The predictive utility of word familiarity for online engagements and funding

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Metacognitive frameworks such as processing fluency often suggest people respond more favorably to simple and common language versus complex and technical language. It is easier for people to process information that is simple and nontechnical compared to complex information, therefore leading to more engagement with targets. In two studies covering 12 field samples (total $n = 1{,}064{,}533$), we establish and replicate this simpler-is-better phenomenon by demonstrating people engage more with nontechnical language when giving their time and attention (e.g., simple online language tends to receive more social engagements). However, people respond to complex language when giving their money (e.g., complex language within charitable giving campaigns and grant abstracts tend to receive more money). This evidence suggests people engage with the heuristic of complex language differently depending on a time or money target. These results underscore language as a lens into social and psychological processes and computational methods to measure text patterns at scale.

processing fluency | automated text analysis | common words | jargon | field studies

People often respond favorably to information when it is presented in simple terms compared to complex terms. Simplicity is often preferred when consuming information because it allows people to understand what is being said and to make effective decisions based on information. In medicine, for example, doctors who use jargon when describing procedures tend to confuse patients (1, 2), which might negatively impact their assessment of health risks (3, 4). People who read complex descriptions about technology compared to simple descriptions about technology tend to process this information poorly and have heightened risk perceptions toward the technology as a result (5). Together, how information is communicated matters and often affects how easily people can process it, leading to downstream consequences for judgments of a target and decision making.

Much of the literature describing the negative consequences of jargon—defined as complex, technical, and specialized language that is the opposite of everyday common language—focuses on processing fluency. If a piece of text contains high rates of technical terms, people are less likely to process it fluently, and they will have more difficulty managing it cognitively. Therefore, processing fluency refers to feelings of ease while processing new information. As Oppenheimer (6) suggests, our processing of words and messages is similar to how we process objects in our visual field. If an object "is blurry, we are aware that it was hard to see. If a word is phonemically irregular, we recognize the challenge in processing it" (6). Therefore, words that are uncommon and technical should be perceived negatively compared to words that are common and nontechnical because they are unfamiliar, feel difficult to process, and present a challenge for comprehension (for reviews, see refs. 7–9).

While the processing fluency literature suggests language complexity affects how people feel while processing information, the strength, robustness, and predictive utility of these effects are unclear in the field (though, see ref. 10). Furthermore, most processing fluency studies rely on perception judgments and ask people how they felt toward information (or a source) after reading simple or complex language. In the current research, we draw on this experimental work to evaluate whether simple and common language (versus complex and technical language) is associated with behavioral outcomes in natural settings. We also make a contribution to the literature by altering the behavioral outcome of each study. That is, we evaluate the relationship between common language and behavioral outcomes that differ as a result of how people express their support. We find that common language associates with receiving more online support in the form of social engagements (e.g., views, comments, likes, upvotes), but complex language associates with receiving more money from others. Together, this work advances explanations and evidence for how people use the heuristic of language complexity to guide their attention and behavior online.

Lexical Fluency and Metacognitive Processing

The idea that simple texts are processed more fluently than complex texts has a long history in psycholinguistics. Readability research, for example, suggests sentences with fewer words and words with fewer syllables are more understandable than sentences with more words and words with more syllables (11). People generally have a limited capacity to maintain long, large, or complex words in memory; syntactically simpler texts are therefore preferred because they are more psychologically manageable than complex texts.

A different yet complementary form of fluency—lexical fluency—considers word choice and how simple words are more easily understood than complex words. A landmark paper by Oppenheimer (12) demonstrated that people had less favorable

Significance

How well do simple or complex language patterns predict meaningful behaviors in the field? We used nearly 1.1 million datapoints across 12 samples to demonstrate that language complexity is a positive or negative heuristic depending on instrumental goal activation (e.g., if effort in a task is associated with value). We substantiate the simpler-is-better hypothesis that suggests without instrumental goal activation, common words associate with favorable outcomes in social media, academia, and entertainment settings. With instrumental goal activation, however, complexity leads to more favorable outcomes in the form of money for charitable giving campaigns and NIH grants. We demonstrate the contingent nature of language complexity as a heuristic, with clear links to behavior in the field.

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perceptions of writers who used complex versus simple words (e.g., using the word "desire" instead of "want"). Writers of personal admissions statements to college were perceived as less intelligent if their essay contained complex words compared to simple words. Other work suggests companies that contain high rates of jargon in their values statements tend to be viewed as less moral, less warm, and less trustworthy than companies with low rates of jargon (13). This general effect has been replicated in many studies, where people form more positive perceptions of a target when simple versus complex language is used (5, 13–15).

Why do people tend to prefer simplicity over complexity? Prior work suggests people use their feeling system to make judgments about others and their preferences (16–18). If a text feels simple to read and approachable, people will respond more favorably toward it compared to a text that feels difficult to read (19). However, people can also form positive evaluations of complexity if they perceive that a task is adequately, or appropriately, challenging (20) and worth pursuing (21). This "instrumentality heuristic" argues that people may appraise a subjectively difficult experience positively if it helps to achieve a particular goal. Labroo and Kim (21) evaluated how perceptual processing fluency of a campaign message (e.g., one campaign was presented clearly, and the other was blurry, but content was identical) affected donation amount to the campaign after goal pursuit was accessible or not (e.g., participants either had a "be kind" goal or a neutral goal). Those randomized to the "be kind" goal donated more money to a charitable giving campaign when the campaign message was difficult to process compared to easy to process. On the other hand, those randomized to a neutral goal donated more money to a charitable giving campaign when the campaign message was easy to process compared to difficult to process, thus reinforcing the simpler-is-better hypothesis.

Taken together, the effects of processing fluency depend on the contextual interpretation of fluency (21–23). When an easy experience is valued, then a fluent experience will be associated with favorable outcomes; and, conversely, when a difficult experience is valued, then a disfluent experience will be associated with favorable outcomes. One of the contributions of this work is to identify the natural conditions under which simplicity (Study 1) and complexity (Study 2) are valued.

The type of processing fluency examined here is lexical fluency, defined as the processing of simple versus complex words. Lexical fluency is crucial for comprehension, recall, and decision making, but most evaluations are small-scale experiments that measure perception effects from a fluent or disfluent experience. In this work, we advance processing fluency research by evaluating how simple or complex language patterns relate to actual behavior in large-scale field studies across a range of settings. Although we cannot directly measure processing fluency because this work is observational by design, a wealth of experimental evidence documents the perceptual correlates of verbal complexity, and we examine its behavioral effects in the wild (7–9). We also consider how instrumental goal activation might modify the relationship between lexical fluency and behavior.

Predictions

In settings where people can engage, and an instrumental goal is not activated, people should respond more actively toward simple (versus complex) text because nontechnical language can elicit positive attitudes and engagement (17). This expectation is consistent with most lexical processing fluency studies that find simpler language is appraised more positively than complex language. This is because people prefer familiar as opposed to novel stimuli (24), suggesting that simpler and familiar language should be engaged with more than complex and unfamiliar language. Simple language simply feels better and is therefore processed more fluently, and as a result more favorably, than complex language (19). Here, we label this expectation the simpler-is-better hypothesis:

H_1: In the absence of instrumental goal activation, people will respond favorably to simple compared to complex language in the form of social engagements

An important contribution of this work is the demonstration that processing fluency effects depend on whether people value an easy or difficult experience (22, 23). Although the value of an easy experience has been well documented (7), we examine circumstances in which a difficult experience can engender favorable outcomes as well. Past research has found that feelings of effort are particularly diagnostic during instrumental goal activation (21–23). Instrumental goal activation is defined as a circumstance in which a person is either striving to achieve something of value or recognizes that someone else is trying to do so. Online cases of instrumental goal pursuit include participating on sites where the goal is to raise money, seek funding, or participate in a competition, to offer a few common examples. In these situations, effort and goal attainment are top of mind, so the instrumentality heuristic, which refers to "…the naive belief that effort signals instrumentality," becomes relevant (21). Thus, when an instrumental goal is activated, a difficult experience should be valued over an easy experience. In support of this claim, when people decide to give money (21), complexity has been shown to positively impact behavior. Similarly, complexity in NSF grant abstracts (e.g., more words, more technical terms) associates with receiving more award money (25). Under circumstances in which an instrumental goal is made explicit, or activated, feelings of effort should be valued and, consequently, rewarded.

Feelings related to goal pursuit can also activate a credibility heuristic alongside complex language (23). The credibility heuristic suggests when people are asked to make quality judgments, they tend to value complexity over simplicity because harder to process ideas are likely to be perceived as more intellectual in the appropriate setting (23). This link between language complexity and quality perceptions has also been supported in the online shopping setting such that more complex and longer verbal descriptions on eBay tend to receive more bids and a higher asking price compared to less complex and shorter verbal descriptions (26), a pattern generally observed in peer-to-peer lending and online altruism campaigns as well (27–29). Together, when financial stakes are involved, complexity can signal that a writer is serious, competent, and credible, which might lead to higher perceptions of quality and, in turn, support from the crowd. Our work evaluates how the complexity of language content connects to financial outcomes when an instrumental goal is activated. Other research has generally considered the link between text length or readability and financial outcomes, but we examine what is said instead of how much is said. These rationales lead to our second hypothesis:

H_2: In the presence of instrumental goal activation, people will respond favorably to complex compared to simple language in the form of money

Our paper is separated into two primary studies consisting of multiple operationalizations that test the same general research question within each study. Table 1 contains an overview of the studies and descriptive statistics for each sample. Each study contains the same independent variable (e.g., the rate of common words). Dependent variables were relatively consistent across samples within each study, and relevant controls for each investigation are also noted in Table 1.

We decided to group our samples into two primary studies to improve the readability of our paper and demonstrate the robustness of the effects as a collection. In *SI Appendix*, we provide additional methodological details for each within-study sample and preprocessing steps for each language sample.

Table 1. Overview of studies, samples, and variables in statistical models

Study	Sample	n	Textual unit of analysis	DV(s)	Controls	M_{WC}	SD_{WC}	M_{common}	SD_{common}
1	News	9,600	Tweet	Likes, retweets	News source (R)	28.39	15.33	52.14	19.65
	Journalists	13,009	Tweet	Likes, retweets	News source (R), writer (R)	24.01	12.19	60.31	17.43
	Politicians	364,430	Tweet	Likes, retweets	Year (F), speaker (R)	17.48	6.34	59.82	17.53
	Reddit	22,945	Thread title	Upvotes, comments	Year (F), thread (R)	14.14	10.88	81.81	18.66
	PLoS One	32,062	Paper title	Views, shares, citations, saves	Year (F), first author (R)	15.13	4.97	66.31	14.27
	PLoS One	30,309	Paper abstract	Views, shares, citations, saves	Year (F), first author (R)	250.05	63.41	70.36	7.49
	TED talks	2,655	Talk title	Views, comments	Talk duration (F), tags (F), talk topic (R), speaker (R)	6.42	2.25	78.56	18.94
	TED talks	2,655	Talk content	Views, comments	Talk duration (F), tags (F), talk topic (R), speaker (R)	2,044.25	944.00	86.92	3.80
2	Kickstarter	160,007	Campaign blurb	Amount pledged	Donors (F), campaign goal (F), campaign success (F), time (F) category (R)	19.05	4.94	75.24	13.99
	Indiegogo	19,171	Project tagline	Funds raised	Time (F), category (R), currency (R)	13.97	3.89	74.15	15.74
	GoFundMe	181,238	Funding story	Funds raised	Funding goal (F), donors (F), shares (F), time (F) category (R), currency (R)	239.31	229.44	86.34	5.57
	NIH	226,452	Grant abstracts	Grant cost	Year (F), time (F)	389.33	102.97	68.00	5.96

In all models, the independent variable was the LIWC dictionary category. DV = dependent variable. (F) = fixed effect in the linear (mixed) model, and (R) = random intercept in the linear (mixed) model. M_{WC} and SD_{WC} = average word count and SD per sample, respectively; M_{common} and SD_{common} = average rate and SD of common words per sample, respectively. Time = time difference between the start and end date of the campaign or grant. Note, in cases when the data contained true zero values, a constant (value = 1) was added to each data point before natural log transformation, where applicable.

Study 1: Method

Our first study investigated the hypothesized relationship that simple language with common words leads to engagement compared to complex language with technical words. We examine this relationship in six settings (1): Tweets from top left-leaning (The New York Times), right-leaning (Fox News), and centrist news organizations (The Associated Press); (2) Tweets from a random selection of journalists or personalities within each of the three news organizations; (3) Tweets from Republican politicians and those within the Trump administration; (4) Reddit thread titles; (5) science paper titles and abstracts; and (6) TED (technology, entertainment, design) talks and talk titles.

Automated Text Analysis. In both studies, we used the automated text analysis tool Linguistic Inquiry and Word Count (LIWC) to count the words in each text (30). LIWC operates on a simple word counting system identifying the rate that a word appears in its internal dictionary of social (e.g., words related to family), psychological (e.g., words related to cognitive processes), and parts of speech categories (e.g., pronouns, articles). The tool counts how many words appear in specific dictionary categories as a percentage of the total word count. For example, the phrase "Today, I will talk about science" contains six words and increments dimensions including but not limited to first-person singular pronouns (e.g., I; 16.67% of the total word count) and prepositions (e.g., about; 16.67% of the total word count). In total, we quantified over 155 million words with LIWC across samples.

Common words. The LIWC dictionary contains over 6,400 words in English that represent "informal, non-technical language" (31). Broadly, as Pennebaker and colleagues describe (30, 31), the dictionary was developed by first collecting words to tap conceptual dimensions (e.g., emotion). Then, human judges (groups of four to eight people) rated how well a word fit within a particular category. Words were retained if a majority of judges deemed that a word adequately fit a category. Base rate tests and reliability checks helped to ensure that entire collections of words formed coherent categories that could be applied to a range of texts, including formal writing, informal writing, social media posts, and natural speech. Therefore, while LIWC is an automated text analysis tool, it is a human validated and statistically reliable source of common and nontechnical words.

Consistent with prior work (13, 25, 31–34), we operationalized the rate of common words as the percent of the LIWC dictionary captured in each text. High scores indicate a greater rate of common words (less jargon or technical language) than low scores. All studies in the paper used the LIWC dictionary category as the measure of simple or common language. Data across studies and samples are located on the Open Science Framework (https://osf.io/493tj/).

Study 1: Results and Discussion

Analytic Approach. For each sample, we included control variables in our statistical models to isolate the relationship between common words and engagement (Study 1) or funding (Study 2) after accounting for other variables relevant to each setting. In general, the controls fell into one of five categories: information source (e.g., news source, speaker, writer, author), time (e.g., year, video length, time since posting, publication date), topic (e.g., topic categories or number of topic categories tagged), money (e.g., in Study 2, if the campaign succeeded or failed, currency type, amount solicited), and engagement (e.g., in Study 2, the number of donors, number of shares). We selected these controls because they were available from each data source and were theoretically relevant variables to account for.

In other cases, we controlled for subject topic in the process of collecting data (e.g., all academic abstracts from Public Library of Science [PLoS] One pertained to psychology). When we could not control for a particular variable directly, we indirectly made adjustments to our outcome measures. That is, since many of our outcome measures are time dependent (e.g., likes in Study 1 are affected by the age of a post), we controlled for time by counting the number of days between a post's publication date and the date we extracted the data. This process was used when a proxy for time was unavailable (e.g., year), for example. Adding or removing a proxy for time (e.g., year) to such models after adjusting our dependent variables did not substantively affect the results. Therefore, our analyses attempted to use a consistent set of controls across samples and studies.

Statistical models in each study included fixed and random effects. We therefore used linear mixed models with the lme4 package in R (35) to predict social engagement from common words (fixed effect) and control variables highlighted in Table 1. We also provide bivariate correlations between our independent and dependent variables in *SI Appendix*.

News. Since older Tweets might naturally have more likes and retweets than recent Tweets, we counted the number of days between the Tweet publication date and the date of data collection (extraction date − publication date) and divided all engagement measures by this difference score. Likes and retweets (natural log transformed) were strongly associated in the positive direction (r = 0.69, P < 0.001). We therefore combined these variables into a "social engagement" index by adding their standardized values. Likes and retweets were also analyzed separately to assess their relative strength and direction.

The relationship between the social engagement index and common words was positive and statistically significant (B = 2.885e-02, SE = 1.397e-03, t = 20.65, P < 0.001, 95% CI: [0.026, 0.032]*, R^2c = 0.23†). At the engagement level, the rate of common words was positively associated with likes (B = 2.235e-02, SE = 1.461e-03, t = 15.30, P < 0.001, 95% CI: [0.019, 0.025], R^2c = 0.26) and retweets (B = 2.228e-02, SE = 9.851e-04, t = 22.62, P < 0.001, 95% CI: [0.020, 0.024], R^2c = 0.17). Therefore, on average, news outlets tend to receive more engagements when Tweet content is verbally simpler compared to complex.

Journalists. Consistent with the news sample, we counted the days between the Tweet publication date and the date of data collection (extraction date − publication date) and divided all engagement measures by this difference score. Natural log transformed likes and retweets were also positively linked (r = 0.78, P < 0.001) and combined into a standardized social engagement index.

The relationship between social engagements and common words was positive and significant (B = 3.375e-03, SE = 4.634e-04, t = 7.28, P < 0.001, 95% CI: [0.002, 0.004], R^2c = 0.80). At the engagement level, the rate of common words was positively associated with likes (B = 1.818e-03, SE = 3.422e-04, t = 5.31, P < 0.001, 95% CI: [0.001, 0.002], R^2c = 0.85) and retweets (B = 3.249e-03, SE = 4.919e-04, t = 6.61, P < 0.001, 95% CI: [0.002, 0.004], R^2c = 0.61). Therefore, on average, news journalists tend to receive more engagements when Tweet content is simple compared to complex.

Politicians. Natural log transformed likes and retweets were positively associated (r = 0.73, P < 0.001) and therefore combined into a social engagement index by adding their standardized values.

The relationship between common words and the social engagement index was positive and significant (B = 4.229e-03, SE = 1.241e-04, t = 34.07, P < 0.001, 95% CI: [3.98e-03, 4.47e-03], R^2c = 0.58). These effects were replicated for likes (P < 0.001) and retweets (P < 0.001).

Reddit threads. We created a social engagement index by combining the standardized rates of upvotes and comments (both natural log transformed) after observing that upvotes and comments were highly correlated (r = 0.89, P < 0.001).

Thread titles with simpler words and more common terms tend to receive more social engagements on Reddit (B = 3.026e-03, SE = 2.648e-04, t = 11.43, P < 0.001, 95% CI: [0.002, 0.004], R^2c = 0.91). At the item level of the social engagement index, thread titles with more common words tend to receive more upvotes (B = 1.778e-03, SE = 3.443e-04, t = 5.16, P < 0.001, 95% CI: [0.001, 0.003], R^2c = 0.93) and comments (B = 4.662e-03, SE = 3.568e-04, t = 13.07, P < 0.001, 95% CI: [0.004, 0.005], R^2c = 0.85). Therefore, on a different social media platform with different conventions and posting structure, we once again observed that simpler text tends to receive more social engagements than complex text.

Science papers: Titles and abstracts. We used four measures to operationalize article impact, including the number of views, saves, shares, and citations per article as listed on the homepage for each PLoS One paper. Since older publications might naturally have more views, saves, and citations than more recent publications, we counted the number of days between the publication date and the date of data collection (extraction date − publication date) and divided all impact measures by this difference score. All measures were then natural log transformed.

Titles. Common words positively predicted the publication impact for views (B = 6.813e-03, SE = 3.071e-04, t = 22.18, P < 0.001, 95% CI: [6.223e-03, 7.433e-03], R^2c = 0.43) and shares (B = 9.981e-05, SE = 1.754e-05, t = 5.69, P < 0.001, 95% CI: [6.506e-05, 0.0001], R^2c = 0.02), and saves (B = 6.236e-05, SE = 5.231e-06, t = 11.92, P < 0.001, 95% CI: [5.159e-05, 7.231e-05], R^2c = 0.44) but not citations (P = 0.793, R^2c = 0.17).

The null relationship between citation rate and common words is reasonable after considering what titles allow people to appraise about a paper and the requirements for citing a research article. Titles allow readers to assess whether a paper, on average, appears interesting, informative, or worth a reader's time. Views, saves, and shares are metrics most likely to be impacted by a simpler or more complex title. Citing an article, however, requires more information to be appraised than just reading the paper's title, as authors must believe that a section or the entire paper's argument is worth referencing in their own research. Therefore, titles are an entryway for a reader to decide if they should investigate the paper further, and as our data suggest, common words are predictive of initial interest in a paper as indicated by rates of views, shares, and saves. This is conceptually similar to the difference between search goods and experience goods from consumer behavior research (36). Search goods describe objects that can be appraised before purchasing (e.g., ripeness of fruit), whereas experience goods are only assessed after consumption or committing to them (e.g., a bottle of wine). Titles might be a type of search good, as they offer only a cursory view of an article. Simpler titles may allow readers to make some inferences (Is the title worth me viewing or sharing?) but not others (Is the content worth citing?).

Abstracts. The prior effects were largely replicated using science paper abstracts as well.‡ Common words positively predicted the publication impact for views (B = 1.166e-02, SE = 6.021e-04, t = 19.36, P < 0.001, 95% CI: [0.011, 0.013], R^2c = 0.44), shares (B = 3.158e-04, SE = 3.270e-05, t = 9.66, P < 0.001, 95% CI: [0.0003, 0.0004], R^2c = 0.02), and saves (B = 1.371e-04, SE = 1.034e-05, t = 13.26, P < 0.001, 95% CI: [0.0001, 0.0002], R^2c = 0.44). However, citation rate was negatively associated with common words (B = −5.627e-05, SE = 9.275e-06, t = −6.07, P < 0.001, 95% CI: [−7.595e-05, −3.856e-05], R^2c = 0.44).

TED talks: Titles and speech content. We counted the days between the talk date and the date of data collection (extraction date − publication date) and divided views and comments by this difference score. Natural log transformed views and comments were positively associated (r = 0.71, P < 0.001) and therefore combined in a standardized social engagement index.

At the index level, TED titles with more common words tend to have more engagements (B = 2.042e-02, SE = 1.690e-03, t = 12.08, P < 0.001, 95% CI: [0.017, 0.024], R^2c = 0.49). That is, TED talk titles with more common words tend to have more views (B = 1.339e-02, SE = 1.078e-03, t = 12.43, P < 0.001, 95% CI: [0.011, 0.016], R^2c = 0.48) and comments (B = 2.430e-02, SE = 2.490e-03, t = 9.76, P < 0.001, 95% CI: [0.019, 0.029], R^2c = 0.43).

TED talks with more common content tend to have more engagements (B = 5.155e-02, SE = 9.153e-03, t = 5.63, P < 0.001, 95% CI: [0.033, 0.068], R^2c = 0.49). Specifically, talks with simpler content in the speech body tend to have more views (B = 4.399e-02, SE = 5.821e-03, t = 7.56, P < 0.001, 95% CI: [0.033, 0.056], R^2c = 0.48) and comments as well (B = 3.690e-02, SE = 1.329e-02, t = 2.78, P = 0.006, 95% CI: [0.010, 0.063], R^2c = 0.43). Thus, consistent with the other findings, public online speeches tend to have a more favorable draw if the title and talk content is simple versus complex.

Taken together, the evidence from Study 1 describes a clear and robust relationship between common words and social

*CIs in this paper are bootstrapped with 1,000 replicates.

†R^2c is the combined variance explained by both fixed and random effects as indicated by the MuMIn package in R (42).

‡Sample sizes for abstracts and titles were slightly different due to some abstracts that were not automatically extractable.

engagement across six settings. In news (e.g., Twitter), social media (e.g., Reddit), science (e.g., PLoS One), and public entertainment speeches (e.g., TED talks), we observed that communicating in a simple and nontechnical manner associates with engagement (e.g., more likes, retweets, upvotes, views, and comments depending on the sample). Our second study tests the link between common words and financial outcomes. Recall, prior evidence suggests people tend to receive more money if their language content is complex compared to simple. This is because when an instrumental goal is activated, an effortful experience should be valued over an effortless experience. When a task is appropriately challenging (20, 37), language complexity should help convince others to support a cause.

Giving money to strangers—based on a limited number of cues such as language patterns—is a challenging task because of two major uncertainties in the online charitable giving process. First, it is unclear if or when lenders will be repaid on certain sites. Second, because lenders and borrowers are strangers, the story behind charitable giving campaigns might be nonverifiable (Does this person really need money?). Such uncertainties make the authenticity of each campaign difficult to appraise and the decision to give money to campaigns an anticipated challenge. Therefore, descriptions that are challenging and more complex should match the expectations of lenders and, as a result, lead borrowers to receive more money from the crowd.

Our next study draws on such prior evidence to investigate the relationship between language complexity and financial outcomes across three charitable giving platforms: 1) Kickstarter, which focuses on raising money for creative projects; 2) Indiegogo, which focuses on charitable giving for creative projects and entrepreneurial startups; and 3) GoFundMe, which focuses on raising money for life events (e.g., medical accidents, home payments). We also investigate how complexity associates with money awarded in NIH grants based on grant abstracts. This examination with the NIH sample also serves as a replication attempt of prior work, which observed that more complex content associates with higher funding amounts from the NSF (25). While there is more to a grant's evaluation than the abstract, we use this set of publicly available texts to reflect the authors' general writing style in the same way that Tweets can proxy a person's writing style but do not reflect their entire verbal output.

Study 2: Method

Data Collection. Because some of the charitable giving campaigns originated outside of the United States and non-English text would naturally score poorly on the LIWC dictionary category, we took an extra step to identify and exclude non-English texts. We used the cld3 package in R (38) to automatically detect the language of each charitable giving campaign and retained only English texts. This package uses a neural network model to identify the language of an input text.

The final selection of Kickstarter (n = 160,007) and Indiegogo campaigns (n = 19,171) were obtained from publicly available repositories.[§] Nearly 1.8 million links were extracted from GoFundMe, though not all campaigns were fully archived or active. Therefore, a random sample of 200,000 campaigns were extracted from the site. Out of the 200,000 campaigns, campaigns with less than 15 words were excluded to prevent low word counts from impacting the results. Furthermore, we exclude those posted within 1 wk of data collection since the probability of them receiving trivial amounts of funding is high. This left 181,238 GoFundMe campaigns in the final sample.

We extracted over 400,000 NIH grant abstracts and metadata from the NIH RePORTER (Research Portfolio Online Reporting Tools Expenditures and Results) tool (2014 to 2019).[¶] We excluded projects with incomplete funding information, duplicate project numbers, and those with less than 15 words in the abstract. Our final sample had 226,452 grant abstracts and metadata including the total cost of the award in dollars (natural log transformed), the fiscal year of the award, and the project duration (e.g., the difference between the project start and project end date) since longer awards or projects might naturally receive more money.

Automated Text Analysis. Consistent with Study 1, we used the LIWC dictionary category as our primary independent variable to associate with funding variables on Kickstarter, Indiegogo, GoFundMe, and NIH grants. The results in Table 1 describe the specific texts under investigation in each sample and descriptive statistics for the average number of words and common words per text.

Study 2: Results and Discussion

Statistical models in each study included fixed and random effects listed in Table 1.

Kickstarter. We used a mixed effects regression model to predict the amount pledged (natural log transformed) from common words and controls including the number of donors (natural log transformed), the campaign goal (natural log transformed), the category of the campaign (e.g., art, music), the time difference between the start and end date of the campaign (natural log transformed), and whether the campaign was successful or not.

Campaigns with more pledged money tend to contain fewer common words ($\beta = -2.999\text{e-}02$, $SE = 2.960\text{e-}03$, $t = -10.13$, $P < 0.001$, 95% CI: [−0.036, −0.024], $R^2\text{c} = 0.88$), suggesting that complex language is advantageous for charitable giving.

Indiegogo. We used a linear mixed model to predict the amount of money raised by Indiegogo campaigns (natural log transformed) from common words, the time difference between the start and end date of the campaign (natural log transformed), the category of the campaign (e.g., film, education, wellness), and currency to control for country-specific norms.

Consistent with the Kickstarter data, Indiegogo campaigns with fewer common words tend to raise more money ($B = -1.548\text{e-}02$, $SE = 1.186\text{e-}03$, $t = -13.05$, $P < 0.001$, 95% CI: [−0.018, −0.013], $R^2\text{c} = 0.33$). These data further demonstrate complexity is associated with more money raised for creativity projects and entrepreneurial startups.

GoFundMe. We used a linear mixed model to predict the amount of money raised by GoFundMe campaigns in US dollars (natural log transformed) from the funding goal in dollars (natural log transformed), the number of donors supporting the campaign (natural log transformed), the number of times the campaign has been shared online (natural log transformed), the category of the campaign (e.g., medical, illness, and healing; babies, kids, and family), the length of time that the campaign has been online (natural log transformed), and the currency (to control for country of origin). We counted the number of days between the campaign publication date and the date of data collection (extraction date − publication date), and then this value was natural log transformed. This variable was included as a fixed effect.

Consistent with the Kickstarter and Indiegogo data, GoFundMe campaigns with fewer common words tend to receive more money ($B = -6.506\text{e-}03$, $SE = 3.598\text{e-}04$, $t = -18.08$, $P < 0.001$, 95% CI: [−0.007, −0.005], $R^2\text{c} = 0.84$).

NIH Grants. A multiple regression model controlling for the year and duration of the project (natural log transformed) revealed that fewer common words associated with receiving more money (natural log transformed) from the NIH ($B = -1.168\text{e-}02$, $SE = 3.692\text{e-}04$, $t = -31.63$, $P < 0.001$, 95% CI: [−0.012, −0.011], $R^2 = 0.128$). Note, we were unable to control for author in a mixed effects regression due to failed model convergence.

Taken together, across three separate giving platforms with different conventions and different sizes of text descriptions, successful charitable campaigns or those that receive more money also tend to be written with complex language content. Further, NIH grant abstracts, which stand as a proxy for the authors'

[§]https://webrobots.io/projects/.

[¶]https://reporter.nih.gov.

writing patterns in general, tend to receive more money with more complex language. Complexity is therefore a likely signal of a target's value (22) and/or credibility (25, 26, 39) and, as such, is more likely to receive financial rewards.

General Discussion

This investigation sought to determine the broad influence of language complexity on behavior. Indeed, an abundance of research studies obtained in the laboratory and through experiments have revealed the consistent influence of language complexity on judgments and decision making through processing fluency (5, 13–15). Despite this consensus, what has been less understood is whether people are actually compelled by the heuristic of language complexity in daily life and within settings of consequence (e.g., when ideas or money are exchanged). This work endeavored to address this limitation by examining over one million datapoints to observe how language complexity corresponded with online social engagement and financial giving. Overall, study results offered support for the predictive utility of language to understand how people respond to the heuristic of complexity.

Our first study examined whether the simpler-is-better hypothesis would obtain support in natural settings. We examined news attention (e.g., Twitter), social media (e.g., Reddit), science (e.g., PLoS One), and public entertainment speeches (e.g., TED talks). Together, these results consistently revealed, as people search these platforms, texts that use common words capture attention more than complex texts. The consistency of this effect across a diversity of samples offers robust and ecological support for the simpler-is-better hypothesis, which advances that—all else being equal—we gravitate toward texts that feel easier to process (17, 18) even in crowded online environments.

In addition to offering robust support for the proposition that linguistically simple texts garner more social engagement, we also sought to qualify this intuitive notion in a theoretically meaningful way. Our second study identified settings where a difficult experience would be valued and, thus, rewarded. According to Labroo and Kim (21), "...when trying to reach a goal, people must ask themselves, 'Is this object any good for accomplishing my goal?' and in this situation, an 'instrumentality heuristic,' or the naive belief that effort signals instrumentality, becomes pertinent." Thus, when engaging in an instrumental task such as donating to a cause or awarding a grant, people want to feel as though they exerted effort because, naively and automatically, this effort feels diagnostic within this context (22, 23). We specifically examined whether language complexity within charitable giving and grant funding would be positively associated with higher monetary rewards. Consistent with this premise, and again across multiple settings, we found that texts with more uncommon words were funded more than texts with more common words. Though this finding reaffirms past research that has observed similar syntactical and word-based trends in other settings (25–29, 39), we contribute to multiple literatures by situating our relationships within a broader understanding of how processing fluency can guide decisions.

Limitations and Future Directions. As noted, we did not have a direct measure of processing fluency due to the observational nature of this work. Despite this limitation, there is an abundance of empirical support for the association between language complexity and subjective measures of processing fluency within laboratory and experimental investigations. Moreover, in addition to this empirical precedent, we included a second study to bolster our theoretical case for the role of processing fluency on outcomes. Our logic suggested that if processing fluency was a plausible mediator of social engagement, then outcomes associated with difficult processing would have to be observed in response to complicated texts as well. Given that donating money has been used in the past as an example of an "instrumental task," sampling from websites and institutions in which monetary rewards were solicited—and provided—offers an appropriate context for examining this relationship. If indeed language complexity evokes feelings of difficulty and effort, then under conditions where cognitive effort is valued, texts that include more uncommon words should be associated with more funding than texts that use common words. Our support for this finding offers further theoretical support for the role of processing fluency in these relationships, despite our inability to measure this concept directly. Second, another limitation due to the observational nature of these data is that we cannot know a person's motivation for engaging with online messages, only whether or not they did so. A common refrain on Twitter is that "likes and/or retweets do not equal endorsements," and the same can be said here. Though we find that simpler language corresponds with more social engagements, we cannot say whether these behaviors indicate more liking or support for the content in question given that people commonly engage with content they dislike or disagree with as well (40, 41). Although we acknowledge our inability to address the motivation for engagement directly, the size and diversity of our samples suggests the presence of differential motivations for engagement are likely distributed evenly across the same sample. If there was a systematic relationship between motivation and engagement affecting the results, this relationship would actually undermine our ability to find effects rather than the other way around—but nevertheless, this remains an open question. And finally, a potentially related point is that our effect sizes generally ranged from small to medium depending on the study and dependent measure. Our ability to detect these effects likely benefitted from the size of our samples.

We encourage future research to pursue other operationalizations of nontechnical language to examine the relationship between common words and behavior. We used a validated text analysis dictionary in this work, and we expect other dictionaries and operationalizations to advance our understanding of the heuristic properties associated with complex language. We also suggest future researchers test different online platforms to understand the boundary conditions of the simpler-is-better hypothesis and the relationship between language complexity and money. Perhaps site-specific conventions change how people write and modify the relationships established here.

In sum, the aim of this work was to offer evidence and a theoretical explanation for how people use the heuristic of language complexity in natural settings of import. Through a field study of over one million instances of online communication behavior, we found evidence that when no explicit instrumental goals exist, and the primary nature of the activity was information seeking and engaging, the simpler-is-better hypothesis received overwhelming support. However, in instances where expending effort is considered valuable, or diagnostic, to the instrumental task at hand, cueing this effort through complex language can pay off.

Data Availability. Observational data from social media, charitable giving, and grant abstracts have been deposited in Open Science Framework (https://osf.io/493tj/).

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