HIDDEN INFLUENCES OF CROWD BEHAVIOR IN CROWDFUNDING: AN EXPERIMENTAL STUDY

Henry K. Dambanemuya
Northwestern University
Evanston, IL 60208
hdambane@u.northwestern.edu

Eunseo Choi
MIT
Cambridge, MA 02139
choie@mit.edu

Darren Gergle
Northwestern University
Evanston, IL 60208
dgergle@northwestern.edu

Emőke-Ágnes Horvát
Northwestern University
Evanston, IL 60208
a-horvat@northwestern.edu

June 14, 2022

ABSTRACT

Crowdfunding continues to transform financing opportunities for many across the globe. While extensive research has explored factors related to fundraising success, less is known about the social signaling mechanisms that lead potential contributors to fund a project. Existing large-scale observational studies point to non-straightforward characteristics of prior contributions (so-called "crowd signals") that forecast further contributions to a project, albeit without theoretical support for their effectiveness in predicting fundraising success. Here, we translate empirical crowd signals based on variations in the amounts and timings of contributions into mock contribution scenarios that allow us to scrutinize the influence of essential signals on contributors' decisions to fund. We conduct two experiments with $1,250$ subjects who have contributed previously to real crowdfunding projects. The first experiment investigates whether high crowd signals, i.e., contributions of varying amounts arriving at unequally spaced time intervals, are making people more likely to contribute to a crowdfunding project. The second experiment further examines the effect of basic competition on the role of the crowd signals. Across both, we observe that high crowd signals attract 19.2% more contributors than low signals. These findings are robust to different project types, fundraising goals, participants' interest level in the projects, their altruistic attitudes, and susceptibility to social influence. Participants' unguided, post-hoc reflections about the reasons behind their choice to fund revealed that most were unaware of their reliance on any crowd signals and instead attributed their decision to nonexistent differences in project descriptions. These results point to the power of crowd signals unbeknownst to those affected by them and lay the groundwork for theory-building, specifically in relation to the essential signaling that is happening on online platforms.

Keywords crowdfunding, crowdsourcing, crowd signals, social influence, altruistic attitudes

1 Introduction

Online fundraising (aka "crowdfunding") is the process of funding a project or venture by raising small amounts of money from a large number of people outside traditional financial institutions and typically via web-based platforms [1]. It is a rapidly-growing industry with several applications, for instance, in disaster relief and political campaigns, as well as supporting artistic, entrepreneurial, and scientific endeavours [2, 3]. Due to its broad societal relevance, crowdfunding has attracted significant interest in industry and policy-making, but also extensive research in various fields including social computing, entrepreneurship, law, public management, and the social sciences [4].

Despite several highly visible success stories (e.g., Khushi Baby[1], Oculus Rift[2], or the Ocean Cleanup[3]), most crowdfunding projects fail to reach their fundraising goal [1, 5]. As a matter of fact, between 2014 and 2022, only 38% of projects posted on Kickstarter and 13.3% of projects on Indiegogo were successfully funded [6]. As signaling theory suggests [7, 8], when deciding which projects to fund, potential contributors[4] pay attention to the characteristics of projects and their creators [9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19]. Despite these details, crowdfunding remains a low-information and high-risk setting for most contributors. In an attempt to make up for the information asymmetry between them and project creators, possible contributors knowingly or unknowingly observe the behavior of others on the platform. For instance, they inspect how much was contributed to a project and when, which provides them with clues about the amount to contribute and when to do so [20, 21, 22, 23, 24, 25, 26]. Such social influence is common especially when it is difficult to establish the merit of a project [27, 21]. This influence, mediated by social signaling can lead to substantial (rational or irrational) herding in crowdfunding [21, 28, 29, 30, 31], depending on whether serial contributors with a successful track record or random novices are being imitated [32].

The crucial signaling among contributors on crowdfunding platforms prompts investigations into crowd behaviors that stimulate participants to contribute, and are therefore associated with successful fundraising. Recent research based on large-scale observational data from real crowdfunding sites has identified *crowd signals* associated with successfully funded projects across different types of crowdfunding markets [25, 33]. The promise of such crowd signals is substantial. First, they can provide useful heuristics when deciding whether to fund or not, even in the presence of incomplete data about projects and their creators. Second, crowd signals use the full potential of the wisdom of crowds. Many contributors who are active on crowdfunding platforms have considerable experience and expertise as investors, and can guide an attentive crowd to meritorious projects. Third, crowd behavior might provide early-warning signals through changes in contribution dynamics that reflect excitement and trust, or, on the contrary, uncertainty and disbelief. Fourth, crowd signals can potentially provide an alternative to relying on traditional proxies of merit and creditworthiness that are prone to social biases. Fifth, according to signaling theory, differential crowd signals offer a potential explanation for how crowdfunding projects of similar quality can end up with different funding outcomes, depending on the approval conveyed via social signaling [17].

Currently, we are lacking essential knowledge to fulfill these promises. Existing evidence about the effectiveness of crowd signals is based entirely on observational data obtained from complex, evolving online platforms [34]. These data may contain multiple confounding factors which can interfere with the effect of the crowd signals. Therefore, **we need experimental validation that can uncover when and how crowd signals work, offering a more nuanced understanding of their efficacy in predicting funding outcomes online**. Although much has been written based on signaling theory about how project creators convey value in crowdfunding (e.g., via writing quality or human capital [13, 18]) and how herding impacts crowdfunding outcomes [21, 30, 31, 35], considerably less is known about the signaling mechanisms that impact people who are on the verge of deciding whether to contribute to a project or not. Arguably, this gap in the literature represents one of the most puzzling questions related to crowdfunding, prompting us to investigate whether and under what conditions some potential funders are less likely to act upon social signaling than others.

To fill this gap, we conducted carefully-designed randomized experiments that allow for direct comparisons between contribution scenarios that encode different crowd behaviors. We used prior observational work to map behaviors onto artificial crowd signals. In our experiments, we created a mock crowdfunding setting to test how the signals affect people's decision to fund a project. This setup enabled testing whether crowd signals were making people more or less likely to contribute to a crowdfunding project (RQ1). Then, we addressed the question of whether observing projects of comparable description quality affects the role of crowd signals in peoples' project choices (RQ2). Finally, we checked whether individual characteristics like interest in the project category, people's altruism, and their susceptibility to social influence were impacting the selection of projects with different crowd signals (RQ3).

We conducted our experiments with $1,250$ Amazon Mechanical Turk (MTurk) workers who were all familiar with crowdfunding, having previously contributed to projects at least once a year. We thoroughly tested the robustness of our results against (i) project category and fundraising goal, (ii) whether people are presented with one project description or offered two competing ones, (iii) differences in participants' interest in the projects, (iv) altruistic attitudes and susceptibility to social influence, and (v) a suite of demographic characteristics, such as age, gender, and socio-economic status. To better understand participants' decision-making, we collected and analysed qualitative reflections about their thought process.

[1] `www.khushibaby.org`

[2] `www.oculus.com/rift`

[3] `www.theoceancleanup.com`

[4] Crowdfunding literature has used various terms to denote people who pledge funds on various types of platforms, calling them "investors," "donors," "backers," or "supporters." Here, we refer to people who provide funds as "contributors" and "funders."

The rest of the paper is structured as follows: First, we introduce literature on indicators of project success in crowdfunding and discuss factors related to crowd behavior that may influence contributors' project selection. Then, we describe the experiment design, i.e., how we created mock crowdfunding projects and artificial crowd signals, and how we chose the measures used to evaluate participants' preferences in terms of project categories, their altruistic tendencies, and susceptibility to social influence. This is followed by a description our experiments, a presentation of the results, and a discussion of the implications of our findings for crowdfunding platforms and users.

2 Related Work

In this section, we introduce prior research that informed our study and experiment design. First, we discuss project-related correlates of success most of which we control for in our experiments. Then, we describe the crowd signals that we experimentally evaluate. Finally, we discuss relevant work on factors that could influence the role of the crowd signals, and hence form the basis of our robustness tests throughout all experiments.

2.1 Project-related indicators of success in crowdfunding

Extensive research has tried to uncover the factors associated with higher probabilities of successful fundraising. The majority of existing work focuses on factors related to characteristics of the projects such as the project description [16, 10, 9, 11, 15], media content (e.g., the use of videos to persuade audiences or capture their attention) [11, 1, 14], project updates [12, 36] and promotional activities on social media [37, 38, 39, 38], as well as the requested amount [1, 40, 41, 42] and the duration of the fundraising effort [40, 42]. Other studies have also looked at the characteristics of the project creators, e.g., their reputation [43], ability to attract funders early in the campaign and build a community of supporters [37, 44, 45], as well as the project creator's social capital [13, 46, 47, 41, 48, 49].

Among these studies, there is general consensus that identifiable signals of project quality and project creators' engagement play a significant role in attracting contributions, which lead to a successfully funded project. However, a significant drawback of relying on project-related factors for prediction in online collective behavior is that these factors inherently depend on changes in the various algorithms that underpin basic functions on these platforms [34, 50, 51]. This is because project-related factors are often specific to the platforms on which the projects are created and hence fail to generalize across different sites where collective action is important. These challenges therefore call for seeking more universal knowledge.

2.2 Crowd signals as indicators of success in crowdfunding

To overcome these challenges, recent work has begun exploring general approaches for evaluating collective outcomes in crowdfunding using signals deduced from the behavior of the contributing crowd. For example, research that examines the effects of crowd behavior on fundraising success demonstrates that the amount of the first contribution to the project [35] and the timing of contributions [52, 44, 53, 37], as well as other descriptors of crowd dynamics [22, 24, 53] are correlated with fundraising success. For instance, having large initial contribution amounts and many early contributors to a fundraising campaign may signal project quality and funders' confidence in a project—factors that can ultimately lead to a project's success [44, 35]. Additionally, having many early contributors can also lead to more opportunities to obtain subsequent contributions through potential information cascades and social influence [54, 21]. The significant signaling among crowd members in online fundraising and its effects on collective decision-making outcomes is therefore incomplete without the study of crowd signals associated with successful fundraising.

As systematized in prior research [33], these signals include the number of contributors of a project, the time between the project is posted online and the arrival of the first contribution, the time between the first and last contribution when the project reached either its goal or the fundraising deadline, the coefficient of variation in the inter-contribution times, and the coefficient of variation in the contribution amounts. Of these signals, those requiring information about the last or all contributions to a project are less practical from the perspective of a decision aid while the project is still running. Additionally, the times between project start and first contribution as well as the time between first and last contribution have been shown to be less stable predictors across crowdfunding markets than the rest [33].

This leaves us with robust and promising evidence for the predictive value of variation in the amounts *and* times of contributions. Specifically, successfully funded projects are associated with greater variation in contribution amounts and inter-contribution times compared to failed projects. Moreover, the predictive value of these crowd signals is higher than the predictive power of project-related factors [33]. As promising as they are, the role of these two crowd signals has not been validated in a controlled setting which would enable deducing a direct link between crowd signals and individual decision-making. Our current work aims to fill this important gap.

2.3 Motivational and predispositional factors impacting crowd behavior on crowdfunding platforms

To test the robustness of the crowd signals we investigate whether they are impacted by social factors that have been demonstrated to affect participation in and contribution behavior on crowdfunding platforms.

These factors include people's interest in the project topic (hereafter project category) [55, 56, 57], their altruistic tendencies [58, 59, 60], and susceptibility to social influence [59]. For example, in online political crowdfunding, prior research shows that people's political interests positively increase their intention to participate [55]. In general, there is also evidence that people tend to gravitate towards supporting causes in which they are interested in personally [56, 57]. Existing research also provides empirical evidence that the altruism of contributors increases individuals' intention to participate and the likelihood of a project's success [58, 59, 60]. Additionally, social relations among contributors and their compliance to social norms has also been shown to influence crowd behavior in online fundraising [59, 35, 46].

While these studies provide ample evidence on how the above factors affect individuals' behavior in crowdfunding, less is known about how they may interact with crowd signals in determining the likelihood of contributing to a project. Therefore, our work also examines whether the effect of the crowd signals depends on such factors.

3 Experiment Design

To conduct experiments, we recruited $1,250$ English-speaking participants located in the United States through Amazon Mechanical Turk (MTurk). To ensure that the participants were representative of crowdfunders, we included screening questions at the beginning of the experiment (see Appendix) and *only recruited crowd workers that* (i) demonstrated familiarity with the concept of crowdfunding, (ii) correctly identified examples of crowdfunding platforms, (iii) participated in crowdfunding at least a few times a year, and (iv) had contributed to or created a crowdfunding campaign in the past. Figure 1 shows a summary of the crowd workers' responses to questions (iii) and (iv). Crowd workers that have never participated in crowdfunding were excluded from participating during a screening survey, prior to the experiments. Of all the $1,250$ crowd workers that attempted the screener, 82.32% passed this screening on familiarity with crowdfunding and got enrolled in the study as participants.

Additionally, considering that crowd workers typically come from specific socio-economic backgrounds that may have implications on how they tend to make decisions online [61, 62], we ensured that the demographics of the crowd workers closely mirrors individuals who take part in crowdfunding campaigns as reported on the crowdfunding platforms KickStarter and Indiegogo[5]. To ensure data reliability, we further restricted the survey to participants with a Human Intelligence Task (HIT) approval rate greater than 98% to be consistent with both influential and recent articles on MTurk methods [63, 64, 65, 66]. Furthermore, we included filters to ensure that participants had not taken prior crowdfunding surveys from our team and were above the age of 18 and capable of consent. Finally, to ensure that participants observed the same experiment design layout, we only considered participants using a desktop or laptop computer and not a mobile device.

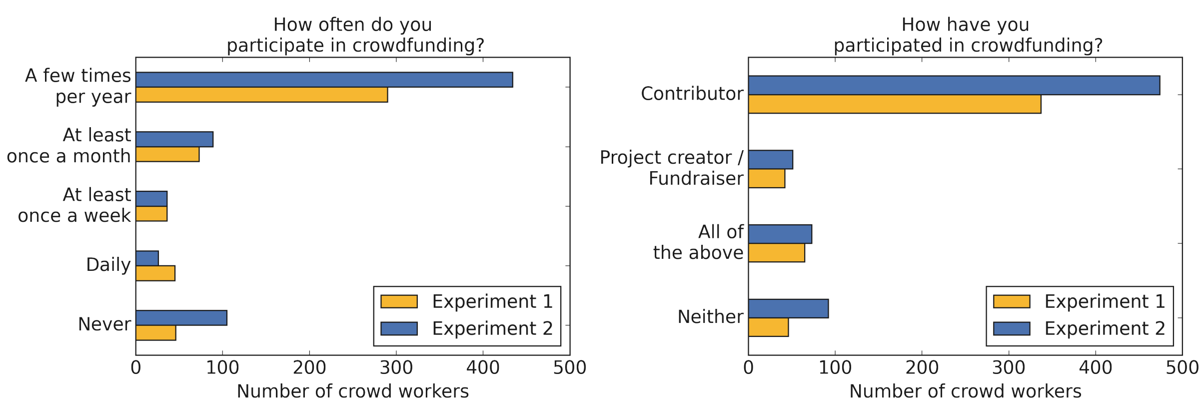

Figure 1: Trends for participation in crowdfunding for our sample of MTurkers. **Left:** Frequency of use of crowdfunding platforms and **Right:** type of use. Crowd workers who indicated that they have never participated in crowdfunding or who did not use such platforms as a contributor or project creator were excluded from participating during a screening survey, prior to the experiments.

[5] `https://artofthekickstart.com/crowdfunding-demographics-kickstarter-project-statistics/`

3.1 Creating Artificial Crowd Signals

Crowdfunding platforms contain "contribution lists" that show users when and how much others have already contributed towards a specific project. Our main goal is to test experimentally whether the amounts and timings of individual contributions (e.g., $20 offered 2 hours after the launch of the crowdfunding campaign) shown in the contribution list are linked to the likelihood that people fund the project. See Section 2.2 for details about why we focus on amounts and timings of contributions.

When creating artificial contributions lists, we made specific details about project contributions the same in order to focus exclusively on the crowd signals that we test. Consistent with most crowdfunding platforms that display a few contributions on each project, every list contained the same number of most recent contributors (four). Moreover, we made sure that the four recent contribution amounts added up to $400 in each list so that no list appeared to be raising more money than the other. We chose to show that 80% of the fundraising goal had been raised to signal that all projects had an equal chance of success. Finally, we specified individual contribution amounts and times that reflect high and low crowd signals.

To compute specific amounts and contribution times for high and low crowd signals, we analysed data from prior observational studies that comprise nearly four million contributions from three different crowdfunding platforms i.e., lending, equity, and charity platforms [33]. From these data, we first computed the mean coefficient of variation in amounts and inter-contribution times on each of the three crowdfunding platforms using the first four contributions for each project. We aimed to create artificial crowd signals that were above and below the computed means on all three real-world platforms.

Specifically, to select the individual values for each contribution list, we considered realistic and easily understandable values for the contribution amounts (see Table 1). For example, a contribution list consisting of the amounts $100, $10, $40, and $ 250 (High A) has a variation in amounts of 1.068, which is higher than average based on observational data and is substantially larger than the variation of the list $85, $100, $120, $95 (0.147, Low A). Similarly, four contributions arriving 2 days, 3 hours, 2 hours and 1 hour before the participant's selection, respectively is indicating high variation in contribution times (1.833, High A), while contributions arriving 2 days, 36 hours, 1 day, and 6 hours before selection indicate low variation in times (0.659, Low A).

For each high/low crowd signal condition, we combined information about amounts and times ensuring that both variances were either high or low. This decision was motivated by prior work that points to the joint value of both components of crowd signals. While it might be worth testing in future work, here we do not aim to untangle whether and what individual effect the amount vs. time-based components of crowd signals have (more about this in Section 6). To ensure that the results are robust to the exact choices of amounts and times, we created two sets of low and high values and combined them into four high crowd condition pairings and four low crowd condition pairings.

Table 1: Components of high and low artificial crowd signals used in the treatment conditions. The contribution times shown to participants are obtained from subtracting each value from 48 hours, as if the project would have started 2 days before the participant makes their decision. To ensure that the contribution lists are truly reflecting high vs. low crowd signals, we use the same number of recent contributions (4) and the same total amount of funds raised ($400). The artificial values are the same across all projects in a category.

Crowd Signal Component	Condition (Value)	Artificial Values
Coefficient of variation in contribution amounts	High A (1.068)	$100, $10, $40, $250
	High B (1.173)	$85, $15, $30, $270
	Low A (0.147)	$85, $100, $120, $95
	Low B (0.183)	$80, $110, $120, $90
Coefficient of variation in inter-contribution times	High A (1.833)	0hrs, 45hrs, 46hrs, 47hrs
	High B (1.568)	0hrs, 40hrs, 46hrs, 47hrs
	Low A (0.659)	0hrs, 12hrs, 24hrs, 42hrs
	Low B (0.673)	12hrs, 24hrs, 32hrs, 47hrs

3.2 Procedure

We conducted two separate experiments (see Figure 2 for a sketch of the experimental procedure). In the first experiment (i.e., "single description layout"), we investigate whether high crowd signals are making people more likely to contribute to a crowdfunding project (RQ1). First, participants are randomly assigned to one of four project categories. Then, they are shown one project description and two different contribution lists to choose from. In this experiment, the single description layout ensures that we are only testing specifically for the effect of the manipulated crowd signals, while minimizing the impact of any potential confounding variables. We repeat this process so that each participant performs the task twice, i.e., they see two projects in total. In the second experiment (i.e., "two-description layout"), we investigate whether observing projects of comparable description quality affects the role of the crowd signals in people's choices of projects (RQ2). Building on the first experiment, we further investigate the effect of the crowd signals on contributors' behavior when there are two comparable project descriptions which mirrors the choice aspect of real-world decision-making scenarios in crowdfunding. In this experiment, participants are split between a control and treatment group and randomly assigned to one of four project categories. Participants in the control group had to select one of two project descriptions of similar quality from the same category. Participants in the treatment group were shown two project descriptions of similar quality from the same category associated with a contribution list each, such that they had to choose one from two projects. In both the control and treatment groups, we repeat this process so that each participant sees two projects in total.

In both experiments, we further asked participants to explain why they selected one project or contribution list over another so as to gain a better understanding of why they behaved the way they did.

To ensure that participants paid attention to the visual information displayed in the contribution lists, we incorporated attention checks into the survey. It is important to highlight that participants responded to the attention check questions *after* completing the selection task and when they could no longer see the project selection screen. Participants therefore had to recall how many contributions were visible on the project description page, what the project's fundraising goal was, and how much money the campaign had raised *when this information was no longer visible to them*. These demanding attention checks are therefore more stringent compared to most commonly used instructional manipulation checks (IMC) e.g., "you should not answer this question if you read it; it is to check your attention". While the chosen attention checks result in a much higher participant task failure rate compared to other MTurk studies that employ IMCs, the reported failure rate is comparable with survey studies and ensures that participants indeed perceived all the aspects of the information that characterize our treatment conditions [67, 68, 69]. Furthermore, we considered task responses from participants that passed at least one attention check on each task.

At the end of each experiment, participants completed a set of questions to assess their interest in the topic of the category, altruistic tendencies, and susceptibility to social influence. Finally, each participant was paid $3 USD upon completing the survey,including crowd workers that failed all attention check questions.

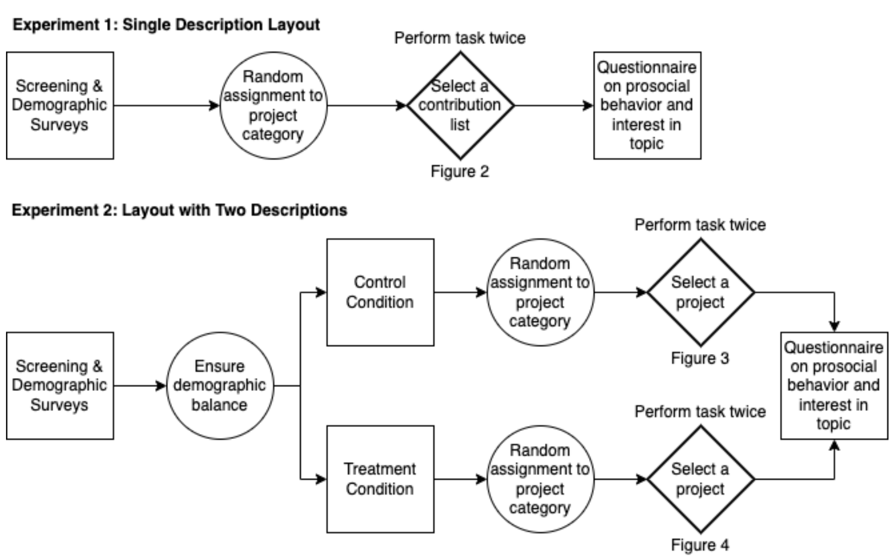

Figure 2: Experiment procedure: Both experiments begin with a screening and demographics survey to ensure that participants are familiar with crowdfunding and are demographically representative of crowdfunders in the real world. Participants in experiment 1 are randomly assigned to one of four project categories where they perform a selection task, twice. Participants in experiment 2 are split between control and treatment groups, randomly assigned to one of four project categories, and also perform a selection task, twice. In both experiments, participants conclude by completing a questionnaire on prosocial behavior and interest in project topic.

3.3 Creating Comparable Mock Crowdfunding Projects

We created mock crowdfunding projects to experimentally validate the role of crowd signals related to the behavior of funders rather than the characteristics of project creators or projects in predicting successful fundraising. The project descriptions are inspired by real crowdfunding listings from the platform GoFundMe.com[6]. To test our hypotheses, we selected four different topic categories at varying fundraising goals. The projects sought funds for homeless people (goal: $5,000), community caddies (goal: $50,000), 3D printing PPE for essential workers (goal: $10,000), and attending a high school robotics competition (goal: $5,000). For each project category, we selected four real crowdfunding projects from GoFundMe. Half of these projects were successfully funded on GoFundMe and half were not. Within each project category, we altered project-related factors that may influence fundraising outcomes to make them consistent. These factors include the project's description length, writing quality, target amount, media content, location information, and details about project execution. For example, we used generic project names (e.g., Community Caddie Fund #1) rather than the real titles to make the projects unidentifiable, removed location information to prevent regional bias, and dropped images and any other media content that might confound the effect of the crowd signals. To make the project descriptions within each category comparable, we modified them to achieve similarity in the number of words (description length). Then, we relied on the proselint[7] score, Grammarly[8] (e.g., readability score, and total score), and Flesch–Kincaid readability tests [70] to measure and compare the description quality. Pre-testing the descriptions with $N = 136$ subjects from MTurk revealed that participants were highly sensitive to the slightest differences in language. For instance, they picked up on certain words that they preferred over others, even though the requests were similar. Therefore, within each category, we manually edited the descriptions to make them as similar as possible. We tested whether participants' preferences for different descriptions from the same category were uniform within the control condition of experiment 2. Section 5.4 details our results.

3.4 Measures of motivational and predispositional factors

The primary outcome we sought to investigate was the number of times a project was selected by participants under the two different treatment conditions, i.e., high/low crowd signals. To achieve this, for each treatment condition, we counted the *number of selections* as the dependent variable.

In addition, we wanted to explore the reasons why participants chose a project in one treatment condition over the other. To do this, we asked participants to provide open-ended responses why they made a specific project selection *after the fact*. We then analysed the responses using qualitative content analysis [71]. This method entails a bottom-up, inductive approach starting with open coding of all the data into the treatment conditions of high/low crowd signals, and iteratively adding other categories as they emerge. Using this method, we came up with five categories that encompass participant's reasons based on subtle differences in the project *descriptions*, different crowd treatment conditions (i.e., *high crowd signals* and *low crowd signals*), as well as selecting projects at *random* and for *other* reasons that were difficult to group into a meaningful category. To enable multiple annotators to label participants' open-ended responses into the above categories, an initial code-book was developed. This code-book emerged without regard to experimental conditions and project categories. For each of the two experiments, two independent annotators coded 20% of the data and discussed disagreements. After this discussion, the annotators coded a different 36% of the corpus and reached an agreement of $k = 0.71$ and $k = 0.80$ in the first and second experiment, respectively.

To investigate whether contribution lists corresponding to high vs low crowd signals shown to the participants could be affected by other factors that might influence fundraising outcomes [58, 60, 59] (see Section 2.3 for more details), we included a post-survey to evaluate the effect of crowd signals depending on participants' level of interest in a project category, their altruistic tendencies, and susceptibility to social influence. After participants made their project selections, we measured their *baseline level of interest* in the project category using a 3-point Likert scale ("Not at all interested" (0), "Somewhat interested" (1), "Very interested" (2)). To assess participants' altruistic tendencies, we used the altruistic personality and the self-report *altruism scale* [72]. The 20-item scale measures the frequency with which one engages in altruistic acts primarily toward strangers on a 5-point scale ranging from "Never" (0) to "Very Often" (4). Finally, to measure participants' *susceptibility to social influence* (SSI), we adapted social influence scales from prior work that investigates social influence in online social networks [73]. The adapted scale captures different facets of SSI such as individuals' susceptibility to informative and normative influence [74], as well as their tendency to seek information from others [75]. The 18-item SSI scale captures people's tendency to comply with social norms and to pay attention to other's behavior. For each item, we used a 5-point Likert scale ("Strongly disagree", "Disagree", "Neither agree or disagree", "Agree", "Strongly agree") as a continuous measure.

[6]www.gofundme.com

[7]www.proselint.com/lintscore

[8]www.grammarly.com/

4 Experiment 1: Single-Description Layout

In the first experiment, we recruited participants ($N = 500$) who were randomly assigned to two of the four possible project categories (homelessness, caddies, PPE, STEM), one for each of their two tasks. Participants were randomly shown one of four possible projects from those categories. Every task included a project description and two artificial contribution lists from the treatment condition, i.e., high and low (see Figure 3). Participants were then asked to indicate which contribution list would make them more likely to give money for the project.

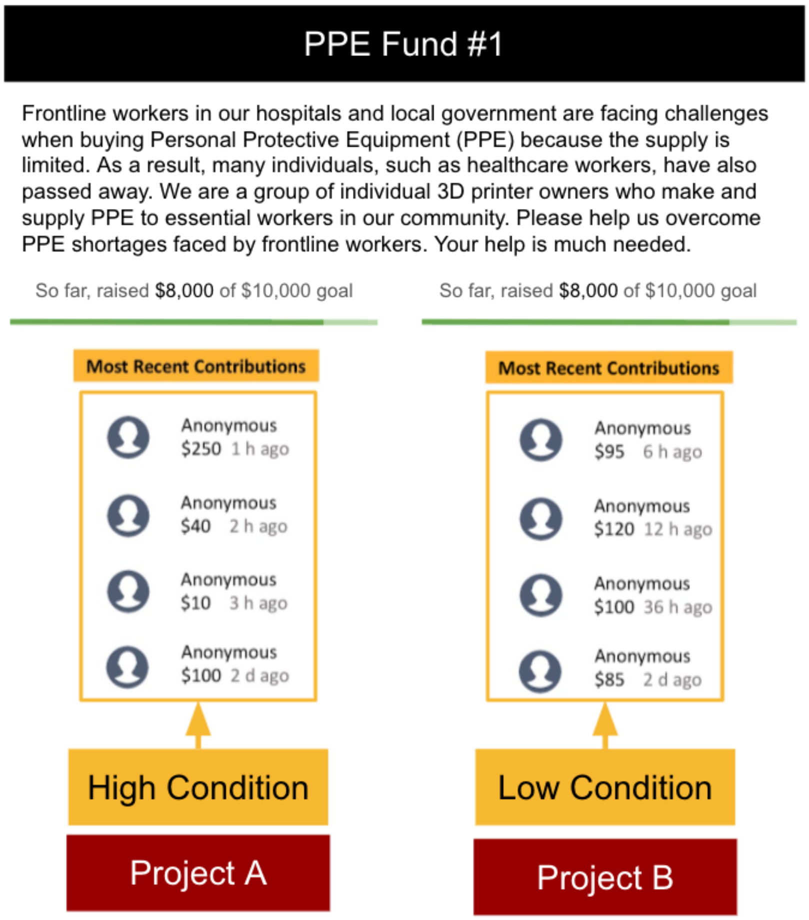

Figure 3: Example task presented to participants in experiment 1. Each participant saw a project description with two different contribution lists belonging to the high and low treatment condition. Project category shown in this example: Supporting the manufacture of Personal Protective Equipment (PPE) with 3D-printing.

4.1 Participants

Of the 500 participants from this experiment, 490 completed the survey and 324 passed at least one of the attention checks. Of these 324 participants, 57% were male. Most of them were between 30-49 years old (62%), Caucasian (78%), had an annual income less than $75,000 (70%), and held a college or advanced degree (69%). Each participant made two independent selections from two different project categories. Therefore, hereafter, we report results at the level of selections instead of participants.

4.2 Results

More participants chose contribution lists with high than low crowd signals. To investigate whether observing high values of momentum and variation in contribution amounts makes people more likely to join a contribution list, we counted the number of occurrences when participants selected to contribute towards a list with high or low crowd signals (329 vs 253 selections, respectively). We observed that a project is 30% more likely to attract contributors when assigned a contribution list with high rather than low crowd signals. This implies that participants systematically choose projects with high over low crowd signals (Table 2).

Table 2: Overall number (and percentage in parentheses) of project selections between high and low treatment condition contribution lists. In both experiments, lists with high crowd signals were selected more than projects with low crowd signals. Altogether, the high condition was chosen 19.2% more often than the low condition.

	Number and Corresponding Percentage of Selections		
	High Condition	Low Condition	Total
Experiment 1	329 (56.5%)	253 (43.5%)	582
Experiment 2	322 (52.4%)	293 (47.6%)	615
Total	651 (54.4%)	546 (45.6%)	1197

Table 3: Participants' project selections by project category and fundraising goal across the two experiments. More respondents preferred projects with high momentum and variation than low momentum and variation in all four project categories, with the exception of caddies in experiment 2.

		Number and Corresponding Percentage of Selections		
Category	Treatment	Experiment 1	Experiment 2	Total
Caddies	High	78 (53.4%)	62 (44.9%)	140 (49.3%)
Goal = $50,000	Low	68 (46.6%)	76 (55.1%)	144 (50.7%)
Homelessness	High	83 (56.8%)	102 (55.1%)	185 (55.9%)
Goal = $5,000	Low	63 (43.2%)	83 (44.9%)	146 (44.1%)
PPE	High	91 (61.5%)	56 (50.9%)	147 (57.0%)
Goal = $10,000	Low	57 (38.5%)	54 (49.1%)	111 (43.0%)
STEM	High	77 (54.2%)	102 (56.0%)	179 (55.2%)
Goal = $5,000	Low	65 (45.8%)	80 (44.0%)	145 (44.8%)
Total	High & Low	582	615	1197

These findings hold across different project categories and target amounts. To investigate whether participants' preference for high crowd signals is influenced by differences in project categories or fundraising goals, we analysed the frequencies in selections separately for each project category. Across the different categories with fundraising goals ranging from $5,000 to $50,000, participants consistently chose projects with high crowd signals (Table 3). Specifically, they preferred the high over low conditions 14.7% more often in the community caddies category, 31.7% in homelessness, 59.6% in PPE, and 18.5% in STEM. This variation between categories is substantial, and does not seem to correlate with the target amount. All in all, our main finding of experiment 1 is robust to different crowdfunding project categories and fundraising goals.

Participants preferred high over low crowd signals in open-ended responses. When further asked why they selected one contribution list over the other, most participants (66.4%) mentioned that they made their selection based on the crowd signals, e.g., "*The even donations caught my eye*" or "*I liked the wider range of contribution amounts in the second list*." Participants produced these explanations *without any prompts* that would have guided them to provide answers related to, e.g., the consistency or variation in amounts. Importantly, according to their free text responses, more participants preferred the high treatment condition (43.99%) than the low treatment condition (24.74%). Most notably, participants interpreted the presence of small contributions in the high treatment condition as a signal for a project's broad appeal across a wide range of demographics. For example, as one participant noted:

> "The list I chose had donation amounts that varied from 10 dollars to 250 dollars. This makes me feel like there is more freedom in the amount you are expected to donate and makes me more willing to donate. The other contribution list had donations that were all around 100 dollars."

Other participants interpreted the presence of uniform contribution amounts and timings in the low treatment condition as a signal for consistency, confidence, or consensus among the funders about the projects' merits. For example, as one participant noted:

"I chose the first list as it had a more even distribution of contributions - they were all relatively in the same dollar range. This made me feel like people seemed to feel the same amount of confidence in the project."

A smaller group of participants (13.4%) indicated that they selected a list at random (e.g., "It was a toss up - they both were equally funded with pretty similar amounts") and the remaining 17.1% provided reasons that could not be classified clearly into any of the above categories (e.g., "I preferred the first one"). Figure 4 (Left) provides a summary of these findings.

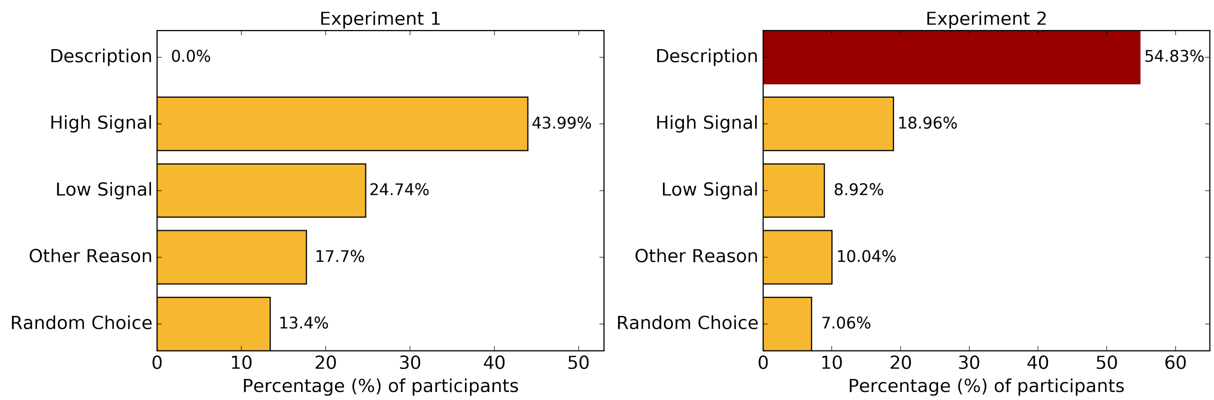

Figure 4: Percentage of participants (x-axis) that made their selection choices based on the reasons indicated on the y-axis.

The influence of crowd signals is strongest among participants who are susceptible to social influence. To better understand whether participants' motivational and predispositional tendencies are associated with their selections in experiment 1, we grouped them based on their reasons for choosing one contribution list over the other. Conducting a one-way omnibus analysis of variance (ANOVA), we observed a significant difference in the distribution of social influence scores ($F = 29.731, p < 0.001$), altruism scores ($F = 8.246, p < 0.001$), and baseline interest in a project category ($F = 5.845, p = 0.001$) across the groups. To further investigate which groups are significantly different from each other, we performed multiple post-hoc pairwise comparisons using Tukey's Honest Significant Difference (HSD) test (Table 4).

Across groups of people who prefer high or low crowd signals, we observed no statistically significant differences in the means of their social influence scores, altruism scores, or baseline interest in a project category. Hence participants' response to the crowd signals is not affected by susceptibility to social influence, altruism, or interest in the project topic. It is however worth noting that participants who selected the low treatment condition because they preferred consistency in contribution amounts (e.g., "I chose randomly as I didn't see which choice was different than the other.") were the most susceptible to social influence. Participants who selected projects at random were the least susceptible to social influence and showed significant differences in the means of their social influence scores in comparison with participants that were influenced by the crowd signals, both low and high. We observed no significant difference in participants' altruism scores or baseline interest in a project topic in any of the pair-wise comparisons.

Table 4: Post-hoc Tukey Honestly Significant Difference (HSD) test results for one-way ANOVA on participants' susceptibility to social influence, altruism, and baseline interest in a project category across different groups based on the coded open-ended reasons for selecting one contribution list over another. Significant at p-values: ***: 0.001, **: 0.01, *: 0.05

	Experiment 1: Post Hoc Tukey test results for ANOVA					
Social Influence	mean (group1)	mean (group2)	diff	se	T	p-tukey
High - Low	31.434	34.264	-2.830	1.439	-1.967	0.201
High - Random *	31.434	26.372	5.062	1.787	2.833	0.024
Low - Random ***	34.264	26.372	7.892	1.942	4.064	0.001

5 Experiment 2: Layout with Two Descriptions

While experiment 1 evaluated the role of crowd signals in participants' selections from two contribution lists for the *same* project description, people typically observe multiple projects on crowdfunding platforms. To evaluate the validity of our main finding from experiment 1, namely that participants prefer consistently the high over the low crowd signal condition, we conducted a second experiment to investigate whether this result is consistent using a different layout that emulates the presence of competing projects. To control for the effect of different project descriptions on participants' choices, we now split participants into control ($N = 250$) and treatment groups ($N = 500$), as described below.

5.1 Control Condition

In the control condition, participants observed project features but no contribution lists, i.e., there was no indication of crowd signals (see Figure 5). Randomly assigned to one of the four possible project categories, participants were shown side-by-side two different project descriptions. They were then asked to indicate which of the two projects they would rather contribute to. They performed this task twice, with two different pairs of project descriptions from the same category. This set-up allowed us to collect the baseline appeal of all campaigns.

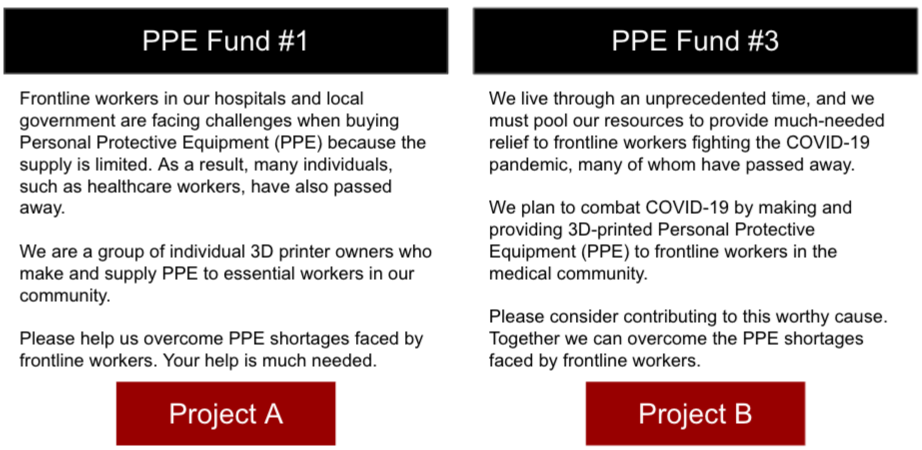

Figure 5: Example task presented to participants in the control group of experiment 2. Each participant saw two project descriptions without any contribution lists. Project descriptions shown in this example are from the PPE category.

5.2 Treatment Condition

In the treatment condition, we provided information about crowd features by using the same artificial contribution amounts and times as in experiment 1 (Table 1).

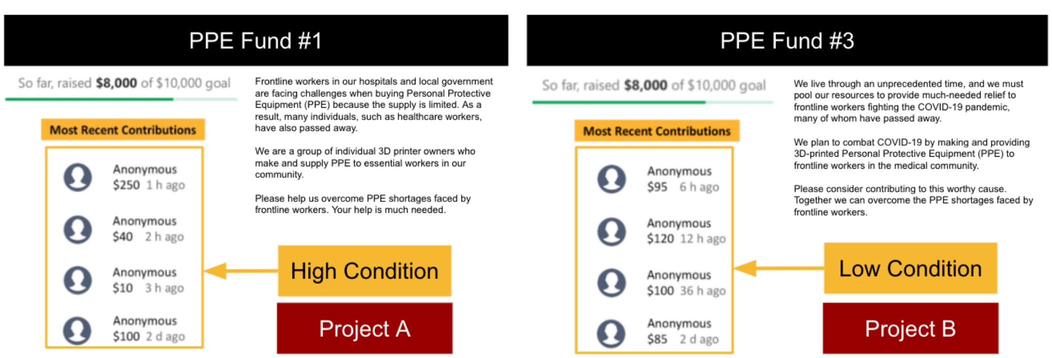

Figure 6: Example task presented to participants in the experiment 2 treatment group. Each participant saw two similar project descriptions with two different contribution lists; one belonging to the high treatment condition and one representing the low treatment condition.

Through the contribution lists, each project signaled therefore either low or high crowd signals. Similar to the control condition of experiment 2, participants were presented side-by-side two project descriptions from the same category. One of the descriptions was followed by a contribution list with low crowd signals, the other was presented with a contribution list from the high condition (see Figure 6). Participants were again asked to select the project that they were more likely to contribute to. They repeated the task with different pairs of descriptions from the same category, such that each participant provided two selections.

5.3 Participants

For experiment 2, we recruited 750 participants in total (250 for the control group and 500 for treatment). 228 of the participants in the control group and 462 participants in the treatment group completed the survey. Of the 462 participants in the treatment group, 308 passed the attention checks. Altogether, we conducted the analysis on the responses of 536 participants. Out of these, 51% were male. Most of them were between 30-49 years old (61%), Caucasian (75%), had an annual income less than $\$75,000$ (68%), and had a college or advanced degree (69%).

5.4 Results

Participants had no strong preferences for different descriptions used in our experiments. To test for possible confounding effects potentially introduced by different project descriptions from the same category, we measured the percentage of times that each project description was selected in our control condition as the project's baseline appeal. Our findings show that each project's baseline appeal ranged from 30.6% to 65.3% with most of the descriptions likely chosen at random (mean = 50.0%, standard deviation = 10.0). Additionally, we found no significant relationship between participants' baseline appeal for each project in the control condition and participants' preferences for different contribution lists in the treatment condition. Therefore, this set-up helped test that the project descriptions used in the layout with two descriptions did not confound the influence of the crowd signals.

As observed in experiment 1, more respondents chose to contribute towards projects with contribution lists that encoded high than low crowd signals. Similar to experiment 1, participants in experiment 2 selected contribution lists in the high treatment condition more often than lists in the low treatment condition (Table 2). This trend was consistent across different project categories, with the exception of golf caddies, which aimed to raise $50,000 (Table 3). We believe that this unique result might be due to a lower interest in the project category (mean=1.565, standard deviation=0.627) compared to the other three categories (mean=2.398, standard deviation=0.632). This decreased interest might have resulted in participants not paying close attention to the selection task in this specific category.

Most participants attribute their choice to negligible differences in project descriptions. In contrast to experiment 1 where participants selected one of two contribution lists belonging to the same project description, participants in experiment 2 had to select one of two separate project descriptions followed by a high and low condition contribution list, respectively. Participants in experiment 2 therefore had to evaluate the information presented in the project descriptions and the crowd signals encoded in the contribution lists. When asked why they preferred one project over another, most of them (54.83%) mentioned that they made their selection based on project descriptions. Participants attributed their choice to negligible differences between the descriptions even though the project descriptions used in our experiments were similar in terms of their description length, proselint[9] score, Grammarly[10] readability and total scores, and the Flesch-Kincaid readability score [70]. This is very interesting because *it suggests that the majority of participants were unaware of any encoded crowd signals, yet they still systematically chose the high treatment condition.* Aside from project descriptions, we found that 27.88% considered the crowd signals. Consistent with experiment 1, more participants stated that they preferred the high treatment condition (18.96%) over the low treatment condition (8.92%).A small group of participants (7.06%) chose at random between the two projects and the remaining 10.04% provided other feedback that could not be classified into the above categories (Figure 4: Right).

Observing competing project descriptions has a small effect on the role of crowd signals. Since many participants in experiment 2 perceived project descriptions to be an important factor in their decision to contribute to a project, we tested whether observing two project descriptions instead of one impact the effect of crowd signals on participants' choices. To investigate the extent to which observing two similar project descriptions affects the influence of crowd signals, we performed a Chi-squared test that determines whether distributions of participants' project selections by treatment condition (as shown in Table 2) differ between experiment 1 and 2. Our findings show that observing simultaneously two projects lowered the percentage of selecting high treatment condition projects in experiment 2

[9] `www.proselint.com/lintscore`
[10] `www.grammarly.com/`

(52.4%) compared to experiment 1 (56.5%) across all project categories ($\chi^2(1, N = 1197) = 11.97, p < 0.01$). Therefore, basic competition between projects has a small effect ($\phi = 0.099$) on crowd signals[11].

Participants who are responsive to project and crowd signals are more susceptible to social influence than those making random selections. Although most participants self-reported that they made their selections based on project descriptions in the treatment condition of experiment 2, we also tested relationships between actual participant choices and measurements of altruism, susceptibility to social influence, and interest in project category. Consistent with the first experiment, an omnibus one-way ANOVA also showed a significant difference in the social influence scores ($F = 7.217, p < 0.001$). To further investigate which groups are significantly different from each other, we performed multiple post-hoc pairwise comparisons using Tukey's Honest Significant Difference (HSD) test (Table 5). We observed significant differences in susceptibility to social influence (SSI) mean scores between participants that selected a project at random and those choosing based on the description ($t = 3.443, p = 0.005$), high crowd signals ($t = 3.040, p = 0.020$), low crowd signals ($t = 4.667, p = 0.001$), and reasons other than the description or crowd signals ($t = 3.053, p = 0.019$). We found no significant difference in SSI scores between any other pair-wise comparison. Consistent with findings from Experiment 1, participants who selected the low treatment condition were the most susceptible to social influence, while those that selected a project at random were the least susceptible to social influence. Even though an omnibus one-way ANOVA also showed a significant difference in the and baseline interest in project category ($F = 3.195, p = 0.024$) across participants' selection groups, post-hoc Tukey's Honest Significant Difference (HSD) tests showed no significant differences in pairwise comparisons except between participants that selected a project at random and those that selected a project for reasons other than the observed project descriptions or crowd signals ($t = 2.863, p = 0.034$). The ANOVA found no significant difference in the participants' altruism scores across the groups.

Table 5: Post-hoc Tukey Honestly Significant Difference (HSD) test results for one-way ANOVA on participants' susceptibility to social influence and baseline interest in a project category across different groups based on the coded open-ended reasons for selecting one contribution list over another. Significant at p-values: ***: 0.001, **: 0.01, *: 0.05

	Experiment 2: Post Hoc Tukey test results for ANOVA					
Social Influence	mean (group1)	mean (group2)	diff	se	T	p-tukey
High - Low	31.108	37.000	-5.892	2.368	-2.488	0.094
High - Random *	31.108	23.289	7.818	2.572	3.040	0.020
Low - Random ***	37.000	23.289	13.711	2.938	4.667	0.001
Description - High	31.318	31.108	0.210	1.554	0.135	0.900
Description - Low	31.318	37.000	-5.682	2.105	-2.699	0.055
Description - Random **	31.318	23.289	8.028	2.332	3.443	0.005

6 Discussion

In this paper we sought to shed light on a critical question regarding social signaling on crowdfunding platforms: *How and when are crowd signals linked to funding outcomes?* We offer the first systematic large-scale experiment combined with a qualitative investigation of individual decision-making that investigated whether and under what conditions crowd signals influence participants' decision to contribute to crowdfunding projects. Based on controlled experiments with former users of crowdfunding platforms who have varying levels of susceptibility to social influence and altruistic attitudes, we presented nuanced evidence that extends previous observational studies and reveals new insights about the fundamental ways in which potential contributors perceive social signaling via prior contributions.

Our research validated previous findings about the role of non-trivial crowd signals in determining fundraising success [25, 33]. This new experimental and qualitative evidence substantially refines our understanding of *how* efficient social signaling is even when potential contributors do not realize the impact crowd signals have on their decisions. Our large participant sample also enabled us to provide essential novel insights about *when* crowd signals work, highlighting that they are salient among participants that are susceptible to social influence. Taken together, our discoveries establish the foundations for further theoretical work on mechanisms of social signaling in and beyond crowdfunding.

[11] Phi ϕ is a measure of effect size (similar to the correlation coefficient r) for Chi-square tests χ^2 and is defined by $\frac{\chi^2}{n}$. A value of 0.1 is considered a small effect, 0.3 a medium effect and 0.5 a large effect.

We argue that the confluence of individual decision-making, social signaling between crowd members, and emergent group behavior resulting in the success or failure of projects is essential for the attractiveness and success of crowdfunding. These platforms provide more than financial transactions; they also satisfy people's social and cognitive needs [56]. For that reason, contributors' autonomy in choosing meritorious projects, their opportunity to learn from others about project quality, and their experience of being part of a successful collective are indispensable for positive perceptions about crowdfunding and the sustainability of this crucial form of crowdsourcing. Our work makes important findings at this important intersection that has received less attention to date.

Although contributors to crowdfunding campaigns knowingly or unknowingly send signals via their observable actions, potential contributors are not always cognizant of how this signaling factors into their decision-making, supplementing observable project attributes. This was the main take-away when contrasting our single description layout (experiment 1) and the layout with two descriptions (experiment 2). While in the former, participants were primed to observe some role of crowd signals, the latter clearly showed that even though participants still overwhelmingly selected high crowd signals, unknowingly of this they attributed their choices to higher needs or opportunities to help that they read into project descriptions.

Further unpacking the link between crowd signals and individual decision-making, we examined participants' open-ended responses about why they chose one project over another. We found compelling qualitative evidence for the reasons why high crowd signals are associated with successful fundraising in observational studies. While existing studies emphasize the importance of large contribution amounts in signaling funders' confidence in a project's potential success [44, 35, 23], our findings suggest that small contribution amounts make contributors who would prefer to make modest pledges more comfortable and confident to contribute. In other words, showing a variety of both small and large contributions can be more beneficial for crowdfunding campaigns than simply showing large contribution amounts as it increases project's appeal to more potential funders.

An interesting finding of our analysis is that participants who systematically chose low crowd signals with uniform contribution amounts and constant inter-contribution event times were, on average, the most susceptible to social influence (SSI). We believe that the high average SSI score within this group of participants reflects their tendency to seek information from others when making individual decisions. This conjecture is further supported by qualitative evidence from participants' open-ended responses about why they selected low crowd signals. However, despite people that chose low crowd signals scoring highest on the susceptibility to social influence scale, overall, we observe that most participants chose consistently high over low crowd signals. In both experiments, we further observed that this tendency was remarkably robust to different project categories and target amounts. By demonstrating the consistent role of these signals in project selection, our work lays the groundwork for theory-building in this area of collective action.

6.1 Implications for Crowdfunding Platforms and Users

Our findings have implications for all three major stakeholders involved in crowdfunding: the platforms, project creators, and potential funders.

Platform maintainers can build on our results to develop crowdfunding sites that harness crowd signals to improve information acquisition by possible contributors, resource allocation to meritorious projects, and ultimately the long-term success of their service. Specifically, based on our evidence that non-trivial differences in how the timings and amounts of contributions are presented to users can significantly affect project outcome, designers should be intentional about the choice of how many contributions they show and how salient they make the amounts and the arrival times of funds. Our findings suggest that these design choices are essential, and platforms can build on this new knowledge to devise ways to promote and support signaling and coordination between funders.

Project creators can also use our results to improve the success of their campaigns. In alignment with prior work that demonstrates the importance of mobilising a community in crowdfunding [45], our results indicate that project creators should diversify their outreach efforts towards multiple funder categories. In particular, they should not only target a few "big funders" to grow the expected level of capital in-flow, but should also reach out to "small contributors" to increase the fundraising effort's public appeal. As demonstrated in our paper, showing high variation in contribution amounts and times can signal a project's broad appeal across various contributor groups which in turn could make make the fundraising effort feel more like an authentic community effort. These endeavors can increase a project's chances of success and enhance project creators' effectiveness on crowdfunding platforms.

Finally, our main finding highlighting the essential role of social signaling between prior and potential contributors has important consequences for funders. Our experiments exposed the impact of specific crowd signals notwithstanding contributors' ignorance of their tendency to perceive and react to such signaling during decision-making. This crucial insight calls for the need to educate platform users to both the positive and negative effects of signaling and herding [21, 30, 31]. More broadly, we argue that such information should represent a fundamental part of digital literacy education efforts in general [76, 77, 78].

6.2 Limitations and future work

Our study has a few limitations that we hope future work can address effectively. First, we investigated *one* operationalization of crowd signals that are associated with successful fundraising. While we relied on extensive prior empirical work on different platforms to create high and low crowd signals linked to funding outcomes [33, 22, 53], we cannot exclude the possibility that other crowd signals would also be worth testing experimentally. Whenever further robust measurements of crowd signaling are discovered, the experiment setup introduced here can serve as a fundamental approach for new investigation.

Second, we only study the effect of the crowd signals towards the end of the crowdfunding campaign period (i.e., at the time when 80% of the funds have been raised). It is unclear to what extent this subtle indication that the fundraising campaign is nearing completion has influenced participants. Further work should investigate how crowd signals influence participant behavior when contributors are indicated that their contributions are solicited, e.g., at the very beginning of the crowdfunding campaign period.

Third, it is important to highlight that participants in our study were not spending their own money. While one can envision experiments that would request participants to spend real funds, these would only be feasible at a small scale if larger amounts (e.g., $250) were involved. Such big contributions represent the necessary counterpoint to small amounts, resulting in a high crowd signal. Hence, if the goal was to scrutinize to what extent involving real money affects participants' decisions, one would likely need to compromise on the scale of the experiments.

6.3 Summary

In this study, we provided experimental validation of the effectiveness of crowd signals quantifying variation in contribution amounts and times in predicting fundraising success. We showed with two related experiments that participants consistently select contribution lists with high crowd signals, even when they attribute their choice to nonexistent differences in project descriptions. Uncovering the link between crowd signals and individual decision-making, we showed that the signals are robust to participants' altruistic tendencies and baseline interest in various project categories. The above findings improve our understanding of peoples' preference for certain crowdfunding projects over others via the (unknown) social signaling that takes place on such platforms. With this, our findings not only provide novel insights into an essential issue in online capital allocation, but also an open problem in understanding the link between mechanisms of social influence and success on online platforms. We hope that our results will contribute to the efficiency of crowd financing and advance further research on mechanisms of social signaling, including outside of crowdfunding.

Acknowledgments

This work was supported by the U.S. National Science Foundation under Grant No. IIS-1755873.

References

[1] Ethan Mollick. The dynamics of crowdfunding: An exploratory study. *Journal of business venturing*, 29(1):1–16, 2014.

[2] Julien Vachelard, Thaise Gambarra-Soares, Gabriela Augustini, Pablo Riul, and Vinicius Maracaja-Coutinho. A guide to scientific crowdfunding. *PLoS biology*, 14(2):e1002373, 2016.

[3] Pei-Yi Kuo and Elizabeth Gerber. Design principles: crowdfunding as a creativity support tool. In *CHI'12 Extended Abstracts on Human Factors in Computing Systems*, pages 1601–1606. 2012.

[4] Wei Zhang, Yan-Chun Zhu, and Xiao-Lin Wu. A bibliometric analysis of crowdfunding related research: Current trends and future prospect. In *Proceedings of the 3rd International Conference on Crowd Science and Engineering*, pages 1–7, 2018.

[5] Michael D. Greenberg and Elizabeth M. Gerber. Learning to fail: Experiencing public failure online through crowdfunding. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '14, pages 581–590, Toronto, Ontario, Canada, April 2014. Association for Computing Machinery.

[6] The Crowdfunding Center. Platforms stats & analytics: Showing period 1st january 2014 - 12th january 2022. *Retrieved from* `https://www.thecrowdfundingcenter.com/data/platforms#platforms_success`, 2022.

[7] M Spence. Job market signaling the quarterly journal of economics, 87 (3). *MIT Press, August*, 355:374, 1973.

[8] Michael Spence. Signaling in retrospect and the informational structure of markets. *American Economic Review*, 92(3):434–459, 2002.

[9] Laura Larrimore, Li Jiang, Jeff Larrimore, David Markowitz, and Scott Gorski. Peer to peer lending: The relationship between language features, trustworthiness, and persuasion success. *Journal of Applied Communication Research*, 39(1):19–37, 2011.

[10] Tim Althoff, Cristian Danescu-Niculescu-Mizil, and Dan Jurafsky. How to ask for a favor: A case study on the success of altruistic requests. In *Eighth International AAAI Conference on Weblogs and Social Media*, 2014.

[11] Tanushree Mitra and Eric Gilbert. The language that gets people to give: Phrases that predict success on kickstarter. In *Proceedings of the 17th ACM Conference on Computer Supported Cooperative Work & Social Computing*, pages 49–61, 2014.

[12] Anbang Xu, Xiao Yang, Huaming Rao, Wai-Tat Fu, Shih-Wen Huang, and Brian P Bailey. Show me the money! An analysis of project updates during crowdfunding campaigns. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pages 591–600, 2014.

[13] Gerrit KC Ahlers, Douglas Cumming, Christina Günther, and Denis Schweizer. Signaling in equity crowdfunding. *Entrepreneurship Theory and Practice*, 39(4):955–980, 2015.

[14] Sanorita Dey, Brittany Duff, Karrie Karahalios, and Wai-Tat Fu. The art and science of persuasion: not all crowdfunding campaign videos are the same. In *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing*, pages 755–769, 2017.

[15] Lauren Rhue and Lionel P. Robert. Emotional delivery in pro-social crowdfunding success. In *Extended Abstracts of the 2018 CHI Conference on Human Factors in Computing Systems*, CHI EA '18, pages 1–6, Montreal QC, Canada, April 2018. Association for Computing Machinery.

[16] Hadar Gafni, Dan Marom, and Orly Sade. Are the life and death of an early-stage venture indeed in the power of the tongue? lessons from online crowdfunding pitches. *Strategic Entrepreneurship Journal*, 13(1):3–23, 2019.

[17] Regan M Stevenson, Michael P Ciuchta, Chaim Letwin, Jenni M Dinger, and Jeffrey B Vancouver. Out of control or right on the money? Funder self-efficacy and crowd bias in equity crowdfunding. *Journal of Business Venturing*, 34(2):348–367, 2019.

[18] Aaron H Anglin, Jeremy C Short, Will Drover, Regan M Stevenson, Aaron F McKenny, and Thomas H Allison. The power of positivity? the influence of positive psychological capital language on crowdfunding performance. *Journal of Business Venturing*, 33(4):470–492, 2018.

[19] Lawrence A Plummer, Thomas H Allison, and Brian L Connelly. Better together? signaling interactions in new venture pursuit of initial external capital. *Academy of Management Journal*, 59(5):1585–1604, 2016.

[20] Jen Shang and Rachel Croson. A field experiment in charitable contribution: The impact of social information on the voluntary provision of public goods. *The Economic Journal*, 119(540):1422–1439, 2009.

[21] Juanjuan Zhang and Peng Liu. Rational herding in microloan markets. *Management Science*, 58(5):892–912, 2012.

[22] Simla Ceyhan, Xiaolin Shi, and Jure Leskovec. Dynamics of bidding in a p2p lending service: Effects of herding and predicting loan success. In *Proceedings of the 20th International Conference on World Wide Web*, pages 547–556. ACM, 2011.

[23] Nir Vulkan, Thomas Astebro, and Manuel Fernandez Sierra. Equity crowdfunding: A new phenomena. *Journal of Business Venturing Insights*, 5:37 – 49, 2016.

[24] Gordon Burtch, Anindya Ghose, and Sunil Wattal. An empirical examination of the antecedents and consequences of contribution patterns in crowd-funded markets. *Information Systems Research*, 24(3):499–519, 2013.

[25] Henry K Dambanemuya and Emőke-Ágnes Horvát. Harnessing collective intelligence in p2p lending. In *Proceedings of the 10th ACM Conference on Web Science*, pages 57–64, 2019.

[26] Claire van Teunenbroek, René Bekkers, et al. Follow the crowd: Social information and crowdfunding donations in a large field experiment. *Journal of Behavioral Public Administration*, 3(1), 2020.

[27] Matthew J Salganik, Peter Sheridan Dodds, and Duncan J Watts. Experimental study of inequality and unpredictability in an artificial cultural market. *Science*, 311(5762):854–856, 2006.

[28] Silvio Vismara. Information cascades among investors in equity crowdfunding. *Entrepreneurship Theory and Practice*, 42(3):467–497, 2018.

[29] Thomas B Astebro, Manuel Fernández Sierra, Stefano Lovo, and Nir Vulkan. Herding in equity crowdfunding. In *Paris december 2018 finance meeting Eurofidai-AFFI*, 2019.

[30] Michael A Zaggl and Joern Block. Do small funding amounts lead to reverse herding? a field experiment in reward-based crowdfunding. *Journal of Business Venturing Insights*, 12:e00139, 2019.

[31] CS Richard Chan, Annaleena Parhankangas, Arvin Sahaym, and Pyayt Oo. Bellwether and the herd? unpacking the u-shaped relationship between prior funding and subsequent contributions in reward-based crowdfunding. *Journal of Business Venturing*, 35(2):105934, 2020.

[32] Igor Zakhlebin and Emőke-Ágnes Horvát. Investor retention in equity crowdfunding. In *Proceedings of the 10th ACM Conference on Web Science*, pages 343–351, 2019.

[33] Henry K Dambanemuya and Emőke-Ágnes Horvát. A multi-platform study of crowd signals associated with successful online fundraising. *Proceedings of the ACM on Human-Computer Interaction*, 5(CSCW1):1–19, 2021.

[34] Abhijnan Chakraborty, Nuno Mota, Asia J Biega, Krishna P Gummadi, and Hoda Heidari. On the impact of choice architectures on inequality in online donation platforms. In *The World Wide Web Conference*, pages 2623–2629, 2019.

[35] Rembrand Koning and Jacob Model. Experimental study of crowdfunding cascades: When nothing is better than something. *Available at SSRN 2308161*, 2013.

[36] SeungHun Lee, KangHee Lee, and Hyun-chul Kim. Content-based Success Prediction of Crowdfunding Campaigns: A Deep Learning Approach. In *Companion of the 2018 ACM Conference on Computer Supported Cooperative Work and Social Computing*, CSCW '18, pages 193–196, Jersey City, NJ, USA, October 2018. Association for Computing Machinery.

[37] Vincent Etter, Matthias Grossglauser, and Patrick Thiran. Launch hard or go home! predicting the success of kickstarter campaigns. In *Proceedings of the first ACM Conference on Online Social Networks*, pages 177–182, 2013.

[38] Chun-Ta Lu, Sihong Xie, Xiangnan Kong, and Philip S Yu. Inferring the impacts of social media on crowdfunding. In *Proceedings of the 7th ACM International Conference on Web Search and data mining*, pages 573–582, 2014.

[39] Qizhen Zhang, Tengyuan Ye, Meryem Essaidi, Shivani Agarwal, Vincent Liu, and Boon Thau Loo. Predicting startup crowdfunding success through longitudinal social engagement analysis. In *Proceedings of the 2017 ACM on Conference on Information and Knowledge Management*, CIKM '17, pages 1937–1946, Singapore, Singapore, November 2017. Association for Computing Machinery.

[40] Douglas J Cumming, Gaël Leboeuf, and Armin Schwienbacher. Crowdfunding models: Keep-it-all vs. all-or-nothing. *Financial Management*, 2015.

[41] Haichao Zheng, Dahui Li, Jing Wu, and Yun Xu. The role of multidimensional social capital in crowdfunding: A comparative study in china and us. *Information & Management*, 51(4):488–496, 2014.

[42] Alessandro Cordova, Johanna Dolci, and Gianfranco Gianfrate. The determinants of crowdfunding success: Evidence from technology projects. *Procedia-Social and Behavioral Sciences*, 181:115–124, 2015.

[43] Benjamin C Collier and Robert Hampshire. Sending mixed signals: Multilevel reputation effects in peer-to-peer lending markets. In *Proceedings of the 2010 ACM Conference on Computer Supported Cooperative Work*, pages 197–206, 2010.

[44] Massimo G Colombo, Chiara Franzoni, and Cristina Rossi-Lamastra. Internal social capital and the attraction of early contributions in crowdfunding. *Entrepreneurship theory and practice*, 39(1):75–100, 2015.

[45] Julie S Hui, Michael D Greenberg, and Elizabeth M Gerber. Understanding the role of community in crowdfunding work. In *Proceedings of the 17th ACM Conference on Computer Supported Cooperative Work & Social Computing*, pages 62–74, 2014.

[46] Emőke-Ágnes Horvát, Jayaram Uparna, and Brian Uzzi. Network vs market relations: The effect of friends in crowdfunding. In *Proceedings of the 2015 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining 2015*, pages 226–233, 2015.

[47] Silvio Vismara. Equity retention and social network theory in equity crowdfunding. *Small Business Economics*, 46(4):579–590, 2016.

[48] Martina E Greiner and Hui Wang. The role of social capital in people-to-people lending marketplaces. *ICIS 2009 Proceedings*, page 29, 2009.

[49] Jinwook Chung and Kyumin Lee. A long-term study of a crowdfunding platform: Predicting project success and fundraising amount. In *Proceedings of the 26th ACM Conference on Hypertext & Social Media*, pages 211–220, 2015.

[50] David Lazer, Eszter Hargittai, Deen Freelon, Sandra Gonzalez-Bailon, Kevin Munger, Katherine Ognyanova, and Jason Radford. Meaningful measures of human society in the twenty-first century. *Nature*, 595(7866):189–196, 2021.

[51] Claudia Wagner, Markus Strohmaier, Alexandra Olteanu, Emre Kıcıman, Noshir Contractor, and Tina Eliassi-Rad. Measuring algorithmically infused societies. *Nature*, 595(7866):197–204, 2021.

[52] Jacob Solomon, Wenjuan Ma, and Rick Wash. Don't wait! how timing affects coordination of crowdfunding donations. In *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing*, pages 547–556, 2015.

[53] Ajay Agrawal, Christian Catalini, and Avi Goldfarb. Crowdfunding: Geography, social networks, and the timing of investment decisions. *Journal of Economics & Management Strategy*, 24(2):253–274, 2015.

[54] Silvio Vismara. Information cascades among investors in equity crowdfunding. *Entrepreneurship Theory and Practice*, 2016.

[55] Riri Kusumarani and Hangjung Zo. Why people participate in online political crowdfunding: A civic voluntarism perspective. *Telematics and Informatics*, 41:168–181, 2019.

[56] Elizabeth M. Gerber and Julie Hui. Crowdfunding: Motivations and deterrents for participation. *ACM Transactions on Computer-Human Interaction (TOCHI)*, 20(6):34:1–34:32, December 2013.

[57] Robert E Kraut and Paul Resnick. Encouraging contribution to online communities. *Building successful online communities: Evidence-based social design*, pages 21–76, 2011.

[58] Norbert Steigenberger. Why supporters contribute to reward-based crowdfunding. *International Journal of Entrepreneurial Behavior & Research*, 2017.

[59] Giancarlo Giudici, Massimiliano Guerini, and Cristina Rossi-Lamastra. Reward-based crowdfunding of entrepreneurial projects: the effect of local altruism and localized social capital on proponents' success. *Small Business Economics*, 50(2):307–324, 2018.

[60] Yusimi Rodriguez-Ricardo, Maria Sicilia, and Manuela López. Altruism and internal locus of control as determinants of the intention to participate in crowdfunding: the mediating role of trust. *Journal of theoretical and applied electronic commerce research*, 14(3):1–16, 2019.

[61] Eszter Hargittai and Aaron Shaw. Comparing internet experiences and prosociality in amazon mechanical turk and population-based survey samples. *Socius*, 6:2378023119889834, 2020.

[62] Aaron Shaw and Eszter Hargittai. Do the online activities of amazon mechanical turk workers mirror those of the general population? a comparison of two survey samples. *International Journal of Communication*, 15:16, 2021.

[63] Adam J Berinsky, Gregory A Huber, and Gabriel S Lenz. Evaluating online labor markets for experimental research: Amazon. com's mechanical turk. *Political analysis*, 20(3):351–368, 2012.

[64] Joseph K Goodman, Cynthia E Cryder, and Amar Cheema. Data collection in a flat world: The strengths and weaknesses of mechanical turk samples. *Journal of Behavioral Decision Making*, 26(3):213–224, 2013.

[65] Gabriele Paolacci, Jesse Chandler, and Panagiotis G Ipeirotis. Running experiments on amazon mechanical turk. *Judgment and Decision making*, 5(5):411–419, 2010.

[66] Eyal Peer, Joachim Vosgerau, and Alessandro Acquisti. Reputation as a sufficient condition for data quality on amazon mechanical turk. *Behavior research methods*, 46(4):1023–1031, 2014.

[67] Leonard J Paas, Sara Dolnicar, and Logi Karlsson. Instructional manipulation checks: A longitudinal analysis with implications for mturk. *International Journal of Research in Marketing*, 35(2):258–269, 2018.

[68] David J Hauser and Norbert Schwarz. Attentive turkers: Mturk participants perform better on online attention checks than do subject pool participants. *Behavior research methods*, 48(1):400–407, 2016.

[69] Daniel M Oppenheimer, Tom Meyvis, and Nicolas Davidenko. Instructional manipulation checks: Detecting satisficing to increase statistical power. *Journal of experimental social psychology*, 45(4):867–872, 2009.

[70] Rudolf Flesch. Flesch-kincaid readability test. *Retrieved October*, 26(3):2007, 2007.

[71] Margrit Schreier. *Qualitative content analysis in practice*. Sage publications, 2012.

[72] J Philippe Rushton, Roland D Chrisjohn, and G Cynthia Fekken. The altruistic personality and the self-report altruism scale. *Personality and Individual Differences*, 2(4):293–302, 1981.

[73] Sabrina Stöckli and Doris Hofer. Susceptibility to social influence predicts behavior on facebook. *PloS one*, 15(3):e0229337, 2020.

[74] William O Bearden, Richard G Netemeyer, and Jesse E Teel. Measurement of consumer susceptibility to interpersonal influence. *Journal of consumer research*, 15(4):473–481, 1989.

[75] Fred D Reynolds and William R Darden. Mutually adaptive effects of interpersonal communication. *Journal of Marketing Research*, 8(4):449–454, 1971.

[76] Alexander JAM Van Deursen, Ellen Helsper, Rebecca Eynon, and Jan AGM Van Dijk. The compoundness and sequentiality of digital inequality. *International Journal of Communication*, 11:452–473, 2017.

[77] Momin M Malik and Jürgen Pfeffer. Identifying platform effects in social media data. In *Tenth International AAAI Conference on Web and Social Media*, 2016.

[78] Eszter Hargittai and Marina Micheli. Internet skills and why they matter. *Society and the internet: How networks of information and communication are changing our lives*, 109, 2019.

Appendix

Screening Questionnaire

The following questions were used to screen participants.

1. Which one of the following is TRUE about crowdfunding?

   (a) Crowdfunding is the practice of financing public and private green investments in environmental goods and services and prevention of damage to the environment.
   (b) Crowdfunding is the practice of funding a project or venture by raising many small amounts of money from a large number of people, typically via online.
   (c) Crowdfunding is an organized social movement to empower developing country producers and promoting sustainability.
   (d) Crowdfunding is a peer-to-peer distributed ledger forged by consensus, combined with a system for smart contracts and other assistive technologies.

2. Examples of crowdfunding include:

   (a) Bing and google
   (b) Call a Bike and Uber
   (c) Kickstarter and Indiegogo
   (d) WeWork and Regus

3. How have you participated crowdfunding?

   (a) Contributor
   (b) Project Creator / Fundraiser
   (c) All of the above
   (d) Neither

4. How often do you participate in crowdfunding?

   (a) Daily
   (b) At least once a week
   (c) At least once a month
   (d) A few times per year
   (e) Never