

# Persuading Teammates to Give: Systematic versus Heuristic Cues for Soliciting Loans

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Dual processing theories in psychology suggest that people process persuasive requests by assessing the quality of arguments (systematic processing) or by relying on heuristic rules (heuristic processing). However, the factors that act as systematic and heuristic processing cues and affect the success of persuasion have not been adequately described in social lending contexts. This research examines the effectiveness of systematic and heuristic cues in persuasive requests in Kiva lending teams intended to convince members to donate. An analysis of 88,596 requests exchanged in 1,610 teams shows that certain heuristic processing cues (e.g., liking between requesters and potential lenders, advocates low authority in their teams and the importance of the team to the lender) strongly predicted whether lenders would contribute to a loan request. In contrast, cues that required systematic processing are less influential. We also found that behavioral cues are more important than verbal ones. We discuss the theoretical and practical implications of our work.

CCS Concepts: • **Human-centered computing** → **Empirical studies in collaborative and social computing**;

Additional Key Words and Phrases: Dual Processing; Persuasion; Team Lending; Reciprocity; Social Proof; Peer to Peer Lending

## ACM Reference Format:

Diyi Yang and Robert E. Kraut. 2017. Persuading Teammates to Give: Systematic versus Heuristic Cues for Soliciting Loans. *Proc. ACM Hum.-Comput. Interact.* 1, 2, Article 114 (November 2017), 21 pages. <https://doi.org/10.1145/3134749>

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## 1 INTRODUCTION

Interpersonal persuasion plays an important role in shaping people's decisions, attitudes and behaviors. The process by which persuasion works and its effects on the targets of persuasion have been deeply studied in a wide range of fields, including social psychology, health communication, politics, advertising and consumer behavior [13, 48, 55]. Social computing researchers have investigated the principles that influence persuasion in computer-mediated settings [22] and recently have examined persuasive messages that influence the success of crowd-funding campaigns [17, 25, 38, 58]. A typical publication in this genre measures characteristics of the project being promoted, the dynamics of the campaign, the social networks among participants and features of

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This work was supported in part by a Google Faculty Research Award and a Carnegie Mellon Presidential Fellowship. The authors want to thank Kiva Microfunds for providing data.

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2573-0142/2017/11-ART114

<https://doi.org/10.1145/3134749>

the persuasive messages to predict a measure of success in a crowd funding campaign, such as whether the campaign researched its target cite or the amount of money it collected. For example, Molick [40] found that personal networks and project quality were associated with the success of crowd-funding efforts.

Empirical studies examining how persuasive messages lead to success typically rely upon theory and empirical research in social psychology and related fields to choose the message attributes to include in their predictive models. For example, several authors have examined elements of crowd funding videos that emphasize the competence and credibility of the innovator seeking funds [18, 54], while Jenq and her colleagues showed that what should be irrelevant factors from a normative perspective, such as a borrower's physical attractiveness, skin color or obesity, influence donors' loan decisions on Kiva, the peer-lending site [27]. Other research takes a more bottom-up approach, casting a very wide net to identify features that predict the success of persuasive messages and then uses the prior psychological literature to make sense of the findings. For example, Mitra and Gilbert [38] included over 20,000 phrases from Kickstarter project pitches to predict the success of the campaigns, and then used constructs from the social psychology literature on persuasion, such as scarcity, social proof, social identity, liking, reciprocity and authority [13], to interpret associations between phrase use and campaign success.

Although these approaches have developed predictive models that are both accurate and insightful, the persuasion variables they include in their predictive models are often ad-hoc, chosen without reference to neither a taxonomy of persuasion techniques nor a principled method of choosing among them. One exception to this general pattern is recent research by Dey and her colleagues who used dual processing models of persuasion in social psychology as a framework for selecting persuasion variables. Chaiken's systemic-heuristic model of social information processing is a widely recognized communication model that attempts to explain how people perceive and process persuasive messages [7, 10]. Petty and Cacioppo's *Elaboration Likelihood Model (ELM)* [44] is similar. Both propose that people process persuasive messages in two distinct ways. Chaiken uses the term "systematic processing" and the ELM uses the term "central processing" to describe persuasion that occurs when the target of a persuasive attempt performs a relatively deep analysis of the quality of an argument and its merits. They contrast this with what Chaiken terms "heuristic processing" and the ELM terms "peripheral processing", in which the target relies on some simple, superficial cues, such as the physical attractiveness of the persuader, without analyzing the true merits of the information presented. Systematic processing requires people to evaluate the information contained in a persuasive attempt based on its relevance and importance and integrate it in forming their judgments. When processing messages systematically, recipients would evaluate the *quality of the evidence* and the *coherence of the argument*. For example, in a crowd funding appeal, the target might judge a pitch in terms of whether the innovator make a good argument about the novelty and utility of the innovation, or in a loan request, they might evaluate whether the borrower is worthy, will use the money for a good purpose or has the ability to repay the loan. Systematic processing is effortful and is generally used only when the target of a request considers the issue to be important and has the cognitive capability to analyze the argument. In contrast, heuristic or peripheral processing demands less cognitive effort and allows people to use simple inferential rules in deciding whether to be influenced by a message's position. For example, without analyzing the substance of the persuasive message, targets might be persuaded by simple heuristics like social proof (e.g., "*The idea must be good if others already agree with it*") or attraction (e.g., "*I'll agree with ideas offered by people I like*").

Dey et al. [17] examined the influence of characteristics of Kickstarter videos in predicting whether a campaign would succeed. They classified the persuasion variables into those that required systemic or central possessing (e.g., evidence about the complexity or relevance of a product, which

are relevant to assessing a product's utility and quality), and heuristic or peripheral ones (e.g., the audio and visual quality of the video, which are irrelevant to assessing product quality). Their analysis showed that both systematic and heuristic cues predicted the success of the Kickstarter campaigns, although the importance of these classes of cues. The central, product-oriented attributes were more important for technology-based products, while the peripheral, audio/video attributes were more important for design-oriented products.

The current research attempts to validate Dey's results differentiating systemic/central processing cues from heuristic/peripheral ones in a new context—the philanthropic lending site Kiva rather than the commercial crowd funding site Kickstarter. In addition, we operationalize systemic/central versus heuristic/peripheral message cues more directly than did Dey et al, by directly measuring attributes of the messages rather than using human observers' judgments as proxies. Dey et al. [17] recruited Mechanical Turk workers to rate attributes of Kickstarter videos and their reactions to them. Some of these ratings directly reflected attributes of the video, such as their evaluation of the product's complexity or the audio or video quality of the video itself. However, other factors used in this research reflect the raters' subject reactions to the products or persuasive messages, providing little information about what aspects of either the product or the videos were responsible for these reactions. For example, one of their factors was rater's involvement with the product, measured using semantic-differential-like questions asking the raters to evaluate the product as "worthless", "appealing" or "boring". These judgments provide no information about the product or message features that induced the involvement. Similarly, one component of their peripheral, video-related attributes was raters' attitude toward the video, comprising semantic-differential-like scales like "good", "interesting" or "pleasant", again without reference to characteristics of the video's that caused this reaction. The current research attempted to use more concrete and objective characteristics of the loans requests and persuasive messages as the predictive variables.

Words in loan requests from advocates are often the primary means of persuasion, which could affect receivers' perceptions, emotions, and actions. Effective persuaders might be aware of the power of words and adjust their messages accordingly. For example, advocates might explicitly emphasize borrowers' miserable situations or sterling character, to persuade potential lenders. Prior research demonstrates that actions (e.g., "I bought this") are more influential than opinions (e.g., "I like this") in influencing consumer purchase decisions [11, 23]. However, the relative effectiveness of actions versus verbal messaging strategies has not been adequately investigated in the context of social lending. In our study, we operationalize both behavioral and verbal persuasive cues in order to understand whether behavior speaks louder than words in lending teams.

We examine our research questions in the context of Kiva, a peer-to-peer lending platform where persuading others to make loans is a key to success. Peer-to-peer lending or micro-lending websites are "online marketplaces where lenders can lend to individuals or small businesses" [35]. As the world's first and largest peer-to-peer micro-finance website, as of April 2017 Kiva.org<sup>1</sup> has distributed \$967.7M in loans from 1.6M lenders to 2.4M borrowers. Despite its success [39], many Kiva lenders only lend once, and then never come back to the site [25, 32]. To increase lender engagement, Kiva.org introduced "Lending Teams" in 2008, through which lenders who have something in common (e.g., interests, social identity or personal relationships) can band together and try to convince each other to support particular loans. One field experiment showed that joining lending teams on Kiva positively increased members' subsequent lending [1]. Lenders can post messages in team forums to persuade other members to lend to a particular borrower. As demonstrated by prior experimental research [9], messages that highlight team identity and the competition among teams cause recipients to lend more. Given that these teams are built

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<sup>1</sup><https://www.kiva.org>

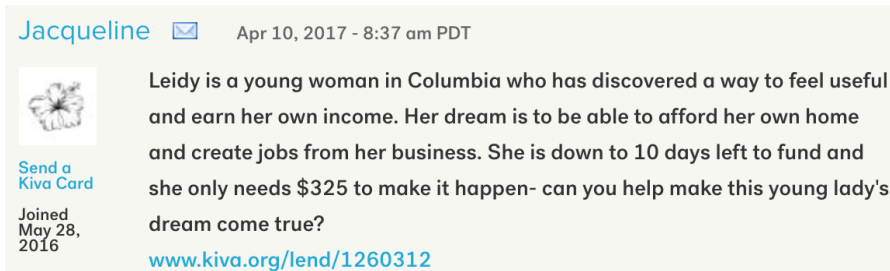


Fig. 1. An example message that advocates for a loan.

around common interests, affiliation, geographic location or personal ties, we hypothesize that the effectiveness of persuasive tactics might differ for different types of teams. For instance, we expect that tactics of highlighting the common identity between advocates and lenders might be more effective for identity-based teams, while cues that rely on liking might be more persuasive in relationship-based teams.

## 2 RESEARCH SITE

Lending members on Kiva can make a zero-interest loan of 25\$ or more to support a borrower. Any lender can create a team or join one or more of them. After a lender joined any number of teams, he or she will be asked next time whether to assign this loan to any of the team that he or she has joined. The dataset provided by Kiva contains basic profile information for members and teams, including name, an “I loan because” statement, location, and registration time. In addition, it contains the complete loan history of all lenders, a catalog of which users belong to which lending teams, and a complete list of messages posted to lending team message boards, as of Jan 2017. A message is considered to be *advocating for a loan* if it contains a loan description and link. One example request is shown in Figure 1, which contains the name of the advocate urging teammates to loan and the request content, as well a link to the loan he/she is advocating. We used data from 1,610 teams that ever had messages in its forums advocating for a loan. The mean team size is 364 members (median=24). The dataset contains 88,596 loan-request messages. Since each message could advocate for multiple loans (i.e., contain multiple links), the dataset consists of 252,184 loan requests. Although the dataset does not include information about whether a potential lender actually read a loan request message, we assume that all team members were potentially exposed to any loan request posted to their team. On average, 2.4 team members offered a loan to the relevant borrower after a loan request was posted.

## 3 FROM THEORIES TO METRICS

As discussed above, the systematic/heuristic processing models of persuasion [7, 8] state that individuals process persuasive messages in two distinct ways: systematically and heuristically. In order to investigate what behavioral or verbal cues in loan advocacy messages encourage lenders to take actions, we first need to identify and operationalize factors that reflect systematic processing and heuristic processing.

## 4 SYSTEMATIC PROCESSING

A number of studies have investigated systematic processing in language and its effect on the success of requests [3, 26]. For instance, to study donations in Random Acts of Pizza in Reddit.com, Althoff et al., [2] assessed the validity of requests via *evidentiality*, by measuring the presence of an

image link, which often demonstrated evidence for recipients' claimed need, such as a screenshot of their empty bank account or a picture of their arm in a cast. However, they did not deeply analyze the images and therefore have no direct evidence about whether givers were paying attention to the validity of the request. Mitra and Gilbert's analysis of a corpus of 45K crowd-funded projects [38], fit models with approximately nine million language features (unigrams, bigrams, trigrams) with reasonable predictive power in accounting for successful funding. Although some of the language features might reflect systematic processing, including phrases such as "fund-raising goal", "funding will help", they did not explicitly or directly identify cues that reflect systematic processing and their influence on eliciting others' responses.

As discussed, receivers of persuasive messages who use systematic processing will judge the semantic content of messages before being persuaded. If they were systematically processing persuasive messages intended to convince them to lend money to a borrower, they should assess whether these messages offer arguments that the loan will go towards a valuable cause or that the borrower is a worthy individual. We measured how much information the loan request provided on these issues.

#### 4.1 Worthiness of the Loan

We operationalized a loan's worthiness into three levels. **Level 1** messages fail to mention any reasons that the loan might be valuable. For example, in the quote below, the advocate mentioned the length of time before the loan opportunity expired, but failed to mention what the loan was for.

*"This loan is set to expire in 1 day. It's also double impact right now".*

**Level 2** messages mention the reason for the loan, but do not provide additional justification about its value, as in the following message:

*"Collecting scrap metal to sell to recyclers. Expiring later today".*

**Level 3** messages include both the reason for the loan and an explicit justification for it, such as the following:

*"Mutabar is asking for a loan to pay for the university tuition for her son. This loan is part of IMON's education program, designed to finance school tuition for students whose families have low incomes. By supporting this loan, you're enabling access to education for students with limited options".*

#### 4.2 Worthiness of the Borrower

In addition to assessing the value of the loan itself, to systematically process a loan request, the potential lender is likely to look for cues that allow an assessment of qualities of the borrower, such as the borrower's family background or work ethic. We operationalized the extent to which the request message provided information about the worthiness of the borrower into three levels:

**Level 1** loan requests do not mention who the borrower is, as in this message:

*"Loaned to SF Hakema and Gyulnara. They are buried somewhere on pages 100+ and 5 respectively, so not sure what good this will do :-(".*

**Level 2** messages mention the borrower, but do not provide a rationale or additional information about whether the borrower is worthy:

*"Sweet Gregoria, has about 7 hours remaining. Fortunately she's a starfish. I hope she makes it!".*

**Level 3** loan requests mention both the borrower and evidence why he or she is worthy. For example, the following quote describes the borrower's family values and work ethic. In addition, it also provides evidence about the worthiness of the loan itself.

*“The featured borrower is a single mother of 2 girls who sells dyed fabrics and palm oil to pay for her daughters’ schooling. I like the field partner Caurie because they help women creating new sources of income and encourage savings so that these women become financially more independent. In addition, Caurie has an excellent repayment rate.”*

### 4.3 Operationalizing the Worthiness of Loan and Borrower

We built machine learning models to automatically estimate the extent to which messages provide information about the worthiness of the loan and of the borrower. First, human codes rated the extent to which 1000 message provided evidence about the worthiness of the loan or borrower. These annotations were the ground truth in developing the automated measure of worthiness. Second, we represented each message as a set of language features as input for the machine learning models. Third, we constructed a statistical model based on the hand-coded data and evaluated its performance. Finally, we applied the validated model to all 88,596 loan request messages in the dataset. The material below describes these steps in more detail.

**4.3.1 Annotating the Messages for Worthiness.** In order to construct a hand-coded dataset, we randomly selected 1000 messages from the corpus and asked Amazon Mechanical Turk (MTurk) workers to rate the extent the messages described the worthiness of the loan and the worthiness of the borrower. We provided turkers with detailed descriptions of the worthiness as defined above. Three turkers rated each message. Turkers were asked to rate the worthiness of the loan and of the borrower in a 1-3 Likert scale. To increase annotation quality, we required turkers to have a 98% approval rate and at least 5000 approved HITs for their previous work on MTurk. We paid \$0.07 for rating each message, and each message was rated by three workers. The intra-class correlation coefficients (ICC) of 0.831 for annotating the worthiness of the borrower and 0.845 for annotating the worthiness of the loan shows that the workers strongly agreed with each other.

**4.3.2 Feature Set Construction.** We represented the loan requests in terms of the following textual features:

**Word Embedding:** We considered the meaning of sentences via Word2Vec [37]. That is, words or phrases from the vocabulary were mapped to vectors that represent their distributional semantic meaning. We measured the vector for each word in the message and then aggregated them using the coordinate-wise mean, to obtain the meaning of each message.

**Linguistic Style:** LIWC [43] dictionaries<sup>2</sup> were selected based on their relevance to the worthiness of the loan or the borrower. For example, *3rd pers singular* such as “she”, “he” might be used to refer to the borrower, whereas *negative emotion* might be used to describe the borrower’s situations or the advocate’s reaction to it. Messages with higher usages of *Causation* (e.g., “because”, “affect”) are more likely to mention the rationale of the loan. We computed the percentage of words in a message that came from LIWC dictionaries and included these weights as features for our regression models.

**POS Tagging:** We extracted part-of-speech (POS) features to capture syntactic cues of the persuasive requests using Stanford’s CoreNLP [34]. Part-of-speech (e.g., nouns, noun phrases) might be helpful for finding named entities such as locations or organizations in these requests.

**4.3.3 Performance in Estimating the Worthiness.** We constructed machine learning models in which the textual features were input to a regression model to predict the average of the three turkers’ rating of the worthiness of the loan and of the borrower. We framed our task as a machine learning regression problem. We also included unigram and bigram features. We trained Lasso

<sup>2</sup>The list of LIWC dictionaries include *1st pers singular*, *1st pers plural*, *2nd person*, *3rd pers singular*, *3rd pers plural*, *impersonal pronouns*, *articles*, *affective process*, *negative emotion*, *positive emotion*, *social process*, *family*, *friend*, *human*, *achievement*, *causation*, *insight*, *tentative*, and *certainty*.

	Loan		Borrower	
	Corr.	Squared Mean Error	Corr.	Squared Mean Error
<b>Bag of Words</b>	0.493	0.398	0.395	0.343
<b>LIWC</b>	0.436	0.425	0.455	0.322
<b>Word Embedding</b>	0.620	0.322	0.546	0.285
<b>Part Of Speech</b>	0.455	0.416	0.449	0.323
<b>ALL</b>	<b>0.661</b>	<b>0.295</b>	<b>0.636</b>	<b>0.242</b>

Table 1. Regression model performances for predicting the worthiness of the loan and the borrower.

linear models with L1 norm [53], which can perform both feature selection and regularization in order to enhance the prediction performance. We set the L1 regularizer weight as 0.3. Models were evaluated with 5-fold cross-validation, using the Pearson Correlation and the Squared Mean Error between the human-coded ratings and predicted ones.

Table 1 summarizes the performances of regression models that incorporate different sets of features for estimating the amount of the worthiness of the loan request. Here, **ALL** refers to the regression model that utilizes bag of words, linguistic style, word embedding and part of speech features. It significantly outperforms other models, achieving correlation scores of 0.661 and 0.636 for the worthiness of the loan and borrower respectively.

The two models were moderately accurate, correlating with the hand-coded ground truth greater than 0.6.<sup>3</sup> We then applied the machine-learning models to estimate the extent to which the messages contained cues relevant to systematic processing: request's worthiness of loan and request's worthiness of borrower.

#### 4.4 Request Length

As a well-studied factor [2, 30], request length has been found to be significantly related to funding success. In general, longer messages are likely to contain more evidence and, in addition, showing greater effort on the part of the advocate. Thus, we measured request's length as the number of words contained in the persuasive message.

## 5 HEURISTIC PROCESSING

Prior research on heuristic processing suggests that people often rely on superficial heuristics to make decisions [6, 21, 24, 58]. For example, rather than systematically determining whether a borrower is worthy, they may rely on impressions of trustworthiness, measured by photographs of potential borrowers [19]. Theories of *social influence* have identified a number of heuristics that are important in persuasive messages [14]. These include liking, reciprocity, social proof, authority, scarcity and social identity. Building on theories of influence, we operationalized a number of these heuristic cues that occur in the persuasive messages and might influence whether lenders loan money to the borrower mentioned in a request.

### 5.1 Reciprocity

The rule of reciprocity is one of the most widespread persuasive principles and states that people feel obligated to return something after receiving a something of value from another, i.e., “we should try to repay, in kind, what another person has provided us” [14]. Mitra and Gilbert identified

<sup>3</sup>We acknowledge that the machine learning models still contain a substantial error of measurement and treat this as a limitation.

phrases involving promises and thank-yous suggesting that reciprocity is a factor in securing donations in Kickstarter campaigns [38]. However, in the Kiva context, these explicit quid pro quos are less likely to be used because of external advocates rather than the borrowers who are making the requests. Instead, we expected that lenders might be more likely to respond positively to loan requests made by someone who once responded to their requests. We operationalize reciprocity as the number of times that an advocate had made loans in response to a potential lender's prior persuasive messages advocating for loans.

## 5.2 Liking

Recipients of persuasive attempts are more likely to comply if they like the requester[14]. Many factors can make two people like each other, for example, the frequency of contact, common friends, physical attractiveness or similarity in many dimensions. In the current research, we focus on similarity as a precursor to liking. The interpersonal similarity in demographics, background, beliefs, and values robustly leads to greater liking between two people [5]. It follows that the recipient of a persuasive message should be more persuaded by it, the more similar the recipient is to the sender [49]. We measured the number of messages exchanged between them (#messages btw lender & author), i.e. how many times one directly replied to the other's messages in the forum as an indicator of the liking between the lender and the advocate.

## 5.3 Authority

People often comply with and respect the requests of an authority in an unthinking way to guide their decisions, especially when they are uncertain of the given situation. On Kiva, team captains have higher status and legitimate authority by virtue of their role. Members might perceive the captain to have a deeper knowledge of the team and the loan. We expect that if a loan request comes from the captain, team members might be more likely to respond. Therefore, we introduced a binary variable is captain to capture whether the advocate is the captain of his/her team. Another factor that team members might use to infer another's authority could be his/her activity in the team forum. We operationalized this inferred authority using the number of advocated messages of this advocate, denoted as messages of advocate.

## 5.4 Social Identity

Social identity is defined as an individual's self-concept of his/her membership of a social group or groups together with the value and emotional significance attached to that membership [20, 51]. The principle of Social Identity suggests that when people identify with a group, they will be more influenced by it and behave more similarly to other group members. One indicator of the degree to which someone identifies with a group is the extent to which the individual is exclusively a member of the focal group or belongs to many other groups as well. As a proxy for lenders' identification with a team, we computed this team's degree of importance to this lender as  $\frac{1}{m}$ , where  $m$  is the total number of teams that he/she has joined, denoted as team importance. Persuasive tactics that take advantage of this principle might emphasize the group membership or group attributes to convince team members, as in this message "A loan that our team members might like to join me on...". One tactic is to explicitly mention social identity, such as mentioning "we" words (mention we words); we calculated the occurrences of words related to the first-person plural using LIWC, designed by Pennebaker et al. [52].



### 5.5 Social Proof

The principle of Social Proof states that people often look to others for cues concerning correct beliefs and behavior. They use others' behavior as cues for what they should think, feel or do. That is, people are more likely to perform an action when they see others doing it [14]. Therefore, many loan requests explicitly mention the effort of lenders who have already contributed, such as “*sixteen members of us have pitched in.*”. The loans that other team members have made are broadcast in the Team Activity section of the Kiva website for each team, allowing people to easily know which loans their fellow members were contributing to. Recipients of a loan request might use this information to determine whether they should contribute. We operationalized this factor using the number of team members who have already contributed to the loan mentioned in the request (*# team members loaned*).

Advocates often mention their own contribution in their loan requests to encourage others to make similar choices. This factor is captured by the variable *explicit mention loaned*, measuring whether a loan request mentions the effort of the advocate. To measure the explicitly mentioning of their loan contribution, we created a contribution lexicon, including words and phrases such as “made a loan”, “joined”, “pitched in”. Since teammates' lending are broadcast in the team activity section, team members might be aware of an advocate's contribution even if the advocate did not make it explicit in his/her message. This presents us with another variable that models the actual contribution behavior of an advocate: *actual loaned or not*.

### 5.6 Scarcity

The rule of Scarcity suggests that people attach more value to an item as soon as it becomes rare, distinct, limited or urgent, such as its two widely used forms “limited-number” and the “deadline”. Advertisements frequently use this tactic by putting a time or number limit on the item availability [14]. Tactics of scarcity might make people aware that they need to act immediately or it will disappear, such as in this message: “*Short notice, this elderly man needs help funding his loan to increase his livestock herd, only 4 hours left!*”.

We operationalized this principle in two ways: (1) *Explicit mention scarcity* refers to an explicit mention of the urgency of the loan, such as emphasizing its remaining hours in the request. We measured this by manually constructing an urgency lexicon that contains words such as “expire”, “remaining”, “left”. (2) *Actual remain hours* indicates from now how many hours this loan has before its expiration date, divided by the duration of this loan. We reversed this variable to make it consistent with the definition of scarcity – a larger number means higher scarcity or less time.

### 5.7 Emotional Language

Prior research demonstrates the impact of emotion on decision-making [47]. One important aspect of persuasion is to be emotional [29]. Emotional messages might make people care and such feelings inspire them to act. Emotional requests create connections with the general audience and make them receptive to the contained opinions. Emotional messages might describe miserable or otherwise undesirable situations and often contain strong sentiment, as in this message “*The picture of widow Bunisia holding one of her children in front of her meager home brings tears to my eyes.*”. To identify this word-emotion association, we computed the affect-relevant measures using existing emotion lexicons [31]: *negative emotion*.

## 6 KIVA TEAM CATEGORIZATION

The nature of team might influence the effectiveness of persuasive cues. For example, messages that emphasize members' shared affiliation might be more likely to succeed in teams built around that

### LGBTQI (Lesbian, Gay, Bisexual, Transgender,...)

7,276 members have lent \$4,869,650 in 173,245 loans

We are everywhere. | Category: Common Interest | Team since: Aug, 2008

**We loan because: We are out and proud and know what it is like to face barriers. We are delighted to help our entrepreneurs achieve their own equality. We thank our friends who join us in our loans & in supporting LGBT rights.**

(a) Common Identity

### Baking Int.

34 members have lent \$35,975 in 1,373 loans

anywhere / everywhere | Category: Common Interest | Team since: Aug, 2011

**We loan because: We love to, and because we love bread. And because bread gives lives.**

(b) Common Interest

### Renfro Family Lending Team

17 members have lent \$302,300 in 3,495 loans

Category: Families | Team since: Dec, 2013

**We loan because: We want to make a positive impact on the world and help others. We have been blessed, and we want to give back to those in need.**

(c) Personal Relation

Fig. 2. Different Types of Teams on Kiva

affiliation, compared to in teams connected by personal ties. In contrast, requests that make use of the requesters' connection with other members might be more persuasive in relationship-based teams compared to teams built around the common interest. To facilitate the investigation of the influences of different persuasive cues in different teams, we first need a categorization of teams to capture the nature and salience of different teams.

Teams on Kiva are "self-organized groups built around common interests, school affiliation or location". When starting a team, the creator needs to choose a team name, write a belief statement and select a category that best fits the team, as shown in Figure 2. Example categories include: *Youth Groups, Local Area, Businesses, University/College*, etc. Members can join as many teams as they like and can rally to support loans by counting their loans at checkout toward the team's impact.

Table 2 summarizes the statistics of teams and their self-selected sectors. However, not all team categories selected by team creators can properly define the nature of their teams. For example, in Figure 2(a), LGBTQI team consists of people who are out and want to support LGBT rights. That is, this team was formed based on members' common identity, but it was labeled as common interest.

Sector	# Teams	Sector	# Teams
Alumni Groups	51	Businesses	115
Business Internal Groups	28	Clubs	31
Common Interest	475	Events	9
Families	145	Local Area	170
Memorials	28	Other	105
Religious Congregations	61	Schools	99
Sports Groups	28	University & College	99
Youth Groups	15		

Table 2. Statistics summary of teams in different sectors

Simply using the self-selected categories might introduce biases in capturing the distinctiveness of different types of teams.

Social psychology studies [36, 36] suggest that the internal dynamics of social groups emerge from the combination of complex cognitive processes such as sense of membership, interaction between people, or collective interest [46], and categorize social groups mainly into common bond and common identity groups [16, 46]. Groups that are formed or serve to build relationships were categorized as common bond or relation based groups, whereas groups that are organized based on social identity are considered as common identity groups. Building on these theories and taking into account the speciality of Kiva, we propose to categorize Kiva teams into three types as follows:

- (1) **Common Identity:** Teams that are formed based on commonality that team members share, such as sharing the same social identity (athletes, gays, mothers, etc.), geographic identity (New Mexico, Albert Canada), or religion identity, etc.
- (2) **Common Interest:** Teams that are formed based on members' interest or activity, such as animals or food, or are formed to do something together such as supporting agriculture, health, etc.
- (3) **Personal Relations:** Teams that are formed based on personal ties between members, such as teams that consist of families, friends or acquaintance.

We also add one *Other* type to capture teams that do not belong to the above three types. Instead of only relying on the team sector that creators chose, the first author manually assigned each team into one of the above types, based on team name, description and "loan because" statement as shown in Figure 2. Based on the percentage of different types shown in Figure 3, 48.8% teams belong to common identity; 34.4% of them lie in the type of common interest and 14.7% teams are formed based on personal relations between members.

## 7 METHOD

In this section, we predict whether a team member will lend to a loan mentioned in a message, building on a set of persuasion principles that reflect either systematic or heuristic processing as we operationalized above. Specifically, for each loan advocated in a message, for each team member, we predict whether this advocacy message can persuade this member to make a loan. Given that each team had around 364 members on average and each message only convinced 2.4 members, we performed an under-sampling, i.e., sampling two negative instances for each positive instance. We build logistic regression models to explore these persuasive cues and present results on which of them are predictive of success.

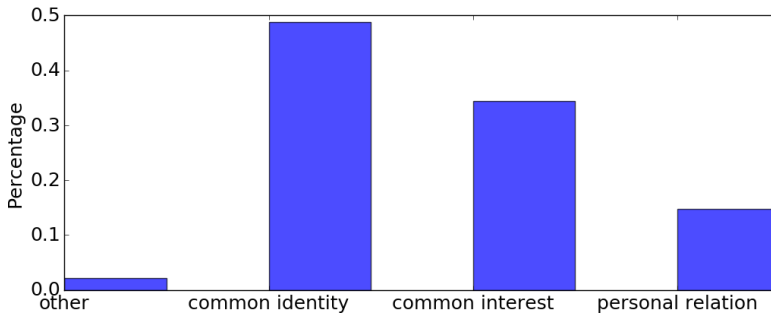


Fig. 3. Percentage of teams of different types. The total number of team is 1610.

## 7.1 Dependent Variable

- **Lending:** This is a binary variable indicating whether a team member will lend to a loan after being exposed to a forum message that advocates for it.

## 7.2 Control Variables

- **Team Loan Amount<sup>4</sup>:** This is the total loan amount contributed by this team before this message (*team loan amount*), which may be viewed as a basic measurement of teams' lending engagement [9].
- **Lender Loan Amount:** This measures the total amount of money contributed by a lender (*lender loan amount*), which is a proxy of his or her involvement on Kiva.
- **Lender Tenure:** This variable measures the number of months after lenders' registration and before this message (*lender tenure*).
- **Borrower Loan Amount:** Smaller funding goals are found to be positively correlated with success [41]. Here, we measure how much the loan or the borrower required (*borrower loan amount*), as stated in the "Total Loan" field in the loan profile<sup>5</sup>.
- **Borrower Demographics:** Prior research suggests that donors appear to discriminate in favor of the female, more attractive, lighter-skinned, and less obese borrowers [27, 42]. Thus we need to control for these demographics of the borrower. We inferred the gender of the borrowers from their profile pictures using the Face++ API<sup>6</sup>. Similarly, we inferred the age and facial expression (whether the borrower smiled) of borrowers from their profile images, resulting in three control variables: *borrower gender*<sup>7</sup>, *borrower age* and *borrower smile*.
- **Loan Links Per Message:** Social Impact theories state that the number of targets plays a role in social impact [28]. Specifically, the number of targets causes the social impact to be divided among all of the targets, leading to reduced impact for each target when more targets are present. We controlled for this effect by measuring how many loans are advocated in this message (*loan links per message*).
- **Loan Description Worthiness:** An advocate's tendency to emphasize the worthiness of the loan or borrower in his/her message might become unnecessary if the loan description already indicates the worthiness of the loan itself or the borrower. Thus, we utilized the

<sup>4</sup>Team message count is highly correlated with Team Loan Amount, with correlations of 0.833. The number of members in a team also highly correlates with Team Loan Amount ( $r=0.834$ ). To avoid multicollinearity, we only included Team Loan Amount.

<sup>5</sup><https://www.kiva.org/lend/1277009>

<sup>6</sup><https://www.faceplusplus.com/>

<sup>7</sup>Here, 1 means female, and 0 refers to male.

	Min	Max	Mean	Median
team loan amount	50	32.4M	12.9M	4.3M
lender loan amount	0	167K	757	47
lender tenure	0	128.49	43.09	41.09
borrower loan amount	25	100K	5169	2075
borrower gender	0	1	0.40	0
borrower smile	0	1	0.35	0
borrower age	1	85	47.89	48
loan links per message	1	100	3.71	1
loan's length	0	1078	158.41	139
loan's worthiness of loan	1	3	1.81	1.80
loan's worthiness of borrower	1	3	1.94	1.95
request's length	0	1078	95.13	36
request's worthiness of loan	1	3	1.58	1.46
request's worthiness of borrower	1	3	1.81	1.75
reciprocity	0	12428	3.79	0
# messages btw lender & advocate	0	1179	6.08	0
# team members loaned	0	153	3.23	1
(explicit) mention loaned	0	1	0.18	0
actual loaned or not	0	1	0.40	0
(explicit) mention scarcity	0	1	0.46	0
actual remain hours	0	1	0.43	0.30
is captain	0	1	0.314	0
messages of advocate	0	9810	563.85	94
negative emotion	0	1	0.01	0
(explicit) mention we words	0	0.667	0.01	0
team importance	0	1	0.38	0

Table 3. Descriptive statistics (min, max, mean, median) of all introduced variables

previous worthiness regressors to obtain the estimated worthiness of the loan and of the borrower, denoted as loan's worthiness of loan and loan's worthiness of borrower. The length of the loan description in terms of words is also controlled (loan's length).

### 7.3 Independent Variables

As described in the sections of Heuristic Processing and Systematic processing, we operationalized a set of variables to capture different persuasive cues, resulting in 15 variables. Table 3 reports the descriptive statistics for these variables, together with a set of control variables, before entering into the regression models.

### 7.4 Operationalization

We grouped multiple indicators of a topic when they were conceptually linked to the same persuasive principle and averaged them to form a single index when doing so led to a high internal consistency, as measured by a Cronbach's alpha greater than 0.6.

*Worthiness*: Since *request's length*, *request's worthiness of loan* and *request's worthiness of borrower* measures are highly correlated with each other ( $\alpha=0.861$ ), we averaged the standardized three

variables to form a single variable **request worthiness**. Similarly, we combined *loan’s length*, *loan’s worthiness of loan* and *loan’s worthiness of borrower* into **loan description worthiness** (alpha=0.742).

*Liking*: We further merged the interaction familiarity (*# messages btw lender & advocate*) and *reciprocity* (the number of times that an advocate made loans in response to a potential lender’s persuasive messages) between lenders and advocates into one variable to measure the generic liking between the lender and the advocate (**liking btw lender & advocate**<sup>8</sup>) (alpha=0.739).

*Authority*: We combined the standardized *is captain* and *messages of advocate* variables into a single variable **authority** to capture the authority status of an advocate (alpha=0.618).

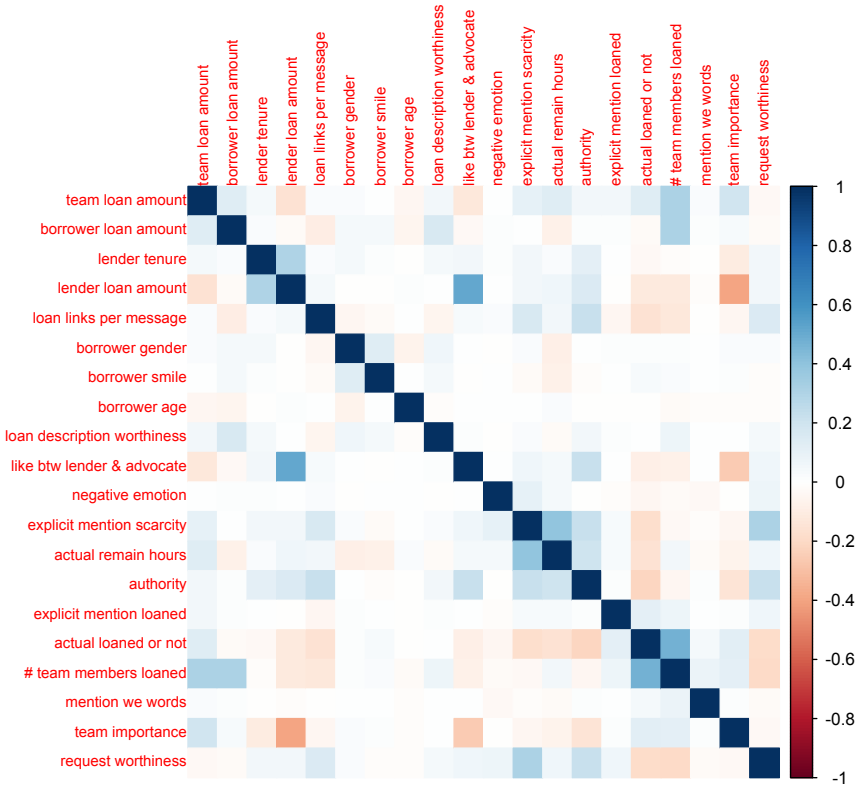


Fig. 4. Correlations between all introduced variables.

Based on these further operationalization, we obtained 11 factors in total that reflect information processing, including: (1) systematic processing: *request worthiness* and (2) heuristic processing: *liking btw lender & advocate*, *negative emotion*, *explicit mention scarcity*, *authority*, *actual remain hours*, *explicit mention loaned*, *actual loaned or not*, *# team members loaned*, *explicit mention identity*, and *team importance*. The correlations between all variables, including both introduced factors and control variables are described in Figure 4. Multicollinearity is not a problem, with none of the correlations higher than 0.5.

<sup>8</sup>Note that *# messages btw lender & advocate* and *reciprocity* are highly skewed even after log transformation, so we binarized them first before their merge.

## 8 RESULT

Table 4 reports the results of several hierarchical logistic regression models, predicting whether a potential lender contributed to a loan based on control variables (Model 1), systematic persuasive variables (Model 2), heuristic persuasive variables (Model 3) and a combination systematic and heuristic variables (Model 4). Model 5 tests whether predictions different for different types of groups. In all models, the loan decision was nested within lender, which in turn was nested within the team. All continuous predictor variables have been standardized, with a mean of zero and standard deviation of one. Results are reported as odds ratios, the change in the odds of lending when a continuous variable is increased by one standard deviation. Odds ratios greater than one indicate an increase in the odds of lending, while odds ratios less than one indicate a decrease in the odds of lending.

Model 1 reports the main effects of the control variables for all types of teams. It shows that, the odds that members lend increases by 45.8% with each standard deviation more money their team has lent in the past. A standard deviation increase in the lender loan amount (i.e., the total amount the focal lender had lent in the past to other loan requests) was associated with five times higher odds (OR=5.961) of the lender lending in response to the current loan request. Lenders, who had been members of their Kiva team longer, were less likely to make loans, as indicated by an odds ratio of 0.324. Other control variables had much smaller effects on lending. The odds of lending to borrowers who smiled on their profile pictures was 3% higher than lending to a non-smiling borrower, confirming prior findings of affective cues on persuasion outcomes [50, 57]. Lenders were less likely to give to women (OR=0.971). Lenders were less likely to give to older borrowers (OR=0.976). Surprisingly, the odds of lending were 5% lower when the borrower's description made the loan seem more worthy (OR=0.948).

### 8.1 Results on Systematic Processing

Model 2 adds the influence of the advocate's message trying to make the loan seem more worthy. One standard deviation increase in the worthiness of the loan as described in the advocate's persuasive message was associated with 5% lower odds of potential lenders contributing to the loan (OR=0.953). Although this result and the parallel result for the worthiness in the borrower's loan description indicates that potential lender paid attention to systematic persuasion variables, the effects were opposite to predictions from conventional theories of persuasion. Lenders were less likely to give when either the borrower or advocate wrote longer loan justifications and tried to make the loan and the borrower seem more worthy of receiving a loan. It appears that in trying to justify a loan, both borrowers and team advocates turned off the potential borrowers. This might happen if their justification were perceived as "coming on too strong" and evoked psychological reluctance [4], increasing potential lenders' resistance to persuasion. Understanding why lenders were less likely to contribute to loan requests that substantively justified the value of the loans will require a deeper analysis of persuasive messages than provided by the machine learning models we developed.

### 8.2 Results on Heuristic Processing

Model 3 adds the influence of different heuristic principles of persuasion on the success of loan requests. Some of these heuristic factors strongly predicted lending behavior, although in general behavior evidence seemed to have larger effects than did the content of message texts. Potential lenders were substantially more likely to give (OR=1.352) when solicited by a team advocate with whom they had some prior relationship (i.e., had exchanged messages in the past or where the advocate had previously given in response to one of the lender's prior loan requests) than to

	Variables	Model 1	Model 2 Systematic	Model 3 Heuristic	Model 4 Systematic & Heuristic	Model 5 Team Type
<b>Control Variables</b>	team loan amount	1.458***	1.456***	1.494***	1.493***	1.179***
	borrower loan amount	1.170***	1.169***	1.190***	1.190***	1.255***
	lender tenure	0.324***	0.325***	0.343***	0.343***	0.329***
	lender loan amount	5.961***	5.982***	6.558***	6.559***	9.343***
	loan links per message	0.991	0.999	1.017**	1.021***	1.003
	borrower gender	0.971*	0.970**	0.964**	0.964***	0.972
	borrower smile	1.034*	1.032*	1.019	1.019	1.038*
	borrower age	0.976***	0.975***	0.976**	0.976***	0.952***
	loan description worthiness	0.948***	0.951***	0.955***	0.955***	0.942***
	<b>Worthiness</b>	request's worthiness		0.953***		0.990
<b>Liking</b>	liking btw lender & advocate			1.352***	1.352***	1.357***
<b>Authority</b>	authority			0.795***	0.797***	0.792***
<b>Identity</b>	mention we words			0.991	0.991	1.007
	team importance			1.598***	1.598***	1.626***
<b>Scarcity</b>	mention scarcity			0.964***	0.967***	0.964***
	actual remain hours			0.940***	0.941***	0.958***
<b>Social Proof</b>	mention loaned			0.974***	0.975***	0.982*
	actual loaned or not			1.047***	1.046***	1.031**
	#team members loaned			0.941***	0.943***	0.912***
<b>Emotional</b>	negative emotion			1.006	1.006	1.001
<b>Team Type Interaction</b>	relation-based (rb) team					0.647***
	liking x rb team					1.020
	authority x rb team					1.036
	team importance x rb team					1.047
	Intercept	0.072***	0.072***	0.074***	0.074***	0.092***
	# Obs	336193				215715
	# Groups	70509				63450
	Lender var(_cons)	8.572	8.590	7.228	7.229	6.970
	AIC	243276	243217.8	239940.7	239939.7	149377.4
	BIC	243394	243346.5	240165.9	240175.7	149644.7
	Likelihood-ratio test	-	p<0.0001	p<0.0001	p>0.05	-

Table 4. Odds ratio of predicting whether team members will lend to loans. Here,  $p < 0.001$ : \*\*\*;  $p < 0.01$ : \*\*;  $p < 0.05$ : \*. Model 1-4 were conducted on the overall corpus. Model 5 tests the interaction of some persuasion factors and team type. It includes just identity-based and relation-based teams, and compares whether selected persuasion factors have different effects on the type types of groups. The Likelihood-ratio test was examined to determine whether a given model fits the data better than the model to its left. Here, AIC refers to Akaike Information Criterion, and BIC refers to Bayesian Information Criterion.

advocates with whom they had no relationship. These results are consistent with prior findings that factors that increase the liking between a persuader and target of persuasion significantly and positively influences the power of persuasive messages [56].



Theories of persuasion propose that people are more persuaded by those with more authority and empirical research is consistent with this hypothesis [14, 59]. However, this hypothesis was dis-confirmed in the present study. A standard deviation increase in the advocates' authority was associated with 20% lower odds of other members' compliance with their requests. This suggests that the status of the advocate by itself—being a captain or previously having sent many loan requests—does not guarantee compliance [15]. One plausible explanation is that team members might simply experience “message overload” from team captains or other frequent posters and over time ignore their messages. Instead, they pay more attention to advocates who are more selective in their advocacy.

Lenders were substantially more likely to give in response to loan requests when the lender more strongly identified with the team. A standard deviation increase in (*team importance*) was associated with 60% higher odds of giving. Consistent with the principle of social identity [12], the more lenders perceive loan requests as associated with teams, lenders were more likely to be influenced by a request when it comes in the context of a group they cared about [9]. However, it appears that advocates were not able to craft their persuasive messages to increase the effects of lenders' team identification. When they highlighted social identity by using words such as “we” in their requests, giving did not increase (OR=0.99). These results are another example of heuristic cues embedded in behavior being more powerful than those included in the language.

Lenders were more likely to contribute if the advocate had already given to the borrower (OR=1.047). However, explicitly mentioning they themselves had given was associated with lower odds of others' giving (OR=0.974). This comparison suggests that lenders are more influenced by advocates who “walk the walk” but not just “talk the talk”. Surprisingly, in terms of social proof, seeing others making loans was associated with lower odds of lending (OR=0.941), which might communicate to members that a loan has already received enough attention.

Both the actual urgency of the loan (i.e., the time remaining until the request expired) and advocates explicitly mention the urgency of loans in their requests was associated with lower odds of persuading team members (OR=0.940 and 0.964 respectively). In this case, both actual scarcity and verbal mention of it had similarly sized effects. Although meta-analyzes shows that scarcity messages stimulate demand in commercial advertising [33], the effect sizes are small and “limited-time offer” messages tend to be less effective than ones that highlight the scarcity of the community being advertised [45]. One explanation for why time scarcity and explicit mentions of it depressed giving in the current setting is the limited time available might have meant that some of these loans had expired before other members read the request and took action. Alternatively, it could be that when the remaining money needed is high and the time left is low, members thought their actions would not have an impact. Unfortunately, we do not have the needed data to assess this unexpected finding on the rule of scarcity and urge future research to pay attention to this issue. Loan requests that contain negative emotion were not predictive of eliciting the request receivers' responses.

### 8.3 Combining Systematic and Heuristic Processing Cues

Model 4 includes both systematic and heuristic processing cues. The likelihood-ratio test comparing Model 4 to Model 3 shows that use of language in loan requests that highlight the worthiness of the loan did not add to the predictive power once the heuristic cues were accounted for. The worthiness of requests was not significantly predictive of persuading receivers to make loans.

### 8.4 Interaction between Team Types and Persuasion Tactics

To investigate whether the effectiveness of persuasive cue depends on group type, we contrast personal relation-based teams and common identity-based teams. The personal relationship/social

identity distinction is a major way that psychologists have differentiated members' attachment to their groups [46]. As seen in Model 5, the odds of giving were 35% lower in relationship-based teams than identity-based ones ( $OR=0.647$ ). For simplicity, we only examined the interaction between team type and persuasive cue only for the most effective cues—liking, authority, and team importance, all of which have odds ratios above 20% in eliciting loans. However, none of the interactions between team type and persuasion cue was significant, suggesting that the tactics are equally effective for different types of teams in text based campaigns. This differs from the findings in Dey et al. [17] that systematic cues such as product related factors work better for technology campaign videos and heuristic cues work better for design and fashion campaign videos.

## 9 DISCUSSION

This research examined the effectiveness of systematic and heuristic cues in requests that attempt to persuade members to donate money in Kiva lending teams. Specifically, we operationalized a set of persuasive principles and examined which persuasive cues predicted members' lending behavior. Based on an analysis of 88,596 requests exchanged in 1,610 teams, we found that certain heuristic processing cues (e.g., liking between requesters and potential lenders, advocates low authority in the team and the importance of the team to the lender—strongly predicted whether lenders would contribute following a loan request. In contrast, cues that required systematic processing are less influential. In particular, messages written by the borrower and by the team advocate were less effective the more they highlighted the worthiness of the loan. The association of advocates' claims of loan-worthiness disappeared when the heuristic processing cues were entered into the model.

The results also suggest that behavioral cues are more important than the verbal ones introduced into a persuasive message. Thus the three strongest cues were all behavioral – liking between requesters and potential lenders, advocates low authority in the team and the importance of the team to the lender. These behavioral cues had stronger associations with giving than language cues, such as the use of “we” words or a team name in a request. Lenders were more likely to give money when the advocate soliciting them had given money but were less likely to give if the advocate told about giving in the request message. Only in the case of scarcity were the predictions for behavioral cues (i.e., actual time remaining) and language cues in the same direction and of roughly the same size. The insignificant interaction between the persuasive principles and team types suggests that such effectiveness of cues were equally effective in different Kiva lending teams.

### 9.1 Theoretical and Design Implications

There are several important theoretical implications from this research. First, our work investigated the reflection of systematic and heuristic processing in loan advocacy requests in a peer-to-peer lending websites, which has not been adequately studied. As a result, we found that requests that come from lenders' liked members, lenders' perceived important teams, and advocates who have already taken actions, are more persuasive in eliciting loans. Systematic processing cues as measured by the worthiness of requests seem not predictive in this context. In addition, we uncovered new nuanced insights. For instance, our results suggest that new members are more likely to give and members prefer to make loans to younger borrowers. We also found that authority and scarcity are not helpful in eliciting loans on Kiva.

The above theoretical findings might enable new features for building more successful peer-to-peer lending websites. For example, advocates can use the effective tactics we found for different types of teams to craft their loan requests with the best chances of success. “Help Center” on these crowd-funding sites could list these persuasive principles to benefit both project creators and advocates. Another practice for requesters is to advocate loans in advance based on our finding on scarcity. Borrowers can position themselves in a positive manner such as wearing a big smile. The

finding that new members are more likely to give might inspire crowd-funding sites practitioners to provide diverse experiences for old-timers to keep them engaged.

## 9.2 Limitation and Future Work

Like many large scale analyses of observational data, we were not able to infer causation from correlational data. That is, we cannot guarantee that only the presence of these tactics can guarantee the success of soliciting loans. Nor do we claim that utilizing these tactics are the only ways to persuade members to take actions. Due to this lack of causality, we urge readers to interpret our results with caution. For example, persuasive cues contained in advocacy messages might reflect an anticipation of future support or reactions to previous support. A natural follow-up could be to conduct interviews or send surveys to measure advocates' self-reported motivation when drafting their advocacy requests.

We only considered the persuasive cues in advocacy requests and a set of attributes of the loan and borrower. We acknowledge that our identified persuasive tactics are not exhaustive, and other factors such as previous support that a loan has already received prior to the advocacy request are also important in the success of soliciting loans. However, our study presents a set of initial insights about how systematic and heuristic cues in advocacy requests persuade members to make loans on Kiva. We urge readers to interpret our results with caution, and future studies to examine other factors to further validate our findings.

We operationalized a set of persuasive factors and grouped them into different aspects based on their conceptual connections as measured by internal consistency. For example, people explicitly using more “we”, “our” related words or devoting more time to participating a specific team both demonstrate their self-concept of their membership. Thus we used both of them as indicators of social identity. Similarly, we designed a set of factors to represent persuasive principles including worthiness, liking, and authority in a bottom-up manner, which has been used in a wide range of prior studies [2, 17]. We acknowledge that this might not be perfect, but since we focus on operationalizing theories into metrics, this conceptual merge based on variables' internal consistency does make sense.

We also acknowledge that, among different persuasion cues that we operationalized, some measures might be less direct and accurate in capturing certain persuasive principles. For instance, we built machine learning models to predict the level of worthiness contained in messages. Although the correlation between estimated worthiness and human annotated worthiness is greater than 0.6, such models still exist measurement errors, which might account for the little effect of systematic processing cues. Future work could build on our annotated corpus and operationalization, and exploit other attributes to develop sophisticated measures.

Limited by the data (Kiva does not record the reading log), we were not able to distinguish between lenders who read messages and did not take actions and lenders who did not read messages. Direct recording about members' browsing and clicking logs would help resolve this issue.

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Received April 2017; revised July 2017; accepted November 2017