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The persuasion of borrowers' voluntary information in peer to peer lending: An empirical study based on elaboration likelihood model

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ABSTRACT

This paper investigates the persuasive process of borrowers' controllable voluntary information which can be easily manipulated and is particularly valuable for borrowers to persuade lenders and enhance the likelihood of funding success in P2P lending marketplace. Using a large scale data set from a Chinese leading P2P lending platform, namely Renrendai, based on a dual-processing persuasion theory-Elaboration Likelihood Model, we introduce four newly persuasive features (*Completeness, Sentiment, Language intensity, The number of certificates*) with central and peripheral cues in voluntary information. The results show that the persuasion of borrowers' voluntary information can be accomplished via two distinct routes in P2P lending, suggesting that not only central cues but also peripheral cues have significant effect on lenders' decision making. Specially, negative sentiment is negatively associated with funding success which is contradictory to the findings in fund-raising appeals say using negative emotions can evoke "empathy-helping". Moreover, we find a negative interaction effect on funding success between *Completeness* and *The number of certificates*. Our study shed some light for deeply understanding the dual-route persuasive process in P2P lending.

1. Introduction

The aim of online lending, for borrowers in Peer-to-Peer (P2P) lending market, is to persuade lenders to fund, and borrowers' voluntary information may plays an important role in persuasion because of its controllable feature. Due to the asymmetric information problem which is especially elevated in P2P lending (Lin, Prabhala, & Viswanathan, 2013), borrowers would disclose as much information as possible on P2P lending platform to alleviate asymmetric information problem and enhance the likelihood of funding success. They can not only provide objective, necessary information demanded by platform, but also submit various voluntary information which is nonstandard, subjective and unverified (Dorfleitner et al., 2016), such as photograph, loan description, and various certificates which are uploaded voluntarily by borrowers and lenders can only confirm the existence of them.

Objective information is pulled directly from the borrowers' credit report and thus could not be easily adjusted by borrowers in a short period of time (Larrimore, Jiang, Larrimore, Markowitz, & Gorski, 2011). Compared with objective (hard) information, voluntary information is more controllable. Thus, voluntary information is particularly valuable for borrowers to persuade lenders and enhance the likelihood of funding success in P2P lending marketplace. Previous research in this domain examined which factors of voluntary information affect funding success, however, the understanding for the persuasive process of voluntary information is still limited. Previous study in electronic commerce also demonstrated that the key to designing a successful persuasive strategy is to understand the communication process between customers and sellers (Tang, Jang, & Morrison, 2012). For P2P lending, understanding the persuasive process of voluntary information can help borrowers to know how to accomplish effective persuasion, and further foster lenders to fund.

Moreover, previous research explored limited aspects of voluntary information, such as the account, identity, language feature, there are still rich features (such as sentiment analysis,

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language intensity of loan description) have not been concerned. Nevertheless, these features were showed have important significance on persuasion in other contexts, such as online product reviews (Li & Zhan, 2011), donation appeals (Fisher, Vandenbosch, & Antia, 2008; Liang, Chen, & Lei, 2016), advertising (Lewinski, Fransen, & Tan, 2016; Tseng & Huang, 2016), product popularity prediction (Wu & Shen, 2015), attracting much attention for the P2P lending.

In order to investigate the role of richer features of voluntary information in persuasion and understand the persuasive process of borrowers' controllable voluntary information in P2P lending marketplace, we draw on the classical dual-processing persuasion theory of Elaboration Likelihood Model (ELM) as the theoretical base. The ELM is developed in the 1980s proposed by Petty and Cacioppo (Petty & Cacioppo, 1984). As a process-orientated method, the ELM provides a framework for understanding the basic processes which underlie the effectiveness of persuasion and attitude change (Petty & Cacioppo, 1984; Yang, 2016). This theory framework has been well documented in many fields such as social psychology (Robert & Dennis, 2005), information technology (Bhattacherjee & Sanford, 2006; Sussman & Siegal, 2003), and electronic commerce (Kim, Chung, Lee, & Preis, 2016; Zhou, Lu, & Wang, 2016). The ELM proposes two routes to persuasion: the central route and the peripheral route, which differ in the amount of thoughtful information processing or "elaboration" demanded of backers (Bhattacherjee & Sanford, 2006; Petty & Cacioppo, 1984). Under the central route, persuasion will likely result from a person's careful and thoughtful consideration of the true merits of the information presented in support of an advocacy. On the other hand, under the peripheral route, persuasion results from a person's simple inference about the merits of the advocated position (Petty & Cacioppo, 1984). Contrary to the central route, the peripheral route requires less effort involvement. This framework is particularly relevant for our data because lenders in P2P lending could potentially be persuaded either by a centrally processed argument such as strong repayment ability mentioned in the borrower's loan description or by a peripherally processed argument such as a trustworthy image presented by the borrower through submitting many certificates.

Given that, we employ ELM to identify a comprehensive set of features with central and peripheral cues in borrowers' controllable voluntary information and address the following two questions in this paper:

1. Whether or not our newly introduced persuasive cues (*Completeness, Sentiment, Language intensity, The number of certificates*) extracted from borrowers' controllable voluntary information have effect on lenders' decision making?
2. How does the persuasive process accomplish and affect lenders' funding decision?

We investigate these two questions using a large scale and complete data set (590,000 loan requests) from a Chinese leading P2P lending platform, namely Renrendai. We start with a series of works to test the incremental influence of our newly identified features on funding success while controlling for *Readability* of loan description which is previously studied and other objective information that nearly all of what a lender knows about a borrower. Further, in order to have a better understanding of the persuasive process, we also examine the interaction effect between the central route features and the peripheral route features on funding success.

Our research differs from prior research in three aspects. **First,** our paper is the first to understand dual-route persuasive process in online P2P lending. The research of the persuasive process of borrowers' controllable voluntary information base on ELM - an influential theoretical framework in the persuasion literature. ELM offers us a well-grounded foundation for understanding the dual-route persuasive process in P2P lending. **Second,** the rich information contained in the voluntary information (e.g., sentiment and completeness) are ignored, using text mining technique, we extract four newly features from borrowers' voluntary information: *Completeness, Sentiment, Language intensity, The number of certificates*. Richer features extraction and empirically study offer better understanding of the role of borrowers' controllable voluntary information in persuasion. **Third,** to the best of our knowledge, this is the first study using a large scale data to understand the role of borrowers' voluntary information in P2P lending.

This paper provides unique and complementary insights to previous literature by investigating the dual-route persuasive process of borrowers' controllable voluntary information in P2P lending. As online lending becomes an alternative and increasingly appealing channel for financing, an understanding of the persuasive process of borrowers' voluntary information can provide important implications for borrowers to effectively use their controllable voluntary information to foster lenders to fund. In addition, our research can also help the managers of lending platform to make strategic decisions to facilitate online lending.

The rest of this paper is organized as follows. We outline previous research related to our study in Section 2. We present theoretical framework and show our research hypotheses in Section 3. Section 4 describes variables used in our study and constructs model. Section 5 presents the empirical results and alternative models to test for robustness. Section 6 concludes and discusses theory and practical implications. Finally, Section 7 discusses limitations of this study and concludes with a proposal for future research.

2. Literature review

In this section, we review the literature relevant to the subject of voluntary information and funding success. Specially, we summarize the P2P lending studies of Chinese platforms. In the end, we discuss how our findings add to the work in this area.

2.1. Factors affecting the funding success of P2P lending

The determinants for funding success investigated by previous studies can be categorized into four types: 1) Loan characteristics, including loan rate, loan amount and loan duration. 2) Borrower's personal information, such as credit level, gender, age, working life and so on. 3) Voluntary information, including photograph and loan description. 4) Soft information, including friendship networks and group affiliation.

Loan characteristics are the fundamental information of borrower's loan listing. Puro, Teich, Wallenius, and Wallenius (2010) showed that borrowers who offer higher interest rate and request smaller loan amount are more likely to receive funding. Some personal information of borrowers also has significant impact on funding success of P2P lending. Lee and Lee (2012) found that borrowers on Popfunding with a history of more successfully funded auctions or with a history of fewer failed auctions attract more bids. Ly and Mason (2012) found that loans to women and groups of women raise funds 38% faster than loans to men and mixed groups on Kiva platform.

Besides providing basic personal information requested by P2P platform, borrowers can also voluntarily submit additional information in their listings. Michels (2012) argued that objective quantitative data often are insufficient, and decision makers may turn to subjective, but potentially diagnostic qualitative data. Pope and Sydnor (2011) used borrowers' photographs from Prosper and discovered a significant racial discrimination phenomenon, loan listings with blacks in the attached photograph are 25%–35% less likely to receive funding than those of whites with similar credit profiles. Gnonzalez and Laura (2014) investigated the effects of lender and borrower personal characteristics (perceived attractiveness, age and gender) on online P2P lending decisions, and found loan success is sensitive to the relative age and attractiveness of lenders and borrowers. Duarte, Siegel, and Young (2012) showed that the likelihood of funding is higher and the interest rate is lower for borrowers who look more trustworthy. Harkness (2016) explored how borrowers' demographic characteristics combine to alter lenders' status assessments and lenders' decisions in an artificial peer-to peer lending market, and found that status is a likely mechanism driving lending discrimination. Previous relevant research also found that borrower's free format loan description has a significant effect on lending outcome (Dorfleitner et al., 2016; Larrimore et al., 2011; Michels, 2012; Sonenshein, Herzenstein, & Dholakia, 2011). Using 512 loan request listings posted by borrowers on Prosper, Sonenshein et al. (2011) found that lenders are more likely to make a favorable funding decision when a borrower uses an explanation and denial account combination. Dorfleitner et al. (2016) investigated the relation of spelling errors, text length and the presence of social and emotional keywords in the description text to the probability of successful funding and to the default probability for two leading European platforms. Larrimore et al. (2011) analyzed over 200,000 loan requests with Linguistic Inquiry and Word Count (LIWC) software, and found that the use of extended narratives, concrete descriptions and quantitative words which are likely related to one's financial situation have positive associations with funding success, whereas humanizing personal details or justifications for one's current financial situation are negatively associated with funding success. Michels (2012) found that the amount of voluntary, unverifiable disclosures in a loan listing increases the number of bids on a loan listing. Herzenstein, Sonenshein, and Dholakia (2011) found that narratives of the loan description influence funding success, borrowers who claimed more identities get an increased likelihood of loan funding.

Prior studies on P2P lending revealed that borrower's social capital can help reduce the adverse selection problems and has a significant impact on lending outcomes Lin et al., 2013; Chen, Zhou, & Wan, 2016). Using a large sample of data from Prosper.com, Lin et al. (2013) found that online friendships of borrowers act as signals of credit quality and friendships increase the probability of successful funding. X. Chen et al. (2016) studied the impact of group social capital on the funding and repayment performance in the online P2P lending market, they found that the borrower's general group social capital and relational social capital yield inconsistent effects, and the borrower's structural social capital has a negative impact on funding and repayment performance.

Scholars also found that there exist herding behavior, home bias in P2P lending (Lee & Lee, 2012; Lin & Viswanathan, 2016). Zhang and Liu (2012) found evidence of rational herding among lenders. Unfavorable listing attributes, such as high credit risks and high debt-to-income ratios, amplify the herding momentum, whereas favorable listing attributes, such as friend endorsements and group membership, weaken the herd. Lin and Viswanathan (2016) showed that home bias exists in P2P lending, they argued rationality-based explanations can not fully explain such behavior and behavioral reasons at least partially drive this remarkable phenomenon.

The determinants for funding success mainly conducted in the United States have been extensively investigated. However, the understanding for the determinants for different credit systems, such as China, is still limited. For members of Prosper (a leading P2P lending platform in the United States), a credit score is extracted directly from Fair, Isaac Credit Organization (FICO). However, there is no such agency to provide credit scores in China, so borrowers' credit scores provided by P2P platforms are calculated based on the information they provide, and lenders may place more importance on information provided in the loan listing pages to evaluate borrowers' trustworthiness. Thus, to better understand the lending behaviors in Chinese setting, some scholars conducted related research on Chinese P2P lending platform (Chen, Lai, & Lin, 2014; Feng, Fan, & Yoon, 2015). Relevant research will be discussed in the next section.

2.2. Research of P2P lending platforms of China

Using survey data from users of PaiPaiDai lending platform, Chen et al. (2014) investigated lenders' willingness in P2P lending and discovered that perceived risk impact trust but cannot impact lending willingness. In a similar spirit, Zhang, Tang, Lu, and Dong (2014) developed a trust model to understand the critical factors that influence lenders' trust-building process. Feng et al. (2015) analyzed borrowers' loan designing strategy in three groups according to the level of their expertise of online P2P lending and found that different types of borrowers emphasize different components when designing a loan.

Although previous studies showed that voluntary information can affect lenders' funding decisions, we still not clear the persuasive process through which such factors affect lenders' funding decisions. This is significant for borrowers to understand the persuasive process, so they can effectively use their controllable voluntary information to foster lenders. Previous study in electronic commerce also demonstrated that the key to designing a successful persuasive strategy is to understand the communication process between customers and sellers (Tang et al., 2012). However, the research of understanding the persuasive process in P2P lending has not got concern. As online lending becomes an alternative and increasingly appealing channel for financing, a better understanding of the persuasive process of borrowers' controllable voluntary information can help provide important managerial and practical implications for the managers of P2P lending platforms and borrowers to facilitate online lending.

3. Theoretical background and hypothesis development

3.1. Elaboration likelihood model

In this paper, we introduce the classical dual-processing persuasion theory of Elaboration Likelihood Model (ELM) to identify a comprehensive set of features from borrower's controllable voluntary information which can be easily manipulated and are particularly valuable for borrowers to persuade lenders to fund, and investigate the persuasive process of voluntary information.

The ELM model is proposed by Petty and Cacioppo (1984) who provided a framework for understanding the basic processes which underlie the effectiveness of persuasion and attitude change (Petty & Cacioppo, 1984; Yang, 2016). The ELM model highlights a dual route of persuasion process that a message is elaborated through the central and peripheral routes which influence the likelihood of persuasion (Kim et al., 2016). According to the ELM model, persuasion accomplish via two routes: **the central route** and **the peripheral one**, which differ in the amount of thoughtful information processing or “elaboration” demanded of information receiver (Bhattacherjee & Sanford, 2006; Petty & Cacioppo, 1984). The central route focuses on the message quality to persuade, which requires that receivers critically consider the arguments embedded in the message and scrutinize the relative advantages and relevance of these arguments (Bhattacherjee & Sanford, 2006).

When lenders are highly motivated and more able to access a message, they are more likely to depend on argument quality. Whereas peripheral route occurs when lenders is unable or unwilling to engage in much thought on the message, where receivers rely on heuristic cues to make their decisions. For example, a listener may decide to agree with a message because the source appears to be an expert, or is attractive. Contrary to the central route, the peripheral route requires less effort involvement.

A prediction of the ELM model is that attitudes which are changed through the central route to persuasion will have different effects from attitudes changed via the peripheral route. Petty and Cacioppo (1984) explained that attitude changes through the central route will show greater temporal persistence, greater prediction of behavior, and greater resistance to counter persuasion than attitude changes through peripheral cues. Thus, in P2P lending, it is useful for borrowers to know how to make attitude change last longer, and have a greater influence on behavior.

3.2. Research hypotheses

The aim of this study is to extract a comprehensive set of features from borrower's voluntary information and understand how persuasion process accomplish and affect lenders' funding decisions under a persuading theoretical framework of the ELM model. We frame our research model as depicted in Fig. 1.

The central route focuses on the message quality to persuade, whereas the peripheral route focuses on the source credibility to persuade. The argument quality refers to the perceived quality of information based only on the message content (Rabjohn, Cheung, & Lee, 2008). According to the existing literature (Liang et al., 2016; Michels, 2012; Toma & Hancock, 2012), we capture argument quality of loan description from three dimensions: ***1) Readability***, which measures the average length of sentence in the loan description. ***2) Completeness***, which measures the comprehensiveness of details disclosed in the loan description. ***3) Sentiment***, which measures the positive/negative feeling conveyed in the loan description. These three variables have been widely applied in existing literature. Hypothesis 1 hypothesizes that all argument quality features (*Readability, Completeness, Sentiment*) are influential on funding success through the central route.

Description which is easy to read should be more helpful and influential compared to other descriptions that are hard to read. Ghose and Ipeirotis (2011) and Li (2008) showed that easy-reading text improves comprehension, retention, and reading speed. Toma and Hancock (2012) used online dating profiles and found that self-descriptions that contain fewer words per sentence would be perceived as more trustworthy. Longer messages are likely to decrease the perceived message clarity and argument quality. Thus, we hypothesize the average length of sentence has a negative influence on funding success, formally stated as Hypothesis 1a.

H1(a). The use of longer sentences associated with a decreased likelihood of funding success.

Borrowers in their loan description would disclosure rich information, such as explaining past experiences, expressing the imperative need for the loan, stating current financial situations, describing how they are going to repay it and so on. However, it may seem surprising that not all borrower disclosure as much information as possible in loan description. One explanation may account for this behavior that is borrowers may not fully understand the effectiveness of disclosures in enhancing the likelihood of funding success. If the market had persisted, then it is possible that learning would have occurred and the amount of disclosures would have increased. Flanagin (2007) and Yang, Hung, Sung and Farn (2006) in electronic commerce found that more detailed product descriptions are associated with better reviews and greater purchasing intention. Thus, in the context of P2P lending, we expect to see funding success increasing in the amount of detail disclosure in the loan description. This leads to Hypothesis 1b.

H1(b). The amount of detail disclosures in a loan description positively associated with funding success.

Although people are equally likely to share positive and negative experiences with others, these expressions serve different functions. Sharing positive emotions elicit positive feedback from others (Sheldon & Lyubomirsky, 2006), and facilitate positive social interactions (Augustine, Mehl, & Larsen, 2011). On the other hand, sharing negative events and emotions sometimes can reduce the intensity of negative affect, evoke comfort and social support from listeners. Fisher et al. (2008) found "empathy-helping" in fund-raising appeals, which showed that negative emotions have a significant positive effect on self-benefit donation appeals. Since P2P lending is also a form of fund-raising, we hypothesize that positive sentiment of loan descriptions is associated with an increased likelihood of funding success, and sharing negative emotions can also positively correlated with funding success, formally stated as Hypothesis 1c.

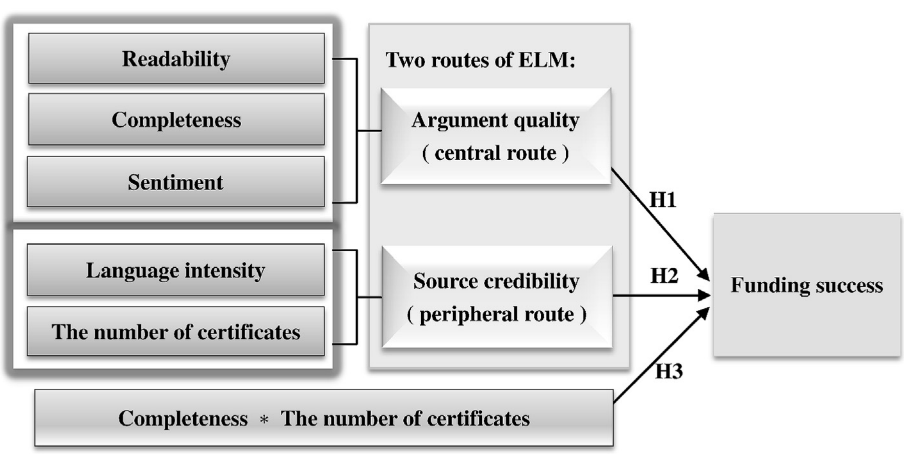

Fig. 1. Illustration of the framework of this paper. The Solid lines show the hypothesize relationships, and the dashed line signifies controls. The two boxes on the left side refer to specific dimensions of the two main routes of persuasive communications provided by the dual-processing persuasion theory - the Elaboration Likelihood Model (ELM); The quantity *Completeness* * *The number of certificates* represents the interaction term between the comprehensiveness of details disclosed in the loan description and the number of certificates voluntarily submitted by the borrower.

H1(c). Positive sentiment of loan descriptions associated with an increased likelihood of funding success, and sharing negative emotions also positively correlated with funding success.

Source credibility, on the other hand, refers to the perceived credibility and authority of the information source (Chaiken, 1980). Credible information sources generally enhance the persuasiveness of a message (Sussman & Siegal, 2003). We capture source credibility from two dimensions: ***1) Language intensity***, which measures stylistic features of the loan description. We use the number of exclamation marks used in the description to measure language intensity which is consistent with previous empirical study (Li & Zhan, 2011). ***2) The number of certificates***, which count the number of certificates submitted voluntarily by the borrower. Hypothesis 2 hypothesize that all source credibility features (*Language intensity, The number of certificates*) have significant impact on funding success through the peripheral route.

Language intensity can impacts the perceived source trustworthiness and persuasive power (Buller, Borland, & Burgoon, 1998). Consisting with previous study (Li & Zhan, 2011), we capture language intensity through exclamation mark, which count the frequency of exclamation mark used in the loan description. Li and Zhan (2011) found that using exclamation marks frequently can reduce persuasive power. In P2P lending, borrowers who use exclamation mark frequently in loan description may convey a message that they need money desperately, and lenders may suspect that they lack thought-out plan to repay the loan, thus we hypothesize that number of exclamation marks negatively correlated with funding success, formally stated as Hypothesis 2a.

H2(a). Number of exclamation mark is negatively correlated with funding success.

There are various types of certificates can be uploaded voluntarily by borrowers on P2P lending platform, such as credit, identification, degree, job, title and so on. Borrowers can decide how many certificates and which kind of certificates to submit and lenders can only confirm the existence of these certificates. Borrowers who submit more certificates should be more credible and could build up stronger trust with lenders than those who submit fewer certificates, because certificates can reduce the information asymmetry to some extent and provide evidence to support the details disclosed in their's loan description. If the borrower does not provide sufficient diagnostic information for lenders to make attributions about the borrower, lenders may suspect that the borrower lacks sufficient distinctive information or is withholding or hiding germane information (Herzenstein et al., 2011). However, not all borrowers submit as many certificates as possible in the P2P lending market. Two explanations may account for this behavior. One is that the process of getting various certificates is time-consuming, so some borrowers would be more inclined to make efforts to persuade lenders through free-format loan description. The other is that some poor quality borrowers, such as low-income borrowers or borrowers with a bad credit report, are not willing to submit relevant certificates. Thus, we hypothesize borrowers who upload more certificates might have more chance to receive a loan because of the higher level of trust from the lenders, formally stated as Hypothesis 2b.

H2(b). More voluntary certificates associated with an increased likelihood of funding success.

In order to have a better understanding dual-route persuasive process in P2P lending, we investigate the interaction effect between the central route features and the peripheral route on funding success. Among the three central route features (*Readability, Completeness, Sentiment*) identified in our study, *Completeness* requires a highest "elaboration" of lenders in that it need lenders to understand specific contexts disclosed in the loan description. On the other hand, the certificates borrowers offer can increase perceived trustworthiness to lenders. Borrowers who offer more certificates should be more credible and could build up stronger trust with lenders than those who submit fewer certificates. Previous researchers argued that a tradeoff exists between central and peripheral processing (Lien, 2001; Petty, Priester, & Brinol, 2002), accordingly, there should be much more likely exist a negative interaction effect between central and peripheral processing in P2P lending. Thus, we hypothesize that there exists a negative interaction effect between *Completeness* and *The number of certificates* on influencing funding success. This line of reasoning leads to Hypothesis 3.

H3. There is a negative interaction effect between Completeness and The number of certificates on influencing funding success.

4. Methodology

4.1. Data sampling

We use a web crawler and extract loan listings from a Chinese P2P lending platform, namely Renrendai. As a leading P2P lending platform in China, Renrendai has attracted more than 2,000,000 registered members and facilitated about 8.9 billion RMB (approximately $1.4 billion) in personal loans as of August 2015 since its inception in 2010.

Renrendai has a similar lending process to other P2P lending sites, such as Prosper, Popfunding and Zopa. First, a borrower must create a public loan listing on the Renrendai platform. Once the loan request is listed on the site, it becomes an auction on which lenders can place bids. Then, based on the listing information, lenders decide whether to lend to this borrower, and if so, how much money they want to offer. When the total bid amount by lenders covers the amount requested by the borrower in seven days (the open duration for bidding on Renrendai platform), the borrower gets funded. However, if the loan fails to attract sufficient amount from lenders, the request is not funded and the lenders do not pay. The loan is automatically canceled by the platform after the open duration expires.

The loan listing page contains two types of information: 1) fundamental information, including loan information (interest rate, loan amount and loan term), general personal information (such as credit level, gender, age, marital status, and degree), loan request history (such as request time, success funding time). 2) voluntary information. On Renrendai platform, voluntary information contains three main specific contents: photograph, loan description and various certificates. However, in contrast to Prosper, few loan applicants on Renrendai upload photograph, and this situation is similar to Smava, a German platform (Barasinska & Schafer, 2014). One explanation account for this phenomenon may be that it has something to do with China so called self-respect. Maybe borrowers think it would be a disgrace when their's friends and acquaintances recognize them on the lending platform. Thus, in this paper, we focus on two types of voluntary information: loan description and certificate material.

Our sample comprises all listings (590,000 loan listings) that seek funding on Renrendai.com since its inception in October 2010 (up to May 2015). We cancel 118 loan listings with non-exist loan ID (such as No.63880). Loan listings are divided into four types by the platform: credit authentication, field certification, institutional guarantee and smart money. The funding success rate of the latter three types of loans is 100% and the loan description of these three types of loans are written by the P2P lending platform, however, not by borrowers themselves, so these observations don't meet our research topic and we eliminate the latter three types of loans. Then we get loan sample with the type of credit authentication which consists of 467,153 loans, account for 79.1% of the total sample. Since we focus on the influence of voluntary information on funding success, we drop the observations which are currently running. We also remove those records with missing values for key variables, then we arrive at a listing sample of 314,046 listings which include 20,386 successfully funded loans. Finally, we get a stratified random sample of 2500 funded listings and 2500 unfunded listings (5000 listings in total). This sampling method is consistent with previous study (Michels, 2012). We use a random sample rather than the entire population of listings because each loan listing must be read and hand-coded in developing the disclosure measure. Table 1 shows summary information of the data related to Renrendai.

4.2. Variables description

Table 2 gives an overview of the dependent variable, independent variables and control variables. Dependent variable and control variables are extracted from the P2P lending site directly. All the independent variables are extracted from borrowers' voluntary information by using text analytic methods which are commonly done in the information system literature (Abrahams, Fan, Wang, Zhang, & Jiao, 2015; Fan & Gordon, 2014).

4.2.1. Dependent variable

One of the predominate measures of funding success is funding outcome (binary variable) which takes the value of either 1 (the funding goal is reached) or 0 (the funding goal is not reached). The other common measure is funding ratio, which is calculated by dividing funds raised by funds required. Since the funding outcome is the same for a loan request that receives 99% funding as one that receives no funding, we use funding outcome as the principal measure of funding success.

4.2.2. Control variables

We control for nearly all of what a lender knows about a borrower when making funding decisions: 1) loan information, including loan amount, interest rate and loan term. 2) borrowers' fundamental information, including gender, age, degree, working life, marital status, credit level. 3) loan request history, including the number of loan application, success funding ratio. A list of all the control variables and explanations used in our study are detailed in Table 2.

4.2.3. Independent variables

We extract three central route features (*Readability, Completeness, Sentiment*) and two peripheral route features (*Language intensity, The number of certificates*) from borrowers' voluntary information based on ELM.

Readability: Previous study in P2P lending has included readability of the loan description (i.e., average word and sentence length) as control variable in English context (Pope & Sydnor, 2011). Considering the data in this study is Chinese context, and we cannot measure the readability by calculating the length of words, so we measure the readability by the average length of sentence in the description, which is calculated by dividing the number of words in the loan description by the number of punctuations at the end of a sentence.

Table 1
Date source (as of August 2015 since its inception in 2010).

Platform	Loan listings	“Credit_auth” loan	Sample size
Renrendai	590,000	467,153	5000

Notes: “Credit_auth” loan represents the loan with the type of credit authentication.

Completeness: We measure the completeness by counting the details disclosed in the loan description, the method is consistent with previous study of P2P lending (Michels, 2012). In addition, we further consider borrower's account (Sonenshein et al., 2011) and define more detailed financial information disclosures in our study. Through read approximately 1000 loan descriptions, we develop our inductively derived list of 10 detail disclosures. The definitions of details disclosed in the loan description and example for data coding are defined in Table 3.

Two research assistants, unaware of our hypotheses, and importantly do not know anything about the parameters of the loan listing other than the loan description while coding. They code each disclosure as a dichotomous variable that receives the value of 1 if one specific disclosure was present in a loan description and 0 if otherwise. The sum of all points awarded to a loan description is “Completeness”. The two research assistants read each listing in the data set, independently at first, and then discussed them to determine the unified code for each listing. According to 5000 sampled listings from our data, Fleiss kappa values used to measure the pairs' agreement range from 0.7451 to 0.9260 (see Table 4, which indicate substantial agreement (based on the interpretation guide offered by Landis and Koch (1977)).

Sentiment: In order to study the sentiment analysis for Chinese text, we use the Chinese version of Linguistic Inquiry and Word Count (CLIWC) to execute Chinese word segmentation which is widely used in Chinese sentiment research (Lin, Lin, Wen, & Chu, 2016). LIWC is an accepted state-of-the-art text mining program which was developed in early 1990s to map psychological and linguistic dimensions of written expression, and then it was keeping updated. Composed by a text processing program and the dictionaries, LIWC could calculate a percentage of words falling into 80 psychologically or linguistically meaningful categories. These categories cover several important psychological aspects of an individual, including emotion, cognition, social contact and personal concerns (Zhao, Jiao, Bai, & Zhu, 2016). Regarding sentiment analysis, we use a commonly used Chinese sentiment dictionary - HowNet to calculate the sentiment of loan description. HowNet determines polarity using its own Chinese common sense knowledge base (Yu, Duan, & Cao, 2013) and is extensively used in prior research Yang & Chao, 2015; Fu, Liu, Guo, & Wang, 2013). We measure the percentage of positive and negative words in the loan description respectively, which is calculated by the number of positive or negative words by the total number of words of the loan description.

Language intensity: Consistent with Li and Zhan's study (Li & Zhan, 2011), we count the total number of exclamation marks used in the description, and use this value to measure language intensity.

The number of certificates: On the Renrendai platform, the borrower can voluntarily submit thirteen types of certificates: credit, identification, degree, job, title, income, house, car, marriage, residence, video, mobile phone and blog. We assign “1” if one specific certificate is submitted on the platform and “0” if it isn't. This variable is measured by counting the total number of certificates that are submitted by the borrower.

4.3. Model construction

Using real-word data from a popular P2P lending site, this study investigates the persuasive process of borrowers' controllable voluntary information. We use econometric models to model the data and analyze the data with statistical regression method, following mainstream research studies in analyzing the data (Mild, Waitz, & Wockl, 2015; Lin & Viswanathan, 2016; Zhang & Liu, 2012). Controlling for loan information, borrower's personal information and loan request history, we use funding outcome

Table 2
Description of variables.

Variable Name	Description
Dependent Variable	
Funding success	The final binary status of loan, either successful or failed.
Independent Variables	
Readability	The average length of sentence in the loan description. This is calculated by dividing the number of words in the loan description by the number of punctuations at the end of a sentence.
Completeness	The details disclosed in the loan description.
Sentiment	Positive sentiment: the percentage of positive words in the loan description. Negative sentiment: the percentage of negative words in the loan description.
Language intensity	The total number of exclamation marks (full-width or half-width) used in the description.
The number of certificates	The total number of certificates that are submitted by the borrowers.
Control Variables	
Interest rate	Max interest rate the borrower will accept for his or her loan listing.
Loan amount	The amount the borrower request.
Loan term	The payback period of the loan.
Gender	Indicator variable, taking value of "1" if the borrower's gender is male, "0" otherwise.
Age	Borrower's age, which is in the range of 20–73.
Degree	The indicator of the borrower's degree takes on values between "1" and "3". We take "1" for college degree or below, "2" for bachelor's degree, "3" for graduate degree or above.
Marital status	A series of dummy variables indicating the marital status of the borrower (Marital statusX), where X = 0 (married—this is the baseline and not included in regressions), 1 (single), and 2 (divorced).
Working life	The indicator of the borrower's working life takes on values between "1" and "4". We take "1" for the working life less than one year, "2" for the working life between one year and three years, "3" for the working life between three years and five years, and "4" for working life more than five year.
Credit level	Levels range from AA (best quality) to HR (worst quality). We assign credit level an integer value ranging from 1 to 7, with 7 reflecting the worst credit grade (HR).
Request time	The number of requests previously submitted by the borrower.
Success funding ratio	The percentage time of listing that has been successfully funded. This is calculated by dividing the number of loan requests which were successfully funded by the number of loan application.

Table 3
Definitions of details disclosed in the loan description and example for data coding.

Detail	Definition	Example
1.Explanation (Elsbach, 1994; Sonenshein et al., 2011)	The borrower explains the deviant act, offering an explanation for a past problem.	"因年前家中添加了很多家电以及交各类保险等费用开支超支,导致年后想购车手里流动资金周转有点困难, 特此申请贷款。希望大家能够多多支持。ID:161802)"
2.Acknowledgment (Elsbach, 1994; Sonenshein et al., 2011)	The borrower admits the deviant act and acknowledges that she/he did something wrong in the past or made a mistake.	"因自己生意操作失误, 急需20,000 周转" (ID:228251)
3.Denial (Elsbach, 1994; Sonenshein et al., 2011)	The borrower refutes the deviant act, denying or refutes something about past history.	" 借款用于房屋装修, 月收入在4,000, 住房公积金1,750月, 增量补贴2,000 月, 年终奖5-10 万, 有住房一套, 之前有信用卡逾期(因是爱人使用, 本人不清楚, 但已还款并销户)" (ID:389865)
4.Loan purpose (Michels, 2012)	The borrower states the intended use of the proceeds of the loan.	" 母亲由糖尿病引起白内障, 需尽快手术治疗！本人系县级高中学校在岗在编教师, 收入稳定, 诚信为本, 按月还款, 绝不拖欠!" (ID:5064)
5.Fixed income (Michels, 2012)	The borrower illustrates a specific monthly or yearly income number in the description.	"本人在一家国企上班, 每月稳定收入3,500 到5,000, 借款用来投资开店创业, 有足够的还款能力, 并且信用良好, 每月按时还款不是问题" (ID:449769)
6.Part-time income (Michels, 2012)	The borrower illustrates his part-time job or income in the description.	" 我是国有企业职工, 家中房屋装修需要资金周转, 所以向人人贷平台借款。本人月工资4,500元左右, 另外家中有小超市月收入2,500元, 还款无压力, 请大家支持, 谢谢。" (ID:301413)
7.Family members' income (Michels, 2012)	The borrower illustrates his family members' income in the description.	"有点急, 宾馆已开业, 还有部分尾款没有付。本人在国企上班, 月薪3,000 元以上, 妻子在地税局上班, 月薪4,000元。宾馆开业后, 平均每天收入在800 元, 本人有住房, 有汽车, 无按揭。" (ID:76505)
8.Borrower's occupation (This paper)	The borrower illustrates his occupation in the description.	" 本人是一名国企职员, 工作较稳定, 近期需要资金周转, 感谢各位。" (ID:449365)
9.Fixed assets (This paper)	The borrower illustrates personal or family fixed assets in the description, such as car, house.	" 借款用于扩大投资; 目前总设备资产200 万元; 主要收入为生产经营所得(每月纯利润3-5 万元); 现扩大生产需二次投入约50 万元; " (ID:396503)
10.Deposit (This paper)	The borrower illustrates personal or family deposit in the description, such as bank deposits, financial product.	" 借款用于购房, 用工资及茶叶生意的利润还款, 信用记录良好, 资产21万。建设银行不动存款3.8 万, 理财产品4.1 万, 个人现金5万, 别人欠款8万。" (ID:374101)

(binary variable) as the dependent variable. The features extracted from borrower's voluntary information are tested as determinants. To investigate the effects of borrowers' voluntary information on funding success, logistic regression is employed to test. This is because normal regression does not allow a dependent variable to be binary. Logistic regression with funding outcome as the dependent variable has been widely used in previous literature (Feng et al., 2015; Pope & Sydnor, 2011; Puro et al., 2010).

We test three hypotheses detailed in Section 3.2 using two regression models. Model 1 examines Hypotheses 1 and Hypotheses 2, which test the influence of three central route features (*Readability, Completeness, and Sentiment*) and two peripheral route features (*Language intensity, The number of certificates*) identified from borrowers' voluntary information on funding success. Model 1 is as following:

$$
\begin{aligned}
P(FundingOutcome = 1) = {} & \beta_0 + \beta_1 Readability + \beta_2 Completeness + \beta_3 Sentiment \\
& + \beta_4 Language\ intensity + \beta_5 The\ number\ of\ certificates \\
& + \beta_6 Controls + \varepsilon.
\end{aligned}
\tag{1}
$$

The variables introduced in this model are three central route features (*Readability, Completeness, Sentiment*) and two peripheral route features (*Language intensity, The number of certificates*). The "Controls" on the right side of Model 1 contains nearly all of variables what lender knows about a borrower (for specific control variables, see Table 2.

In contrast, Model 2 tests the interaction effect between *Completeness* and *The number of certificates*. Based on model 1, we additionally include a full set of interaction items between the three central route features and two peripheral route features. Model 2 is as following:

$$
\begin{aligned}
P(Funding\ Outcome = 1) = {} & \beta_0 + \beta_1 Readability + \beta_2 Completeness + \beta_3 Sentiment \\
& + \beta_4 Language\ intensity + \beta_5 The\ number\ of\ certificates \\
& + \beta_6 Completeness{*}The\ number\ of\ certificates \\
& + \beta_7 Other\ controls + \varepsilon.
\end{aligned}
\tag{2}
$$

The "Other controls" on the right side of Model 2 not only includes the "Controls" previously identified in model 1, but also contains a full set of interaction items between the three central route features and two peripheral route features except the interaction item between *Completeness* and *The number of certificates*. The variables *Loan amount* is logistically transformed before included in the regression model because of the skewness of data, which is consistent with previous study (Mild et al., 2015). This applies to all models in this study.

5. Results

5.1. Descriptive statistics

Descriptive statistics for the variables used in our study are presented below in Table 5. The average interest rate borrowers will accept for the loan listing is 13.4%. Borrowers have an average goal of 46,591 RMB. The average loan term is almost 15 months. A typical borrower submits one loan request and has only 5.7% success funding rate. The results show that the loan descriptions have a mean sentence length of 11 words, and a typical borrower submits 2 certificates.

Notes: Table 5 presents descriptive statistics for 5000 sample loan listings posted on Renrendai. "General personal information", "loan information" and "loan history" categories provide information that is obtained directly from variables provided by Renrendai. The "Features extracted from borrower's voluntary information" category provides related information extracted from the borrower's loan description and the number of certificates that the borrower posts.

5.2. Empirically results and discussions

We analyze correlation coefficients for all variables used in our analysis, where the correlation coefficients of key variables are given in Table 6. As a test for multicollinearity, Table 7 reports the variance inflation factors (VIFs) of these variables. All VIFs are below the conventional cutoff of 10 (Hair, Anderson, Tatham, Black, 2006), which suggests that multicollinearity problems don't arise.

Table 8 reports the regression results of the tests of H1–H3 based on models described in Section 4.3. Column (1) displays the result of model not only control all variables detailed in Table 2, but also control *Readability* of loan description which is previously studied (Pope & Sydnor, 2011) as control variable. Column (2) test the incremental influence of four newly variables (*Completeness, Sentiment, Language intensity, The number of certificates*) identified from voluntary information on funding success while controlling for all the variables contained in Column (1) (detailed in H1 and H2). Column (3) differs from Column (2) by including interaction item of *Completeness* and *The number of certificates*, which reports

Table 4
Pairs' agreement and the Fleiss kappa values.

	Coders' agreement rate (%)	Fleiss Kappa	Z	Prob > Z	Interpretation of Kappa[a]
Explanation	88.54	0.7651	54.19	0	substantial
Acknowledgment	88.06	0.7549	53.49	0	substantial
Denial	89.58	0.7870	55.69	0	substantial
Occupation	90.80	0.8125	57.47	0	substantial
Loan purpose	96.36	0.9260	65.51	0	almost perfect
Fixed income	91.66	0.8298	58.70	0	substantial
Part-time income	88.72	0.7688	54.45	0	substantial
family member's income	90.84	0.8134	57.54	0	substantial
Fixed assets	87.60	0.7451	52.84	0	substantial
Deposit	94.10	0.8808	62.34	0	substantial

[a] Based on Landis and Koch (1977).

Table 5
Descriptive Statistics for 5000 data sample of Renrendai.

Variable Name	Mean	Std. Dev.	Min	Max
Loan information				
Interest rate	0.134	0.028	0.030	0.244
Loan amount	46,591.280	77,803.700	2000	1,000,000
Loan term	14.951	9.004	3	36
General personal information				
Gender	0.859	0.348	0	1
Age	32.389	6.945	20	73
Degree	1.302	0.508	1	3
Marital status	0.486	0.573	0	3
Working life	2.573	1.031	1	4
Credit level	6.684	0.913	1	7
Loan history				
Request time	2.145	2.660	0	72
Success funding ratio	0.057	0.161	0	0.952
Features extracted from borrower's voluntary information				
Readability	10.757	10.997	0.991	155
Completeness	2.156	1.180	0	7
Positive sentiment	0.102	0.089	0	0.727
Negative sentiment	0.014	0.026	0	0.196
Language intensity	0.338	0.929	0	6
The number of certificates	1.665	1.865	0	12

the regression result of the test of H3. Column (4) further tests the interaction effect of *Completeness* and *The number of certificates* after controlling extensively for other five interaction items between central route features and peripheral route features.

We first examine the variables have been already identified in previous literature. As seen from Column (1) of Table 8, interest rate, loan amount and loan term are significantly associated with funding success. The higher loan amount a borrower request, the less likely his/her loan listing will be funded. This is consistent with finding of previous study (Puro et al., 2010). However, counter intuitively, interest rate is negatively associated with funding success, and loan term is positively associated with funding success. Such findings run counter to previous studies (Puro et al., 2010; Lin & Viswanathan, 2016). We then randomly extract another ten sets of data with 5000 loan listings in each data set, however, we obtain the same result. So we suppose that lenders on Renrendai have adverse thinking, they might be less interested in loans with higher interest rate and short-term, and they seek long-term and stable investment. In order to test our assumption, we conduct a comparative study with Paipaidai, another leading P2P lending platform in China. We crawl 150,000 loan listings from Paipaidai as

Table 7
Variance inflation factors (VIFs) of the variables.

Variable	VIF	1/VIF
Credit level	1.60	0.6244
The number of certificates	1.54	0.6482
Success funding ratio	1.51	0.6634
Age	1.39	0.7182
Request time	1.35	0.7418
Working life	1.30	0.7706
Marital status	1.13	0.8836
Loan amount	1.11	0.8989
Completeness	1.11	0.8990
Positive sentiment	1.11	0.9006
Loan term	1.09	0.9136
Interest rate	1.07	0.9334
Language intensity	1.06	0.9440
Negative sentiment	1.06	0.9442
Degree	1.06	0.9478
Completeness * The number of certificates	1.04	0.9621
Readability	1.03	0.9699
Mean VIF	1.20	

Notes: All VIFs are below the conventional cutoff of 10 (Hair et al., 2006).

of January 2016 since December 2015. Controlling for borrower's credit level, a variable which proved to have a significant impact on funding success in previous studies, we employ logistic regression model with funding outcome as the dependent variable. Our empirical model is as following:

$$P(FundingOutcome=1) = \beta_0+\beta_1 Interest\ rate+\beta_2 Loan\ amount + \beta_3 Loan\ term+\beta_4 Credit\ level+\varepsilon. \quad (3)$$

The comparative descriptive statistics for the variables used in the above model of the two leading P2P lending platform of China are presented in Table 9. The experimental results show the interest rate the borrower will accept for his or her loan on Renrendai range from 0.03 to 0.24, while the value on Paipaidai range from 0.07 to 0.36. This suggest that the average interest rate the borrower will accept for his or her loan on Renrendai is lower than that on Paipaidai. Moreover, we find the average loan amount the borrower request on Renrendai is higher than on Paipaidai. The average loan term of the loan listing on Renrendai is also longer than on Paipaidai. This suggests that borrowers on Renrendai are generally request long-term loan with lower interest rate. To some extent, borrowers on Renrendai seems more stable and lower risk

Table 6
Pearson correlations between all variables.

	Funding success	Interest rate	Loan amount	Loan term	Credit level	Request time	Success funding ratio	Read- ability	Comp- lete- ness	Posi- senti	Nega- senti	Language intensity	The- numb- er of certificates	inter- action item
Funding success	1													
Interest rate	−0.217	1												
Loan term	−0.106	0.123	0.162	1										
Credit level	−0.322	0.063	−0.052	0.165	1									
Request time	0.191	−0.021	−0.071	−0.12	−0.385	1								
Success funding ratio	0.264	−0.061	−0.032	−0.159	−0.468	0.443	1							
Readability	−0.079	0.051	−0.005	−0.02	0.025	0.005	−0.025	1						
Completeness	0.064	−0.062	0.047	0.073	0.068	−0.077	−0.065	−0.004	1					
Posi-sentiment	−0.011	0.024	−0.053	−0.028	0.019	0.033	0.019	0.044	−0.236	1				
Nega-sentiment	−0.060	0.001	−0.001	0.0075	0.0370	−0.024	−0.027	0.040	−0.130	0.205	1			
Language intensity	0.011	0.074	−0.033	−0.09	−0.082	0.095	0.108	−0.119	−0.077	0.081	1			
The number of certificates	0.584	−0.154	−0.076	−0.134	−0.482	0.323	0.407	−0.057	0.059	−0.004	0.063	1		
interaction item	−0.043	0.019	−0.021	0.015	0.108	−0.112	−0.108	−0.002	0.061	0.001	−0.029	0.005	1	

Notes: Interaction item refers to *Completeness* * *The number of certificates*. Pearson correlations between all variables used in our analysis below 0.6.

Table 8
Logistic regression results for the influence of voluntary information on funding success.

	(1)	(2)	(3)	(4)
Interest rate	−17.97***	−15.66***	−16.01***	−16.31***
	(−12.31)	(−9.24)	(−9.30)	(−9.39)
Loan amount (log)	−0.776***	−0.935***	−0.948***	−0.952***
	(−20.07)	(−19.74)	(−19.84)	(−19.88)
Loan term	0.0341***	0.0392***	0.0395***	0.0396***
	(7.92)	(7.79)	(7.80)	(7.80)
Gender (dummy)	0.192*	0.113	0.122	0.120
	(1.92)	(0.99)	(1.06)	(1.04)
Age	0.0354***	0.0244***	0.0231***	0.0236***
	(5.57)	(3.25)	(3.06)	(3.11)
Degree	0.539***	0.295***	0.311***	0.312***
	(7.48)	(3.47)	(3.64)	(3.64)
Working life	0.368***	0.304***	0.301***	0.301***
	(9.67)	(6.78)	(6.67)	(6.65)
Marital status1 (dummy)	−0.401***	−0.244* *	−0.241* *	−0.237* *
	(−4.92)	(−2.55)	(−2.50)	(−2.46)
Marital status2 (dummy)	−0.598***	−0.389*	−0.376*	−0.376*
	(−3.33)	(−1.82)	(−1.74)	(−1.74)
Credit level	−1.647***	−0.972***	−0.951***	−0.956***
	(−14.18)	(−8.68)	(-8.42)	(−8.43)
Request time	0.142***	0.008	0.009	0.008
	(6.07)	(0.32)	(0.39)	(0.34)
Success funding ratio	2.102***	0.111	0.0416	0.0224
	(6.31)	(0.30)	(0.11)	(0.06)
Readability	−0.0152***	−0.0138***	−0.0133***	−0.0104* *
	(−4.41)	(−3.55)	(−3.36)	(−2.04)
Completeness		0.138***	0.0530	0.0577
		(3.72)	(1.35)	(1.44)
Positive Sentiment		0.849*	0.906*	1.308* *
		(1.88)	(1.93)	(2.39)
Negative Sentiment		−4.527***	−4.404* *	−4.582* *
		(-2.58)	(-2.42)	(-2.43)
Language intensity		−0.140***	−0.146***	−0.181***
		(-2.79)	(-2.83)	(-3.01)
The number of certificates		1.110***	1.149***	1.151***
		(26.23)	(26.33)	(26.24)
Completeness * The number of certificates			−0.188***	−0.186***
			(-5.97)	(-5.89)
Readability * The number of certificates				0.006
				(1.31)
Positive Sentiment *				0.0168
The number of certificates				(0.45)
Negative Sentiment *				0.175
The number of certificates				(1.07)
Readability * Language				−0.003
intensity				(-0.96)
Completeness * Language				−0.002
intensity				(-0.12)
Positive sentiment *				0.616
Language intensity				(1.48)
Negative sentiment *				−0.462
Language intensity				(-0.36)
_cons	17.93***	13.81***	13.99***	14.02***
	(18.49)	(13.65)	(13.75)	(13.72)
R^2	0.2784	0.4503	0.4552	0.4564
Observations	5000	5000	5000	5000

Notes: Each column in Table 8 is a separate linear regression with funding outcome (binary variable) as the dependent variable. Column (1) replays the result of baseline model which control for all variables detailed in Table 2 and *Readability* of loan description which is previously studied (Pope & Sydnor, 2011) as control variable. Column (2) tests the incremental influence of four newly identified variables (*Completeness, Sentiment, Language intensity, The number of certificates*) on funding success while controlling for all variables contained in Column (1). Column (3) differs from Column (2) by including interaction item of *Completeness* and *The number of certificates*. Column (4) further tests this interaction effect of *Completeness* and *The number of certificates* after controlling extensively for other five interaction items.
t statistics in parentheses.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

compared with borrowers on Paipaidai.

Table 10 reports comparative regression results of Renrendai and Paipaidai. Panel A and B present the results using data from Renrendai and PaiPaidai, respectively. The empirically results of Panel B is consistent with the study of Feng et al. (2015) who use the data of Paipaidai. The experimental results show that the coefficients of interest rate, loan amount and loan term of the two P2P lending platforms are totally opposite, which indicates that lenders on Paipaidai seek short-term investment with high return, while lenders on Renrendai have adverse thinking and they seek long-term and stable investment. We further randomly extract another three sets of data in two lending platforms respectively, and the results of empirical analysis are consistent.

As seen from Column (2) of Table 8, all the features extracted

Table 9
Descriptive statistics for the variables on Renrendai or Paipaidai respectively.

Variable	Renrendai				Paipaidai			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Interest rate	0.13	0.03	0.03	0.24	0.18	0.09	0.07	0.36
Loan amount	46,591	77,803	2000	1,000,000	2760	8722	100	390,000
Loan term	14.95	9.00	3	36	11.42	2.21	1	24
Credit level	6.68	0.91	1	7	5.99	2.05	1	8

Notes: Credit level on Renrendai range from AA (best quality) to HR (worst quality). We assign credit level an integer value ranging from 1 to 7, with 7 reflecting the worst credit grade (HR), while credit level on Paipaidai range from AAA (best quality) to F (worst quality). We assign credit level an integer value ranging from 1 to 8, with 8 reflecting the worst credit grade (F).

Table 10
Comparatively regression results of Renrendai and PaiPaidai.

	Panel A Renrendai	Panel B PaiPaidai
Interest rate	-17.39^{***}	33.58^{***}
	(-12.97)	(26.74)
Loan amount (log)	-0.601^{***}	1.055^{***}
	(-17.78)	(-17.78)
Loan term	0.0242^{***}	-0.0941^{***}
	(6.13)	(-4.22)
Credit level	-1.946^{***}	-0.993^{***}
	(-16.86)	(-28.19)
_cons	21.26^{***}	-7.245^{***}
	(23.01)	(-14.40)
Observations	5000	5000

Notes: Each column in Table 10 is a separate linear regression with funding outcome (binary variable) as the dependent variable. Panel A presents the result using data from Renrendai, and Panel B presents the result using data from PaiPaidai.
t statistics in parentheses.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

from borrowers' voluntary information based on the ELM model as it relates to our hypotheses are significant. The results suggest that the persuasion process accomplish via both central route and peripheral route. Lenders pursuing the high elaboration route may consider factors that are not only central cues (*Readability, Completeness, Sentiment*) but also peripheral cues (*Language intensity, The number of certificates*). As seen from Column (3) of Table 8, there is a negative interaction effect between *Completeness* and *The number of certificates*. These results hold consistent when we further control for other five interaction items between central route features and peripheral route features, as shown in the Column (4) of Table 8. The specific impacts are discussed in details below.

H1(a) supported: H1(a) hypothesize that the use of longer sentences associated with a decreased likelihood of funding success. As seen from Column (1) and Column (2) of Table 8, we find *Readability* is significantly and negatively associated with funding success. Specifically, if the borrower use longer sentence (lower readability) in the loan description, he/she is less likely to be successfully funded. Thus, H1(a) is supported. The marginal effect from the logistic regression implies a slightly smaller but still economically meaningful difference of 0.01 points.

H1(b) supported: H1(b) hypothesize that the amount of detail disclosures in a loan description positively associated with funding success. Column (2) of Table 8 shows that *Completeness* is significantly and positively associated with funding success, suggesting that borrower who disclosure more details in his or her loan description is more likely to be successfully funded. Thus, H1(b) is also supported. The marginal effect from the logistic regression implies that all else equal listings with more detail disclosures in a loan description are 0.14 points more likely to fund.

H1(c) partially supported: As show in Column (2) of Table 8, *positive sentiment* of loan description positively associated with funding success, it is consistent with previous findings which showed that sharing positive emotions elicit positive feedback from others (Sheldon & Lyubomirsky, 2006) and facilitate positive social interactions (Augustine et al., 2011), suggesting that lenders in P2P lending prefer the optimism expressed in loan description. This result is consistent with our hypothesis. However, we find *negative sentiment* of loan description is significant negatively correlative with funding success. This result hold consistent when we control for the interaction between *Completeness* and *The number of certificates*, as shown in the column (3) of Table 8. Because we expect that positive sentiment and negative sentiment of loan descriptions associated with an increased likelihood of funding success. Thus, H1c is partially supported. This finding contradicts to previous study in fund-raising appeals which showed that negative emotions can evoke "empathy-helping" and have a significant positive effect on self-benefit donation appeals. That is to say, although P2P lending is also a form of fund-raising, "empathy-helping" effect doesn't work in this new context. The reason loan description are not expected to have negative sentiment might be because of the nature of marketing.

H2(a) supported: H2(a) hypothesizes that number of exclamation marks negatively correlated with funding success. As seen from Column (2) of Table 8, we find *Language intensity* (measured by the number of exclamation marks) is significantly and negatively associated with funding success, suggesting that if a borrower use more exclamation marks in his/her loan description, the loan is less likely to be funded. Thus, H2(a) is supported. The marginal effect from the logistic regression implies an economically meaningful difference of 0.14 points.

H2(b) supported: H2(b) hypothesizes that more voluntary certificates associated with an increased likelihood of funding success. Column (2) of Table 8 shows that *The number of certificates* is significantly and positively associated with funding success. It suggests that borrower who submits more certificates on the platform is more likely to be funded. Thus, H2b is supported. The marginal effect from the logistic regression implies that all else equal listings with more certificates are 1.11 points more likely to fund.

H3 supported: H3 hypothesizes that there is a negative interaction effect between *Completeness* and *The number of certificates* on influencing funding success. Column (3) and Column (4) of Table 8 display the results when the interactive effect of *Completeness* and *The number of certificates* is considered. The result of Column (3) shows that the interaction effect is negatively associated with funding success, and it is still statistically significant after we further control other five interaction items. It suggests that when *Completeness* of loan description becomes a more important determinant of persuasion, *The number of certificates* becomes a less significant determinant, and vice versa, Thus, H3 is supported. Table 11 presents a concluding overview of our main empirical results.

Table 11
Summary of hypothesis test results.

Number	Hypothesis	Result	
H1	H1a	The use of longer sentences associated with a decreased likelihood of funding success	Supported
	H1b	The amount of detail disclosures in a loan description positively associated with funding success	Supported
	H1c	Positive sentiment of loan descriptions associated with an increased likelihood of funding success, and sharing negative emotions also positively correlated with funding success	Partially supported
H2	H2a	Number of exclamation mark negatively correlated with funding success	Supported
	H2b	More voluntary certificates associated with an increased likelihood of funding success	Supported
H3		There is a negative interaction effect between *Completeness* and *The number of certificates* on influencing funding success	Supported

Notes: H1 hypothesizes that all argument quality features (*Readability, Completeness, Sentiment*) are influential on funding success through the central route. H2 hypothesizes that all source credibility features (*language intensity, the number of certificates*) have significant impact on funding success through the peripheral route.

5.3. Robustness testing

In order to further verify the robustness of our results, we test our hypotheses using the actual percent funded (funding ratio) as dependent variable. The funding ratio is another way to measure funding success, which has been used in previous literature (Sonenshein et al., 2011). This variable is calculated by dividing funds raised by funds requested. Since funding ratio is discrete, we employ Probit regression to test. The results show similar patterns compared to the model when funding outcome is used as the dependent variable. This confirms that using the binary dependent variable instead of using the actual percent funding did not greatly impact the results. The results of this extended regression are provided in Table 12. As another robustness test of sentiment analysis, we also use another Chinese sentiment dictionary-National Taiwan University Sentiment Dictionary (NTUSD) to measure sentiment and we found consistent results.

6. Conclusion and discussion

In this paper, we draw on the classical dual-processing persuasion theory of Elaboration Likelihood Model (ELM) as the theoretical base to understand the persuasive process of borrowers' controllable voluntary information which can be easily manipulated and is particularly valuable for borrowers to persuade lenders and enhance the likelihood of funding success in P2P lending marketplace. We introduced four persuasive features (*Completeness, Sentiment, Language intensity, The number of certificates*) with central and peripheral cues in voluntary information and proposed three hypotheses. H1 hypothesizes that all argument quality features are influential on funding success through the central route. H2 hypothesizes that all source credibility features have significant impact on funding success through the peripheral route. H3 hypothesizes that there is a negative interaction effect between *Completeness* and *The number of certificates* on influencing funding success. Using a large-scale data set collected from a leading P2P lending platform in China, namely Renrendai, we further conducted a series of empirical test. **We get the following conclusions:**

First, all argument quality features were influential on funding success through the central route. Specifically, borrowers who used longer sentences in loan description were less likely to be successfully funded; Disclosing more details in loan description contributed to loan success; Sentiment of loan description had significant effect on funding success. *Positive sentiment* of loan description positively associated with funding success, whereas *negative sentiment* of loan description was significant negatively correlative with funding success, which was contradictory to the research in fund-raising appeals say using negative emotions can evoke “empathy-helping”. Moreover, all source credibility features had significant impact on funding success through the peripheral route. In particular, borrower who used exclamation mark frequently are more difficult to get to succeed; More certificates a borrower submitted more chance he could get fund, which suggested that lenders employ both central route processed argument quality and peripheral route processed source credibility simultaneously to make funding decisions.

Second, we found a negative interaction effect between *Completeness* and *The number of certificates*. When the completeness of loan description became a more important determinant of persuasion, the number of certificates a borrower submitted became a less significant determinant, and vice versa.

6.1. Theoretical implications

This study has some theoretical implications for the study of P2P lending.

First, this study extracted important features from borrower's voluntary information based on classical persuasion theory of elaboration likelihood model. Although there might be additional influential characteristics that we had not yet identified, the ELM model provides us with a well-grounded foundation for the identification of possible characteristics, including sentiment, language intensity, and the number of certificates which were ignored in previous studies.

Second, this study provided theoretical understanding the persuasive process of borrower's controllable voluntary information. We found that the persuasion of borrowers' voluntary information can be accomplished via two distinct routes, suggesting that not only central cues (*Readability, Completeness, Negative sentiment*) but also peripheral cues (*Language intensity, The number of certificates*) have effect on lenders' decision making. We also discovered that in P2P lending marketplace, there exists a negative interaction effect between one feature of the central route (*Completeness*) and one feature of the peripheral route (*The number of certificates*).

6.2. Practical application

This study has several implications for P2P platform, borrowers and lenders.

For the P2P platform, it is important to understand the role of voluntary information in improving funding success, so that practitioners and policy makers can make strategic decisions to facilitate online lending. For example, the lending platform can request minimum words of the borrower's loan description to promote more details disclosed by them.

For borrowers, this study provides borrowers with insights for increasing the likelihood of funding success. For example, borrows can express positive emotions or disclose as many details as they can in free format loan description to enhance the perceived argument quality, and be cautions to avoid negative emotions. Borrows also can change their perceived source credibility by providing more certificates.

Table 12
Probit regression when funding ratio is used as the dependent variable.

	(1)	(2)	(3)	(4)
Interest rate	−8.449*** (-10.74)	−5.673*** (-5.92)	−5.739*** (-5.94)	−5.795*** (-5.98)
Loan amount (log)	−0.497*** (-22.72)	−0.622*** (-21.76)	−0.626*** (-21.80)	−0.628*** (-21.81)
Loan term	0.0174*** (6.93)	0.0172*** (5.71)	0.0173*** (5.73)	0.0172*** (5.70)
Gender	0.0937 (1.59)	0.0166 (0.24)	0.0206 (0.29)	0.0223 (0.32)
Age	0.0236*** (6.25)	0.0166*** (3.65)	0.0157*** (3.44)	0.0159*** (3.46)
Degree	0.291*** (6.89)	0.0868 (1.71)	0.0873* (1.72)	0.0879* (1.72)
Working life	0.216*** (9.55)	0.151*** (5.52)	0.151*** (5.50)	0.151*** (5.49)
Marital status 1	−0.227*** (-4.71)	−0.133** (-2.27)	−0.130** (-2.23)	−0.129** (-2.20)
Marital status 2	−0.373*** (-3.41)	−0.273** (-2.05)	−0.261* (-1.95)	−0.261* (-1.95)
Credit level	−0.859*** (-16.18)	−0.498*** (-9.03)	−0.497*** (-8.93)	−0.502*** (-8.97)
Request time	0.0732*** (5.77)	−0.0264* (-1.92)	−0.0264** (-1.98)	−0.0278** (-2.00)
Success funding ratio	0.974*** (5.42)	−0.341* (-1.79)	−0.336* (-1.75)	−0.341* (-1.78)
Readability	−0.00743*** (-3.89)	−0.00556** (-2.51)	−0.00537** (-2.40)	−0.00484* (-1.78)
Completeness		0.0524** (2.33)	0.0425* (1.89)	0.0435* (1.92)
Positive Sentiment		0.480* (1.64)	0.482* (1.65)	0.660** (2.00)
Negative Sentiment		−2.787** (-2.52)	−2.655** (-2.35)	−2.824** (-2.44)
Language intensity		−0.0585** (-1.98)	−0.0525* (-1.74)	−0.0667* (-1.88)
The number of certificates		1.868*** (34.01)	1.893*** (34.13)	1.896*** (33.99)
Completeness * The number of certificates			−0.0729*** (-4.85)	−0.0714*** (-4.74)
Readability * The number of certificates				0.00255 (1.10)
Positive sentiment * The number of certificates				0.00239 (0.29)
Negative sentiment * The number of certificates				0.00137 (0.20)
Readability * Language intensity				−0.00135 (-0.75)
Completeness * Language intensity				−0.00217 (-0.25)
Positive sentiment * Language intensity				0.347 (1.37)
Negative sentiment * Language intensity				−0.402 (-0.48)
_cons	9.928*** (20.80)	7.715*** (14.21)	7.781*** (14.23)	7.810*** (14.23)
R^2	0.2779	0.5233	0.5266	0.5273
Observations	5000	5000	5000	5000

Notes: Each column in Table 12 is a separate linear regression with funding ratio as the dependent variable. Column (1) replays the result of baseline model which control for all variables detailed in Table 2 and *Readability* of loan description which is previously studied (Pope & Sydnor, 2011) as control variable. Column (2) tests the incremental influence of four newly identified variables (*Completeness, Sentiment, Language intensity, The number of certificates*) on funding success while controlling for all variables contained in Column (1). Column (3) differs from Column (2) by including interaction item of *Completeness* and *The number of certificates*. Column (4) further tests the interaction effect of *Completeness* and *The number of certificates* after controlling extensively for other five interaction items between central route features and peripheral route features.
t statistics in parentheses.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Similarly, lenders can also assess these characteristics to avoid opportunity costs by identifying loan listings that are more likely to be successfully funded.

7. Limitations and future research

This study is subject to several limitations. **First,** our measure of *Completeness* of loan description is a count of details disclosed in the loan description, however, the specific content of what is revealed in a given disclosure is also likely to be important in determining its effect. **Second,** we conducted our study based on data from one P2P lending platform. Although Renrendai is recognized as a successful and popular P2P lending platform in China, it is just one of many platforms, and it differs from other platforms in a variety of aspects. This limits the generality of our results. It would be interesting if future studies further compare borrowers' persuading strategies and their effects on lenders' funding decisions on different platforms. **Third,** although our data include important information about borrowers, we have no additional information about lenders. Additional research could capture the mental maps of lenders as they evaluate borrower's voluntary information.

This study also provides valuable opportunities for future research. First, some of the limitations described above can be addressed. For example, future studies can focus on extracting specific content of disclosures and study their persuasive effects on funding success in order to get a deeply understanding of the role of borrowers' voluntary information.

Second, further research can investigate the potential differences of voluntary information's persuasive effects on funding success between first-time and repeated loan requests. The first-time loan requests don't contain any borrowing history, this kind of loan requests may has greater information asymmetry than repeated loan requests. For those loan requests with greater information uncertainty, whether lenders may more tend to rely upon borrowers' voluntary information?

Third, having observed that borrowers' voluntary information do impact funding success, natural extension is to examine whether these information can accurately reflect borrowers' real credit. Future research can develop and test hypotheses about the relations between borrowers' voluntary information and loan default.

Fourth, most current research focuses on profit-oriented lending platforms (e.g., prosper.com, lendingclub.com). However, there also have charitable P2P platforms, where borrowers can obtain a loan to be reimbursed without paying interests, such as Kiva. It's an open question to compare P2P lending platforms with different operation models to gain more insights into their similarities and differences.

Last, but not least, researchers in electronic commerce have found that agents are more likely to conduct transactions with parties who are similar to them. When both lenders and borrowers have similar lives, needs, or experiences in P2P lending, whether the preference transaction behavior may still exist? Related research can be conducted when necessary data of lenders become available. We encourage future research to explore these areas and advance our knowledge regarding P2P lending.

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