) state that public LinkedIn profiles contain fewer lies about verifiable information because there is a higher chance of being caught than paper resumes. The email and LinkedIn could be considered as more public environments with higher threats of investigation than their offline counterparts, and can also be explained according to the impression management theory. Even though Hancock et al. (2007) find frequent deceptions in online dating, the contrasting human behavior regarding deceptions online can be explained correspondingly since an online dating platform is still a more private environment with fewer chances of detection compared to offline dating environments, where detection of deception happens more instantly. Based on the literature, we expect visitors to show behaviors intended to manage their impressions within their networks of friend when the behaviors are relatively public, taking place at a public online environment. Contrarily, we expect visitors to display uninhibited behaviors when the behaviors are rather private, taking place at a private online environment.

Webster and Driskell (1983) acknowledge the premium attributed to physically attractive people, and claim that physical attractiveness should be considered as a status characteristic, signifying worth and competence even in the absence of logical connection between the assignment and the characteristic. As individuals attempt to enhance their status by befriending those with higher status characteristics (Dijkstra et al. 2013), physically attractive people are common targets for friendship (Greitemeyer and Kunz 2013). We consider the public display of physically attractive acquaintances as a potential strategy of impression management, and expect higher sharing likelihood for the cases of physically attractive patients, while such preference might not replicate in the less exposed decision to donate or not.

On the other hand, unfavorable evaluations of physically attractive women within the same gender group is another common observation. Research indicates that physically attractive women are penalized in the hiring process (Ruffle and Shtudiner 2015) and medical crowdfunding context (Park et al. 2019) due to the potential jealous for others, particularly those similar as oneself, such as having the same gender. To the extent of our knowledge, no research has empirically documented the within-sex hostility toward the physically attractive member for men. Accordingly, we expect to observe unfavorable reactions of female visitors to female patients in private behavior. When the behavior is rather public, we expect female visitors to display less discriminating reactions toward physical attractiveness female patients.

3.2.3 Medical Crowdfunding

Medical crowdfunding is a type of donation-based crowdfunding which raises donations from the crowd on the Internet to finance healthcare-related expenses (Burtch and Chan 2019, Kenworthy et al. 2020, Murdoch et al. 2019, Young and Scheinberg 2017). Medical crowdfunding is a rapidly growing phenomenon in diverse countries, including the United States, Canada, United Kingdom, and China (Hur et al. 2019, Saleh et al. 2020). As of 2017, medical crowdfunding projects accumulate to the third of all crowdfunding projects in the major United States crowdfunding platforms (Nathan 2019).

One unique feature of medical crowdfunding from other types of crowdfunding is that medical crowdfunding targets to raise funds for a person, not a product. The written, or graphic depictions given in a medical crowdfunding post aim to solicit donations for the patient of a medical crowdfunding case, which suggests that the identity of the patient would play a big role in a donor's decisions. A few studies attempt to examine the role that a patient's identity plays in the success of a medical crowdfunding case. As for written description of a patient's identity, Hur et al. (2019) find that a patient's demographics (i.e., age, gender, and medical condition) impact the patient's donation likelihood. On the other hand, existing works report contrasting findings regarding the impact of the physical attractiveness of the donation recipients. Ravina (2012) and Jenq et al. (2015) find biases for physically attractive borrowers in online charitable microfinance lending, whereas Park et al. (2019) report that such premium reverses when the donor is of female gender for the female patients. This study acknowledges the controversies in the existing findings, and seeks to contribute to the literature by conducting a large-scale, randomized field experiment.

Moreover, this study adds to the literature on medical crowdfunding by studying two types of donor behaviors: donation and sharing. Not only have the existing works on medical crowdfunding and online micro-lending tended to explore the success of medical crowdfunding campaigns by directly assessing only the donation behavior of potential donors, but the literature on other types of crowdfunding tend to report limited findings regarding the diffusion of a crowdfunding case. Features such as the personality traits of a fundraiser (Thies et al. 2016) and the distance between the fundraiser and the investor (Guo et al. 2018) are identified as the contributing factors of diffusion for reward-based crowdfunding cases. Still, considering how the success of a crowdfunding case also depends on its exposure, there is a need to discover the factors that contribute to the diffusion of a crowdfunding case. In this study, we examine the two types of donor responses (donation and sharing) to discover if physical attractiveness impacts both the diffusion and the direct contribution of a medical crowdfunding post.

3.3 Methodology

3.3.1 Research Context and Experiment Design

We collaborated with a leading medical crowdfunding platform in China to conduct a large-scale randomized field experiment. The company we worked with was founded in

June 2016 and has seen rapid growth in users and transaction volume since. By September 2018, more than 630,000 fundraisers successfully received funds through the platform to cover medical expenses, with the monthly amount of donations averaging around 1.5 million RMB (about 200,000 USD). In 2019, the platform has raised a total of 13 billion RMB (approximately 2 billion USD) in donations, and reports successful accrual of donations, fundraisers, and visitors up to date.

Unlike other crowdfunding websites, the platform employs a unique access structure in which the access to a case is strictly restricted to directly clicking a distinct link address. As the company provides neither a search system nor pop-up suggestions for visitors, a medical crowdfunding case can only reach its potential donors upon active distribution of the case links through the extended social networks of the case fundraiser and the patient. Should a person decides to share a crowdfunding case link to his/her acquaintances, free of which sharing medium the person uses, the case link would appear to the recipients in the form of a case thumbnail. As depicted in Figure 3-1, the case thumbnail comprises of the three components: the first 25 characters of the case title (in bold black), the first few sentences of the case description (in gray), and the first picture uploaded to the case (as uploaded by the fundraiser; only smaller in size to fit the thumbnail).

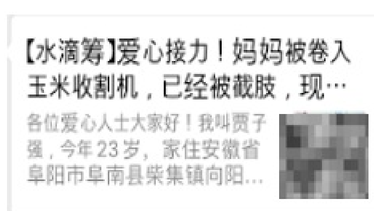

Figure 3-1. Case Thumbnail of a Medical Crowdfunding Case

The two popular distribution methods are sharing the case link to friends via WeChat direct message (similar to Facebook message) and posting the case link on WeChat Moments (similar to Facebook posts). The platform's unique access structure limits the target audience of sharing to a focal visitor's friends and acquaintances, staging sharing as a non-anonymous, non-private behavior.

The platform also offers an extensive procedure for fundraisers to follow in their creation of fundraising posts. All potential fundraisers interested in creating a fundraising case starts their journey by clicking the "case creation" button on the platform website. Upon clicking, the fundraisers are directed to several stages which require them to submit the care information to the platform. Documentations, including medical certificates, pictures of the patient, and proof from the hospital(s) treating the patient, are usually required to evaluate the validity of the case. The platform's employees would review each case and the supporting documentations extensively. Fundraisers have to follow a very strict guideline in order to pass the review process; the platform suggests the specific types of pictures that should be uploaded (i.e., a picture of a patient before he/she was sick, a picture of a patient in his/her current situation). Only the cases that passes the internal evaluation can begin to collect donations from those who visit by clicking the case links. Since the fundraisers are either patients themselves, or family/close friends to the patients, a good portion of fundraisers have access to the required documentations of the patients.

Our randomized field experiment was conducted for five days, from 2018/07/06 to 2018/07/10. During the experiment, all fundraisers were randomly assigned to either the control group or the treatment group. The control group and the treatment group received the same guidelines for case creation, except for the single difference in the photo uploading stage. In the beginning of the case creation, the platform advices both the control and the treatment group to include at least three types of pictures in the picture uploading section, which are: pictures of the patient's medical certificate, pictures of hospital documentation (if the patient is currently hospitalized), and pictures that describe the patient's identity (personal pictures and/or pictures of the ID cards). Later on in the picture uploading section, the control group received the standard guidelines for uploading pictures. The treatment group saw the same standard guidelines as the control group, except the instruction right above the actual picture uploading tool that reads: "Please upload the picture that shows your best appearance, taken before your hospitalization, as the first picture." The first picture, or the "thumbnail picture", would be the photo displayed in the case summary and the first photo among all uploaded photos when visitors click to see more case details and it likely shapes a visitor's impression of the patient. While we cannot directly observe whether fundraisers conform with the instruction on picking a photo of best appearance, we confirm the validity of this manipulation by manually rating the thumbnail picture and confirm that pictures uploaded by the treatment group have a higher physical attractiveness score.

3.3.2 Data and Measures

We have collected data on all page visits that happened for the first week of case creation to all cases created during the five-day period and exposed to our experiment. Since approximately 90% of all donations occur within the first week of case creation, we believe our dataset is representative of all visits to the cases. The experiment period did not overlap with public holidays or days of celebration. Also, no unique patterns, such as unusual peaks in the number of total active fundraising cases and total donations, were observed in this period. We further aggregate the data to only one observation per visitor for each case and aggregate behavioral information (whether the visitor eventually donated to the case and whether the visitor eventually shared the case) if a visitor visited the same case page multiple times. Since we aim to study the behaviors of visitors, instead of fundraisers, we used propensity score matching to replicate a randomized experiment setting. After matching, the final set of data contains 2,322,049 observations, consisting of views of 460 unique cases. To verify that our treatment correctly manipulated the variable of our interest, we hired three RAs (two females and one male) to manually score the physical attractiveness of the first thumbnail pictures of all cases based on a five-point scale (1 meaning very physically unattractive and 5 meaning very physically attractive). The measures are reliable with Cronbach's alpha at 0.86 (Hinton et al. 2004; Nunnally 1978).

For each observation in the data, we collect both case-level and visitor-level variables. The case-level variables include patient gender, age, disease condition (cancer or noncancer), the goal amount set in the case, socioeconomic environment (represented by the PPP (Purchasing Power Parity) per capita of the resident city), hospital verification (whether the medical status of a patient was verified from a hospital), whether the patient has basic medical insurance, whether the patient has commercial insurance, the total number of medical verifications a case received (verifications from friends and families that the patient is ill), the amount the patient has spent him/herself, the number of pictures included in the case, the number of words in case description, and the average clarity and physical attractiveness of the pictures. The visitor-level variables include: whether a visitor verified the medical condition of the patient (the platform has a 'verify' option for visitors to indicate their support for the patient if the visitors wish to confirm that the patient's condition is as described in the case description; the platform however, does not keep contact the visitors further to validate whether their indication is true or not), case maturity (the number of days past between the creation of a case and a visitor's visit to the case), whether a visitor is visiting for the first time (0/1), identity disclosure (0/1; whether a visitor chooses to enter his/her demographics information), friends invited to the platform (cumulative number of friends that have visited the platform by the invitations of a visitor), friends donated to the platform (cumulative number of friends that donated to the platform) and previous order indicator (0/1). For a small subsample of visitors that purchased insurance from the platform (there are many types of insurance offered in the platform, such as medical insurance, annuity insurance, accident insurance, etc.), we also have information on visitor age, gender, and residence.

We report the summary statistics of the variables in Table 1. To obtain generalizability in our analysis, we exclude cases with medical conditions specific to gender (i.e., prostate cancer, cervical cancer) and infants (i.e., premature birth). To enhance the validity of our findings, we also remove all visits to the cases that did not pass the platform's evaluation and the cases that did not include a picture of an identifiable person as the first picture. Table 3-1 reports the summary statistics of the variables for the approximately 2.3 million observations used in our analysis.

Table 3-1. Variable Types and Summary Statistics

Variables	Mean (StD)	Min	Max
Male Patient (0/1)	0.643 (0.479)	0	1
Patient Age	37.849 (17.799)	0	82

Table 3-1 (continued)

Cancer (0/1)	0.319 (0.466)	0	1
Target Donation Amount (RMB)	260,142.811 (163,457.523)	5,000	1,000,000
Socioeconomic Environment (PPP per Capita for Each Province)	7,789.477 (2,569.243)	4,221	17,617
Hospital Verification (0/1)	0.020 (0.141)	0	1
Patient has Medical Insurance (0/1)	0.812 (0.391)	0	1
Patient has Commercial Insurance (0/1)	0.026 (0.158)	0	1
Total Number of Medical Verifications	65.244 (39.564)	0	187
Amount Patient Spent (RMB)	23,467.053 (70,152.354)	0	600,000
Number of Pictures in a Case	7.302 (5.147)	1	39
Word Count in a Case	532.165 (307.309)	60	1,997
Average Clarity of the First Picture	1.363 (0.603)	1	5
Average Physical Attractiveness of the First Picture	2.706 (1.161)	1	5
Verified Medical Condition of the Patient (0/1)	0.007 (0.082)	0	1
Case Maturity	1.480 (1.510)	0.000	6.999
First-time Visitor (0/1)	0.126 (0.332)	0	1
Identity Disclosure	0.113 (0.317)	0	1
Friends Invited to the Platform (0 for first-timers)	7.670 (44.814)	0	44,414
Friends Donated to the Platform (0 for first-timers)	4.778 (19.271)	0	2,940
Previous Order (0/1) (0 for first-timers)	0.291 (0.454)	0	1
Total Observations 2,322,049			

Since our randomization is performed on the case-level, there is a potential self-selection concern that visitors clicking to view a case in the treatment group and those clicking to view a case in the control group could have different characteristics. To address this issue, we conduct 1:1 nearest-neighbor propensity score matching with 0.25 of the pooled standard deviation of the logit of the propensity scores, to ensure that on the visitor-case-view level, all attributes are also comparable for observations coming from the control and treatment groups. All variables in Table 3-1, except for the average physical attractiveness of the first picture, are used in matching. To check for the balance of the covariates, we refer to absolute standardized percentage bias, the scaled mean difference by the square root of the average treatment and control sample variances (Rosenbaum and Rubin 1985). Table 3-2 shows that all covariates except for average physical attractiveness display absolute standardized percentage bias (|*%bias*|) of <5% between the control and the treatment groups, which is sufficient according to Caliendo and Kopeinig (2008), confirming substantial balance across the control and the treatment after matching. For average physical attractiveness, since this variable is what we initiated to manipulate in the experiment, the imbalance between the average physical attractiveness scores in the control and the treatment confirms our experiment was carried out successfully.

Table 3-2. Balance Check for the Control and Treatment Groups after Matching

Variables	Mean		|%bias|
	Treated	Control	
Male Patient (0/1)	0.639	0.646	1.6
Patient Age	37.984	37.715	1.5
Cancer (0/1)	0.329	0.309	4.3
Target Donation Amount (RMB)	260,226.341	260,059.281	3.6
Socioeconomic Environment	7,835.2	7743.8	3.5
Hospital Verification (0/1)	0.021	0.020	0.5
Patient has Medical Insurance (0/1)	0.813	0.810	0.8
Patient has Commercial Insurance (0/1)	0.028	0.023	1.9
Total Number of Medical Verifications	65.456	65.032	0.8
Amount Patient Spent (RMB)	23,384	23,550	0.1
Number of Pictures in a Case	7.347	7.257	1.8
Word Count in a Case	533.12	531.21	0.6
Average Clarity of the First Picture	1.354	1.372	3.0
Average Physical Attractiveness of the First Picture	2.993	2.418	46.9
Verified Medical Condition of the Patient (0/1)	0.007	0.007	0.2

Table 3-2 (continued)

Case Maturity	1.483	1.477	0.4
First-time Visitor (0/1)	0.126	0.127	0.1
Identity Disclosure	0.113	0.113	0.1
Friends Invited to the Platform (0 for first-timers)	7.599	7.741	0.3
Friends Donated to the Platform (0 for first-timers)	4.725	4.833	0.6
Previous Order (0/1) (0 for first-timers)	0.289	0.292	0.6

For the main analyses, we examine the influence of the treatment (which successfully manipulates physical attractiveness of the first picture of a case) in donation likelihood and sharing likelihood as constructed by the Equations (1) and (2). We project donation as a private behavior as a donation can occur anonymously without letting others know about the decision of a focal visitor. In contrast, we define sharing as a public behavior, since an anonymous visitor restores his identity as he shares a case to his network of friends. We then proceed to run the Equations (1) and (2) on the subsets of the dataset based on patient gender and donor gender to identify if gender moderates the impact of the treatment.

$$log\left(\frac{Pr(Donation_i = 1)}{1 - Pr(Donation_i = 1)}\right) = \beta_0 + \beta_1 Treatment_i + \beta_2 Controls_i + \beta_3 Controls_i * Treatment_i + \varepsilon_i \quad (1)$$

$$log\left(\frac{Pr(Share_i = 1)}{1 - Pr(Share_i = 1)}\right) = \beta_0 + \beta_1 Treatment_i + \beta_2 Controls_i + \beta_3 Controls_i * Treatment_i + \varepsilon_i \quad (2)$$

To further validate that the differences in donation behavior and sharing behavior are due to the privacy and publicity of the online behavior, we estimate Equations (1) and (2) adding two moderators of privacy and publicity: identity disclosure and social network size. Identity disclosure is a binary variable reflecting whether the visitor chooses to enter his/her demographics information (as opposed to remaining completely anonymous). Social network size refers to the cumulative number of friends who visited the platform by the invitations of the focal visitor.

3.4 Results

We estimate Equations (1) and (2) on the different segmentation of the data (i.e., whole sample, the samples divided by the gender of the patients, and the samples divided by the genders of the patients and the visitors) and report the results in this section.

3.4.1 The Impact of Physical Attractiveness on Sharing and Donation

Table 3-3 reports findings from the initial analysis. Using the whole sample of observations, the findings in Table 3-3 indicate that physical attractiveness of a patient decreases the overall probability of raising donations. The beauty treatment coefficient in Table 3-3 is -0.171 for column 1, which suggests that increasing physical attractiveness of the first picture of a case decreases donation likelihood by 15.7% (($e^{-0.171}$-1) *100%).

Contrastingly, such penalty of displaying a physically attractive first picture reverses for the overall probability of sharing the case. The beauty treatment coefficient is 0.196 for column 2 in Table 3-3, which means that the same treatment increases the sharing likelihood by 21.7% (($e^{0.196}$-1) *100%). These findings show that visitors react differently to the physical attractiveness of a patient as they initiate different types (private vs. public) of prosocial behavior.

Table 3-3. Effect of Beauty Manipulation in Donation Likelihood and Sharing Likelihood

	(1)	(2)
Sample	Whole Sample	Whole Sample
Model	Logit Model	Logit Model
Dep. Var.	Donation (0/1)	Sharing (0/1)
Beauty Treatment	-0.171^{***}	0.196^{***}
	(-8.14)	(5.97)
Control variables	Patient gender, age, medical condition, target donation amount, socioeconomic environment, hospital verification (0/1), medical insurance status, commercial insurance status, total number of medical verifications, amount spent by the patient, number of pictures uploaded, word count in a case, average clarity of the first picture, medical condition verification, case maturity, whether the visitor visits for the first time, the identity disclosure indicator for the visitor, number of friends invited to the platform, number of friends donated to the platform, and the previous order indicator for the visitor	
Constant	-2.134^{***}	-2.911^{***}
	(-143.43)	(-129.51)
N	2,322,049	2,322,049

Notes:

i. Reporting donation / sharing behavior results on the whole sample;

ii. Robust clustered standard errors clustered by cases reported in parentheses, *p<0.1; **p<0.05; ***p<0.01.

3.4.2 The Impact of Physical Attractiveness on Sharing and Donation by Patient Gender

To further pinpoint the source of the effects observed in Table 3-3, we split the dataset based on patient gender. Table 3-4 shows that the impacts of the increasing physical attractiveness of the first picture of a case are specific to gender in both private and public behavior. Specifically, the column 1, Table 3-4 shows that the physical attractiveness manipulation treatment decreases the donation likelihood of female patients by 30.7% (($e^{-0.367}$-1) * 100%), but does not affect the donation likelihood of male patients (column 2,

Table 3-4). The same treatment increases the sharing likelihood of male patients by 45.5% (($e^{0.375}$-1) *100%; column 4, Table 3-4), but does not affect the sharing likelihood of female patients (column 3, Table 3-4).

The findings from Table 3-4 suggest that visitors react differently to patients' physical attractiveness based on patient gender. If so, incorporating the gender of the visitors can potentially deepen our understanding of the phenomenon. Park et al. (2019) also explore charitable giving by incorporating the genders of both the recipient and the donor, and nominate the unwillingness of female donors as the drivers of the physical attractiveness penalty for female recipients. In Table 3-5, we incorporate the genders of the visitors into our analysis to discover the drivers of the physical attractiveness penalty for female recipients in donation. Likewise, in Table 3-6, we incorporate the genders of the visitors and the patients to discover the drivers of the physical attractiveness premium for male recipients in sharing.

Table 3-4. Effect of Beauty Manipulation in Donation Likelihood and Sharing Likelihood by Patient Gender

	Private Behavior		Public Behavior	
	(1)	(2)	(3)	(4)
Sample	Female Patients	Male Patients	Female Patients	Male Patients
Model	Logit Model	Logit Model	Logit Model	Logit Model
Dep. Var.	Donation (0/1)	Donation (0/1)	Sharing (0/1)	Sharing (0/1)
Beauty Treatment	-0.367*** (-10.75)	0.018 (0.65)	-0.039 (-0.75)	0.375*** (9.02)
Control variables	Patient gender, age, medical condition, target donation amount, socioeconomic environment, hospital verification (0/1), medical insurance status, commercial insurance status, total number of medical verifications, amount spent by the patient, number of pictures uploaded, word count in a case, average clarity of the first picture, medical condition verification, case maturity, whether the visitor visits for the first time, the identity disclosure indicator for the visitor, number of friends invited to the platform, number of friends donated to the platform, and the previous order indicator for the visitor			

Table 3-4 (continued)

Constant	-2.014***	-2.303***	-2.994***	-2.863***
	(-79.12)	(-115.77)	(-74.67)	(-94.97)
N	829079	1492970	829079	1492970

Notes:

i. Reporting donation / sharing behavior results on the subsets based on patient gender;

ii. Robust clustered standard errors clustered by cases reported in parentheses, *p<0.1; **p<0.05; ***p<0.01.

3.4.3 The Impact of Patient Attractiveness on Donation by Patient and Visitor Gender

Since visitors can make donations anonymously, we only observe the demographics information for a subsample of visitors (262,730 out of 2,322,049 observations). Using this subsample, we discover that the negative impact of the physical attractiveness manipulation treatment in donation behavior occurs from female visitors to female patients. We discover that increasing physical attractiveness of the first picture of a case decreases the donation willingness of female visitors toward female patients by 19.8% (($e^{-0.221}$-1) *100%; column 1, Table 3-5) in the specified subsample. Neither physical attractiveness premium nor penalty is applied to other subsets specified in Table 3-4 (columns 2-4, Table 3-5).

Table 3-5. Effect of Beauty Manipulation in Donation Likelihood by Patient Gender & Donor Gender

(Table 3-4, Columns 1 and 2 further divided by Visitor Gender)

	(1) Female Visitor Female Patient Logit Model Donation(0/1)	(2) Male Visitor Female Patient Logit Model Donation(0/1)	(3) Female Visitor Male Patient Logit Model Donation(0/1)	(4) Male Visitor Male Patient Logit Model Donation(0/1)
Beauty	-0.221**	-0.143	0.0881	0.129
Treatment	(-2.03)	(-1.25)	(0.97)	(1.39)

Table 3-5 (continued)

Control variables	Patient gender, age, medical condition, target donation amount, socioeconomic environment, hospital verification (0/1), medical insurance status, commercial insurance status, total number of medical verifications, amount spent by the patient, number of pictures uploaded, word count in a case, average clarity of the first picture, medical condition verification, case maturity, whether the visitor visits for the first time, the identity disclosure indicator for the visitor, number of friends invited to the platform, number of friends donated to the platform, and the previous order indicator for the visitor			
Constant	-0.848*** (-10.48)	-0.850*** (-9.82)	-1.069*** (-17.08)	-1.053*** (-16.01)
N	46796	43507	88462	83965

Notes:

i. Reporting donation behavior results on the subsets based on patient gender and visitor gender;

ii. Robust clustered standard errors clustered by cases reported in parentheses, *p<0.1; **p<0.05; ***p<0.01.

3.4.4 The Impact of Physical Attractiveness on Sharing by Patient and Visitor Gender

We also discover that the positive impact of the treatment in sharing behavior occurs from both female and male visitors to male patients. Table 3-6 shows that increasing physical attractiveness of the first picture of a case increases the sharing willingness of female visitors toward male patients by 45.2% (($e^{0.373}$-1) *100%; column 3, Table 3-6), and the sharing willingness of male visitors toward male patients by 44.5% (($e^{0.368}$-1) *100%; column 4, Table 3-6) in the specified subsample. We observe that the negative impact of the treatment in donation behavior of female visitors to female patients is not replicated in sharing behavior (column 1, Table 3-6). At the same time, we could not observe the physical attractiveness premium for male patients in the overall donation probability (columns 3 and 4, Table 3-5).

Table 3-6. Effect of Beauty Manipulation in Sharing Likelihood by Patient Gender & Donor Gender

(Table 3-4, Columns 3 and 4 further divided by Visitor Gender)

	(1) Female Visitor Female Patient Logit Model Sharing(0/1)	(2) Male Visitor Female Patient Logit Model Sharing(0/1)	(3) Female Visitor Male Patient Logit Model Sharing(0/1)	(4) Male Visitor Male Patient Logit Model Sharing(0/1)
Beauty	-0.0541	0.149	0.373^{***}	0.368^{**}
Treatment	(-0.33)	(0.80)	(2.74)	(2.48)
Controls	Yes	Yes	Yes	Yes
Constant	-2.166^{***}	-2.353^{***}	-1.932^{***}	-2.153^{***}
	(-17.61)	(-16.39)	(-20.40)	(-20.25)
N	46796	43507	88462	83965

Notes:

i. Reporting sharing behavior results on the subsets based on patient gender and visitor gender;

ii. Robust clustered standard errors clustered by cases reported in parentheses, *p<0.1; **p<0.05; ***p<0.01.

We also find that the cases of physically attractive male patients reach more potential donors because both female and male visitors are more likely to share the cases of more physically attractive male patients. Such valuation is not fundamental, as the same preference does not repeat in a rather private environment. To understand the appreciation of physically attractive males in sharing, we refer to how individuals attempt to enhance their statuses by befriending those with higher status (Dijkstra et al. 2013); male physical attractiveness could be among the most pursued status characteristics as it is a rarity. The statistics from our dataset supports this notion. The average physical attractiveness for female patients is 3.08, while the average physical attractiveness for male patients marks 2.50 ($t=-375.120$; $p<0.0001$). Furthermore, the top 25 percentile of physical attractiveness value for male patients is 3.3, whereas the top 25 percentile of physical attractiveness value for female patients is 4.3, confirming differences in the distributions of the physical attractiveness values for male and female patients. Additionally, we refer to the negative stereotypes about men who actively favor beautiful women as a potential cause of the insignificant impact of physically attractive thumbnail photos of female patients in male donors' sharing behavior.

3.5 Additional Results

To validate that our findings are due to the privacy and publicity of the online behavior, we refer to two moderators, each relevant to the degrees of privacy and publicity and not the other, respectively. The first moderator of our focus is identity disclosure. The platform we collaborated with allows visitors to make donations and/or share crowdfunding cases freely without having to disclose their personal information, such as their names, age, and gender. Tables 3-5 and 3-6 use the subset of visitors who ever entered personal information on the platform (e.g. purchasing another product on the platform, subscribing to the newsletter). These visitors likely perceive their actions as more publicly since they provided personal information to associate with their account, in comparison to the visitors who have not disclosed their personal information to the platform. Our conjecture is that female visitors who disclosed identity should display less hostility toward female patients in donation decisions, compared to the female visitors who did not, as the behavior might result in a negative reputation. For sharing, however, the appreciation of male physical attractiveness in sharing should not be affected much with this moderation, as sharing already is a public activity. Table 3-7 affirms our supposition. In column 1, Table 3-7, anonymous female donors decrease their donation intentions to female patients by 32% (($e^{-0.385}$-1) *100%) upon the physical attractiveness manipulation treatment. On the other hand, in column 2, Table 3-7, female donors with identity disclosure display much less magnitude in their reactions to female patients (17.3% (($e^{-0.190}$-1) *100%)). These two coefficients are statistically significant (t=2.249, p=0.025). As expected, identity disclosure does not affect visitors' sharing behavior. The coefficients in columns 3 and 4 are not significantly different (t=0.009, p=0.993).

Table 3-7. Effect of Beauty Manipulation and Identity Disclosure in Donation Likelihood and Sharing Likelihood

	Private Behavior (affecting only female patients)		Public Behavior (affecting only male patients)	
	(1)	(2)	(3)	(4)
Sample	Female Patients & Donors who did not Disclose Private Information	Female Patients & Donors who Disclosed Private Information	Male Patients & Donors who Did not Disclose Private Information	Male Patients & Donors who Disclosed Private Information
Model	Logit Model	Logit Model	Logit Model	Logit Model
Dep. Var.	Donation(0/1)	Donation(0/1)	Sharing(0/1)	Sharing(0/1)
Beauty Treatment	-0.385^{***} (-10.12)	-0.190^{**} (-2.43)	0.365^{***} (7.96)	0.356^{***} (3.58)
Controls	Yes	Yes	Yes	Yes
Constant	-2.071^{***} (-73.07)	-0.835^{***} (-14.21)	-2.872^{***} (-85.99)	-2.027^{***} (-28.85)
N	738776	90303	1320543	172427

Notes:

i. Reporting donation behavior results for female patients and donors based on donor identity disclosure (0/1)

ii. Reporting sharing behavior results for male patients and donors based on donor identity disclosure (0/1)

iii. Robust clustered standard errors clustered by cases reported in parentheses, *p<0.1; **p<0.05; ***p<0.01.

The second moderator we employ is the social network size of the visitors. We estimate individual behaviors to change depending on the individual perception of an environment (private vs. public). Theoretically, a public environment exposes individuals to their social network and ensuing evaluations, unlike a private environment with no audience to judge. If so, the degree of private behavior would not necessarily change along with the size of a focal visitor's social network. However, the degree of public behavior would because those with more extensive social networks have more people to impress. We utilize the cumulative number of friends that have visited the platform upon the invitations of a focal visitor as a proxy for the visitor's social network size. For the variable to represent the social network size accurately, we include the cumulative number of friends that donated to the platform (among those who visited by the focal visitor's invitation) as one of the control variables.

We exclude first-timers for this analysis to obtain two comparable subsamples that differ in the number of friends invited to the platform. Based on the mean value, we set the cutoff for social network size as 9 friends. The findings from Table 3-8 are consistent with our expectations. Visitors with larger social networks are likely to share the cases of physically attractive male patients by 52.7% (($e^{0.423}$-1) *100%) more upon the physical attractiveness manipulation treatment (column 4, Table 3-8). By contrast, visitors with smaller social networks react with much less magnitude in their reactions to physically attractive male patients (18.1% (($e^{0.166}$-1) *100%); column 3, Table 3-8). Expectedly, these two coefficients are statistically significant (t=-2.299, p=0.003). On the other hand, social network size does not significantly affect visitor reactions in donation. The treatment coefficients are not statistically significant across the columns 1 and 2 of Table 3-8 (t=0.036, p=0.971). We also verify our results by using the median (4) as the cutoff.

Table 3-8. Effect of Beauty Manipulation and Social Network Size in Donation Likelihood and Sharing Likelihood

	Private Behavior		Public Behavior	
	(1)	(2)	(3)	(4)
Sample	Returning Visitors who have Friends<9	Returning Visitors who have Friends>=9	Returning Visitors who have Friends<9	Returning Visitors who have Friends>=9
Model	Logit Model	Logit Model	Logit Model	Logit Model
Dep. Var.	Donation(0/1)	Donation(0/1)	Sharing(0/1)	Sharing(0/1)
Beauty Treatment	-0.134^{***}	-0.138^{***}	0.166^{***}	0.423^{***}
	(-5.13)	(-2.53)	(4.19)	(5.74)
Controls	Yes	Yes	Yes	Yes
Constant	-1.798^{***}	-2.870^{***}	-2.907^{***}	-2.991^{***}
	(-96.46)	(-73.54)	(-102.54)	(-56.33)
N	1605087	423255	1605087	423255

Notes:

i. Reporting donation behavior results based on social network size (9 as the cutoff) for donation and sharing behaviors

ii. Robust clustered standard errors clustered by cases reported in parentheses, *p<0.1; **p<0.05; ***p<0.01.

3.6 Discussion and Conclusion

This study examines the impact of physical attractiveness on the two types of online helping behaviors of donation and sharing. Based on the impression management theory, we discover that people's response to physical attractiveness is not static; rather, people's response to physical attractiveness can depend on the publicity/ privacy of people's online behavior. In a more public setting, individuals tend to engage impression management and behave in a manner that sustains a positive self-image. In contrast, individuals behave in manners more honest to their true intentions in a private setting.

Our main finding is that the impact of physical attractiveness can be different as people become aware that their actions are open to judgments from the others. We observe that female visitors do not publicly oppose physically attractive females when they do so in a private environment. We also find that physically attractive male patients are favored by both female and male visitors, whereas neither female nor male visitors continue to appreciate physically attractive male patients in a private environment.

This study contributes to several streams of literature. First, this study adds to the literature on the impact of physical attractiveness on charitable giving and the impact of physical attractiveness in online setting. Prior research on the impact of physical attractiveness on charitable giving report both premium and penalty for physically attractive recipients, without succinctly clarifying the cause for the controversies in the findings. In this paper, we utilize the online setting and observe the two types of behaviors to show that people's response to physical attractiveness can be positive, or negative, depending on circumstances, one of which is the publicity / privacy of the response. If the behavior is not very likely to be observed by the others, then people would freely express more honest sentiments toward physical attractiveness, whereas if the behavior likely has a sizeable audience, people would utilize physically attractive acquaintances to manage their impressions, or at least not behave in a way that could potentially bring them bad reputations. Such findings also convey managerial implications. Second, this study encompasses previous pieces of evidences from a vast range of literature (Chen and Hwang 2020, Guillory and Hancock 2012, Hancock et al. 2014) to formally theorize the alternations in online behaviors from the public vs. private behavior perspectives. As this paper marks the beginning of the studies to examine the non-static, ever changing behaviors of people on the Internet, future studies can further explore the conditions and the factors that direct people's reactions as intended. Lastly, this study contributes to the literature on medical crowdfunding. In accordance with Park at al. (2019), this study finds that displaying physically attractive picture as the first picture reduces donation likelihood for female patients from female visitors. Since displaying physically attractive pictures does not increase sharing likelihood for female patients, it is more beneficial for female patients to not display physically attractive pictures as the first picture in their profiles. On the other hand, we find that displaying physically attractive pictures increases sharing likelihood for male patients, while such practice does not hurt the donation likelihood for male patients. Therefore, it is more beneficial for male patients to display physically attractive pictures of themselves.

This paper is among the first to attempt to comprehend the discrepancies in reactions to physical attractiveness from the scope of privacy and publicity. We find that individual opinions in a comparably public online environment might not be the most accurate depiction of the actual opinions and desires. For instance, the positive buzz toward physically attractive persons on the Internet might not always transcend to truly favorable attitude toward the products associated with the persons, or the persons themselves. The findings of this paper not only present important guidelines for male patients in medical crowdfunding to reach more potential donors but can also be extended to establish strategic online marketing strategies in general.

3.7 References

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