Natural Language Processing versus Rule-Based Text Analysis: Comparing BERT Score and Readability Indices to Predict Crowdfunding Outcomes†

C. S. Richard Chan *
Associate Professor
College of Business
Stony Brook University
Stony Brook, NY 11794
E-mail: richard.chan@stonybrook.edu

Charuta Pethe
Ph.D. Candidate
Computer Science
Stony Brook University
Stony Brook, NY 11794
E-mail: cpethe@cs.stonybrook.edu

Steven Skiena
SUNY Empire Innovation Professor and Director
AI Institute
Computer Science
Stony Brook University
Stony Brook, NY 11794
Email: skiena@cs.stonybrook.edu

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†The authors contributed equally.
***Corresponding author

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ABSTRACT

We explore how natural language processing can be applied to predict crowdfunding outcomes. Using the Bidirectional Encoder Representations from Transformers (BERT) technique, we find that crowdfunding projects that use a story section description with ndina higher average BERT score (indicating a lower quality of writing) tend to raise more funding than those with lower average BERT scores. In contrast, risk descriptions that have higher BERT scores tend to receive less funding and attract fewer backers. These relationships remain consistent after controlling for various traditional readability indices, highlighting the potential benefits of incorporating natural language processing techniques in entrepreneurship research.

Keywords: Natural Language Processing, Bidirectional Encoder Representations from Transformers, Readability, Crowdfunding Outcomes

1. Introduction

New ventures have a hard time attracting funding. Many recommend that entrepreneurs communicate effectively with investors, using simple language so important information will be easier to understand (Lehavy et al., 2011; You and Zhang, 2009). Yet, such approaches have received variable empirical support. Studies have documented null, positive, negative, or even curvilinear effects of readability on funding success (e.g., Block et al., 2018; Chan et al., 2020; Cumming et al., 2019; Thapa, 2020; Zhou et al., 2018). One explanation is that traditional rule-based readability measures do not sufficiently capture writing quality, which may rely on simple matters like word count and sentence length, while ignoring complex ideas and schemata (e.g., Bailin and Grafstein, 2001; Zamanian and Heydari, 2012). Thus, the traditional rule-based measures of readability cannot fully measure the writing quality of written text, leading to conflicting results in terms on studying funding.

These shortcomings can be addressed by using Natural Language Processing (NLP), a subfield of linguistics and computer science that utilizes artificial intelligence to process, organize, and extract embedded information from texts. A NLP technique known as Bidirectional Encoder Representations from Transformers (BERT) was recently developed at Google to improve language understanding tasks (Devlin et al., 2018), BERT has achieved superior results on a number of natural language understanding tasks, such as paraphrasing and summarization, compared with other NLP tools (Devlin et al., 2018; Gabriel et al., 2019; Yoshimura et al., 2019; Zhang et al., 2019), prompting others to examine and confirm its ability to effectively predict readability levels of English and Chinese corpora (Deutsch, Jasbi, & Shieber, 2020; Tseng et al., 2019). Because of these advancements, BERT may be utilized to predict new venture fundraising outcomes more effectively than the traditional rule-based readability measures.

Using the field setting of Kickstarter projects, we found that the crowdfunding projects with story descriptions that had a higher average BERT score (i.e., a lower quality of writing) tended to receive more funding than those with a lower average BERT score, after controlling for various readability measures and curvilinear relationships. In contrast, risk descriptions with higher BERT scores is associated with less funding and attract fewer backers.

This exploratory study contributes to the literature in two ways. First, we contribute to a better understanding of the role of language in entrepreneurial finance by demonstrating how NLP techniques can effectively predict funding outcomes. Joining recent studies (Kaminski and

Hopp, 2019; Obschonka and Audretsch, 2019; Townsend, and Hunt, 2019), we illustrate the value of artificial intelligence techniques in entrepreneurship research. Second, our study contributes to the use of computational linguistic approaches in entrepreneurship research. We document how both NLP and traditional rule-based approaches may effectively predict funding outcomes, and that such distinct approaches can nicely complement each other.

2. Method

2.1. Research Context

We constructed a dataset using Kickstarter projects. Kickstarter is a popular reward-based crowdfunding platform for new ventures to raise small monetary contributions from a large number of individuals online in exchange for tangible and/or social rewards (Mollick, 2014). By May 2021 approximately 202,000 Kickstarter campaigns have raised $5.8 billion from more than 19 million backers (https://www.kickstarter.com/help/stats). While most projects (61.26%) do not get funded, some have evolved into successful ventures (Mollick, 2014).

Following prior crowdfunding research (e.g., Chan and Parhankangas, 2017; Mollick and Kuppuswamy, 2014), we included only those Kickstarter campaigns in the technology and product design categories to represent typical startups which offer product rewards. To control for country and macroeconomic effects, we chose campaigns located in the United States, and were initiated between January and August of 2020. These criteria resulted in 1,359 campaigns. Based on their campaign webpages, we scraped basic campaign characteristics such as requested funding, duration, etc., as important control variables (e.g., Mollick, 2014). We decided to extract texts from two main sections of the campaign description, story and risks because these two serve very distinct purposes. While a story description depicts a product and its creation and implementation process, a risk description highlights only the potential factors that might jeopardize a crowdfunding project. Prior studies have illustrated (e.g., Chan et al., 2020; Short & Anglin, 2019) that the same linguistic feature could have differential meanings and impacts across contexts. Readability of different descriptions may also distinctively impact crowdfunding outcomes, so we have constructed separate independent variables for each description.

2.2. Variables

For our dependent variable, we followed prior studies to capture the total pledged amount a campaign had received as a proxy of crowdfunding outcomes (Mollick, 2014; Oo et al., 2019). This is measured as the natural logarithm of total pledged amount plus one, where a high value indicates a large amount of funding. It captures the overall attractiveness of a campaign and can serve as an important element of crowdfunding outcome. In the robustness section, we used other proxies of crowdfunding outcomes to test the boundary conditions of our findings.

For our independent variables, we used BERT, an automatic language evaluation approach, to generate a NLP-based readability score (Devlin et al., 2018). BERT generates word representations from unlabeled text, using both left and right contexts. This model has been pre-trained on large datasets such as the Corpus of Linguistic Acceptability and Wikipedia, and can be finetuned. We used the BERT base uncased pretrained model (12 layers, 768-dimensional, 12 heads, 110M parameters) from the Python library Huggingface (Wolf et al., 2019).

With the story and risk descriptions, we first calculated the BERT score for each sentence. Similar to prior studies (Islam, 2021; Wang & Cho, 2019), we obtained the score by changing BERT's default masking strategy. Instead of masking a percentage of words at random, we masked one word at a time to predict the probability of that word appearing in that position, given the rest of the sentence. We then obtained a BERT score was compiled as the exponentiated cross-entropy loss over all tokens in the sentence. For each token position, the model predicts the probability of the token, given left and right contexts. The lower the probability, the greater the loss. Hence, a smaller loss value (lower BERT score) indicates better predictability for the tokens in the sentence. We then computed the average of these scores to represent the document's overall writing quality. A lower average BERT score will reflect a greater degree of grammatical correctness and fluency, representing better writing quality.

Following prior studies (Chan et al., 2020; Ferrari et al., 2013; Jansen, 2011), we measured the control variable *readability* using the Flesch Reading Ease test. We also included an extensive set of control variables to rule out confounding effects (e.g., Mollick, 2014; Oo et al., 2019). Please see Table 1 for a detailed depiction. Finally, to account for the heterogeneity of the evolving crowdfunding landscape, we included major city and category fixed effects.

3. Analysis

3.1. Main results

Variance inflation factor (VIF) statistics ruled out any potential multicollinearity issues in both datasets. Table 2 reports the mean, standard deviation, and correlation of variables. Although the correlation between BERT scores is low, it is significantly positive, suggesting some consistency in the construction of story and risk descriptions. BERT and Flesch Reading Ease Readability scores are not highly correlated as expected. Table 3 reports standardized coefficients for our key variables, using OLS regression with *total pledged amount* as the dependent variable while controlling for major city and category fixed effects.

Model 1 is our base model, which includes all variables other than main independent variables. This was statistically significant ($R^2 = 0.19$, $p = 0.000 < 0.001$). Model 2 introduces the *BERT scores* of story description and risk description, and demonstrates a significant improvement over the previous model, using a likelihood ratio test ($\Delta R^2 = 0.0055$, LR Chi2 =

15.20, $p = 0.0005 < 0.001$). It shows the relationship between *BERT score of story section* and *total pledged amount* to be positive and significant ($\beta = 0.20$, $p = 0.001 < 0.01$), illustrating how a lower quality of writing (i.e., a higher BERT score) may increase favorable funding outcomes. In contrast, a negative and significant relationship exists between *BERT score of risks section* and *total pledged amount* to ($\beta = -1.04$, $p = 0.047 < 0.05$), illustrating how a lower quality of writing (i.e., a higher BERT score) may result in unfavorable outcomes, perhaps because poor writing quality can hinder backers' ability to understand the risks associated with a campaign.

Given that the relationship between writing quality and funding outcomes may be curvilinear (e.g., Chan et al., 2020; Thapa, 2020), Model 3 includes the squared terms of *BERT scores of story and risks sections* to rule out higher order effects. This model does not improve significantly over Model 2 ($\Delta R^2 = 0.0006$, LR Chi2 = 2.43 $p = 0.2966 > 0.05$), but shows that the effects of *story section and risk section* BERT scores remains fairly consistent ($\beta = 0.27$, $p = 0.001 < 0.01$; $\beta = -0.15$, $p = 0.059 < 0.10$), while the effect of their squared terms was not significant ($\beta = -0.04$, $p = 0.10 > 0.05$; $\beta = 0.01$, $p = 0.642 > 0.05$). Models 4-12 measure readability, using such proxies as the Gunning Fog Index, Linear Write Formula, Dale-Chall Readability Score, Automated Readability Index, Coleman–Liau index, Flesch-Kincaid Grade Level, SMOG Index, Readability Consensus, and Difficult Words. Overall, our results were consistent for *BERT score of story section*, as all 11 models showed its significant and positive relationship with *total pledged amount*. The effect of *BERT score of risk section* on *total pledged amount* was less consistent as 7 of 11 models showed a significant negative relationship.

3.2. Robustness tests and effect size

Given the other aspects of crowdfunding outcomes, we constructed two more proxies as our dependent variables for additional robustness tests (e.g., Calic & Shevchenko, 2020; Short &

Anglin, 2019; Rose et al., 2020). We first measured the total number of backers as the natural logarithm of backers pledged to a particular project, plus one. This represents the overall market size a campaign was able to capture. Table 4 reports standardized coefficients of our variables using OLS regression with *total number of backers* as the dependent variable. Our results were less robust for the BERT score of the risk section, as 4 of 10 models showed significant and negative relationships between the BERT score and the total number of backers. Further, we did not find any significant impacts of the BERT score of story section. These findings suggest that BERT scores mainly prompt more financial support from existing backers who are willing to pledge, but do not attract more new backers. We suspect that this is because readability of crowdfunding descriptions only influences existing backers who intend to read these descriptions carefully. For those who initially are not interested to pledge their support, however, they will not attend to these descriptions, leading to inconsistent impacts of BERT scores on backer numbers.

We created a binary variable to measure the ultimate success of Kickstarter campaigns as related to funding success, with 1 indicating a campaign had been successfully funded, and zero otherwise. This measure covers an important aspect of crowdfunding outcomes, since Kickstarter campaigns do not receive funding when entrepreneurs fail to reach an initial funding amount. Table 5 reports standardized coefficients for our variables using logistic regression, with *funding success* as the dependent variable. We failed to find any significant relationships between *BERT scores* and *funding success*, which are not surprising given that funding success is co-determined by entrepreneurs and backers. If an entrepreneur set a higher funding goal, it will be more difficult for backers to provide sufficient funding, no matter how well the campaign description is written. We have also collected additional control variables to attenuate omitted variable biases and check for finding consistency (Schweinsberg et al., 2021). To control for the effects of collaborators, we created a new variable, Number of Collaborators, to capture how many collaborators a project has involved. We created two variables to capture prior crowdfunding experiences of entrepreneurial teams, including Number of Previous Projects and Number of Previous Successful Projects. Findings remain consistent (Table 6). Finally, after removing outliers, we found consistent results (Appendix B)

The effect sizes of the BERT scores are comparable to those of most variables. By holding other variables at their mean, an increase of one standard deviation in the BERT score of the story section at the mean will increase the total pledged amount that a crowdfunding project may receive by 2.75% (estimated to be $322.62) while an increase of one standard deviation in the BERT score of the risk section will decrease the total pledged amount a crowdfunding project may receive by 1.79 % (estimated to be $178.16) and decrease the number of backers by 2.85% (estimated to be 2.05 backers). This finding suggests that the effects of BERT scores are not only qualitatively meaningful, but may have a substantial impact on funding outcomes.

3.3. Post hoc text assessment task

We conducted a post-hoc text assessment task to better understand how BERT scores may influence readers' perceptions of different characteristics and shape funding evaluation (Appendix A). To ensure empirical realism, we purposely selected four projects, from our main study, that had a story or risk description with a high BERT score and a low Flesch Reading Ease score (see Appendix A.1.), so that we could capture how a high BERT score might influence perceived campaigns characteristics, subsequently shaping funding evaluations. We randomly presented these descriptions to 119 MTurk workers for their evaluations.

Tables A.1a and A.1b show that descriptions with a higher BERT score tend to be perceived as lower writing quality. In Table A.2, Model A1 confirms our suspicion for a negative and significant relationship between BERT score and perceived writing quality (β = -0.17, p < 0.001). Model A2 shows BERT scores significantly associated with higher perceived information processing effort (β = 0.27, p < 0.001). Model A3 delineates a significant and positive relationship between the BERT score and perceived idea complexity (β = 0.22, p < 0.001), while Model A4 indicates a lack of significant relationship between BERT score and perceived entrepreneurial capability. Model A5 demonstrates that the BERT score was positively associated with perceived project risks (β = 0.12, p < 0.001). Finally, model A6 indicates that the evaluations of funding success were positively associated with perceived idea complexity (β = 0.12, p < 0.001), perceived entrepreneurial capability (β = 0.48, p < 0.001), perceived writing quality (β = 0.26, p < 0.001), but negatively associated with perceived project risk (β = -0.17, p < 0.001). Overall, these results suggest that descriptions with low BERT score likely led to favorable funding evaluations due to high perceived writing quality and low perceived project risk, whereas descriptions with high BERT scores were considered favorable as they are able to convey more complex business ideas.

4. Discussion and Conclusion

We have examined how a new natural language processing technique can enable entrepreneurship scholars to understand the relationship between the quality of document writing and new venture funding outcomes. We created an average BERT score as the measure of writing quality to understand how it may predict funding outcomes for crowdfunding projects. Using a sample of 1,359 crowdfunding campaigns, our results and robustness tests illustrate that the significant effects of the average BERT score on crowdfunding outcomes rise above traditional rule-based readability scores, but such effects may be weakened when crowdfunding outcomes, such as funding success, could be co-determined by entrepreneurs and backers.

4.1. Theoretical Speculation and Contributions

Joining a growing body of entrepreneurial finance research (e.g., Allison et al., 2013; Drover et al., 2017), this study shows how the presentation of information may shape funding success. Entrepreneurs are often advised to present business ideas in a simple and readable manner so that investors can easily process and interpret any communicated message. This intuitive prescription is well covered in the entrepreneurial finance literature, yet prior studies have documented positive, negative, insignificant, and even nonlinear relationships between readability and funding outcomes (Block et al., 2018; Chan et al., 2020; Cumming et al., 2019; Thapa, 2020; Zhou et al., 2018).

While we agree with their insights, we would point to another reason for inconsistent findings, specifically measurement issues. Prior studies have relied on traditional readability scores derived from a simple rule-based approach as a proxy for writing quality. Such approaches reflect the surface structure of text, including words and sentence length, while ignoring important factors involving idea complexity and schemata. Thus, traditional readability indices may not fully capture writing quality (Bailin and Grafstein, 2001; Zamanian and Heydari, 2012). Indeed, our study demonstrates that BERT scores derived from advanced computational linguistic techniques (Devlin et al., 2018; Zhang et al., 2019) may allow us to predict the funding outcomes of crowdfunding projects, complementing the traditional rule-based readability score. These findings respond to scholarly calls for granularity provided by big data and advanced computational methods (e.g., George et al., 2016; Pandey and Pandey, 2019; Simsek et al., 2019). This study also joins recent research (Kaminski and Hopp, 2019; Obschonka and Audretsch, 2019) to illustrate the value of artificial intelligence in entrepreneurship research.

Our study also contributes to the interface between computational linguistics and entrepreneurship research. Given the availability of written documents, and the increasing use of computer-aided text analysis (CATA), it is imperative that researchers augment CATA with newer techniques. While the CATA approach offers researchers a new set of tools for investigating questions of interest, it is "less context-sensitive than human coders for detecting the meaning of a word within a sentence" (Short et al., 2010, p. 341). This limitation can be mitigated by using more advanced NLP techniques (Choudhury et al., 2019; Pandey and Pandey, 2019). Indeed, we have witnessed a drastic increase of crowdfunding studies that incorporated advanced NLP methods (Table 7). Most have utilized topic modeling that addresses the topic segmentation of discourse. A similar pattern has also been observed in management research (Hannigan et al., 2019). Yet, there are various methods that could effectively address other types of NLP tasks (Eisenstein, 2019). Our technique, i.e., BERT, was developed to address natural language understanding tasks, so our findings demonstrate the fruitfulness of incorporating other NLP tools to predict crowdfunding outcomes.

As we have demonstrated, the superior performance of the average BERT score over traditional readability indices represents the potential to incorporate the latest computational methods in advanced entrepreneurship and entrepreneurial finance research. At the same time, out study documents the consistent effects of traditional rule-based readability measures on funding outcomes, suggesting that NLP may not fully replace traditional text analysis techniques, but rather, that such distinct techniques may complement each other well.

4.2. Practical Implications

Our study could help entrepreneurs create documents with low average BERT scores, since these have been shown to result in favorable funding outcomes, by checking the average BERT score after drafting a document, or even using BERT to generate pitch documents (e.g., Wang and Cho, 2019). This is another advantage over traditional readability measures, which are ineffective in creating new text or revising existing documents (e.g., Davison and Kantor, 1982).

Venture investors may also benefit from these findings. Given the influence of writing quality, investors may wish to de-bias their decision-making by having a third party extract relevant information or paraphrasing key ideas. By removing the source of such effects, investors could be less swayed by writing quality when it comes to making investment decisions.

4.3. Limitations and Future Research Directions

The limitations of this study highlight future research directions. As with most NLP techniques using deep learning models, it is difficult to determine how BERT actually captures writing quality, making it a challenge to understand how these scores influence investment outcomes or theorize what actually shapes these patterns. As management scholars are currently debating whether and how to incorporate advanced computational methods into our field (Leavitt et al., 2020; Lindebaum, & Ashraf, 2021), our post-hoc task may represent one approach for future studies to shed more light on this process by isolating the underlying mechanisms mediating the relationship between average BERT score and funding outcomes.

The boundary conditions of average BERT score predictability are also unclear. It is possible that predictability is attenuated when entrepreneurs pitch ideas in person, and that in this instance, investors are swayed by visual cues (Chan and Park, 2015; Tsay, 2020), weakening the effect of average BERT scores in a pitch. This is an important aspect of generalizability to investigate in the future, where speech-to-text transcripts of such presentations could provide a natural source of data to power such a study. In addition, prior studies have demonstrated the importance of testing the generalizability of findings using CATA across different crowdfunding contexts (e.g., Short and Anglin, 2019). The same generalizability issues are likely to be observed with NLP approaches and need to be carefully examined in future research.

Also, BERT may eventually be replaced by newer and better techniques, such GPT-2 and RoBERTa. However, BERT model may not be as outdated as it might seem. GPT-2 is an improved version of traditional language models while RoBERTa is an optimized version of BERT (Yakovenko, 2019). Ultimately, these newer techniques are based on existing paradigms, suggesting our findings may remain consistent. Yet, once a breakthrough technique has been developed, it could easily overshadow the performance of these existing techniques.

A number of studies have demonstrated that how individuals utilize information can significantly shape decisions (Allison et al., 2017; Chan and Park, 2013; Mitteness, Sudek, and Cardon, 2012). How would individual differences moderate the relationship between BERT score and funding outcome could be an interesting topic for future researchers to investigate.

Overall, our research demonstrates that BERT scores of campaign descriptions could effectively predict crowdfunding outcomes. Such evidence enables entrepreneurs to improve their funding success, and show the benefit of incorporating advanced computational models in entrepreneurship. By employing BERT and other NLP techniques, future researchers would enhance our understanding of the factors that shape venture investment funding outcomes.

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Table 1: Descriptions of venture characteristics control variables

Variable Name	**Variable Description**
Flesch Reading Ease of Story Description	Based on the story section of these project descriptions, we calculated the Flesch Reading Ease score using a linear combination of average sentence length (number of words divided by number of sentences) and average number of syllables per word (number of syllables divided by number of words). A high score represents an highly readable document, while a low score indicates that the material is relatively more difficult to read.
Flesch Reading Ease of Risk Description	Based on the risks section of these project descriptions, we calculated the Flesch Reading Ease score using a linear combination of average sentence length (number of words divided by number of sentences) and average number of syllables per word (number of syllables divided by number of words). A high score represents an highly readable document, while a low score indicates that the material is relatively more difficult to read.
Ln (Funding Goal)	The natural logarithm of the investment amounts requested by a new venture plus one.
Funding Duration	The number of days available for backers to pledge for a particular crowdfunding projects. Crowdfunding research shows that shorter durations can lead to more favorable funding outcomes (e.g., Mollick, 2014).
Project We Love	This binary variable indicates whether a project has received a badge from Kickstarter to feature projects that go the extra mile.
Number of Images	The number of images presented in the crowdfunding campaign page.
Number of Videos	The number of videos presented in the story section of crowdfunding campaign page.
Number of Words	The number of words used in the in the crowdfunding campaign page.
Frequently Asked Questions Number	The number of frequently asked questions appeared in the crowdfunding campaign page.
Number of Updates	The number of project updates associated with the crowdfunding campaign.
Number of Comments	The number of comments associated with the crowdfunding campaign page.
Number of Facebook Reactions	The number of Facebook reactions associated with the crowdfunding campaign page.

Table 2: Variables, descriptive statistics, and correlations [a]

		Mean	S.D.	1	2	3	4	5	6	7	8	9	10
1	Ln (total pledged amount)	7.34	3.44	1									
2	Ln (total backer number)	3.20	2.78	0.90	1								
3	Success	0.46	0.50	0.72	0.77	1							
4	BERT Score of Story Description	3.92	1.36	0.16	0.11	0.11	1						
5	BERT Score of Risk Description	3.60	2.11	-0.04	-0.04	-0.03	0.10	1					
6	Flesch Reading Ease of Story Description	62.67	21.09	0.03	0.06	0.05	-0.03	0.00	1				
7	Flesch Reading Ease of Risk Description	57.36	20.79	-0.10	-0.09	-0.04	0.01	0.06	0.23	1			
8	Ln (Funding Goal)	9.09	1.68	-0.05	-0.10	-0.35	0.02	0.01	-0.10	-0.14	1		
9	Funding Duration	35.14	12.64	-0.08	-0.08	-0.16	0.01	0.04	-0.08	-0.04	0.26	1	
10	Project We Love	0.09	0.28	0.36	0.36	0.28	0.05	-0.02	0.03	-0.03	0.06	0.00	1
11	Number of Images	16.61	19.53	0.65	0.65	0.54	0.16	0.02	-0.03	-0.13	0.01	-0.03	0.25
12	Number of Videos	0.85	1.80	0.31	0.28	0.18	0.06	-0.03	-0.03	-0.07	0.12	-0.01	0.18
13	Number of Words	659.68	549.79	0.39	0.36	0.26	0.05	0.00	-0.09	-0.11	0.14	-0.05	0.21
14	Frequently Asked Questions Number	2.23	5.36	0.48	0.50	0.35	0.09	0.00	-0.02	-0.06	0.10	0.04	0.36
15	Number of Updates	4.48	5.82	0.61	0.66	0.63	0.07	-0.02	0.03	-0.03	-0.11	-0.04	0.23
16	Number of Comments	97.16	507.95	0.32	0.35	0.21	0.02	-0.01	-0.01	-0.02	0.07	0.04	0.25
17	Number of Facebook Reactions	237.56	1004.42	0.29	0.30	0.17	0.03	-0.02	0.04	0.00	0.09	0.05	0.23

[a] All values greater than 0.05 or less than -0.05 are significant at 5% level.

		11	12	13	14	15	16	17
11	Number of Images	1						
12	Number of Videos	0.41	1					
13	Number of Words	0.47	0.39	1				
14	Frequently Asked Questions Number	0.50	0.26	0.3	1			
15	Number of Updates	0.50	0.27	0.31	0.41	1		
16	Number of Comments	0.27	0.25	0.15	0.38	0.29	1	
17	Number of Facebook Reactions	0.21	0.22	0.15	0.33	0.23	0.45	1

[a] All values greater than 0.05 or less than -0.05 are significant at 5% level.

Table 3: Main Tests with Total Funding Amount as Dependent Variable

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
BERT Score of Story Section		0.20***	0.27***	0.20***	0.20***	0.20***	0.20**	0.20***	0.19**	0.20***	0.20***	0.18**
		(0.06)	(0.08)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
BERT Score of Risk Section		-0.13*	-0.16+	-0.12+	-0.11+	-0.14*	-0.15*	-0.12+	-0.18**	-0.14*	-0.12*	-0.14*
		(0.06)	(0.08)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
BERT Score of Story Section ^2			-0.04+									
			(0.02)									
BERT Score of Risk Section ^2			0.01									
			(0.02)									
Flesch Reading Ease of Story Section	-0.05	-0.00	-0.03									
	(0.08)	(0.09)	(0.09)									
Flesch Reading Ease of Risk Section	-0.21**	-0.26**	-0.25**									
	(0.08)	(0.09)	(0.09)									
Flesch Kincaid Grade of Story Section				-0.05								
				(0.05)								
Flesch Kincaid Grade of Risk Section				0.17*								
				(0.09)								
Gunning Fog of Story Section					-0.06							
					(0.05)							
Gunning Fog of Risk Section					0.19*							
					(0.09)							
Linsear Write Formula of Story Section						0.02						
						(0.06)						
Linsear Write Formula of Risk Section						0.03						
						(0.07)						
Dale Chall Readability of Story Section							0.12					
							(0.10)					
Dale Chall Readability of Risk Section							0.19*					
							(0.08)					
Automated Readability Index of Story Section								-0.02				
								(0.06)				
Automated Readability Index of Risk Section								0.17*				

								(0.09)				
Coleman Liau Index of Story Section									0.31+			
									(0.17)			
Coleman Liau Index of Risk Section									0.52***			
									(0.10)			
Smog Index of Story Section										0.05		
										(0.08)		
Smog Index of Risk Section										0.40***		
										(0.07)		
Text Standard of Story Section											-0.05	
											(0.05)	
Text Standard of Risk Section											0.22*	
											(0.09)	
Difficult Words of Story Section												0.71***
												(0.19)
Difficult Words of Risk Section												0.21**
												(0.07)
Ln (Funding Goal)	-0.04	-0.05	-0.04	-0.03	-0.03	-0.03	-0.04	-0.04	-0.06	-0.03	-0.04	-0.04
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Funding Duration	-0.09	-0.09	-0.09	-0.08	-0.08	-0.08	-0.09	-0.09	-0.08	-0.06	-0.08	-0.08
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Project We Love	0.42***	0.42***	0.41***	0.42***	0.42***	0.42***	0.41***	0.42***	0.40***	0.40***	0.42***	0.40***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)
Number of Images	1.15***	1.13***	1.12***	1.14***	1.13***	1.15***	1.13***	1.14***	1.10***	1.09***	1.12***	1.10***
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Number of Videos	0.02	0.01	0.01	0.02	0.02	0.01	0.02	0.02	0.01	0.01	0.01	0.02
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Number of Words	0.27***	0.28***	0.27***	0.28***	0.28***	0.29***	0.31***	0.28***	0.27***	0.21**	0.28***	-0.40*
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.19)
Frequently Asked Questions Number	0.29**	0.28**	0.28**	0.27**	0.27**	0.28**	0.28**	0.27**	0.28**	0.25**	0.27**	0.25**
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.08)	(0.09)	(0.09)
Number of Updates	0.99***	0.98***	0.98***	0.98***	0.98***	0.98***	0.98***	0.98***	0.97***	0.96***	0.98***	0.96***
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.07)
Number of Comments	0.09	0.10	0.11	0.10	0.11	0.10	0.10	0.10	0.10	0.12	0.11	0.12
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.08)
Number of Facebook Reactions	0.20*	0.20*	0.20*	0.20*	0.20*	0.19*	0.20*	0.20*	0.21*	0.19*	0.19*	0.19+

	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.09)	(0.09)	(0.10)
Constant	7.04***	7.13***	7.15***	7.03***	7.02***	6.98***	7.07***	7.04***	7.16***	7.03***	7.09***	7.09***
	(0.38)	(0.38)	(0.38)	(0.38)	(0.38)	(0.38)	(0.38)	(0.38)	(0.37)	(0.36)	(0.38)	(0.37)
Major City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Category FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.61	0.62	0.62	0.62	0.62	0.62	0.62	0.62	0.63	0.63	0.62	0.62

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.10

Table 4: Robustness Tests with Total Backer Number as Dependent Variable

VARIABLES	Model 13	Model 14	Model 15	Model 16	Model 17	Model 18	Model 19	Model 20	Model 21	Model 22
BERT Score of Story Description	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.01
	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)	(0.04)	(0.05)
BERT Score of Risk Description	-0.09*	-0.08+	-0.08+	-0.09+	-0.11*	-0.08+	-0.13**	-0.09*	-0.08+	-0.09+
	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)
Flesch Reading Ease of Story Description	0.09									
	(0.06)									
Flesch Reading Ease of Risk Description	-0.21**									
	(0.07)									
Flesch Kincaid Grade of Story Section		-0.09*								
		(0.04)								
Flesch Kincaid Grade of Risk Section		0.15*								
		(0.07)								
Gunning Fog of Story Section			-0.09*							
			(0.03)							
Gunning Fog of Risk Section			0.16*							
			(0.07)							
Linsear Write Formula of Story Section				-0.04						
				(0.05)						
Linsear Write Formula of Risk Section				0.04						
				(0.05)						
Dale Chall Readability of Story Section					-0.04					
					(0.07)					
Dale Chall Readability of Risk Section					0.14*					
					(0.06)					
Automated Readability Index of Story Section						-0.06				
						(0.04)				
Automated Readability Index of Risk Section						0.16*				
						(0.07)				
Coleman Liau Index of Story Section							0.08			
							(0.12)			
Coleman Liau Index of Risk Section							0.40***			

							(0.08)			
Smog Index of Story Section								0.04		
								(0.05)		
Smog Index of Risk Section								0.26***		
								(0.05)		
Text Standard of Story Section									-0.07*	
									(0.03)	
Text Standard of Risk Section									0.16**	
									(0.06)	
Difficult Words of Story Section										0.16
										(0.16)
Difficult Words of Risk Section										0.21***
										(0.05)
Ln (Funding Goal)	-0.10**	-0.09**	-0.09**	-0.09**	-0.09**	-0.09**	-0.11***	-0.09**	-0.09**	-0.10**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Funding Duration	-0.05	-0.05	-0.05	-0.05	-0.05	-0.06	-0.05	-0.04	-0.05	-0.05
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Project We Love	0.34***	0.34***	0.34***	0.34***	0.34***	0.34***	0.33***	0.33***	0.34***	0.33***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Number of Images	0.90***	0.90***	0.90***	0.91***	0.91***	0.90***	0.88***	0.87***	0.89***	0.88***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Number of Videos	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	-0.10	-0.09	-0.09	-0.09
	(0.06)	(0.07)	(0.06)	(0.07)	(0.07)	(0.07)	(0.06)	(0.07)	(0.06)	(0.07)
Number of Words	0.11+	0.11+	0.11+	0.11+	0.11+	0.11+	0.10	0.06	0.11+	-0.06
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.16)
Frequently Asked Questions Number	0.27**	0.27**	0.27**	0.27**	0.27**	0.27**	0.27**	0.26**	0.27**	0.26**
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.08)	(0.09)	(0.08)
Number of Updates	0.94***	0.94***	0.94***	0.94***	0.94***	0.94***	0.93***	0.92***	0.94***	0.93***
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.07)
Number of Comments	0.19	0.19	0.19	0.18	0.18	0.19	0.19	0.20+	0.19	0.19+
	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.11)
Number of Facebook Reactions	0.17*	0.17*	0.17*	0.17*	0.18*	0.17*	0.18*	0.17*	0.17*	0.17*
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Constant	3.60***	3.53***	3.52***	3.49***	3.53***	3.54***	3.64***	3.54***	3.57***	3.59***
	(0.29)	(0.29)	(0.29)	(0.29)	(0.29)	(0.29)	(0.29)	(0.29)	(0.30)	(0.29)
Major City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Category FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.66	0.65	0.65	0.65	0.65	0.65	0.66	0.66	0.65	0.66

Robust standard errors in parentheses

*** $p<0.001$, ** $p<0.01$, * $p<0.05$, + $p<0.10$

Table 5: Robustness Tests with Success as Dependent Variable

VARIABLES	Model 23	Model 24	Model 25	Model 26	Model 27	Model 28	Model 29
BERT Score of Story Description	0.07	0.07	0.08	0.08	0.07	0.07	0.06
	(0.12)	(0.12)	(0.12)	(0.13)	(0.12)	(0.13)	(0.13)
BERT Score of Risk Description	-0.16	-0.14	-0.14	-0.14	-0.16	-0.13	-0.19
	(0.14)	(0.15)	(0.15)	(0.16)	(0.15)	(0.15)	(0.13)
Flesch Reading Ease of Story Description	-0.32**						
	(0.12)						
Flesch Reading Ease of Risk Description	-0.13						
	(0.14)						
Flesch Kincaid Grade of Story Section		0.19**					
		(0.07)					
Flesch Kincaid Grade of Risk Section		0.12					
		(0.11)					
Gunning Fog of Story Section			0.16*				
			(0.07)				
Gunning Fog of Risk Section			0.12				
			(0.11)				
Linsear Write Formula of Story Section				0.19+			
				(0.11)			
Linsear Write Formula of Risk Section				0.05			
				(0.14)			
Dale Chall Readability of Story Section					0.28		
					(0.19)		
Dale Chall Readability of Risk Section					0.04		
					(0.15)		
Automated Readability Index of Story Section						0.14	
						(0.10)	
Automated Readability Index of Risk Section						0.18*	
						(0.09)	
Coleman Liau Index of Story Section							0.14
							(0.28)
Coleman Liau Index of Risk Section							0.46*
							(0.21)
Smog Index of Story Section							
Smog Index of Risk Section							
Text Standard of Story Section							
Text Standard of Risk Section							
Difficult Words of Story Section							
Difficult Words of Risk Section							
Ln (Funding Goal)	-1.03***	-1.02***	-1.01***	-1.01***	-1.01***	-1.01***	-1.03***

	(0.10)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
Funding Duration	-0.33*	-0.32*	-0.32*	-0.30*	-0.31*	-0.32*	-0.31*
	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)
Project We Love	0.46**	0.46**	0.46**	0.47**	0.45**	0.46**	0.44*
	(0.17)	(0.17)	(0.17)	(0.18)	(0.17)	(0.17)	(0.18)
Number of Images	0.49*	0.50*	0.50*	0.52*	0.51*	0.49*	0.48*
	(0.23)	(0.23)	(0.23)	(0.23)	(0.23)	(0.23)	(0.23)
Number of Videos	-0.20	-0.21	-0.21	-0.21	-0.22	-0.21	-0.21
	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)	(0.19)
Number of Words	0.38**	0.38**	0.39**	0.38**	0.44**	0.38**	0.37**
	(0.14)	(0.14)	(0.14)	(0.14)	(0.15)	(0.14)	(0.14)
Frequently Asked Questions Number	-0.03	-0.03	-0.03	-0.05	-0.04	-0.02	-0.01
	(0.25)	(0.25)	(0.25)	(0.25)	(0.25)	(0.25)	(0.25)
Number of Updates	1.77***	1.77***	1.78***	1.77***	1.77***	1.78***	1.75***
	(0.43)	(0.44)	(0.44)	(0.44)	(0.44)	(0.43)	(0.42)
Number of Comments	68.46***	68.33***	68.18***	69.62***	68.91***	67.91***	67.48***
	(12.37)	(12.44)	(12.48)	(12.72)	(12.51)	(12.49)	(12.48)
Number of Facebook Reactions	0.24*	0.23*	0.22*	0.22*	0.23*	0.22*	0.22*
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)
Constant	20.72***	20.60***	20.57***	20.78***	20.64***	20.51***	20.54***
	(2.43)	(2.42)	(2.41)	(2.46)	(2.44)	(2.42)	(2.44)
Major City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Category FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.10

Table 6: Robustness Tests with Additional Control Variables

VARIABLES	Model 33 DV: Total Pledged Amount	Model 34 DV: Total Backer Number	Model 35# DV: Success
BERT Score of Story Section	0.19**	0.01	0.05
	(0.06)	(0.04)	(0.13)
BERT Score of Risk Section	-0.14*	-0.10*	-0.21
	(0.06)	(0.04)	(0.16)
Flesch Reading Ease of Story Section	0.00	0.10	-0.33**
	(0.08)	(0.06)	(0.12)
Flesch Reading Ease of Risk Section	-0.26**	-0.21**	-0.17
	(0.08)	(0.07)	(0.13)
Ln (Funding Goal)	-0.01	-0.06*	-0.97***
	(0.04)	(0.03)	(0.10)
Funding Duration	-0.07	-0.04	-0.24+
	(0.06)	(0.05)	(0.14)
Project We Love	0.36***	0.28***	0.39*
	(0.06)	(0.05)	(0.19)
Number of Images	1.00***	0.79***	0.41+
	(0.08)	(0.07)	(0.22)
Number of Videos	0.07	-0.04	-0.17
	(0.07)	(0.06)	(0.19)
Number of Words	0.26***	0.08	0.33*
	(0.07)	(0.06)	(0.14)
Frequently Asked Questions Number	0.26**	0.25***	0.01
	(0.08)	(0.08)	(0.27)
Number of Updates	0.92***	0.88***	1.62***
	(0.08)	(0.07)	(0.41)
Number of Comments	0.05	0.14	63.60***
	(0.07)	(0.10)	(12.31)
Number of Facebook Reactions	0.20*	0.18*	0.25*
	(0.10)	(0.08)	(0.11)
Number of Collaborators	0.29***	0.24***	0.41+
	(0.06)	(0.05)	(0.23)
Number of Previous Projects	0.01	-0.00	
	(0.01)	(0.01)	
Number of Previous Successful	0.36***	0.37***	1.19**
Projects	(0.05)	(0.05)	(0.36)
Constant	6.87***	3.32***	19.68***
	(0.38)	(0.29)	(2.48)
Major City FE	Yes	Yes	Yes
Category FE	Yes	Yes	Yes
R-squared	0.63	0.68	

#Number of previous projects predicts success perfectly, so it is dropped from Model A3.
Robust standard errors in parentheses; *** p<0.001, ** p<0.01, * p<0.05, + p<0.10

Table 7 Recent Crowdfunding Studies Using Advanced NLP

Authors* (Year)	Method: Constructs	Findings
Bellavitis, Cumming, & Vanacker (2020)	Natural Language Processing – Sentiment Analysis: Google News sentiment and Twitter Sentiment	Found Google News and Twitter sentiments, as control variables, to significantly predict the number and average rating of ICOs launched.
Jiang, Wang, Yang, Shen, & Hahn (2021)	Natural Language Processing - Topic Modeling (Latent Dirichlet Allocation (LDA)): Eight reward types (Gratitude, Acknowledgement, Standard product, Special product, Discount product, Early access product, Interaction, and Involvement	Found eight distinct types of crowdfunding rewards are associated with three specific value dimensions, i.e., utilitarian value, socioemotional value, and participatory value, that distinctively shape funding outcomes.
Kaminski, & Hopp (2019)	Natural Language Processing – Topic Modeling (Doc2Vec): preserving the semantics of natural language information	Found that natural language processing techniques and neural network models, based on word and paragraph vector models of text, speech, and video information, achieves a superb prediction accuracy of 73% in explaining campaign success or failure.
Resch, & Kock (2021)	Natural Language Processing - Topic Modeling (LDA): Information depth and breadth	Found a favorable broker position is strengthen by information depth, but is weaken by information breadth.
Taeuscher, Bouncken, & Pesch (2021)	Natural Language Processing - Topic Modeling (LDA): Distinctiveness	Found higher levels of distinctiveness lead to superior crowdfunding performance and such effect intensified with the absence of alternative sources of legitimacy.
Vossen & Ihl (2020)	Natural Language Processing - Topic Modeling (word2vec): Strategic Differentiation, Narrative Anchoring, and Narrative Anchoring	Found that semantically anchoring a product's narrative within claimed categories would strengthen the benefits of differentiation, especially when products span across multiple categories. When a product spans only few categories, a narrative that enriched with unclaimed categories' cultural meaning makes them more favorably evaluated.
Williamson, Short, & Wolfe (2021)	Natural Language Processing - Topic Modeling (LDA): Distinctiveness	Found that distinctiveness in men's campaigns is associated with faster funding, and such effect for women's campaigns vary across sectors.

*In Alphabetical Order

Appendix A: Post hoc text assessment task

We conducted a *post hoc* text assessment task to discover evidence of how high BERT scores for story and risk descriptions may be perceived by individual raters. Based on prior studies, we reasoned that like readability indices, BERT scores may influence different characteristics associated with crowdfunding campaigns. Prior studies have suggested that more readable documents generally require less effort to process, are easier to understand, and are perceived to be less complicated (e.g., Alter & Oppenheimer, 2009; Lawrence, 2013; Schwarz, 2002; You & Zhang, 2009), while less readable documents may suggest to funders that entrepreneurs possess greater intellectual capability (Chan et al., 2018; Pennebaker & King, 1999; Perelman, 2008). Based on these arguments, and the fact that BERT scores can effectively predict readability levels of corpora (e.g., Deutsch, Jasbi, & Shieber, 2020; Tseng et al., 2019), such scores are likely to elicit similar perceptions. We gave four story and risk descriptions to individuals to evaluate which featured a variety of high BERT scores and low Flesch Reading Ease scores.

A.1. Sample and Procedure

We recruited text evaluators from an online labor marketplace, Amazon's Mechanical Turk (MTurk). MTurk recruits represent a demographically diverse population and have proven to provided quality performance on various tasks in psychology, economics, and business (Buhrmester, Kwang & Gosling, 2011; Mason & Suri, 2012).

Once recruited, MTurk workers were informed that they would read and evaluate story and risk descriptions of different crowdfunding projects. We then randomly presented these descriptions to MTurk workers for them to evaluate on a number of perceived characteristics. After completing the task, they reported demographic information, and were debriefed, thanked, and compensated ($2.00 per worker).

A.2. Task design and materials

All MTurk workers rated the same story descriptions and risk descriptions for four different crowdfunding projects in our dataset. To ensure empirical realism, the descriptions were extracted from four crowdfunding projects in our main study. We purposely identified projects that had a story or risk description with a high BERT score and a low Flesch Reading Ease score (see Appendix A.1.), so that we could capture how a high BERT score might influence perceived characteristics of corresponding descriptions.

The MTurk recruits were instructed to read and evaluate these descriptions using modified items used in prior studies (e.g., Chan et al., 2018; Wood, McKelvie, & Haynie, 2014). The recruits were asked to use 5-point scales to evaluate perceived information processing effort, idea complexity, entrepreneurial capability, writing quality, project risk, and funding success (see Appendix A.2.). At the end, they were asked to completed demographic items.

A.3. Results

The 119 MTurk evaluators were comprised of 65 males and 54 females, with ages ranging from 23 to 68 years (mean = 42.54; S.D. = 11.33). Of these, 21 (17.65%) had startup experience and

43 (36.13%) had pledged contributions to crowdfunding projects. On average, MTurk recruits with prior crowdfunding experience had backed 3.23 crowdfunding projects.

Tables A.1a and A.1b show that BERT scores seems to elicit our suspected changes in perceived writing quality. For both story and risk descriptions, those descriptions with higher BERT score tend to be perceived as lower writing quality with a rating distribution of perceived writing quality congregating around lower end of 5-point scale.

We then used hierarchical linear modeling (HLM) as our analytical technique as the workers were asked to evaluate multiple descriptions. The intraclass correlation coefficient (ICC) for a two-level model, with workers as the higher level grouping and perceived characteristics as dependent variables, ranged from 0.05 to 0.19, suggesting that HLM analysis was appropriate (Gelman & Hill, 2007).

Table A.2, Model A1 confirms our suspicion for a negative and significant relationship between BERT score and perceived writing quality ($\beta = -0.17$, $p < 0.001$). Model A2 shows BERT scores significantly associated with higher perceived information processing effort ($\beta = 0.27$, $p < 0.001$). Model A3 delineates a significant and positive relationship between the BERT score and perceived idea complexity ($\beta = 0.22$, $p < 0.001$), while Model A4 indicates a lack of significant relationship between BERT score and perceived entrepreneurial capability. Model A5 demonstrates that the BERT score was positively associated with perceived project risks ($\beta = 0.12$, $p < 0.001$). Finally, model A6 indicates that the evaluations of funding success were positively associated with perceived idea complexity ($\beta = 0.12$, $p < 0.001$), perceived entrepreneurial capability ($\beta = 0.48$, $p < 0.001$), perceived writing quality ($\beta = 0.26$, $p < 0.001$), but negatively associated with perceived project risk ($\beta = -0.17$, $p < 0.001$). These findings suggest that BERT scores may not only directly influence a number of perceived characteristics but also indirectly shape crowdfunding success evaluations via impact on perceived idea complexity, writing quality and project risk. These indirect effects differed from traditional readability scores documented in prior studies, suggesting a future research direction.

A.4. Discussion of *post hoc* experiment

These findings allowed us to understand how BERT scores might influence individual perceptions and crowdfunding evaluation. Overall we found that a higher BERT score effectively reflected lower perceived writing quality, and significantly influenced a number of perceived characteristics, which could subsequently shape how an individual might evaluate crowdfunding campaigns. Our results suggest that campaign descriptions with low BERT scores may lead to favorable funding evaluations, due in part to high perceptions of writing quality and low perceptions of project risk, whereas campaign descriptions with a higher BERT score were more favorable because they conveyed more complex business ideas.

Appendix A.1: Story and Risk Descriptions with Varying Levels of BERT Score

Medium BERT Score Version (Standardized BERT Score = 1.36; Standardized Flesch Reading Ease = -1.05)

Risks and challenges

The biggest risk we currently face is distribution. We are experienced manufacturers but large scale distribution is new territory for us.

Medium-High BERT Score Version (Standardized BERT Score = 2.02; Standardized Flesch Reading Ease score= -1.23)

Story

This daily undated planner journal is different than most - it incorporates goal planning and daily planning into one functional and sleek journal design. It encompasses both structured sections and creative sections and will include a main goal section, mini goal sections, daily plans, goal check-ins, wellness trackers, motivational quotes and more. Multiple colors will be available.

High BERT Score Version (Standardized BERT Score = 3.28; Standardized Flesch Reading Ease score= -1.53)

Story

Main purpose of fundraiser is to facilitate inventory for rotating orders and reduce wait time for customers. Extreme temperatures have always been an issue even before our recognition of human impact on Global Climate. The Smart Pocket/ Project Warmsuit helps regulate body temperature with a simple yet useful hands free design, that aggressively nullifies external temperatures.

The company is seeking retail placement for consumer convenience.

Fundraiser is for product awareness & importance of body temperature regulation. Project Goal is 150 units.

New Designs is a new company created in 2012. New Designs will offer state of the art clothing & wetsuits that will regulate the wear's body temperature, making diving in cold water more comfortable and help athletes stay warm while exercising. Accepting Pre-Orders for Compression Tops & Wetsuits

New Designs Company Mission Statement:

Regulate the wearer's Body Temperature.

Make Diving in cold water more comfortable.

Help athletes stay warm or cool while exercising.

How it works:

The Integrated Pocket Technology Design allows the wearer to insert hot or cold packs into the garment.

Benefits of the "IPTD" include increased Body Performance; Therapeutic & Rehabilitative qualities.

All Garments with "IPTD" are compatible with any variety hot/cold packs.

High BERT Score Version (Standardized BERT Score = 5.66; Standardized Flesch Reading Ease score= -3.96)

Risks and challenges

organizing and sourcing cost-effective, sustainable materials for monthly ritual subscription boxes

ethically sourcing and building sustainable eco-friendly boxes and materials

Appendix A.2: Survey items for perceived characteristics

Perceived Information Processing Effort

How much effort did it take to understand these sentences?

Far below average	Somewhat below average	Average	Somewhat above average	Far above average
1	2	3	4	5

Perceived Idea Complexity

How complex is this business solution?

Far below average	Somewhat below average	Average	Somewhat above average	Far above average
1	2	3	4	5

Perceived Entrepreneurial Capability

How capable do these entrepreneurs appear to be?

Far below average	Somewhat below average	Average	Somewhat above average	Far above average
1	2	3	4	5

Perceived Writing Quality

How good is the writing quality of these sentences?

Far below average	Somewhat below average	Average	Somewhat above average	Far above average
1	2	3	4	5

Perceived Project Risk

How risky is this crowdfunding project?

Far below average	Somewhat below average	Average	Somewhat above average	Far above average
1	2	3	4	5

Evaluation of Funding Success

How successful will this crowdfunding project be in raising funding?

Far below average	Somewhat below average	Average	Somewhat above average	Far above average
1	2	3	4	5

Table A.1a: Writing Quality Rating Distribution, Mean, and Standard Deviation of Story Description BERT Scores

Standardized BERT Score	Writing Quality =1	Writing Quality =2	Writing Quality =3	Writing Quality =4	Writing Quality =5	Writing Quality Mean	Writing Quality S.D.
2.02	N=0	N=4	N=42	N=54	N=19	3.74	0.76
3.28	N=3	N=19	N=34	N=41	N=22	3.50	1.05

Table A.1b: Writing Quality Rating Distribution, Mean, and Standard Deviation of Risk Description BERT Scores

Standardized BERT Score	Writing Quality =1	Writing Quality =2	Writing Quality =3	Writing Quality =4	Writing Quality =5	Writing Quality Mean	Writing Quality S.D.
1.36	N=2	N=11	N=64	N=35	N=7	3.29	0.78
5.66	N=12	N=46	N=43	N=16	N=2	2.58	0.91

Table A.2: Effects of BERT Score on Perceived Characteristics

VARIABLES	Model A1 DV: Perceived Writing Quality	Model A2 DV: Perceived Information Processing Effort	Model A3 DV: Perceived Idea Complexity	Model A4 DV: Perceived Entrepreneurial Capability	Model A5 DV: Perceived Project Risk	Model A6 DV: Funding Success
Perceived Writing Quality						0.26***
						(0.040)
Perceived Information Processing Effort						-0.00
						(0.033)
Perceived Idea Complexity						0.12***
						(0.034)
Perceived Entrepreneurial Capability						0.48***
						(0.042)
Perceived Project Risk						-0.17***
						(0.030)
BERT Score	-0.17***	0.27***	0.22***	-0.04	0.12***	-0.00
	(0.027)	(0.027)	(0.029)	(0.028)	(0.031)	(0.021)
Successful Champaign	0.02	-0.41***	-1.00***	-0.25**	-0.29**	0.01
	(0.087)	(0.086)	(0.091)	(0.088)	(0.097)	(0.064)
Story Description	0.54***	0.68***	0.59***	0.63***	-0.18*	-0.04
	(0.080)	(0.079)	(0.083)	(0.081)	(0.089)	(0.060)
Startup Experience	-0.14	0.47**	0.19	0.01	0.08	0.04
	(0.121)	(0.145)	(0.132)	(0.129)	(0.138)	(0.089)
Crowdfunding Experience	0.11	-0.25*	0.05	0.16	-0.13	-0.05
	(0.098)	(0.118)	(0.107)	(0.104)	(0.112)	(0.072)
Number of Backed Champaigns	0.01	0.00	0.01	0.01	0.01	0.01+
	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.005)
Age	0.00	0.01	0.01	0.00	0.01	-0.00
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)
Gender	-0.00	0.07	0.05	-0.07	0.24*	-0.10
	(0.094)	(0.112)	(0.102)	(0.100)	(0.107)	(0.068)
Product Experience	-0.14	-0.20	0.18	0.05	0.06	-0.09

	(0.458)	(0.549)	(0.500)	(0.487)	(0.523)	(0.333)
Constant	4.47	-4.19	-4.99	-1.62	3.72	1.44
	(3.972)	(4.765)	(4.340)	(4.229)	(4.540)	(2.903)

Robust standard errors in parentheses;
*** p<0.001, ** p<0.01, * p<0.05, + p<0.10

Appendix B: BERT Scores Outliers - Histograms and Robustness Tests

Figure B1: Histogram of BERT Score of Story Description

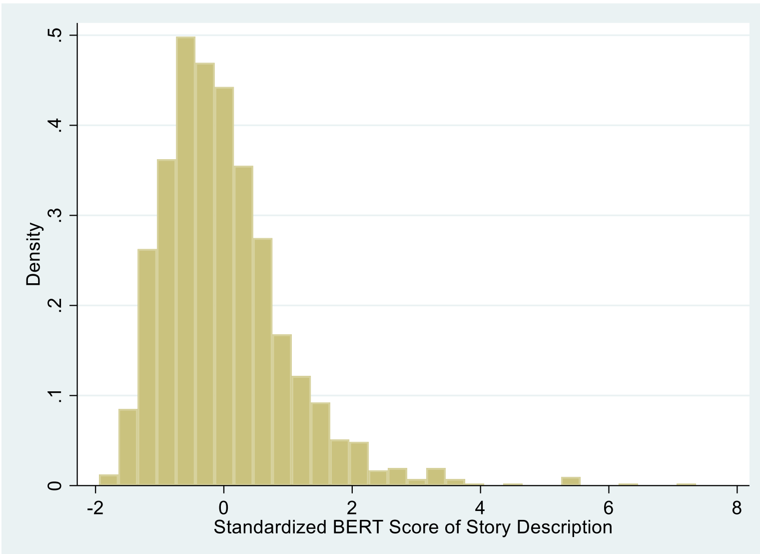

Figure B2: Histogram of BERT Score of Risk Description

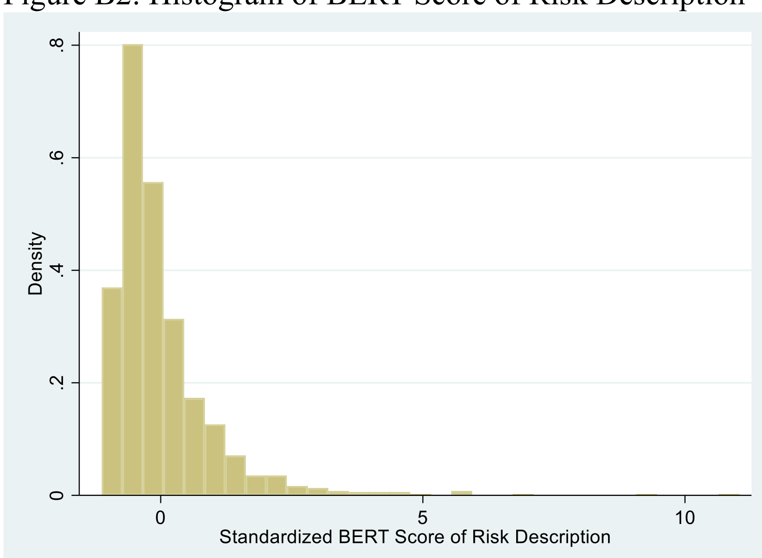

Table B Robustness Analysis – Removing BERT scores above +3 or below -3 S.D.

VARIABLES	Model B1 DV: Total Pledged Amount	Model B2 DV: Total Backer Number	Model B3 DV: Success
BERT Score of Story Description	0.25***	0.07	0.09
	(0.07)	(0.05)	(0.15)
BERT Score of Risk Description	-0.15+	-0.16**	-0.35*
	(0.08)	(0.06)	(0.16)
Flesch Reading Ease of Story Description	-0.10	0.03	-0.36+
	(0.12)	(0.09)	(0.20)
Flesch Reading Ease of Risk Description	-0.23**	-0.19**	-0.07
	(0.09)	(0.07)	(0.14)
Ln (Funding Goal)	-0.04	-0.10**	-1.02***
	(0.04)	(0.03)	(0.10)
Funding Duration	-0.11+	-0.06	-0.35**
	(0.06)	(0.05)	(0.13)
Project We Love	0.42***	0.34***	0.45**
	(0.05)	(0.05)	(0.17)
Number of Images	1.11***	0.89***	0.45*
	(0.08)	(0.07)	(0.22)
Number of Videos	0.01	-0.09	-0.20
	(0.07)	(0.06)	(0.20)
Number of Words	0.27***	0.10	0.39**
	(0.07)	(0.06)	(0.14)
Frequently Asked Questions Number	0.27**	0.26**	-0.04
	(0.09)	(0.09)	(0.24)
Number of Updates	1.00***	0.95***	1.78***
	(0.08)	(0.08)	(0.44)
Number of Comments	0.10	0.18	68.64***
	(0.09)	(0.12)	(12.33)
Number of Facebook Reactions	0.20*	0.17*	0.24*
	(0.10)	(0.08)	(0.11)
Constant	7.11***	3.59***	20.58***
	(0.38)	(0.30)	(2.41)
Major City FE	Yes	Yes	Yes
Category FE	Yes	Yes	Yes
R-squared	0.62	0.66	

Robust standard errors in parentheses;
*** p<0.001, ** p<0.01, * p<0.05, + p<0.10