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# The role of emotion in P2P microfinance funding: A sentiment analysis approach

Supavich (Fone) Pengnate*, Frederick J. Riggins

*Department of Accounting and Information Systems, College of Business, North Dakota State University, Richard H. Barry Hall 246, Dept. 2410, PO Box 6050, Fargo, ND 58108-6050 USA*

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ABSTRACT

Online peer-to-peer (P2P) lending platforms are gaining popularity for providing financing and loans to small and micro entrepreneurs, particularly in developing parts of the world. This study investigates how individual borrowers in the P2P platform can improve the chance of their loans being funded. Based on theories related to cognitive and affective aspects of information processing, a set of loan description features is identified and evaluated based on their influence on funding success. Sentiment analysis, a text mining technique, is used to analyze and extract emotions from an unstructured P2P loan data set. The results reveal valuable information in the P2P lending context such that, in the absence of market interest rates, borrowers can improve the chance of funding success by improving the textual quality of their loan descriptions in terms of readability and linguistic correctness. In addition, borrowers can make the loan descriptions more attractive to potential lenders by expressing certain emotions in the descriptions.

## 1. Introduction

Microfinance has been recognized as a key development strategy for providing financial support to individuals who are not served by traditional financial services (e.g., Mushtaq & Bruneau, 2019). Ledgerwood (2000) defines microfinance as “the provision of financial services to poor or low-income clients, including consumers and the self-employed.” A 2019 study showed that at the end of 2018 there were more than 900 microfinance institutions (MFIs) worldwide providing loans to more than 139 million borrowers (Convergences, 2019). As the microfinance industry matures, MFIs have moved toward a dual mission of financial performance, also referred to as sustainability, and social performance, often measured by the extent of their outreach. During the 1990s there was a drive toward making MFIs more financially self-sustainable rather than relying only on donors (Morduch, 1999). However, this trend led many MFIs to favor financial performance goals over social performance goals and to neglect clientele with the greatest need. More recently, social performance has increased in importance as the industry adopts new tools and methodologies that can help MFIs achieve social performance goals by extending financial services to the poorest individuals while still maintaining economic sustainability (Bédécarrats & Marconi, 2009; Copestake, 2007). Some of these new tools and methodologies include employing sophisticated information and communications technologies (ICTs) and investigating new business models enabled by ICTs.

Over the past decade, the provision of loans to microentrepreneurs has substantially increased due to the rapid adoption of online channels in various parts of the world and the proliferation of peer-to-peer (P2P) applications. In P2P microfinance lending, the lending platform provides microfinance services that match lenders with borrowers without the use of an official financial institution as an intermediary (Investopedia, 2018). The major driver of the proliferation of P2P lending is the advanced use of web technologies and the development of P2P lending platforms on the Internet, which has provided new opportunities for microentrepreneurs in developing countries to raise funds. Using an online P2P platform, borrowers can post pictures and provide detailed information about an individual or a group of borrowers requesting a loan. With this information available online individual lenders from all over the world can view profiles of borrowers and decide which projects to fund.

However, while the Internet has provided a new dimension to the establishment of the relationship between P2P borrowers and lenders, it has also created a number of challenges in online P2P lending platforms, including unanswered questions regarding the motivation for individual lenders to fund loans. In general, many P2P platforms do not pay interest to lenders. Therefore, several other uncertainties and risks are associated with a lender’s decision to fund some projects and not others (Zohir & Matin, 2004). In addition, there are concerns that

* Corresponding author.
*E-mail addresses:* fone.pengnate@ndsu.edu (S.F. Pengnate), fred.riggins@ndsu.edu (F.J. Riggins).

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online P2P microfinance lending may include certain inefficiencies due to incomplete information such as identification bias, which is partly due to the information asymmetries between the individual lender and loan recipient (Riggins & Weber, 2017). Furthermore, in the absence of receiving interest, emotion may play a key role in the lending decision (e.g., Black, 2009).

Consequently, the major objective of this study is to explore the cognitive and affective characteristics of P2P loans especially linguistic features of loan descriptions that influence funding success. Although previous studies have explored loan characteristics that influence funding success (e.g., Epstein & Yuthas, 2011; Heller & Badding, 2012; Riggins & Weber, 2017), several areas, particularly those related to loan descriptions, have not been thoroughly investigated. Therefore, we aim to fill this gap by examining features of P2P loan descriptions based on several frameworks related to cognitive and affective information processing (e.g., Hilgard, 1980; McAllister, 1995). The results of this study contribute to the literature on P2P lending platforms by increasing our understanding of the importance of textual information in the online P2P lending context and providing practical guidance to micro-entrepreneurs and to P2P loan platform managers seeking to understand ways to improve P2P lending success.

## 2. Literature review and hypothesis development

### 2.1. Online P2P lending

Several commercial and non-commercial online P2P lending platforms are currently available including SoFi, LendingClub, LendingTree, and Kiva. In general, these platforms employ similar lending procedures to provide P2P lending services. Potential borrowers and lenders can create an account through the platform's website prior to posting or funding a loan project. Borrowers deemed creditworthy are invited to create their loan listings, which generally include information about the loan such as free-format descriptions of the purpose of the loan, loan amount requested, interest rate if any, and personal information about the borrower. Lenders, who are typically geographically distant from the borrower, can then make a lending decision for the entire loan or a portion of a loan based on the information provided in the listing. Depending on the P2P platform a loan can be funded by individual lenders who do not collect interest or by field partners who collect interest on the funds.

Once a listing of a loan is closed, either when the loan is fully funded or when the listing expires, funds are disbursed to the borrower either directly transferred from the lender's account to the borrower's account or through an intermediary. In general, if the funds are transferred through an intermediary, they will charge a service fee to be collected from the borrower. Once the repayment period begins the borrower's repayments will be transferred from the borrower's account to the lender's account. If the repayment is overdue beyond a predetermined period, the borrower's default will be recorded and a debt collection process may be initiated.

In this study, we set the scope of our investigation on the philanthropic aspects, which do not explicitly consider monetary benefits such as interest payments to lenders and fund transfer fees collected by P2P lending platforms. Given that previous studies have widely examined key loan features that influence the success of P2P lending, we seek to improve the understanding of how unstructured textual information influences the desired outcomes of P2P lending, which has not been well studied in the literature. To do so, we examine online P2P loans listed through Kiva.org, which is one of the most popular non-profit P2P lending platforms that provides international services to developing countries to help alleviate poverty.

### 2.2. P2P loan descriptions: Textual quality

As in many other areas in the online environment, risk is inherent in P2P lending, especially in the non-profit context. Previous studies in P2P lending have provided evidence that trust—in borrowers and in the intermediary—is a key component of P2P lending success (e.g., Chen, Lai, & Lin, 2014; Sun, Wang, Yin, & Zhang, 2015). Specifically, we focus on loan features that create interpersonal trust (McKnight, Cummings, & Chervany, 1998), which refers to beliefs about a trustee's competence or ability to carry out his or her obligations. In our context, interpersonal trust is typically developed by the lender through the features or attributes of the P2P loan and is based on the rational knowledge that a borrower will use the funds as promised.

Previous studies in several domains have provided empirical evidence of the importance of textual information in influencing critical factors in readers' responses, such as trust, emotions, and behaviors (e.g., Karimov, Brengman, & Van Hove, 2011; Liao, Palvia, & Lin, 2006; Yoon & Occeña, 2015), which lead to the success of the platform (e.g., online review community or online business). In the P2P lending context, previous studies have reported that loan description can impact the level of identification bias in the relationship between borrowers and lenders (e.g., Riggins & Weber, 2017) and it appears to be one of the most important factors in funding success (e.g., Heller & Badding, 2012). Consequently, using the lens of cognitive and affective trust formation (McAllister, 1995), this study identifies and investigates cognitive and affective features of P2P loan descriptions that may influence P2P loan success.

It has long been known that the interpretation of textual information, especially in a computer-mediated communication system, is subject to information overload—a state in which an individual becomes unable to fully comprehend the given information (Hiltz & Turoff, 1985). Therefore, specific to our context, potential P2P lenders face several cognitive challenges when examining a large quantity of unstructured loan descriptions. In addition to the overwhelming amount of information, as with other unstructured textual information, loan descriptions can be written arbitrarily. Therefore, the descriptions may be difficult to analyze and may provide misinformation and contain unclear messages and mistakes (e.g., Bridges, 2019), such that comprehending the content may require a higher level of cognitive effort from potential lenders (e.g., Piolat, Roussey, Olive, & Amada, 2004).

As mentioned previously, we consider the cognitive and affective aspects of P2P loan description features to shed light on how the information contributes to funding success. Regarding the cognitive aspect, McKnight et al. (1998) suggested that in the absence of personal interactions, interpersonal trust can be established through cognitive cues. Therefore, in our context, the cognitive features of P2P loans (e.g., purpose, amount, and the borrower's personal information) may be used as cognitive cues to develop the relationship between borrowers and lenders; that is, we propose that in addition to the structured financial quantitative attributes of P2P loans, loan descriptions can provide cognitive cues to lenders who are considering supporting the loans. Lenders can critically evaluate loans by scrutinizing loan descriptions prior to forming an informed judgement. Consequently, in the cognitive aspect, we evaluate the textual quality of loan descriptions based on four major qualities of textual data as proposed by Wang and Strong (1996): intrinsic quality, contextual quality, representational quality, and accessibility quality. Intrinsic quality refers to the believability and reputation of the data, contextual quality includes the timeliness and accuracy of the data, representational quality emphasizes aspects related to the format (e.g., concise and consistent representation) and meaning (e.g., interpretability and ease of understanding), and accessibility quality concerns the availability of the data for authorized users. Like traditional financial loans, the P2P lending platform typically requires identity verification of the borrowers to ensure that the borrowers are actual people and the loan information is valid before making the loans available for lenders on their website. Therefore, the intrinsic and accessibility quality dimensions are maintained by the P2P lending platforms, while our investigation focuses on the contextual and representational qualities of the loan descriptions since they are typically determined by the lender's evaluation.

Previous studies have examined the contextual text quality features and provided evidence that they can generate a positive influence on readers' perceptions. In addition, according to the literature, while the interpretation of loan descriptions is subjective and dependent on the readers' preferences and individual differences, several studies have reported that the length of text appears to be a key indicator of the depth of the textual information. For example, Mudambi and Schuff (2010) suggested that lengthier reviews increase the helpfulness of the review and that the effect was stronger for search goods than for experience goods. Baek, Ahn, and Choi (2012) reported that lengthy reviews were perceived as more helpful by online customers, a finding that has been echoed by Lee, Trimi, and Yang (2018), which suggests that lengthy reviews influence customers' purchase decisions. Salehan and Kim (2016) also reported that review length positively influences the readership and helpfulness of product reviews.

Specifically, in a recent study in microfinance, Dorfleitner et al. (2016) confirmed that soft information in loan descriptions, especially description length, mitigates information asymmetry between lenders and borrowers and thus can be used as a predictive factor for loan default probability. While previous studies have attested to the importance of text length, this factor has rarely been examined in the online P2P lending context. Therefore, using the insights of previous literature to investigate how description length is related to P2P funding success, we propose that lenders in P2P lending perceive that requests with a longer loan description provide more information, that they are more in-depth and complete, which subsequently influences funding success. Therefore, we propose:

**H1.** *The length of a loan description is positively correlated with funding success.*

In addition to the length of text, studies in text quality have suggested various dimensions of textual information that can influence readers' perceptions. For example, in the online review text literature, Liu et al. (Liu, Cao, Lin, Huang, & Zhou, 2007) reported that informativeness, readability, and subjectiveness significantly influenced the readers' perceptions of text quality. In addition, Ghose and Ipeirotis (2011) found that linguistic correctness significantly influenced perceived usefulness and product sales.

Among the diverse features of textual information, in this study we focus on two text quality features that have been reported as key factors in influencing readers' cognitive processing, perceptions and behaviors—namely, readability and linguistic correctness. In our context, readability refers to the level of ease of understanding of a loan description, which can be measured by readability indices such as the Gunning Fog index (Gunning, 1969) and the Coleman-Liau index (Coleman & Liau, 1975). However, it is important to note that Gunning Fog and Coleman-Liau readability indices indicate the education level required to understand the text, therefore a higher index value indicates that the text is more difficult to understand.

Theoretically, according to cognitive fit theory (Vessey, 1991) and cognitive load theory (Sweller, 1994), readability is considered as a feature of the textual information that can directly determine the level of cognitive effort required of the readers to understand the text. Cognitive effort may reflect the opportunity cost related to not being able to allocate cognitive resources to alternative options that are potentially more rewarding (e.g., a loan description that is easier to read), and hence can impact perceptions and attitudes of the readers (e.g., Hong, Thong, & Tam, 2004; Kurzban, Duckworth, Kable, & Myers, 2013).

In the text analytics area, readability has been frequently used as an indicator to determine the sophistication and semantic complexity of textual information (e.g., Agichtein, Castillo, Donato, Gionis, & Mishne, 2008; Coleman & Liau, 1975). Prior studies in the online context have demonstrated that readability is an effective indicator of the quality of textual information. For example, readability of textual data in crowdsourcing is positively associated with the quality of the crowdsourced contributions (Rhyn & Blohm, 2017). In parallel with our work, readability of online product reviews has been widely studied and its positive effects on quality of the reviews and other favorable outcomes have been consistently presented in the literature (e.g., Ghose & Ipeirotis, 2011; Hong, Xu, Wang, & Fan, 2017; Li, Goh, & Jin, 2018; Srivastava & Kalro, 2019). Therefore, we hypothesize:

**H2.** *The level of readability in P2P loan descriptions is positively correlated with funding success.*

In addition to readability we also investigate linguistic correctness in the loan descriptions. Linguistic correctness refers to the linguistic property of a loan description that demonstrates the quality of the description. Evidence from the language and communication study literature shows that the level of linguistic correctness is low when spelling errors and grammatical mistakes are present in the text (e.g., Connor, Davis Kenneth, & De Rycker, 1995). As noted earlier, according to cognitive load theory the number of errors in text can overwhelm readers' cognitive effort to absorb the information, which subsequently negatively influences the readers' perceptions (e.g., Petty, Harkins, & Williams, 1980).

In the online P2P lending context, it has been suggested that the level of linguistic correctness in a loan description can influence the potential lenders' judgements about the credibility and accuracy of the loan (e.g., Metzger & Flanagin, 2013). Consequently, lenders may find borrowers that provide more linguistically correct loan descriptions to be more credible and capable of successfully managing and paying back the loan. In this study, we explore two major features of linguistic correctness—spelling errors and grammatical mistakes. Prior work has looked at how spelling errors affect customer attitudes and responses. For example, in social media, punctuation and typos indicating low conformance to common writing practices are reported to reduce readers' perceptions of quality of social media content (e.g., Agichtein et al., 2008). In online reviews, previous studies have suggested that the number of spelling errors is considered one of peripheral text features that could impact review helpfulness (e.g., Ghose & Ipeirotis, 2011; Srivastava & Kalro, 2019). In addition, spelling errors have also been investigated in the crowdsourcing literature, suggesting that the number of spelling errors is negatively associated with crowdsourced contributions (e.g., Rhyn & Blohm, 2017). Therefore, we propose that:

**H3a.** *The number of spelling errors in P2P loan descriptions is negatively correlated with funding success.*

In addition to spelling errors we also investigated the effect of grammatical mistakes as another important linguistic correctness feature on funding success. Apparently, spelling errors and grammatical mistakes are closely related since both reflect the clarity and quality of textual data. However, spelling errors are typically considered more superficial than grammatical mistakes since they frequently result from low text visual quality (e.g., excessive punctuation) and phonetic errors (e.g., Johnson, Wilson, & Roscoe, 2017). Grammatical mistakes on the other hand can be considered as a higher-level error that requires deeper systematic information processing since they affect other elements of text processing such as reading speed (e.g., Vasishth, Brüssow, Lewis, & Drenhaus, 2008), reaction time (e.g., Bates, 1999), and recall (e.g., Goldman, Saul, & Coté, 1995).

Previous studies have provided evidence that the number of grammatical mistakes negatively influences readers' perceptions. For example, in journalism grammatical errors increase reading difficulty and consequently reduce readers' perception of credibility of the source and recall of the stories (e.g., Appelman & Bolls, 2011). Similar to spelling errors, previous studies in online reviews also provide empirical support that the number of grammatical mistakes can negatively influence customers' perception of review helpfulness (e.g., Liu, Jin, Ji, Harding, & Fung, 2013; Srivastava & Kalro, 2019). Accordingly, we hypothesize:

**H3b.** *The number of grammatical errors in P2P loan descriptions is negatively correlated with funding success.*

### 2.3. P2P loan descriptions: Emotion in textual information

Above and beyond the cognitive-based features of P2P loan descriptions, we argue that the affect-related factors (especially emotions) in loan descriptions influence P2P funding success. According to McAllister (1995), affect-related factors can create emotional ties to establish the relationship between potential lenders and borrowers. A large amount of previous research suggests that emotion shapes readers' attitudes and judgments (e.g., Chaiken & Maheswaran, 1994; MacInnis, Moorman, & Jaworski, 1991). Specifically, in the marketing domain product description has been reported to be a crucial factor for sellers in persuading customers of the product quality (e.g., Flanagin, 2007).

This effect can be explained by the concept of "affect-as-information" (Nisbett & Wilson, 1977; Schwarz, 1986) which explains the relationship between emotional states and responses. Affect-as-information suggests that emotional states can serve as information in human decision-making such that emotions can create bias when individuals attempt to make a rational decision (Nisbett & Wilson, 1977; Schwarz, 1986). Individuals may assess their current emotions and use those emotions as a basis for their judgements. The affect-as-information model has been widely used in designing communication that influences a recipient's attitude toward supporting the message's recommendation (e.g., Petty & Cacioppo, 1986).

With the wide use of the Internet and other communication technologies, people have several platforms for sharing their opinions and generating content; consequently, a massive amount of textual information is continuously generated (e.g., Macdonald, 2019). Such user-generated content has become a crucial component of the marketing strategy of many organizations (e.g., Leung, 2009). For example, in the online commerce literature emotion has been widely studied and its importance has been consistently shown to be a crucial determinant of several key factors in the success of online commerce such as trust (Hwang & Kim, 2007), satisfaction (Hsu, Chang, & Chen, 2012), and evaluations and responses (Éthier, Hadaya, Talbot, & Cadieux, 2006).

Given the enormous amount of unstructured textual data, previous studies have employed automated text analytic techniques to assess emotions. For example, Greco and Polli (2019) investigated emotions in a large data set of Twitter messages and found that text sentiments could be used to create customer profiles enabling managers to develop effective brand management strategies. Albarrak, Elnahass, Papagiannidis, and Salama (2020) provided evidence that sentiments in financial-related Twitter messages reduced the level of information asymmetry among stakeholders and potential investors. Furthermore, Yang, Liu, Liang, and Tang (2019) examined sentiments in online customer reviews and suggested that positive and negative feelings extracted from the reviews could be used as indicators of the experience users had with products.

Extrapolating from previous literature, P2P loan borrowers may also be able to develop persuasive strategies using affect-based linguistic features that provide executional cues to stimulate potential lenders' emotions, which can be carried over to the lenders' evaluations of the loan borrowers. Although previous studies have widely explored the affective aspect of textual information using text analytics methods, most of these studies have focused only on a broad concept of sentiment polarity (e.g., positive, negative, and neutral) and much less attention has been devoted to a better understanding of how different types of emotional states could impact loan success. Therefore, in this study we focus on the effects of specific emotions in the textual information, which can shed further light on how loan descriptions affect funding success in the P2P lending context.

Prior studies in online commerce have suggested that positive emotions generate positive outcomes, e.g., satisfaction, credibility, and intentions (e.g., Hwang & Kim, 2007; Kim & Tadisina, 2010). However, in P2P lending emotions may yield different effects. Specifically, it is not clear how emotions work in the P2P online lending and microfinancing context since negative emotions may increase the chance of funding success based on the lenders' assumptions that borrowers' suffering is worthy of concern (e.g., Black, 2009). For example, a lender may feel sympathy for a borrower's hardship expressed in the loan description and then become more willing to support the loan. Consequently, a loan with sadness as the main emotion in the description may activate a lender's lending behavior more so than joy resulting in loan procurement success.

In this study, based on contemporary theories of emotions we investigate a set of basic emotions—anger, fear, joy, disgust, and sadness—which are thought to serve distinct functions in individuals' motivation and behavior (Ekman, 1992; Frijda, 1986; Izard, 1993). Emotions may induce different motivational properties, antecedent conditions, physiological correlates, frequency of occurrence and duration (Scherer, 1986). Regardless of the valence of the emotion, we propose that a persuasive message in P2P loan descriptions evokes the emotions of potential lenders, which further influences the lender's evaluation of the borrower and decision to fund the loan (Larrimore, Jiang, Larrimore, Markowitz, & Gorski, 2011). Therefore, we propose:

**H4.** *Emotions in a loan description are related to funding success.*

In addition to emotion in the loan description, we also investigate emotion in lenders' descriptions in their lending messages. This description is a free-format message that lenders can create in their profile to describe their preferences and interests in funding a P2P loan. Building on the concept of shared emotion representation (Fehr & Russell, 1984; Frijda, 1993), associations between an emotion and lenders' responses should be stronger if the emotion elicits actions that are more compatible with the lenders' lending interests and preferences, which consequently influence funding success. In addition, evidence from field studies suggests that lenders favor borrowers that share similarities with themselves (e.g., Galak, Small, & Stephen, 2011; Riggins & Weber, 2017). Therefore, we propose that if the emotion in a lender's lending description matches the emotion found in a loan description the lenders and borrowers might share the same interests. Consequently, the chance that the lender supports the loan increases, which subsequently improves the funding success of the loan. With this background, we hypothesize:

**H5.** *Matching emotion positively increases funding success.*

## 3. Methodology

### 3.1. Data collection

This investigation is based on an open public access data source retrieved from www.kiva.org. Kiva is a non-profit organization that provides microfinance services to people from more than 83 countries (www.kiva.org/about). Kiva's lending model is based on a typical crowdfunding model, where any individual can fund a particular loan by contributing to a loan individually or as a part of a lending group. Typical microloans are in increments of $25. Kiva's dataset contains a set of variables including information about lenders, loans, lending group, and borrowers.

### 3.2. Data preparation procedure

Our original dataset comprised P2P loans that were collected between November 2011 and December 2016. However, most of the loans were excluded from the analysis because they were fully funded by field partners who sought to generate profit from P2P lending by collecting interest or fees. Therefore, those loans fulfilled by such financial

**Table 1**
Variables and descriptions.

| Variable | Description | Average | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| ***Dependent variable*** | | | | | |
| Funding time | Length of time (in days) for a loan to be fully funded | 23.55 | 12.56 | 2 | 58 |
| ***Cognitive features: Message quality variables*** | | | | | |
| Number of words | Number of words in loan description | 229.12 | 12.56 | 63 | 688 |
| Gunning Fog Index | Educational grade level required—the lower the grade, the more readable the text | 12.499 | 2.868 | 5.200 | 29.500 |
| Coleman-Liau Index | Educational grade level required—the lower the grade, the more readable the text | 9.247 | 2.079 | 4.000 | 15.300 |
| Spelling Error Count | Number of spelling errors | 6.060 | 22.286 | 0 | 179 |
| Grammatical Error Count | Number of grammatical errors | 5.510 | 4.228 | 0 | 24 |
| ***Affective features: Emotion variables*** | | | | | |
| Sentiment Score | Strength of sentiment in loan description (between -1 and 1) | 0.433 | 0.315 | −0.421 | 0.959 |
| Anger Emotion Score | Strength of anger emotion detected in loan description (between 0 and 1) | 0.119 | 0.092 | 0.008 | 0.601 |
| Disgust Emotion Score | Strength of disgust emotion detected in loan description (between 0 and 1) | 0.118 | 0.091 | 0.001 | 0.612 |
| Fear Emotion Score | Strength of fear emotion detected in loan description (between 0 and 1) | 0.159 | 0.135 | 0.004 | 0.663 |
| Joy Emotion Score | Strength of joy emotion detected in loan description (between 0 and 1) | 0.525 | 0.142 | 0.017 | 0.964 |
| Sadness Emotion Score | Strength of sadness emotion detected in loan description (between 0 and 1) | 0.368 | 0.157 | 0.007 | 0.767 |
| Matching emotion | Dummy variable for matching major emotions found in loan descriptions and lending messages (0 = Not match, 1 = match) | – | – | – | – |
| ***Financial quantitative features: Control variables*** | | | | | |
| Loan amount | Amount of loan | 7,660.96 | 2,859.53 | 500 | 10,000 |
| Loan repayment term | Number of loan repayments. The first repayment begins one month after borrowers receive the funds. | 32.2 | 6.4 | 6 | 42 |

intermediaries did not represent the actual P2P lending interactions between individual borrowers and lenders. Thus, they did not fit into the scope of this study which is aimed at assessing the factors influencing funding success in the context of philanthropic giving. After the deletions, the dataset included 815 loans that were funded solely by individual lenders, with the funds being directly transferred from the lender's account to the borrower's account without going through an intermediary.

### 3.3. Extraction and analysis of textual quality features

As previously mentioned, this research examines the four indicators of cognitive textual quality features in loan descriptions—number of words, readability, spelling errors, and grammatical errors. The number of words was derived from the word count in the description. The readability of the loan descriptions was determined by the Gunning Fog index and the Coleman-Liau index reading metrics that are commonly used in the literature (e.g., Ghose & Ipeirotis, 2011; Hong et al., 2017). The number of spelling errors and grammatical mistakes in the loan descriptions were counted as indicators of linguistic correctness.

The loan description data set was analyzed using an online text analysis tool, Readable (www.readable.com), and the results were cross-validated with the results from a manual classification of the number of words, spelling errors, and grammatical errors and the readability rating of a randomly selected sample set of descriptions from the data set. The results from Readable appeared be significantly correlated and consistent with the manual classification and therefore were deemed reliable.

### 3.4. Sentiment analysis

According to Pang and Lee (2008), sentiment analysis refers to the use of data mining techniques to identify and extract subjective information in source material. Sentiment analysis addresses the polarity of texts—positive, negative, or neutral—at different levels and for various aspects, including emotions, which are the focus in this study. In the literature, sentiment analysis has been applied to several research domains, for example customer reviews (e.g., Yang, Chen, & Chang, 2015), blogs (e.g., Mukherjee & Bala, 2017), social media (e.g., Zavattaro, French, & Mohanty, 2015), crowdfunding (e.g., Wang, Zhu, Wang, & Wu, 2017), and finance (e.g., Boudt & Thewissen, 2019).

In this study, the proprietary sentiment analysis tool IBM Watson Natural Language Understanding (NLU) was used to analyze emotions in Kiva loan descriptions. Watson NLU is a well-established application and is available on the IBM cloud computing PaaS (Platform-as-a-Service). Watson NLU provides a set of services to build applications for domain-independent natural language processing (NLP) and emotion recognition. For our study, the detected emotions include the five basic emotions suggested by Ekman (1992): anger, disgust, fear, joy, and sadness.

A programming script was created in Python to pass the loan descriptions to Watson NLU, which extracted the emotions and emotion score values associated with the descriptions. Specifically, Watson NLU relies on the Matrix Factorization with Lexical Knowledge (MFLK) approach based on a non-negative matrix factorization method to derive the emotion and sentiment scores, a method which is reported to be more effective than the traditional simple dictionary-based tagging approach when performing domain-independent sentiment analysis (Li, Zhang, & Sindhwani, 2009).

The emotion score values ranged from 0.0 to 1.0 and represent the prominence of the emotions conveyed in a loan description. A higher value represents a more prominent emotion, and if a score is above 0.5 the corresponding emotion is considered the major emotion in the description. In addition to the emotion score values, Watson NLU evaluated sentiment (positive, negative, or neutral) and provided sentiment score values that were used in our analysis to indicate the significance of sentiment in loan descriptions. A sample of the loan descriptions and their characteristics is presented in the Appendix A.

## 4. Analysis and results

### 4.1. Dependent and independent variables

The dependent variable, independent variables, and control variables used in the analysis are shown in Table 1. The continuous dependent variable—funding success—is determined by the length of time (in days) for a loan to be fully funded. All the loans in our dataset were fully funded, which is typical for loans listed on Kiva because the loans can be funded either by individual lenders or field partners; if a loan is not fully funded by individual lenders, field partners can provide funds and collect interest from the borrower. As explained above, loans that were funded (or partially funded) by field partners were excluded from the data set since the underlying mechanism for their funding success may be different from the cognitive and affective features of interpersonal trust which is the focus in this study. In general, the average funding time for the loan descriptions in our study was approximately 23 days with a standard deviation of 12.56 and a range of 2–58 days.

The set of independent variables proposed in the hypotheses was examined. The following cognitive loan description features were analyzed: number of words, Gunning Fog index, Coleman-Liau index, number of spelling errors, and number of grammatical errors. Regarding the affective linguistic features, the sentiment score and the emotion scores (anger, disgust, fear, joy, and sadness) and matching emotion (as a categorical variable assessing whether the major emotion in a lender's lending description matches the major emotion in the funded loan description) were included in the analysis.

### 4.2. Control variables

Since we focused only on the linguistic features of loan descriptions, we controlled for the effects of financial quantitative factors of P2P loans. These control variables included loan amount and repayment terms. *Loan amount* represented the size of a loan, which was controlled since it directly affected the time for the loan to be funded as reported in the literature. In addition, we controlled for the effect of the *loan repayment terms*, specifically the estimated number of periodic payments to the lender to repay the loan. Studies in microfinance have identified a number of loan repayment terms as a predictor of loan default (e.g., Angaine & Waari, 2014; Njoku & Odii, 1991; Oladeebo & Oladeebo, 2008). In the online P2P lending context, while most of the P2P lending platforms do not have a uniform loan repayment schedule, certain platforms assist borrowers in scheduling the loan repayment period. This feature, which is available on only a few online lending platforms, including Kiva, allows lenders to find loans that fit within their risk tolerance.

### 4.3. Emotion in microfinancing loan descriptions

The results from the emotion analysis reveal that joy and sadness are the highest and second-highest emotions found in loan descriptions, respectively, as shown in Fig. 1. We then determined the major emotions conveyed in loan descriptions based on two criteria—(1) the emotion that appears to have the highest frequency and (2) the emotion with a documented emotion score above 0.5 (IBM Watson, 2018). The major emotions for thirteen loan sectors, classified by Kiva, are presented in Table 2.

**Table 2**
Emotion in loan descriptions in different sectors.

| Category | Frequency | Percent | Major Emotion (%) |
|---|---|---|---|
| Agriculture | 122 | 15.0 % | Joy (49.3 %) |
| Arts | 45 | 5.5 % | Joy (66.9 %) |
| Clothing | 71 | 8.7 % | Joy (84.7 %) |
| Construction | 7 | 0.9 % | Sadness (78.6 %) |
| Education | 15 | 1.8 % | Joy (76.9 %) |
| Entertainment | 10 | 1.2 % | Joy (60.0 %) |
| Food | 178 | 21.8 % | Joy (74.0 %) |
| Health | 1 | 0.1 % | Sadness (100 %) |
| Housing | 6 | 0.7 % | Sadness (100 %) |
| Manufacturing | 5 | 0.6 % | Joy (100 %) |
| Retail | 122 | 15.0 % | Joy (71.5 %) |
| Services | 222 | 27.2 % | Joy (72.7 %) |
| Transportation | 11 | 1.3 % | Joy (81.8 %) |
| Total | 815 | 100.0 % | |

### 4.4. Emotion in lenders' lending descriptions

**Table 3**
Emotion in borrowers' lending descriptions.

| Emotion | Frequency | Percent |
|---|---|---|
| Joy | 829 | 66.1 % |
| Sadness | 297 | 23.7 % |
| Fear | 63 | 5.0 % |
| Disgust | 35 | 2.8 % |
| Anger | 31 | 2.5 % |
| Total | 815 | 100.0 % |

The analysis of emotions in lenders' lending descriptions was carried out in the dataset of 1255 lenders who funded loan projects. The lenders' lending descriptions were analyzed using IBM Watson and the results are similar to those of the loan descriptions. As shown in Table 3, joy and sadness appear to be the highest and second-highest emotions in the lending descriptions—66.1 % and 23.7 %, respectively.

### 4.5. Analysis and hypothesis testing

A series of multiple regression analyses were carried out to examine the influence of loan features including emotions on the dependent variable, funding time. The results of the overall loans and the four major loan sectors—Agriculture (15.0 %), Food (21.8 %), Retail (15.0 %) and Services (27.2 %)—are displayed in Table 4.

Multicollinearity was tested in our data by assessing the variance inflation factor (VIF) for each independent variable. While the VIF values shown in Table 4 did not exceed 10.0, indicating that multicollinearity did not emerge as a serious problem (Hair, Tatham,

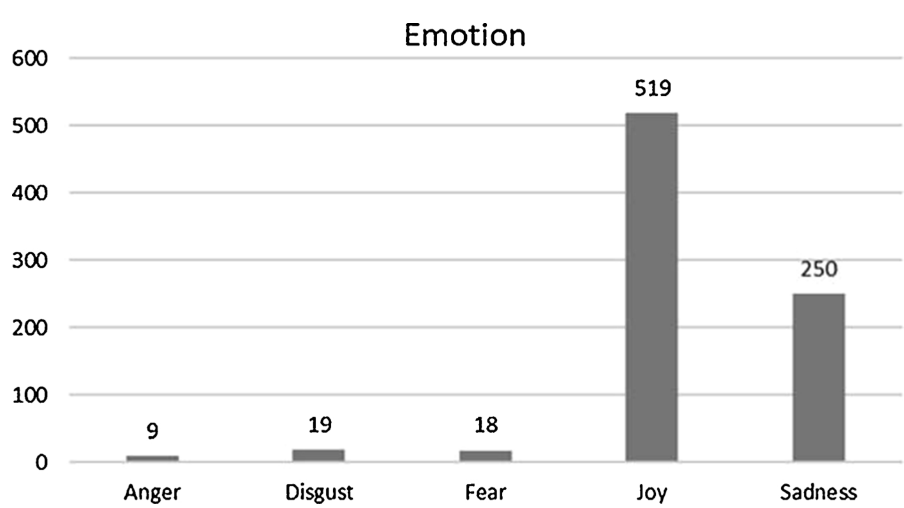


**Fig. 1.** Emotions found in loan descriptions.

**Table 4**
Regression analysis results.

| | Independent Variable | Coefficient | Std. Error | Std. Coefficient | *t* | Sig. | VIF |
|---|---|---|---|---|---|---|---|
| **Overall (R2 = 13.8 %)** | **Cognitive features** | | | | | | |
| | - Number of words | 0.042 | 0.005 | 0.364 | 7.899 | < 0.001* | 2.994 |
| | - Gunning Fog index | 0.062 | 0.164 | 0.014 | 0.378 | 0.705 | 2.018 |
| | - Coleman-Liau index | −0.282 | 0.243 | −0.047 | −1.159 | 0.247 | 2.285 |
| | - Spelling errors | −0.140 | 0.019 | −0.254 | −7.365 | < 0.001* | 1.673 |
| | - Grammatical errors | −0.617 | 0.124 | −0.212 | −4.988 | < 0.001* | 2.539 |
| | **Affective features** | | | | | | |
| | - Sentiment | 4.303 | 1.377 | 0.109 | 3.125 | 0.002* | 1.702 |
| | - Anger | −20.926 | 4.865 | −0.137 | −4.301 | < 0.001* | 1.431 |
| | - Disgust | −6.061 | 4.076 | −0.045 | −1.487 | 0.137 | 1.304 |
| | - Fear | −1.495 | 2.767 | −0.016 | −0.540 | 0.589 | 1.293 |
| | - Joy | 4.409 | 3.746 | 0.049 | 1.177 | 0.239 | 2.433 |
| | - Sadness | 4.408 | 3.326 | 0.056 | 1.326 | 0.185 | 2.518 |
| | - Emotion matching | 0.011 | 0.704 | < 0.001 | 0.016 | 0.987 | 1.122 |
| | **Control variables** | | | | | | |
| | - Loan amount | 0.001 | < 0.001 | 0.214 | 4.093 | < 0.001* | 3.842 |
| | - Repayment term | −0.305 | 0.101 | −0.158 | −3.005 | 0.003* | 3.908 |
| **Agriculture (R2 = 30.7 %)** | **Cognitive features** | | | | | | |
| | - Number of words | 0.039 | 0.010 | 0.439 | 3.865 | < 0.001* | 5.325 |
| | - Gunning Fog index | −0.323 | 0.364 | −0.099 | −0.888 | 0.375 | 5.089 |
| | - Coleman-Liau index | 0.836 | 0.613 | 0.164 | 1.364 | 0.174 | 5.980 |
| | - Spelling errors | −0.536 | 0.309 | −0.116 | −1.734 | 0.084 | 1.846 |
| | - Grammatical errors | −0.072 | 0.252 | −0.031 | −0.284 | 0.776 | 5.018 |
| | **Affective features** | | | | | | |
| | - Sentiment | 1.352 | 2.363 | 0.039 | 0.572 | 0.568 | 1.959 |
| | - Anger | −32.300 | 8.511 | −0.296 | −3.795 | < 0.001* | 2.505 |
| | - Disgust | 19.055 | 6.920 | 0.150 | 2.754 | 0.006* | 1.220 |
| | - Fear | 6.593 | 4.917 | 0.096 | 1.341 | 0.181 | 2.122 |
| | - Joy | −12.964 | 6.970 | −0.167 | −1.860 | 0.064 t | 3.321 |
| | - Sadness | −20.568 | 6.814 | −0.278 | −3.018 | 0.003* | 3.504 |
| | - Emotion matching | −4.072 | 1.210 | −0.183 | −3.364 | 0.001* | 1.217 |
| | **Control variables** | | | | | | |
| | - Loan amount | 0.002 | < 0.001 | 0.533 | 4.306 | < 0.001* | 6.310 |
| | - Repayment term | −0.735 | 0.221 | −0.411 | −3.329 | 0.001* | 6.273 |
| **Food (R2 = 40.5 %)** | **Cognitive features** | | | | | | |
| | - Number of words | 0.090 | 0.009 | 0.662 | 9.694 | < 0.001* | 2.408 |
| | - Gunning Fog index | −1.545 | 0.264 | −0.391 | −5.841 | < 0.001* | 2.307 |
| | - Coleman-Liau index | −0.798 | 0.435 | −0.157 | −1.833 | 0.068t | 3.804 |
| | - Spelling errors | −0.301 | 0.200 | −0.115 | −1.508 | 0.133 | 2.983 |
| | - Grammatical errors | −2.469 | 0.250 | −0.744 | −9.895 | < 0.001* | 2.919 |
| | **Affective features** | | | | | | |
| | - Sentiment | 19.600 | 3.242 | 0.569 | 6.046 | < 0.001* | 4.567 |
| | - Anger | 19.003 | 9.693 | 0.149 | 1.960 | 0.052 t | 2.969 |
| | - Disgust | −18.324 | 6.643 | −0.178 | −2.759 | 0.006* | 2.143 |
| | - Fear | −12.784 | 8.237 | −0.120 | −1.552 | 0.122 | 3.069 |
| | - Joy | −16.826 | 6.829 | −0.264 | −2.464 | 0.014* | 5.941 |
| | - Sadness | −4.974 | 6.077 | −0.079 | −0.819 | 0.414 | 4.835 |
| | - Emotion matching | 0.870 | 0.995 | 0.042 | 0.874 | 0.383 | 1.211 |
| | **Control variables** | | | | | | |
| | - Loan amount | 0.001 | < 0.001 | 0.031 | 0.292 | 0.771 | 5.943 |
| | - Repayment term | 0.221 | 0.196 | 0.114 | 1.126 | 0.261 | 5.305 |
| **Retail (R2 = 53.8 %)** | **Cognitive features** | | | | | | |
| | - Number of words | 0.044 | 0.012 | 0.340 | 3.782 | < 0.001* | 2.385 |
| | - Gunning Fog index | 0.102 | 0.636 | 0.019 | 0.160 | 0.873 | 4.267 |
| | - Coleman-Liau index | −4.765 | 1.089 | −0.678 | −4.375 | < 0.001* | 7.075 |
| | - Spelling errors | 0.133 | 0.071 | 0.157 | 1.873 | 0.063 t | 2.065 |
| | - Grammatical errors | 0.114 | 0.342 | 0.027 | 0.332 | 0.740 | 1.964 |
| | **Affective features** | | | | | | |
| | - Sentiment | 40.376 | 6.750 | 0.993 | 5.982 | < 0.001* | 8.112 |
| | - Anger | −8.730 | 24.859 | −0.034 | −0.351 | 0.726 | 2.759 |
| | - Disgust | 49.486 | 26.952 | 0.194 | 1.836 | 0.069 t | 3.300 |
| | - Fear | −11.745 | 8.001 | −0.119 | −1.468 | 0.145 | 1.932 |
| | - Joy | −21.174 | 13.656 | −0.219 | −1.551 | 0.124 | 5.857 |
| | - Sadness | 34.874 | 8.866 | 0.448 | 3.933 | < 0.001* | 3.813 |
| | - Emotion matching | −4.772 | 1.783 | −0.178 | −2.676 | 0.008* | 1.299 |
| | **Control variables** | | | | | | |
| | - Loan amount | 0.001 | 0.001 | 0.178 | 0.989 | 0.325 | 9.532 |
| | - Repayment term | −0.184 | 0.328 | −0.108 | −0.561 | 0.576 | 9.851 |

(*continued on next page*)

**Table 4** (*continued*)

| | Independent Variable | Coefficient | Std. Error | Std. Coefficient | *t* | Sig. | VIF |
|---|---|---|---|---|---|---|---|
| **Services (R2 = 34.9 %)** | **Cognitive features** | | | | | | |
| | - Number of words | 0.020 | 0.014 | 0.177 | 1.481 | 0.140 | 6.608 |
| | - Gunning Fog index | −1.278 | 0.328 | 0.259 | 3.895 | < 0.001* | 2.051 |
| | - Coleman-Liau index | −2.241 | 0.465 | −0.275 | −4.815 | < 0.001* | 1.514 |
| | - Spelling errors | −0.054 | 0.031 | −0.168 | −1.728 | 0.085 t | 4.420 |
| | - Grammatical errors | −0.836 | 0.249 | −0.322 | −3.361 | 0.001* | 4.269 |
| | **Affective features** | | | | | | |
| | - Sentiment | 4.283 | 3.399 | 0.093 | 1.260 | 0.209 | 2.557 |
| | - Anger | −26.374 | 8.851 | −0.161 | −2.980 | 0.003* | 1.353 |
| | - Disgust | −29.620 | 7.870 | −0.236 | −3.764 | < 0.001* | 1.827 |
| | - Fear | −0.561 | 6.504 | −0.006 | −0.086 | 0.931 | 2.167 |
| | - Joy | 12.931 | 10.246 | 0.090 | 1.262 | 0.208 | 2.342 |
| | - Sadness | 31.884 | 7.318 | 0.343 | 4.357 | < 0.001* | 2.876 |
| | - Emotion matching | −2.970 | 1.415 | −0.108 | −2.098 | 0.037* | 1.232 |
| | **Control variables** | | | | | | |
| | - Loan amount | 0.001 | 0.001 | 0.172 | 1.538 | 0.125 | 5.793 |
| | - Repayment term | −0.133 | 0.217 | −0.066 | −0.610 | 0.542 | 5.489 |

**p* < 0.05, ᵗ*p* < 0.10.

Anderson, & Black, 1995), it should be noted that there were relatively high correlation coefficients among certain variables, especially between loan amount and repayment term ($r = 0.828$, $p < 0.001$), between number of words and number of grammatical errors ($r = 0.693$, $p < 0.001$), and between Sadness and Joy ($r = -0.614$, $p < 0.001$). These high correlation values are mainly caused by the overlap of the predictor variables. For example, it is reasonable to assume that a larger loan amount would take longer to repay, and lengthier loan descriptions would be more likely to include grammatical errors. However, we decided to include these variables in the analysis to observe their influences on the funding success in the P2P lending context.

Regarding the hypothesis testing for the cognitive loan description features, except the loans in the Services sector, the results suggest that the length of loan descriptions is positively and significantly correlated to the loan funding time at the 0.05 level. That is, P2P loans with longer descriptions may take longer to be funded. Consequently, the effect of the loan description length is opposite to our prediction and Hypothesis 1 is not supported.

For the level of readability of loan descriptions, the results indicate that, in general, the Gunning Fog and Coleman-Liau indices are negatively related to funding time for the loans in the Food, Retail, and Services sectors. However, such an effect does not reach a statistically significant level in the overall loan data and the Agriculture sector. The Gunning Fog and Coleman-Liau indices indicate the educational level required to comprehend the text; therefore, our results reveal that in the Food, Retail, and Services sectors loans with a description that is more difficult to understand is funded in less time. Apparently, the effect of loan description readability is also opposite to that predicted; thus, Hypothesis 2 is not supported. Further discussion regarding the level of readability is provided in the discussion and conclusion section.

Regarding the numbers of spelling errors and grammatical errors in loan descriptions the results are broadly consistent across loan sectors. The number of spelling errors appears to significantly increase the funding time in the overall loan data. While the effect does not reach a statistically significant level in the major loan sectors, the influence of spelling errors is as expected; therefore, Hypothesis 3a is largely supported. The results for the number of grammatical errors are generally consistent with those for the number of spelling errors. That is, loan descriptions with fewer grammatical errors tend to be funded more quickly, especially for overall loans and loans in the Food and Services sectors. Therefore, Hypothesis 3b is supported.

As for emotions in the loan descriptions (Hypothesis 4), negative emotions can potentially increase funding success at the 0.05 significance level. Table 5 presents the summary of the effects of emotions on funding success for overall loans and loans in the major sectors.

**Table 5**
Summary of the impacts of emotions on loan descriptions.

| Loan Sector | Emotion Significantly Impacts Funding Success | |
|---|---|---|
| | Increases Funding Success | Decreases Funding Success |
| Overall loan sectors | • Anger | • Positive sentiment |
| Agriculture | • Anger<br>• Sadness | • Disgust<br>• Fear |
| Food | • Disgust<br>• Joy | • Positive sentiment |
| Retail | | • Positive sentiment<br>• Sadness |
| Services | • Anger | • Disgust<br>• Sadness |

However, it is important to interpret the results with caution such that simply including negative emotions (e.g., Anger, Sadness, and Disgust) in the loan descriptions may not improve the funding success. In fact, doing so is more likely to create an unpleasant experience for the lenders, which may subsequently unfavorably affect the lending decision. Instead, the negative emotions should be used to describe the borrowers' current welfare; and hence address the borrowers' needs for essential financial support to improve their lives. A more detailed discussion related to the impact of negative emotions on funding success is provided in the next section.

With respect to matching emotions between borrowers' loan descriptions and lenders' lending descriptions, the findings suggest that the matching emotion influences loan funding time at the 0.05 significance level in the Agriculture, Retail and Services sectors. These results indicate that potential lenders expressing positive emotion in the lending descriptions may be more likely to lend funds to borrowers who expressed the same emotions in the loan descriptions. It seems that positive people want to fund positive sounding loan descriptions, while negative individuals want to fund negative sounding loan descriptions. This finding represents a new form of identification bias in P2P lending (Riggins & Weber, 2017). Therefore, Hypothesis 5 is partially supported.

## 5. Discussion

While online microfinancing can provide financial support to individuals who are not served by traditional financial services, our understanding of the effects of different P2P loan features on funding success is limited. Given the rich information and numerous features embedded in P2P loans, it is not clear how those features contribute to the loans' effectiveness in attracting lenders which can improve the chance of funding success. In the current study, we contribute to the microfinance literature by providing empirical evidence that the loan description is an important factor in a P2P loan listing that can increase funding success.

Overall, our results indicate that textual quality of loan descriptions is relevant to the success of P2P loan funding, however the results may vary across loan sectors. Regarding the length of loan descriptions (Hypothesis 1), the results suggest that while the length of a loan description was found to be significant in affecting funding success, the effect is in the opposite direction as hypothesized. While previous studies in the text analytics area have suggested that lengthier text can increase the chance of a desired outcome since it provides more detail and information (e.g., Baek et al., 2012; Lee et al., 2018; Mudambi & Schuff, 2010), our findings do not support such an idea. In our study, longer P2P loan descriptions appear to be associated with a longer funding time. One possible explanation is that longer loan descriptions in the P2P lending context may not be perceived as more helpful in providing in-depth details as reported in prior studies in other areas (e.g., online reviews (Hong et al., 2017)). Consequently, our study provides evidence that text length is not an effective indicator of a desirable outcome in the online P2P lending context.

Additionally, the effect of the level of loan description readability on funding success was examined (Hypothesis 2) in this study. Overall, the results show that there is a negative relationship between the level of readability and funding success. Our findings indicate that P2P loan descriptions with a higher level of reading difficulty are potentially related to a shorter funding time. While the positive effect of readability has been suggested primarily in the literature (e.g., Hong et al., 2017; Li et al., 2018; Srivastava & Kalro, 2019), its negative effect has also been reported in previous studies. For example, Yin, Mitra, and Zhang (2016) reported a positive coefficient of the Gunning Fog index (i.e., more complex reviews) on the helpfulness of online reviews. Korfiatis, García-Bariocanal, and Sánchez-Alonso (2012) also reported a positive coefficient of the Coleman-Liau index on review helpfulness scores. However, Ghose and Ipeirotis (2011) reported mixed results for text readability in influencing product sales in different product categories. In their investigation, while the positive effect of readability on product sales was reported for reviews for audio-video players and DVDs, a negative coefficient was reported for reviews on digital camera. It is possible that, when the text is written in more authoritative and sophisticated language, it tends to be more complex and thus is perceived as more credible and informative as reported in news (e.g., Graefe, Haim, Haarmann, & Brosius, 2018) and firms' financial disclosures (e.g., Tan, Ying Wang, & Zhou, 2014). Apparently, contextual factors can play a significant role in moderating the relationship between text readability and the outcome variables, and therefore, warrants further investigation.

The current study also extends previous research in microfinance by exploring how the linguistic correctness features of loan descriptions such as the number of spelling errors (Hypothesis 3a) and the number of grammatical errors (Hypothesis 3b) influence funding success. Overall, our results are consistent with prior studies (e.g., Agichtein et al., 2008; Appelman & Bolls, 2011; Liu et al., 2013), which indicate that spelling errors and grammatical mistakes can generate a negative effect on funding success. Specifically, our results reveal that loan descriptions that contain spelling and grammatical mistakes could take significantly longer to get funded.

In line with previous research in emotions and sentiment, we hypothesized that emotions in loan descriptions are related to funding success (Hypothesis 4). Our study confirms that affective factors in textual information can contribute to desirable outcomes. In addition to the polarity of sentiment in textual information reported in the literature (e.g., Greco & Polli, 2019), we provide further evidence that specific emotions influence the outcome variable in the online P2P lending context. However, while previous studies have largely suggested that positive emotions generate positive results and negative emotions create negative reactions (e.g., Bhattacherjee & Sanford, 2006; Eroglu, Machleit, & Davis, 2003; Éthier et al., 2006), our findings indicate that in microfinance negative emotions may be more effective in increasing funding success. Specifically, we find that the standardized coefficients of the negative emotions are higher than those of the positive emotions as reported in Table 4. Nevertheless, it should not be assumed that a more negative loan description will necessarily increase funding success. The results should be cautiously interpreted especially with knowledge of the context and borrower motivations. Apparently, if borrowers use negative-dominant emotions in loan descriptions to explicitly rant about a bad experience, it would make potential lenders feel uncomfortable to fund the loans. However, if borrowers express negative emotions to elaborate the hardship they are facing, this would evoke lenders' empathy which may lead to altruistic reactions to make lending decisions to alleviate the borrowers' financial constraints (e.g., Batson, 2010). Such influence of negative emotions on positive reactions has been reported in previous studies. For example, anxiety and anger observed in online reviews positively influenced readers' perceptions of review helpfulness (Yin, Bond, & Zhang, 2014). In the news context, stories with negative content, especially those with endings that were embarrassing or violating social norms were positively correlated with joy (e.g., Berthoz, Armony, Blair, & Dolan, 2002; Ouwerkerk, van Dijk, Vonkeman, & Spears, 2018). In P2P lending, it has been suggested that lenders may feel sympathy with the borrower's situation if the requested loans are not funded (e.g., Black, 2009; Kristjánsson, 2010), and consequently our study confirms this notion and contributes to the literature indicating that negative emotions in loan descriptions may increase funding likelihood.

In addition, the results of our analysis suggest that if the emotions in borrowers' loan descriptions match the emotions expressed in lenders' lending message, the funding success can potentially increase (Hypothesis 5). As reported in the literature, online users' characteristics and individual differences may influence the users' rationale and decision-making, which subsequently drive their intentions and behaviors (e.g., Choden, Bagchi, Udo, & Kirs, 2019; Zhou, Jin, Vogel, Fang, & Chen, 2011). While the effect is rather weak, our results provide preliminary evidence that lenders' characteristics may be a key factor driving loan support decisions, a finding which is clearly worth further investigation.

### 5.1. Theoretical contributions

Theoretically, by highlighting the cognitive and affective framework of information processing (e.g., Hilgard, 1980; McAllister, 1995), our study introduces how linguistic features of textual information contribute to the success of P2P funding in the microfinance context. Specifically, while previous studies in microfinance have largely explored quantitative financial attributes of P2P loans, we explored various cognitive and affective linguistic features of P2P loan descriptions and addressed their potential effects on funding success.

Regarding the cognitive aspect, we applied the cognitive fit theory (Vessey, 1991) and cognitive load theory (Sweller, 1994) as an overarching framework to identify the cognitive linguistic features of P2P loan descriptions. Overall, our findings suggest that the impact of cognitive linguistic features can generate mixed impacts on funding success. According to earlier research, a higher level of cognitive processing generally increases task difficultly and, consequently, generates a negative impact on user responses (e.g., Ghose & Ipeirotis, 2011; Hong et al., 2017; Li et al., 2018; Srivastava & Kalro, 2019). In contrast, the results of this study contradict extant evidence by suggesting that loan descriptions that are more difficult to understand can potentially improve the chance of funding success. However, regarding the other cognitive linguistic features (spelling and grammatical errors), our results support the previous findings (e.g., Ghose & Ipeirotis, 2011; Srivastava & Kalro, 2019) that such errors might increase users' cognitive load and subsequently negatively influence user response.

With respect to the affective perspective, while the importance of structured financial quantitative attributes of P2P loans in impacting lenders' decision-making have been largely investigated in microfinance (e.g., Angaine & Waari, 2014; Derban, Binner, & Mullineux, 2005), the affective factors of P2P loans are often overlooked. Given previous evidence of bias in P2P lending (Riggins & Weber, 2017), we believe affective factors may be particularly important in lenders' decision-making. Therefore, we contribute to this literature by exploring specific roles of emotion in P2P lending. Overall, the results are in line with previous studies indicating that emotion can be an important driver of users' decision-making as suggested by the affect-as-information model (e.g., Nisbett & Wilson, 1977; Schwarz, 1986). In addition, our results raise important issues concerning the applications of emotions in the P2P loan settings, especially regarding negative emotions. Our study offers evidence that certain emotions in textual information may evoke distinct readers' perceptions in different context. Typically, one would assume that text with negative emotions would evoke readers' negative reactions. However, this is not always the case since our results provide evidence that certain negative emotions in loan descriptions may stimulate sympathy and subsequently yield preferable outcomes. Therefore, the current study supports prior research suggesting that contextual factors can play a significant role in moderating the impact of emotion on user responses.

Our research also provides initial evidence to supplement literature on the concepts of individual differences and preferences. Previous studies in the affective area tend to focus on the role of emotion within the individual, omitting the important role in influencing interpersonal purposes that emotions often play (e.g., Van Kleef, 2010). In P2P lending, emotions can be a crucial interpersonal factor such that the feelings conveyed in a loan description may impact potential lenders who use the loan description as input to their lending decisions. Consequently, we extend the notion of shared emotion representation (Fehr & Russell, 1984; Frijda, 1993) by providing evidence supporting the influence of emotions in interpersonal space. This presents interesting opportunities for future research on the consequences of emotions in the crowdfunding context.

### 5.2. Implications for practice

In addition to the theoretical contributions, our study provides several interesting findings that would be of interest to P2P borrowers and lending platform managers. First, our results suggest that the length of loan descriptions may not be related to their success. Therefore, P2P borrowers may consider avoiding long and pointless statements in the descriptions. Loan descriptions that are unnecessarily lengthy may overwhelm potential lenders' cognitive resources and provide relatively low information value, which would subsequently negatively impact the lenders' perceptions. Therefore, P2P borrowers should be concise when addressing the loan purposes in their descriptions. Furthermore, as widely implemented in social media platforms (e.g., Twitter™), P2P lending platform managers may assist future loan borrowers by limiting loan descriptions to a reasonable length so that the descriptions are more concise and effective.

Our findings also suggest that P2P loans with higher level of description readability may not necessary increase the funding success. While it should not be assumed that a loan description that is more complex and difficult to read will be more successful, it is reasonably to argue that the description should be professionally written with appropriate language and tone to establish the borrower's credibility (e.g., Landsheer, Van Der Heijden, & Van Gils, 1999). Consequently, P2P lending platform managers might consider aiding borrowers who have limited language abilities to create professional and effective loan descriptions. The findings of our study also suggest that linguistic correctness of loan descriptions can influence funding success; therefore, P2P borrowers should carefully proofread the descriptions before posting them to ensure that they are free of spelling and grammatical mistakes. Poorly written loan descriptions with linguistic errors may have a detrimental effect on borrowers' credibility or perhaps the P2P lending platforms' trustworthiness. Therefore, at the platform level, P2P lending platform managers might utilize automated text correction applications that are reliable and useful in correcting linguistic errors and provide suggestions to borrowers when writing loan descriptions.

Regarding emotions in loan descriptions, our study reveals that P2P borrowers can incorporate certain emotions in loan descriptions to make the loans more appealing to potential lenders. In general, negative emotions (e.g., anger, sadness, and disgust) may result in shorter funding time, especially for loans in the Agriculture, Food, and Services sectors. In addition, fear and overall positive sentiment were reported to be associated with longer funding time, which borrowers should be cautious when writing their loan descriptions. Therefore, borrowers should pay attention to the context and the motivations of incorporating emotions in the descriptions since they can potentially moderate the effects of emotions on lenders' perceptions and lending decisions. In addition, overly sensationalized descriptions may cause lenders to feel that the descriptions are exaggerated (e.g., Grabe, Zhou, & Barnett, 2001) and possibly fraudulent (e.g., Wang, Qi, Fu, & Liu, 2016). Nevertheless, online P2P lending platforms may not expect borrowers to amplify or suppress specific emotions in their loan descriptions. Instead, the lending platforms may instruct borrowers to reasonably express their feelings but carefully consider the tone and content of the descriptions. Furthermore, P2P lending platforms might use our findings to offer writing guidelines involving certain emotions to produce more effective loan descriptions.

Our findings suggest that lenders' data can potentially be used to generate effective strategies for P2P lending platforms. Platform managers can further analyze the characteristics of their users (borrowers and lenders) to innovatively develop strategies to improve the success of the platforms. For example, by examining the emotions in the lending messages, platform managers could develop a recommendation system that suggests the loans that match the lenders' preferences. Such a system is common among online shopping and entertainment streaming sites.

### 5.3. Limitations and future research directions

Despite the contributions, some limitations of this study should be noted. First, we examined only loan description data derived from Kiva.org. Therefore, future studies should consider evaluating P2P loan descriptions from other online platforms that may be designated to support microfinance loans in specific borrower groups (e.g., Women's Microfinance Initiative – www.wmionline.org) or loan sectors to generalize the results of our investigation. Moreover, our findings reveal different results across loan sectors. Therefore, it would be interesting to hypothesize the context as an independent variable in future research.

Second, while we did not find a significant, positive relationship between loan description length and funding success as suggested by previous studies, the interpretation that more textual information provides more details and subsequently is perceived as more helpful may be misleading. The length of loan descriptions alone may not be an effective indicator of loan success since longer descriptions may not necessarily convey useful information. Therefore, it may be more appropriate to use text length as a control variable in future studies. In addition, since the effect of loan description readability is not clear, how and to what extent readability affects loan success in the P2P lending context warrants future investigation.

Third, while we suggested that the strength of emotion (either positive or negative) positively influences funding success, further research is needed to better understand this relationship. Findings from previous studies suggest that affective-related factors (e.g., emotional arousal) may form an inverted U-shaped relationship with users' perceptions (e.g., Baldi & Bucherelli, 2005). Therefore, future investigation may assess the effect of different levels of emotional strength in P2P funding success.

Finally, we examined only the lending messages of lenders; future investigation should attempt to incorporate additional characteristics of P2P lenders in the analysis to provide deeper insight into the formation of the borrower-lender relationship.

## 6. Conclusions

Overall, the factors related to funding success in the microfinance area have been studied too little by scholars and the results applied too sparsely by practitioners. This paper articulates the importance of loan description features on funding success. In the current research, we provide empirical evidence that loan description is an important factor in online P2P lending by adding to the literature that emphasizes cognitive and affective features extracted from the descriptions. This study shows that P2P loan descriptions contain a diverse set of linguistic features and emotions that are distinctively associated with funding success. The results provide practical solutions that can be effectively implemented and a theoretical foundation for future research, which can subsequently lead to the sustainability of the development of microfinance services.

This study also shows why additional research in this area is needed. The alleviation of poverty is a noble goal where microfinance services and P2P lending platforms can play an important role in achieving that goal. However, given the information asymmetries that exist in these platforms these lending mechanisms are rife with inefficiencies. In particular, how the loan description is written and structured has an important impact on funding success or lack of success. If P2P lending platforms continue to grow in usage and importance, a better understanding of their impacts needs to be developed. If the inherent inefficiencies in these platforms cannot be reduced this important mechanism for reducing poverty and raising funds for microentrepreneurs may not be used to their fullest extent. We believe the current research helps reduce the gap in understanding of how these P2P lending platform function, yet also raises important issues for further study.

## CRediT authorship contribution statement

**Supavich (Fone) Pengnate:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing - original draft, Writing - review & editing. **Frederick J. Riggins:** Conceptualization, Formal analysis, Writing - review & editing.

## Appendix A. A sample of loan descriptions and their characteristics (names were hidden to maintain the borrowers' confidentiality)

**Description #XXXX314**

"My name is XXXX from Chicago, IL now living in sunny Arizona. Wife and mother of 4, grandmother of 17, and now great grandmother of 3. I am starting a new chapter in my life as business owner. I've always made baskets for special occasions my children came to me and said, "mom you make beautiful baskets why don't you make a business out of it since you're out of work". That's what I did. My thoughts for the future would like to have a storefront where people can come and pick items they want in a basket prepare it for them to pick up and provide gift wrapping services as well."

- Funding time: 26 days
- Number of words: 111
- Gunning Fog index: 9.6
- Coleman-Liau index: 7.1
- Spelling errors: 0
- Grammatical errors: 5
- Sentiment: 0.497537
- Anger: 0.078204
- Disgust: 0.097657
- Fear: 0.075516
- Joy: 0.543365
- Sadness: 0.444988
- Loan amount: $2500
- Repayment term: 24 months

**Description # XXXX116**

I am married to one wife and blessed with one boy. I live in Thika District where I also work. Before I started my bureau service, I was a care taker in one of the buildings in Thika town. In the same building, I got a small room with a monthly rent of 2000 Kenyan shillings.. .I have three computers, two printers, and a photocopier. After acquiring these assets, I decided to resign from my employer to become a self employed businessman. I now work with two other employees…I was inspired by to become an entrepreneur by the challenges I faced in my former employment. I would point out a profitable idea but it was not embraced. This challenged me to start my own business where I could implement my own ideas…My goal is to own an outstanding printing firm where our main value is to provide quality services to our clients.. .

- Funding time: 8 days
- Number of words: 154
- Gunning Fog index: 8.8
- Coleman-Liau index: 5.5
- Spelling errors: 0
- Grammatical errors: 2
- Sentiment: 0.039384
- Anger: 0.115328
- Disgust: 0.102391
- Fear: 0.155461
- Joy: 0.545916
- Sadness: 0.448064
- Loan amount: $75
- Repayment term: 2 months

**Description # XXXX238**

I grew up in Kibera, a slum on the outskirts of Nairobi. In Kibera, my life was not that easy because my parents were financially unstable. I still live in Kibera, and my dreams are to have some wealth and financial stability and be able to support those who are disadvantaged.. .I was employed as a security officer locally here in Kibera. Because I worked as a security guard at night, I was able to do other work during the day. I used my salary from my security job to purchase a hand-cart (a push wagon) to rent to people so they can transport goods around Kibera. With that extra income, I was able to purchase two more handcarts that I also rent to my neighbors and members in the community.

- Funding time: 7 days
- Number of words: 133
- Gunning Fog index: 6.6
- Coleman-Liau index: 4.7
- Spelling errors: 1
- Grammatical errors: 3
- Sentiment: -0.41359
- Anger: 0.127927
- Disgust: 0.162247
- Fear: 0.399659
- Joy: 0.488075
- Sadness: 0.564434
- Loan amount: $150
- Repayment term: 3 months

**Description #XXXX164**

I was born and bred in a rural area in the western part of Kenya. I am the first born in a family of five children. All my siblings are working as farmers in the rural area…I have been living in Nairobi since 2009 in an informal settlement area known as Lunga Lunga.. .I work hard and believe that in this way I will become a good business woman. I want to be able to cater for my family by providing them with food, clothing, shelter and education. Not just education, but quality education.

- Funding time: 23 days
- Number of words: 94
- Gunning Fog index: 12.4
- Coleman-Liau index: 7.1
- Spelling errors: 0

**Description #XXXX798**

I was born and raised in China and spent most of my life in Western China near the Silk Road. I studied Mathematics in university and used my skills working in various businesses and in a number of different industries. But I always thought about food because it's what people love and consume everyday. Life was good in China but I wanted to make a better life for my family…I came to the United States in 2000 with my entire family. I have 1 daughter and 1 son. During the first few years in the United States I worked many different restaurant jobs and saved enough money to open up my first restaurant, TW Burmese Restaurant, where we serve Asian inspired cuisine from Southeast Asia.

- Funding time: 26 days
- Number of words: 123
- Gunning Fog index: 9.6
- Coleman-Liau index: 7.1
- Spelling errors: 0

**Description #XXXX073**

I was born in Vialo in Vihiga district on 1 st June 1972. I am the fourth born in the family. I went to Vialo primary school up to class 8. My parents did not have enough money to continue my education and I was not lucky enough to attend secondary school.. .I am married with 5 children…Because I did not have a good chance of finding a well-paying job, I decided to venture into self-business. I started selling briquettes in 2008 after I received training by GVEP International. I am happy with what am doing currently. I produce 7 bags of 90 kg briquettes daily. This will give me a good income enough to support my family. I have plans of constructing a kiln for carbonizing bagasse to get feedstock/char for briquette making.

- Funding time: 15 days
- Number of words: 131
- Gunning Fog index: 13
- Coleman-Liau index: 9.2
- Spelling errors: 2

- Grammatical errors: 3
- Sentiment: 0.536741
- Anger: 0.087917
- Disgust: 0.090581
- Fear: 0.091942
- Joy: 0.439411
- Sadness: 0.540019
- Loan amount: $900
- Repayment term: 12 months

**Description #XXXX270**

My name is XXXX. I am 44 years old and a single mother of 2 children. I was born as the second born in a family of 10 children. I grew up in abject poverty and for me to complete primary level education it was by the grace of God and it was so obvious that my parents could not afford to take me to high school. My education came to an end and I started helping my parents take care of my other younger siblings.. .I have previously been in the fresh fruits and vegetables business but I abandoned it to go and take care of my child when she was sick. I have also tried a hand in the second hand shoes but the business was not good and I incurred losses…I am currently practising small scale poultry farming in my plot where I live. Poultry farming business is a good business since the eggs and chicken meat has a ready market. It is my desire to improve, upgrade and expand my poultry rearing business to generate more income to enable me support and educate my 2 children..

- Funding time: 2 days
- Number of words: 189
- Gunning Fog index: 7.5
- Coleman-Liau index: 6.8
- Spelling errors: 1
- Grammatical errors: 1
- Sentiment: 0.00901
- Anger: 0.109623
- Disgust: 0.419674
- Fear: 0.083101
- Joy: 0.492313
- Sadness: 0.591986
- Loan amount: $150
- Repayment term: 1 month

- Grammatical errors: 3
- Sentiment: 0.497537
- Anger: 0.078204
- Disgust: 0.097657
- Fear: 0.075516
- Joy: 0.543365
- Sadness: 0.444988
- Loan amount: $2500
- Repayment term: 24 months

**Description #XXXX991**

My name is XXXX and I am 24years old. I was born in a polygamous family of 10.I grew up in Busia in Western Kenya. I went to school back in the rural ares in Western Kenya. I finished my class eight in 2002 and moved to Nairobi in 2003. I came to Nairobi after getting to learn about the activities of Seed of Hope.. When I was growing up my career goal was to undertake a course in criminology and possibly end up as a detective. I love watching movies, reading and meditating. I am very social and love interacting with people.

- Funding time: 29 days
- Number of words: 102
- Gunning Fog index: 7.8
- Coleman-Liau index: 6.2
- Spelling errors: 1
- Grammatical errors: 5
- Sentiment: 0.885119
- Anger: 0.077605
- Disgust: 0.078686
- Fear: 0.083379
- Joy: 0.517828
- Sadness: 0.548323
- Loan amount: $275
- Repayment term: 12 months

- Grammatical errors: 5
- Sentiment: -0.00868
- Anger: 0.136354
- Disgust: 0.088333
- Fear: 0.081414
- Joy: 0.512807
- Sadness: 0.541263
- Loan amount: $250
- Repayment term: 6 months

**Description #XXXX985**

This is XXXX a married man aged 33 years and a father of 2 children. He lives in Nairobi with his family and also it's where he carries on with his business. He is an electronics dealer and his wife operates a shop. They help and support one another in taking care of their family. His business involves selling TV's, radios and microwaves which he enjoys doing. He gets satisfaction when he sees his clients happy and contented with the services and goods that he provides to them. His challenges had been having finances to grow his business which he relies on and to meet their day to day needs of the family. The Kiva loan will assist him to pay his children's school fees which he plans to pay using the profits he gets from his business. His business has given employment to young men who assist in selling at the shop as well as carrying the goods to his premises. This is the second loan that Benson has taken and his dream is for his children to inherit his business in future and expand it to a big firm.

- Funding time: 3 days
- Number of words: 189
- Gunning Fog index: 10.9
- Coleman-Liau index: 7.8
- Spelling errors: 1
- Grammatical errors: 4
- Sentiment: 0.62025
- Anger: 0.099056
- Disgust: 0.272255
- Fear: 0.089177
- Joy: 0.321467
- Sadness: 0.425071
- Loan amount: $275
- Repayment term: 12 months

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