ABSTRACT

Title of Dissertation: ENVIRONMENTAL ADVOCACY MESSAGES: RELATIONSHIPS BETWEEN THE MESSAGES THAT CONSTITUENTS SEND TO DECISION MAKERS AND ORGANIZATIONAL ENGAGEMENT

Directed By: Dr. Miroslaw J. Skibniewski
Department of Civil and Environmental Engineering

Environmental advocacy organizations aim to help citizens contact their policymakers, to recruit new members, and to increase their contacts' level of engagement with organization issues. They use online petitions and form-letter services for these purposes. These services put citizens in contact with policymakers and encourage citizens to take follow-up actions, such as sending another message, referring a friend, or making a donation. While these services effectively recruit members, they marginally influence policymakers. To increase influence, organizations now ask petitioners to include personal messages in their communications. This dissertation asks if text analysis of these personal messages can help advocacy organizations further fulfill their recruitment and engagement goals. It investigates text-metrics both for predicting engagement from existing contacts and for services, such as chatbots, to suggest follow-up actions to new contacts. Methods employ rule-based text analysis tools (LIWC, VADER, Flesch Reading Ease, and Regular Expressions) to pilot the use of pronouns, sentiment, writing complexity, and the identification of personal stories as predictors of engagement. Data include over two million messages and nearly 500,000 personal messages from over 150,000 individuals supporting sustainable policies and projects. Results reveal relationships between messages and two engagement factors: (1) the number of messages that groups of contacts send and (2) payment of membership dues. Results also bolster research that highlights the importance of identifying contacts who can share stories about how environmental issues have affected them. Conclusions encourage advocacy organizations and policymakers to analyze messages to increase engagement and understand constituency support of policies and projects. Future work may integrate text analysis into membership models and advocacy services. Future work may also improve personal story classification and investigate machine-learning for identifying potential members.

ENVIRONMENTAL ADVOCACY MESSAGES: RELATIONSHIPS BETWEEN THE MESSAGES THAT CONSTITUENTS SEND TO DECISION MAKERS AND ORGANIZATIONAL ENGAGEMENT

by

David F. Choy

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Advisory Committee:
Prof. Miroslaw J. Skibniewski, Chairman
Prof. Gregory B. Baecher
Assoc. Prof. Qingbin Cui
Asst. Prof. Michelle (Shelby) Bensi
Prof. Brian Butler, Dean's Representative

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CHAPTER 1. INTRODUCTION

This dissertation investigates relationships between the words that constituents write to decision makers and these constituents' engagement with environmental nonprofit organizations. Findings benefit advocacy organizations, developers of online advocacy services, policymakers, and civil project managers. Findings contribute to research in applications of linguistic analysis processing to predict behaviors (e.g. McHaney et al. 2018, Pennebaker 2011, Robinson 2013) and research in the value of personal stories (Sandhu 2017, The Congressional Management Foundation 2017, The Social Change Agency 2017a, 2017b, Karpf 2016). Methods employ popular rule-based linguistic tools, including the Natural Language Toolkit (Bird et al. 2019), Linguistic Inquiry and Word Count 2015 (LIWC 2018), Valence Aware Dictionary and sEntiment Reasoner (VADER; Hutto and Gilbert 2014), and Flesch Reading Ease Analysis (Flesch 1948). Data include over two million messages and nearly 500,000 originally authored messages from over 150,000 individuals distributed across the United States. Messages support campaigns to preserve national parks, curb toxic emissions, and expedite U.S. energy independence. Results provide evidence to support advocacy organizations delivering messages, and the policymakers reading them, to employ text analysis tools in order to predict organizational engagement and understand constituency support of civil and environmental policies and projects.

1.1. Background and Need

1.1.1. Green Technology Needs Green Policy: Advocacy Organizations, Policymakers, and Project Managers

Civil and environmental scientists and engineers recognize climate change. They develop ways to provide renewable energy, limit greenhouse gas emissions, and recycle waste. Project managers recognize that research innovations, however, only transition to practice, and scale, through policy and community support. Policy determines the direction and success of studying and protecting our environment. It regulates how communities use natural resources to generate electricity. It protects habitats and national parks. It determines how NASA budgets earth science vs. space exploration. It encourages and incentivizes recycled materials in pavement. It makes residential investment in solar energy feasible for homeowners.

In the U.S., local and national nonprofit organizations advocate for environmental policies in several ways — education and awareness campaigns, petitions, letter-writing campaigns to policymakers and editors, clean-ups, protests, legal action, and investigations. Most importantly, advocacy organizations hold policymakers accountable for their promises to protect the environment and deliver energy independence from fossil fuels, and advocacy organizations expose policymakers when they break their promises.

These advocacy organizations use petitions and online letter-writing campaigns to, explicitly, empower residents to connect with their policymakers, and advocate for environmental sustainability. These petitions and letter-writing campaigns, less explicitly, also help advocacy organizations recruit participants (Suárez 2009, Cruickshank et al. 2010, Carpenter 2016, Parry et al. 2011, Jacobs 2016), fulfill advocacy organizations' needs to understand the behaviors and demographics of their constituents (e.g. members, volunteers, allies), and empower participants to take first steps up Arnstien's "ladder of citizen participation" (i.e. the "engagement ladder," Arnstien 1969): sign more petitions, send more letters, send more personal letters, share more personal stories that support specific campaigns, enlist their friends, partner and organize with the organizations, and become leaders themselves. Joining an organization as a dues-paying member is also part of this more-or-less explicit intent of organizations' use of petition tools and surveys. Advocacy organizations ask citizens to support a laudable cause before asking for money. For example, President Barack Obama's campaign ladder consisted of four rungs: (a) liking the presidential campaign on a Facebook page, (b) signing a birthday card, (c) filling out a survey or sharing a personal story — and at the top — (d) contributing in exchange for campaign swag. This ladder helped the campaign successfully mobilize a large, grassroots base.

In the same way that an online marketing firm or political campaign recognizes an ad click as an action, advocacy organizations recognize, and carefully track, the behaviors of their contacts in contact relationship management (CRM) databases (e.g. Blackbaud Raiser's Edge, Convio, Neon, Salesforce). Commercial companies refer to CRM services as customer relationship management services; advocacy organizations refer to CRM services as constituent relationship management services. Both use CRM services, however, in similar ways. Both collect contact information, event attendance records, donation histories, demographics, addresses, interests, household relationships, and other interactions. In A/B hypothesis tests, both compare levels of response to different email news headlines and social media posts (Karpf 2016) with organizational engagement.

One unique set of data that advocacy organizations collect are the messages that their contacts send to their policymakers. They collect them through petition, letter-writing, and chat-bot services that they provide online. They refer to these tools as advocacy actions services, and refer to the messages that constituents author and send through them as advocacy action messages. Environmental advocacy organizations use the information from online petitions and letter-writing campaigns to learn more about their contacts and interact with them. When collecting signatures on door-to-door canvases, canvassers can write down notes about their conversations (or door slams), political yard signs, the demographics of the people they meet, the family members of the people they meet, and more. Advocacy organizations can then centrally parse this information into CRM fields. Online campaign managers learn different, seemingly more limited kinds of information than canvassers — letters to Congress, for example, require citizens to report their address or zip code to be taken seriously by members for Congress. As the message carrier, advocacy organizations can then collect these zip codes and feed them into services like WealthEngine (2019) to learn more about the potential of message writers to donate to the organization and join the organization as dues-paying members.

A new data analyst at one large environmental advocacy organization calls its organization’s database “well collected, but not well informed” (pers. comm 2018) — meaning the organization has collected information about its contacts, but the organization still has work to do to extract actionable evidence from the information.

Organizations are currently in the processes of developing lumped engagement scores for their contacts to make their data more meaningful. They are first looking at fields that fit nicely into Boolean, integer, and short text fields. They are looking at, for example, the number of events a person has attended, their contribution history, their zip code, their age, their gender, and the issues that they have expressed interest in on surveys.

While organization analysts are hard at work modeling engagement, campaign organizers are paying attention to research from the Congressional Management Foundation (2017) and the Social Change Agency (2017a, 2017b), who have revealed people with lived experiences affected by campaign issues will be noticed by policymakers, climb the engagement ladder more quickly, and can become campaign organizers themselves. Seth Long, regional online organizer, agrees. He wants to develop a deeper understanding of how personal messages impact “advocacy outcomes, equity values, and movement building: organizing, communications, and legal” at the Sierra Club (pers. comm. 2018). Personal stories, additionally, become testimony in courts, and ethos and pathos in articles.

Simultaneously, while analysts are building engagement models, and while campaign managers are recognizing the importance of personal stories, digital product managers — in advocacy, in congressional offices, and everywhere — are hiring developers to build and add chat-bot services to their portfolio of communication tools. Form-based action campaigns on websites still exist, but chatbots reach people in focused, personal ways that websites cannot. They operate inside the communication tools people already use to connect with their friends and associates on a regular basis — sms, iMessage, Facebook Messenger, etc. They democratize action without overwhelming congressional offices, and have recently become successful in doing so (Putorti 2019).

Considering analysts' goals to understand their organization's members and contacts with the data they have, organizers' recognition and search for those with lived experiences, and product managers' and service developers' new efforts to develop chatbots, this study tests deriving several predictor metrics from just one of the fields that organizations are collecting data for, but are not currently utilizing without manual review. The metrics from this one field could be useful to all three of these types of people in the environmental advocacy world — advocacy organization managers, campaign organizers, and product developers. The metrics from this one field may also be useful to policymakers receiving advocacy messages, and the civil project managers that policymakers share data with, in their search to understand and highlight, whether fairly or not, the opinions of their constituents concerning the environmental impacts of their policy decisions. This one field is the personal message text field where activists write their messages.

Large advertising companies have built their businesses with machine learning and natural language processing (NLP). Google, for example, has a history of processing user emails to support ad targeting. Facebook extracts "entities" from business messages, such as greetings, sentiment, location, and quantities (Facebook 2019). This study asks if analysis of personal messages could also help organizations paint a more comprehensive picture of their organization, explain constituent behaviors, and increase organizational engagement in ways that business-as-usual methods (e.g. demographic profiling, relationship tracking, interaction tracking), alone, cannot.

Treating this personal message field as a Boolean variable — answering the question, did a contact originally author and attach a personal message to their communication or not — this study confirms that the presence of content in the field, alone, can act as a predictor of engagement without further analysis. Some baseline results from this study confirm what campaign organizers say — contacts who send personal messages are also more likely to send more messages and make financial contributions towards organization membership. Results show that most contacts (97% of the study contacts) who write personal messages at rates of 18% or higher are also more likely to send more than one message. Results also show the membership rate for those sending personal messages is 27% compared to the overall 13% membership rate for those sending any type of message, personal or otherwise — more than double.

Beyond the presence of sending personal messages at all, this study applies rule-based linguistics analyses to messages to learn more about their authors. It begins by asking if analysts can use frequencies of pronouns in messages to predict the number of messages a contact will send. To do this, this study begins by using the Linguistic Inquiry and Word Count (LIWC) tool, which has been successful in both predicting human behaviors, as well as deepening the academic understanding of how people write and speak in different situations. LIWC is well established; textbook writers teach students about it (e.g. Krippendorff 2018) and scholars have cited articles describing its development and operation (e.g. Pennebaker et al. 2015) thousands of times.

Of interest to this study, LIWC is often used to analyze the words of people in power. Lenard (2016), Jones (2017), and Pennebaker (2011) apply it to U.S. candidates and political figures. It is no-doubt interesting to see how candidates and politicians in power talk to their constituents, their opponents in debates, and their fellow representatives on the floor. This study flips the focus of these analysis to study the people speaking up to their policymakers instead of studying the way policymakers speak (at times, down) to them. From an engineering project management and public representative point of view, understanding and empathizing with customers and constituents is key to serving them.

Beyond LIWC, researchers have studied the words that people have used in reaction to political candidates, environmental policies, energy, and construction projects — new and proposed (e.g. Wang 2012, Ding 2018). These studies are written for candidates, lawmakers, project managers, and project stakeholders that are judging risk of, and the public perception of enacting policies and making project decisions. These audiences are often, but not necessarily, concerned with the environmental impacts of their projects. In the same way this study turns its focus away from learning about how policymakers talk to their constituents, and to the way constituents talk to policymakers, it also deprioritizes how lawmakers might evaluate the risk and public acceptance of a project (for bad or good), and prioritizes how environmental advocacy organizations can improve and support (or not support) projects to keep the earth green. This study is also different than past and upcoming studies (e.g. Ding 2018, Li et al. 2019) in that it studies messages that are directly written to policymakers vs. public tweets. It tests relationships between messages and data inconvenient to collect by anyone other than advocacy service providers and their advocacy organization clients. Even policymakers, who are the recipients of environmental advocacy messages concerning a particular issue, often do not have access to the messages sent to other policymakers on similar, or even the same, issue.

This dissertation (a) studies the words of constituents instead of the words of policymakers and leaders, (b) focuses first on how environmental advocacy organizations can affect policies and projects before it focuses on how policymakers and project managers can judge public acceptance of their proposals and projects, and (c) relies on data convenient to collect only by advocacy organizations and service developers. The methods and findings from this dissertation are nonetheless significant to policymakers and project managers. Results support offices of policymakers to employ methods in this dissertation, even if they only have access to the messages sent directly to them. Results also support policymakers in better understanding advocacy organization summaries of messages and directly analyzing any additional message data that they may receive. Policymakers, unlike advocacy organizations and service providers, are, in fact, uniquely situated to have immediate access to messages sent from multiple audiences. Using methods in this dissertation, policymakers may gain insight into the strength of different lobbies advocating differing opinions.

1.1.2. Exploration: Membership

Nonprofit contributions have grown more than 10%, on average, every year since 2012 to over $34B in 2018 (Nonprofits Source 2018). Giving Tuesday raised $380M in one day for nonprofits in 2018 and $511M in 2019 (Giving Tuesday 2019). Of all nonprofits, environmental advocacy organizations led the group of organizations with the largest increases in contributions in 2018 (Nonprofits Source 2018). For this study, membership signifies a monthly or annual financial contribution commitment.

During the course of summarizing data and investigating pronouns, this study noticed the dictionary of swear words, negative words, long words, and punctuation in the LIWC program could also potentially predict engagement. At this same time, this study began looking at membership in addition to the number of messages a person sends as an indicator of organizational engagement, where membership indicates a financial contribution and commitment. These factors, in conjunction with the knowledge of the importance of personal stories, inspired a series of explorations to investigate what relationships additional text analyses can reveal about membership. These explorations (1) developed and tested rule-based linguistic regular expressions to search for words and phrases indicative of personal stories with input from a campaign manager that professionally reads and searches for personal stories, (2) assessed the sentiment of messages with the well-established rule-based Valence Aware Dictionary and sEntiment Reasoner (VADER) tool, built specifically for looking at short online messages, and (3) assessed the complexity of messages as a function of syllables per word and words per sentence with the popular Flesch reading easy model. The Flesch model provides a readability score tied to an education level that a reader might need to comprehend a piece of text. Metrics from these three assessments were then piloted as predictors of membership. Results show that looking at patterns of words — built out from a foundation of phrases centered around lived experiences — can better indicate organizational membership than looking at the rate that contacts use words from LIWC dimensions alone. They also show that sentiment and the ease of messages for people to read at different grade levels can also help identify non-members and members.

1.1.3. In the Words of Advocacy Data Analysts and Product Managers

An analyst at one environmental nonprofit organization agrees that measures and metrics commonly calculated in text analysis may be piloted as predictor variables to engagement. They are interested, first, in natural language processing (NLP) to summarize message length and personal stories. They point out, for this study, "we currently do not have the capacity or skills in house to do NLP but have a high degree of interest in personal messages and how they relate to engagement." Further, "NLP gives us a view into this data that we don't have and with resulting distribution or segmentation from different NLP analysis, we could run tests on those audiences to see how their engagement differs. If this is effective in future targeting and activist engagement, we would also have a solid evidence for more organizational investment in NLP, modelling tools and skill sets working with [organization] data" (2018).

Parul Sharma, Associate Product Director of an online advocacy system at the Sierra Club called AddUp (2019), points out that AddUp currently recommends action steps to users based upon the user's location and the user's last action, but she wants to know if message content factors can play a role in making recommendations and giving users "a more personalized journey." She wants to know "what types of issues do people want to write personal messages for" and "is there a common theme around types of issues vs. sentiments." She wants to know if content analysis can help predict if individuals "are at a 'pre-member' stage? Likely will give donations or become volunteers … or in the future, will become event organizers or creators?" If, for example, AddUp could recognize (a) personal stories and (b) writing styles indicative of a future organizer from an individual's first contact with the organization, then AddUp could provide tailored next steps to engage that individual. In the future, from an advancement (i.e. fundraising) point of view, writing characteristics could supplement location and financial data from services like WealthEngine (2019) in suggesting contribution levels to new contacts.

In summary: Advocacy organizations want to know the feasibility of summarizing messages and relating them to other constituent data. They want to know if doing so can aid them in encouraging more messages, more sharing, more personal and localized prompts, and other higher value actions from their constituents (e.g. attendance, membership, leadership). They want to know if they can spot and amplify personal stories in messages, and then empower the authors of these stories to support their campaigns.

1.1.4. Advocacy Campaign and Data Flow and Potential Beneficiaries

This study commenced addressing needs of advocacy organizations and service developers, but results and conclusions show policymakers may equally directly benefit from it (Section 7.2). Civil and environmental project managers whom policymakers share data with will also benefit. Figure 1.1.1 illustrates how these parties work together.

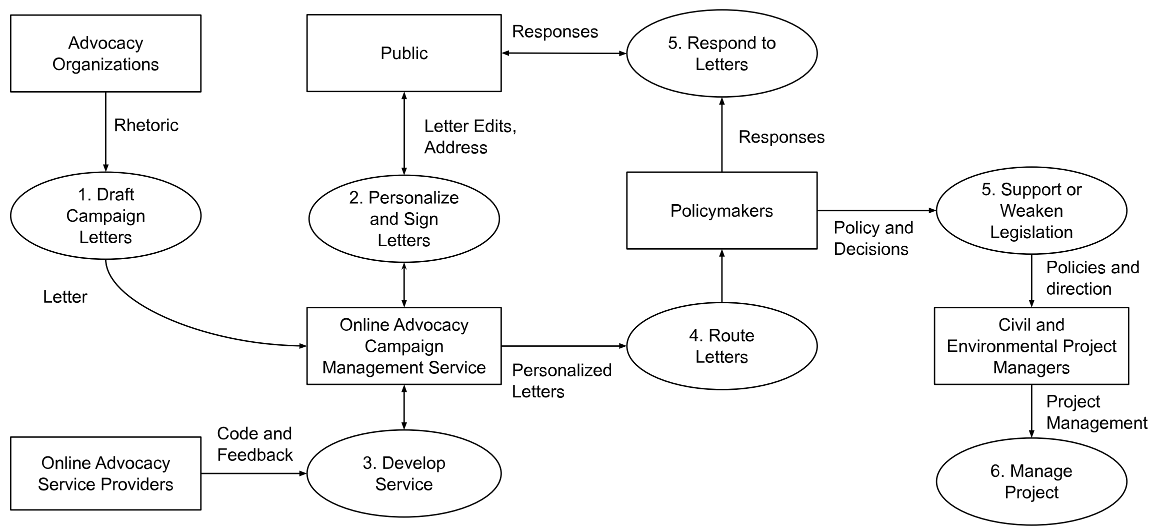


Figure 1.1.1 Advocacy Campaign Dataflow Diagram

1.2. Goal, Objectives, and Research Questions

The goal of this study is to explore relationships between the messages that constituents send their policymakers and these constituents' engagement with advocacy organizations that provide the systems that enable them to send these messages. It focuses on environmental advocacy organizations. It fulfills two main objectives. Objective One, answering three originally proposed hypotheses, tests relationships between three properties of messages and the number of messages contacts send as a first measure of engagement. Those properties are: (a) pronoun usage, (b) personal message rate, and (c) message length. Objective Two, within a series of explorations, tests relationships between additional text metrics and membership as a second measure of engagement. Those additional metrics are based on (a) regular expression searches for personal stories, (b) reading ease analysis, (c) sentiment analysis, (d) frequently used words, and (e) collections of words.

These objectives should help answer the following research questions: (1) How can managers of advocacy organizations and policy offices analyze and categorize messages? (2) How can they relate messages factors to organizational engagement factors? (3) What methods can they use to explore these relationships and spot trends? (4) How can they identify personal stories among personal messages? (5) What baseline, text-analysis metrics could be used in CRMs and online tools? Results (Chapter 4 and Chapter 5) reveal observations to answer these questions; discussion and conclusion chapters (Chapter 6 and Chapter 7) summarize answers. For the first three questions, the discussion of results summarizes relationships and methods. Results and conclusions emphasize the importance of the number of contacts in groups of individuals on the applicability of tests to reveal trends (Section 4.1.2.3, Section 6.3). For the fourth question, Exploration Three (Section 5.3) introduces how this study used regular expressions in an attempt to identify personal stories and Exploration Seven (Section 5.7) and the discussion chapter (Chapter 6) discuss their capabilities. Appendix B lists regular expressions. (Regular expressions found some personal messages, but they also found other types of messages.) For the fifth question, methods, results, and conclusions summarize how simple message analysis, including one that simply counts types of messages, establish engagement baselines (Section 3.1, Chapter 5, and Chapter 7). In describing future work to develop an engagement model, conclusions discuss theoretical and machine learning approaches to identifying engagement predictors (Section 7.3.1) and (b) question if problems identified in organizing campaign canvasses offline could be present online (Section 7.3.2).

1.3. Objective One Hypotheses: Message Content and Number of Messages Contacts Send

This study begins by investigating three specific questions of interest to environmental advocacy organizations given only a minimal table of messages with contact identifiers.

1. Literature has shown correlations between an individual's linguistic style and their behaviors – from their ability to succeed in health (Pennebaker 2011) and academic programs (Robinson 2013) to selection and categorization of decision support simulation models used in mining, public health, water resources, and other applications (McHaney et al. 2018). The first hypothesis predicts similar relationships exist between the writing styles an activist employs and their engagement with an advocacy organization. To test this hypothesis, this study uses personal pronouns to identify writing styles and the number of actions an activist has taken to indicate organizational engagement. The study can accept the hypothesis if relationships exist between average LIWC pronoun scores (pronoun rates of use) for groups of contacts who have sent the same number of messages and the number of messages that they have sent.
2. A second hypothesis states that there is a relationship between the number of personal messages contacts write and the total number of messages that they send (with or without personal comment). For online campaign managers, accepting this hypothesis would indicate that target groups that return high rates of personal messages are more likely to send additional messages in the future.
3. A third hypothesis states that there is a relationship between message length with the number of messages that contacts send. It tests the questions, do contacts tend

to write more or less often if they also write long messages? A negative relationship would akin message words to limited units of person-hours on a project, where contacts sending more messages may not have time to write longer ones.

These hypotheses use the total number of messages sent by contacts as a measure of organizational engagement for them. In doing so, they disregard the importance of personal stories to policymakers and organizations (Congressional Management Foundation 2017, Social Change Agency 2017a). They do address, however, the common case, reviewed in the literature review (Chapter Two), where congressional staffers reduce messages to yay and nay summary piles (Miler 2014), losing personal stories, but increasing the value of a contact's output as a measure of influence.

1.4. Objective Two Hypotheses: Exploration of Personal Stories, Sentiment, Writing Level, Popular Words, Groups of Words, and Membership

After testing the three initial hypotheses, this study investigates relationships between additional text metrics and membership. It tests a general hypothesis: There are differences in membership rates between (a) all contacts who have sent personal messages (27% membership rate) and (b) groups of contacts who have written messages that satisfy text conditions. Text conditions are based on the number of messages contacts send, personal stories in messages, message writing complexity, message sentiment, and the use of popular words and dictionaries of words in messages.

In evaluating membership rates for groups of contacts satisfying conditions, this study considers 5%, 10%, and 15% membership rate differences from the average 27% membership rate for those who have sent personal messages as moderate, strong, and very strong differences, respectively. A 10% difference above the 27% average membership rate for those who have sent personal messages is equal to a strong 37% (27% + 10% = 37%) membership rate. This, coincidentally, equates to a 37% increase (10% / 27% = 37%). It also equals a 185% increase above the membership rate for those who have sent any type of message (with or without a personally authored message), which is 13% (37% - 13% = 24%; 24% / 13% = 185%). Hypotheses for each text condition are significant if the chi-square test p-values for comparing contingency tables of observed and expected values are less than 0.01.

CHAPTER 2. LITERATURE & TECHNOLOGY REVIEW

2.1. Petitions, Slacktivism, Creative Campaigns, and Letters in Between

Modern advocacy services such as MoveOn, AddUp, SwingLeft, and Change.org are coded around a timeless "embedded recruitment technology" that has contributed to historical successes of organizers prior to the internet, such as French Calvinists in the 1560s and American Antislavery leaders in the 1830s (Carpenter 2016) – the petition. Adopted online, earlier by environmental advocacy organizations than other types of advocacy organizations (Suárez 2009), climate change awareness organizers used petitions and letter-writing campaigns to reach global audiences, including, notably, to support the 2015 Paris Agreement and the 2014 People's Climate March leading up to it (Jacobs 2016, Avaaz 2015).

The reach of online advocacy services grew as U.S. home internet use accelerated from 0 to 60 percent between the years 2000 and 2010 (Pew Research 2019). At the time, MoveOn was a visible example of resistance to the Iraq War. MoveOn's founders credit its growth to their "realization" of petitions as organizing tools in 1998 (MoveOn 2019). At a minimal level, like in-person petition canvases (Parry et al. 2011), online advocacy systems recruit members and benefit the organizations that run them (Bhagat 2005). While petitions increase organizational engagement, researchers have argued that the gains come at the expense of disengaging policymakers, who become overwhelmed by impersonal messages. For this reason, researchers have embraced the term, coined by a reporter for the act of conveniently sending online communications to a policymaker, "slacktivism" (Morozov 2009). Another reporter, White (2010), calls the act "clicktivism" in a scathing comparison of online advocacy systems, like MoveOn, with marketing firms that exchange “faith in the power of ideas, or the poetry of deeds, to enact social change” for unread messages. Miler, in 2014, further provides evidence that online messages are one of the least noticed forms of advocacy. She shows that these messages are only counted by issue into yay or nay piles by (often low-paid or unpaid) congressional staff and, many times, never read at all. Actual stories of lived experiences and thoughtful suggestions are lost between pages of faxed form letters. This observation, alone, adds a dark significance to this study’s use of the number of messages (personal or form) as a measure of organizational engagement in Objective One. Miler shows congressional offices are much more likely to notice and respond to constituents who they can “see:” donors, lobbyists, and creative activists.

Morozov, White, and Miler have emphasized the effectiveness of well-articulated and moneyed campaigns over “slacktivism.” Without money, the resources to be “seen,” however, require luck, ingenuity, or earned ethos. Activist Kristen Mink, in an example of luck, was able to give the final push to remove fossil fuel lobbyist Scott Pruitt out of the office of the Administrator of the EPA after accidentally running into, and then publicly confronting him while her husband recorded the encounter on her phone in 2018. The video went viral. In an example of ingenuity, when thousands of daily emails, phone calls, and faxes started flooding one Republican senator’s office shortly after the 2016 presidential election, to the point where the office was no longer able to count the messages, “creative” activists sent their messages as hitchhikers inside pizza deliveries to the Congress (Schulz 2017). In an example of earned ethos, Dr. Gerry Galloway, research professor at the University of Maryland, serves as an expert to municipalities planning for the effects that sea level rise (pers. comm. 2019). The developer of Resistbot, one online advocacy system, would not question the importance and laudability of these examples, but would also name them examples of privilege (Putorti 2019). While Resistbot has, in the past, been guilty of overwhelming representative offices with faxes and disengaging policymakers, today, it delivers messages over a new electronic system recently created for, and advertised by, Congress, called Communicating with Congress (CWC; U.S. House of Representatives 2017). Responses by congressional offices to a 2015 survey administered by the Congressional Management Foundation (2017) show electronic "individualized" messages, like those couriered by Resistbot to CWC, now have greater influence on undecided positions than postal letters, editorials, telephone town halls, phone calls, lobbyist visits, and form letters. Only (1) in-person visits by constituents, and (2) contacts from constituent representatives, are more effective. The new system cuts the paper-gap; but the messages still need to be read.

This literature shows: (1) Petitions and letter-writing campaigns are inherently organizing tools that help organizations recruit and engage members. Organizations that track the number of messages individuals send, therefore, are collecting one measure of organizational engagement. (This study shows that, with text analysis, the words in the messages that organizations collect are as important, or more important, than the count of the number of messages.) (2) While flooding congressional offices with form letters disengages them, Congress has told the Congressional Management Foundation that personal, "individualized" messages sent through the new, more manageable CWC system influence their positions on undecided issues more than most other forms of communication that they receive. These findings show that Congress can now more conveniently run text-analysis on the messages that they receive. While this study focuses first on the importance of messages to advocacy organizations, as described in the introduction, policymakers have access to an equally unique set of messages: messages coming from different organizations.

2.2. Custom, Individual, Personal, Testimony

The Social Change Agency (2017a) with Sandhu (2017) show that members of the European Parliament (MPs) agree with the U.S. Congress. Personal stories are important; barrages of impersonal form letters are not. Beyond that, they report, "digital campaigns that truly centre the voices of lived experience have the potential to be groundbreaking. However, there is currently little space for those with lived experience to genuinely speak to power using their own voices" (2017b). The Social Change Agency calls those with lived experiences "lost." Once found, beyond using their stories as legal testimony, the Social Change Agency tells advocacy organizations that successful campaigns are led by those directly affected by them, and suggests ways to putting those directly affected by campaigns in organizing and leadership positions. Their findings encourage participatory project management, and encourage existing leaders to see themselves as allies of those with lived experiences.

If Arnstien's "ladder of citizen participation" (1969) or President Barack Obama's engagement ladder (see Section 1.1) were constrained to only the types of messages people send to their representatives, unsigned petitions and form letters without reliable contact information would sit on the bottom rung of the ladder. Messages individualized with contact information would sit above those, then customized form letters above those, then personal messages, which have personally-authored words attached to them, above those, then personal stories, which express lived experiences and could be used as examples in legal testimony, at the top. This dissertation uses these terms, “messages,” “custom messages,” “personal messages,” and “personal stories” to describe these different types of messages. They are detailed in Section 3.2.

2.3. Lost Voices and Secret Lives: Personal Stories and Personal Pronouns

While the Social Change Agency labels individuals with personal stories “lost voices” in the title of their publications (2017a, 2017b), Pennebaker says pronouns, among other words, have “secret lives” in the title of his book (2011). Interesting to this study, personal stories use personal pronouns. Further, Pennebaker has shown people who are suffering frequently use “I” words. Although this study does not employ experts to manually identify people suffering from a condition, such as asthma from air poor air quality, and then test them for their use of “I” words, people using “I” words could be expressing lived experiences, and this study does test the use of “I” words as a predictor of organizational engagement. Pennebaker, alternatively, shows people who are focusing on a task tend to use low rates of “I” words. He also shows third-person singular pronouns like “he or she” express friends or people held in esteem, while third-person plural “they” pronouns are used by authors to put adversarial parties or parties that the author is worried about at a distance from themselves.

In development and application of the text analysis tool, Linguistic Inquiry and Word Count (LIWC 2018), Pennebaker has shown relationships between the use of different types of personal pronouns in journal entries and social status. Of interest to nonprofit organizations, and likely to the Social Change Agency, he suggests that future research could show correlations between the use of personal pronouns and individual leadership traits. Robinson (2013) used LIWC to show language analysis of students’ course introductions at the beginning of a semester can be used to predict final semester grades. The test of the first hypothesis in this study employs LIWC to count and categorize pronouns in personal advocacy messages. It tests if there are relationships between the use of personal pronouns and the number of messages people send as a measure of organizational engagement.

2.4. Listening to Power Before Listening to Those Speaking Up to It

While writers have used “we” to refer to “me and you” as well as a first-person group of people, in this study, none of them penned *pluralis majestatis* — the royal form of “we,” into any of their messages. Researchers, however, love analyzing those today who might have used the term long ago. Lenard (2016) uses LIWC to look at gender differences in how representatives in the 113th U.S. Congress use pronouns in representing their constituents and Jones (2017) does this for Hillary Clinton. Lenard shows male politicians use the pronoun “you” more than female politicians and that no significant gender differences exist in the use of other pronouns. She does show, however, all politicians frequently use “I” words in formal addresses. Jones (2017) shows how Hillary Clinton from 1992 to 2013 spoke with an increasingly masculine pronoun vocabulary, with less and less “I” words (4.34% to 2.77%) and more and more “we” words (2.50% to 3.44%). Jones also illustrates Pennebaker’s (2011) findings on the use of pronouns to describe friends vs. adversaries. Jones does this with an extreme example of how President Donald Trump references his family and executives with first-person personal pronouns, such as “my,” while he distances himself from “out-group” parties with the article “the” in referencing “the gays,” “the women” and “the Hispanics.”

Pronoun analyses can be contradictory with each other. While Jones and Pennebaker (2011) associate "I" words with the female gender, outside of politics, Mulac et al. (2013) calls them masculine words. In another example, Pennebaker faults presidential candidate John Kerry's speech writers' advice to Kerry to use the first-person plural "we" words in greater frequency (Pennebaker 2011). Pennebaker contends the advice led to lower ratings. The speech writers, defending themselves, might have called the style inclusive, not *nosism*. Ruijuan (2010), alternatively, credits President Obama's frequent use of "we" in conversational patterns along with "you" words to create an "intimate dialog" during a presidential victory speech. For this study, a negative relationship between the use of "I" words and engagement and a positive relationship between "we" words and engagement would support the theory that highly engaged political activists speak in the more masculine form that Jones (2017) shows politicians leaning toward. (Jones points out President Trump is a notable, sole outlier; he uses first-person singular "I" words at very high rates.)

2.5. VADER and Flesch Ease of Reading Tests

As described in the introduction, while summarizing results from Objective One, this study noticed examples of swear words, negative words, short messages, and minimal punctuation from contacts who were not active members. These observations, and advice from sociologist Wojciech Sokolowski (pers. comm. 2019), inspired an exploration between popular rule-based sentiment and writing complexity. Frame alignment theory in nonprofit research (Snow et al. 1986, Sokolowski 1996) supports the idea that individuals may adopt the language of organizations that they belong to. If an advocacy organization, for example, uses positive language in their communications with their members, engaged members may also use positive language in writing policymakers.

Researchers have used sentiment analysis on Twitter data to evaluate project acceptance (Ding 2018) and estimate damage of natural disasters (Li et al. 2019). Valence Aware Dictionary and sEntiment Reasoner (VADER; Hutto and Gilbert 2014) was selected among other sentiment classifiers for its logical, rule-based model. It considers a dictionary of words, crowd-validated as positive or negative. It was made specifically to evaluate social media messages, which are similar to many of the online messages in this study. Its lexicon, openly available to browsing on GitHub, contains not only words, but also emojis, emoticons, and netspeak. Unlike network-derived models, individual VADER scores are easily explained, and the VADER project authors give clear guidance on how to interpret them. VADER reports positive, negative, and compound scores. Project authors recommend testing messages on their compound scores: Messages with compound scores above or equal to 0.05 are positive; messages with compound scores below or equal to -0.05 are negative; other messages are neutral. VADER is accessible with Python via the Natural Language Toolkit (NLTK; Bird et al. 2019). This study pilots the validation of VADER with a random sample of 400 messages and six human reviewers. Appendix C describes the validation process.

If VADER is the standard for lexical-based sentiment analysis of short messages without machine learning, then Flesch (1948) readability tests are the same for assessing readability of a passage of text. Flesch ease of reading scores are based on the number of syllables per word and the number of words per sentence in a message. As shown in Section 5.4, Flesch scores are tied to education grade levels from grade-school reading levels to college graduate reading levels. The Bureau of Labor Statistics (2015) shows that education is the best indicator of citizen volunteer rates among other predictors factors, including age, race, marriage, children, and employment. If writing grade level is an indicator of education, and if membership is an indicator of volunteering, then this study should expect, therefore, people who write at higher grade levels to have higher membership rates.

For policymakers and civil project managers, text analysis of messages sent directly to them may tell them different things than messages observed on Twitter. If relationships between messages and membership exist, and policymakers have messages segmented by communication channel, policymakers may then be able to assess the strength of individual advocacy groups delivering the messages in addition to public sentiment. For advocacy organizations, relationships could be used to directly address the need that they have to suggest next steps to individuals, with minimal information, after they send a message.

CHAPTER 3. METHODOLOGY

3.1. Approach

This study begins by employing basic, exploratory, deductive research methods to achieve Objective One introduced in Chapter 1 (Section 3.3). It tests three hypotheses to investigate relationships between the number of messages that contacts send and the following message and text metrics:

1. The use of pronouns
2. The number of personally authored messages
3. The length of messages that contacts write

The total number of messages that contacts send is the first measure of engagement to which this study relates text predictors. In conducting these initial tests, tangential, incomplete observations of message frequency, message content, and organizational membership status of message authors inspire notions that membership rates increase with the following message and text metrics:

1. The number of messages contacts send
2. Personal stories in messages
3. Positive message sentiment
4. Message writing complexity (i.e. writing grade level)

These conjectures, along with education and volunteering data from the Bureau of Labor Statistics (2015), and along with and frame alignment theory (Snow et al. 1986, Sokolowski 1996), encourage additional explorations into message predictors of membership (Section 3.4, Chapter 5). This study labels these additional explorations as Objective Two explorations. It begins these additional explorations by calculating baseline membership rates (rates of dues paying members) for contacts grouped by the number of messages and the number of personally authored messages that they send – two message metrics that require no text analysis. Next, it compares these baseline membership rates to membership rates of groups of contacts using lower and higher rates of pronouns, personal stories, positive sentiment, and complex sentences, with the following tools: Linguistic Inquiry and Word Count (LIWC), expert judgement and regular expressions, Valence Aware Dictionary for sEntiment Reasoning (VADER), and the Flesch ease of reading test. This study uses Pearson's Chi-Squared test to determine whether membership differences for these groups of contacts are significant.

From an applied research perspective, conditions that create the largest groups of contacts, with the highest membership rate differences from their alternative-condition groups, are, alone, the best predictors of membership and candidates for the future development of a predictive engagement model. In an applied, methodical, search for conditions (i.e. patterns), sans any theoretical basis, this study concludes Objective Two explorations with the calculation of membership rates of (a) 10,000 groups of contacts using or not using the 5,000 most popular words found in messages and (b) groups of contacts using or not using words from each LIWC dimension.

The study alternates between deductive and inductive reasoning in exploring message metrics and text metrics indicative of two types of organizational engagement: the number of messages contacts send (Objective One) and organizational membership (Objective Two). Observations made while completing Objective One tests informed the development of Objective Two tests.

While the *applied* needs of environmental advocacy organizations, policymakers, and advocacy service providers motivate this study, the lack of research in predicting organizational engagement from message analysis and text analysis of advocacy messages sent directly to policymakers (vs. publicly on social networks) drives the *basic* research goals to describe data and test theories found in related studies. The most applied methods that this study employs are the tests of membership rates for groups of contacts using popular words and the tests of membership for groups of contacts using words in LIWC dimension dictionaries. Future applied research can build on this study's findings to develop organizational engagement prediction models. Table 3.1.1 summarizes the variables, data, and methods that this study uses, for the two objectives, to study the relationships between message predictors and the two measures of engagement. Section 3.3 lists the tools that this study uses to accomplish these tasks.

Table 3.1.1 Independent Message Predictor Variables and Dependent Engagement Variables

	Objective One	Objective Two: Exploration
Measure of Engagement *dependent variables*	Number of Messages Contacts Send	Membership Rate Number of contacts in a group that are members divided by the total number of contacts in that group
Message and Text Predictors of Engagement *independent variables* (Test results in parenthetical section references)	Pronoun Use Rates (Section 4.1) Personal Message Rate (Section 4.2) Average Message Length (Section 4.3)	Number of Messages (Section 5.1.1) Use of Pronouns (Section 5.1.2) Message Length (Section 5.1.3) Personal Stories (Section 5.3) Writing Complexity (Section 5.4) E5. Sentiment (Section 5.5) E6. Popular Words (Section 5.6) E7. All LIWC Dimensions (Section 5.7)
Methods Overview	Objective One methods review data, construct databases, group contacts by the number of messages that they have sent, top-code contacts who have sent over 20 messages into a single group, calculate lumped predictor variable values (pronouns use rates, personal message rate, average message length) for each group, and describe correlations and trends to test hypotheses	Objective Two methods define membership baselines and significant membership difference scales, group contacts by predictor variable rates, calculate membership rates for these groups, and compare these membership rates to baseline membership rates

3.2. Data: Terms, Collection, and Database Construction

This section begins by describing the original data collected by this study and discusses how, without access to contact tables, to use contact data in message records. It then defines message terms required for understanding subsequent method descriptions in this chapter and findings in the results and conclusion chapters. This section, most importantly for this purpose, defines distinctions between all messages, custom messages, personal messages, and personal stories. Finally, this section describes the data collection period, schema for database fields required by this study to conduct analyses, and guidance on database constructing for future studies.

3.2.1. Original Data: Contact Data in Message Records

Original study data include over two million messages and nearly 500,000 originally authored messages from over 150,000 individuals across the U.S. (Appendix A). The messages support sustainable civil and environmental policies and projects. While many messages to public officials are public information, collecting messages requires coordination with both organizations encouraging messages and the software service providers delivering messages. Messages in this study have been collected by these advocacy organizations and service providers through a variety of website services, CRM databases, and chatbot reports.

After being prepared for testing hypotheses, data consist of message and contact tables. Message tables contain records of advocacy messages that contacts send their policymakers. Message records include both the messages themselves and metadata about the messages Metadata include fields for the systems that messages are sent through, such as CQ (https://cqrollcall.com/), Capwiz (now obsolete), Salesforce (https://www.salesforce.com/), Convio (http://www.convio.com/), Facebook (facebook.com/), and custom campaign websites built around CiviCRM (https://civicrm.org/). Metadata also include fields for advocacy topics, such as air and water quality, climate change, energy, transportation, water supply, wildlife, birds, and ivory. Contact tables contain records of people that advocacy campaigns have interacted with. Contact data include the online advocacy systems that contacts have used, their paid membership statuses, event attendance information, and other demographic information.

With the messages table and the contacts tables, this study can define message and text metrics for each message, lump message metrics into contact message metrics, and lump contact message metrics into contact group message metrics.

While this study would have ideally started with two tables, one for messages and one for contacts, most contact data was originally stored in message table fields and this study extracted it into a contact table via unique contact IDs. Future studies may encounter this problem. While it is safe for researchers to assume all contact relationship management systems have tables of contacts, contact reports are not always available or easily generated by advocacy product managers for privacy, convenience, and system compatibility reasons. Some advocacy service providers, for example, do not retain or report contact tables for older campaigns at all. Advocacy organizations, additionally, can have separate membership management and online advocacy systems for which contact IDs are separate. While this study had access to partial information from contact tables, it relied on contact metadata stored in message records.

Retrieving contact information dispersed in multiple message tables requires more work than retrieving contact information from a single contact table. It requires more join queries and more logic to handle discrepancies. It is also storage inefficient. For example, the birthday and gender values that contacts report do not usually change and should generally be stored in contact tables, not message tables. This study did notice, however, that future work could use some contact data when it is stored in message tables. Multiple, timestamped records of a contact membership statuses, for example, could help test a temporal engagement hypothesis in the future; e.g. the relationship between advocacy message frequency and membership renewal times. Changes in mailing addresses recorded in an action table, furthermore, could aid future spatiotemporal studies, such as the study of relationships between address changes, locations of coal-fired power plants, and related personal stories in messages.

Organizations and service providers continually clean their databases to maintain data accuracy and consistency. For this study, they have previously both checked, and protected input fields that collect, the data used in this study for duplicate contacts, human entry errors, and non-humans (e.g. spam bots). Additionally, name fields, phone number fields, email fields, complete address fields, and other personally identifiable information have been removed prior to the analysis of messages. Finally, some of the example messages used to illustrate points in this dissertation (not analyzed data) have been modified to preserve the privacy of the message authors.

3.2.2. Messages Category Terms: Messages, Custom Messages, Personal Messages, and Personal Stories

This study divides messages into three principal categories: (1) not custom and not personal messages (1,586,252; abbreviated NOTCORP messages), (2) personal messages (491,027; abbreviated PM), and (3) custom messages (122,345; abbreviated as CM). See Figure 3.2.1. The first category of messages, not custom and not personal messages, does not contain individually authored text. This study, therefore, cannot perform text analysis on messages in this category to describe individual authors' writing styles or sentiment. Policymakers treat these non-customized, prewritten messages more like petition signatures than individual letters. They devalue these messages (Section 2.1).

The second category, personal messages, contains messages originally authored by message senders. Some personal messages, moreover, contain stories of "lived experiences" (Sandhu 2017) concerning the effect of environmental issues on the authors' lives. This study performs text analysis on all personal messages.

Finally, the third category, custom messages, contains prewritten messages (i.e. form letters) that individuals have edited. Future studies may be able to extract the individually written part of custom messages for text analysis.

While contacts could have customized or attached personal messages to many NOTCORP messages before they were sent, data records do not reveal if some NOTCORP messages lacked the option for contacts to customize them. In total, data consists of 2,199,624 messages – personal, customized, or not – which were sent by 690,631 unique contacts (an average of 3.6 messages per contact). Of these, 194,409 contacts have sent personal messages. A very small number of personal messages (0.015%) in the data have custom messages attached to them. This study categorizes these messages as PM for text analysis, not CM.

Beyond these categories of messages (NOTCORP, PM, and CM), this study further categorizes and describes personal messages, both objectively and subjectively, to define potential predictors and measures of engagement. With only the single "message" field in message records, which contain words that comprise the body text of each personal message, several potential linguistic predictors of engagement and descriptive metrics can be derived. First, counting the number of words in this field yields a word count (WC) value. Then, with the LIWC tool, this study learns about the percentage of words used in each message across LIWC dictionary dimensions, including the pronoun dimensions pertinent to Hypothesis One and family dimension pertinent to Objective Two. LIWC also calculates words per sentence (WPS). WC and WPS are both objective message metadata. While the selection of words in LIWC dictionaries are subjective, they have been developed and refined by past research (Pennebaker et al. 2015). Given these dictionaries, the calculation of LIWC rates are objective calculations, reported as percentages of dictionary words in individual messages (from 0% to 100%). These calculations enable messages to be compared to each other, lumped into per-contact rates, and compared to messages in other corpuses.

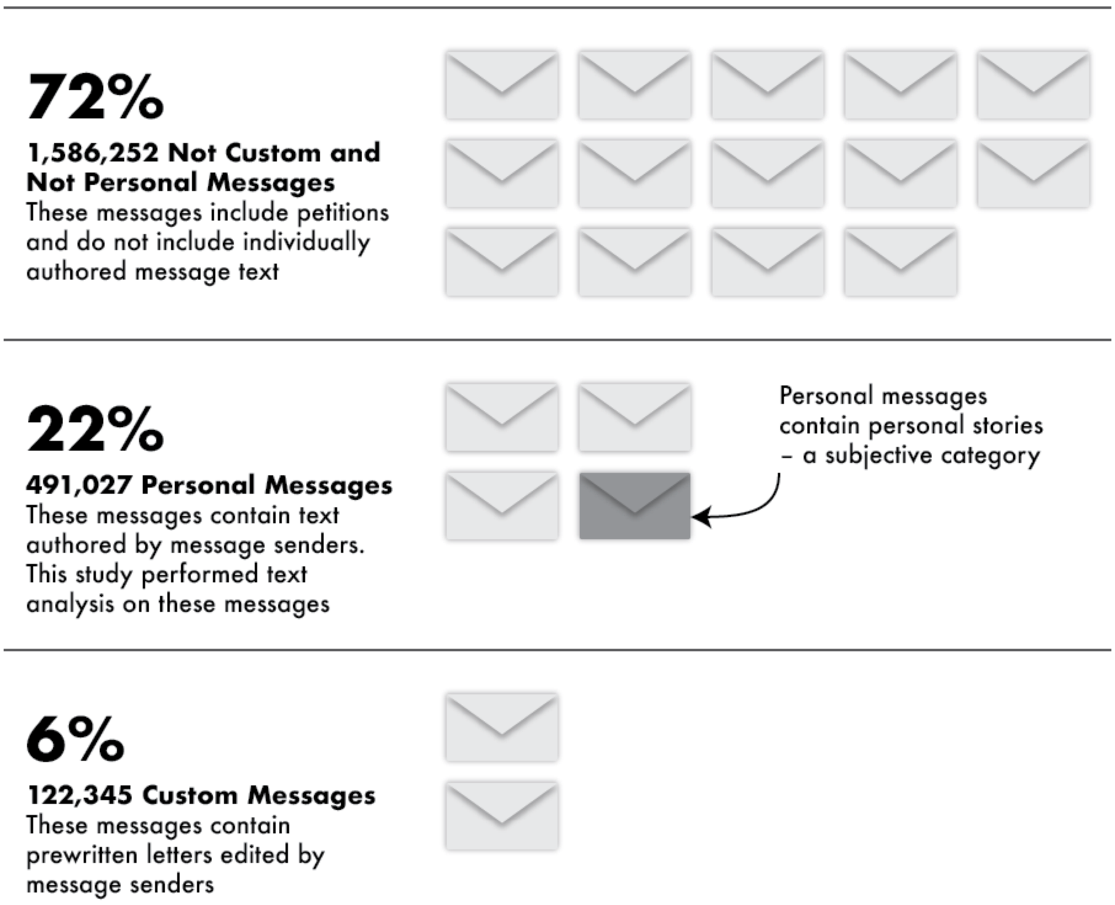


Figure 3.2.1 Message Categories
This study divides 2,199,624 total messages into three top level categories: not custom and not personal messages (1,586,252), personal messages (491,027), and custom messages (122,345). Personal messages contain subjectively categorized personal stories.

3.2.3. Collection Period

This study collected messages that were sent between July 1, 2017 and October 31, 2018 for one set of data and from 2012 to 2014 for a smaller set. For the messages that this study collected in 2017 and 2018, this study collected personal (PM) and custom messages (CM) messages between July 1, 2017 and October 10, 2018 (16 months) and other (NOTCORP) messages between July 1, 2018 and October 10, 2018 (four months). This study computed LIWC scores for personal messages and used all messages to compute the number of messages sent per contact as a measure of engagement. The results for testing Hypothesis One describe the effects of limiting the analysis of messages to those sent during the personal messages time period and excluding NOTCORP messages completely.

3.2.4. Database Schema

3.2.4.1.Messages Table

After preparing data for analysis, the messages table contains the fields shown in Table 3.2.1 necessary to first test the three hypotheses defined by Objective One and, second, test the relationships defined by Objective Two explorations.

Table 3.2.1 Messages Table

Field	Description
Message ID	Unique, primary key (integer)
Contact ID	Contact key (integer)
Message	Text
Message category	Personal, custom, not personal or custom enumerated values (enum)
VADER Score	Sentiment score from -1 to 1 (float)
Flesch Reading Ease Score	Score (float)

LIWC Rates
• Pronouns
• Personal Pronouns
  ○ First-Person Singular “I” Pronouns
  ○ First-Person Plural “We” Pronouns
  ○ Second-Person “You” Pronouns
  ○ Third-Person Singular “He/She” Pronouns
  ○ Third-Person Singular “They” Pronouns
• Impersonal Pronouns
	Percentages of words (float)

The Contact ID field identifies unique contacts. It is a necessary field for summarizing message data for individual contacts, which, in turn, is necessary for summarizing groups of contacts who have sent the same number of messages. The message category field is necessary to determine which messages have personal messages attached to them so that this study can determine linguistic properties authentic to their authors. (Note: While message category is expressed here as a single field, in many study calculations, message category was expressed with multiple category-named tables fields for query convenience, efficiency, and readability.) This field is also essential to testing Hypothesis Two – the relationship between personal and all messages. Although Objective Two methods look at relationships between each LIWC pronoun dimension and engagement, the test of Hypothesis One only required usage percentages for the personal pronouns.

3.2.4.2.Contacts Table

After preparing data for analysis, the contacts table contains the fields in Table 3.2.2.

Table 3.2.2 Contacts Table

Field	Description
Contact ID	Unique, primary key (integer)
Member	Boolean field describing if a contact has ever been a member at the time of sending a message
Number of Personal Messages	Number (int)
Total Number of Messages	Number (int)

Average LIWC Rates
• Pronouns
• Personal Pronouns
  ○ First-Person Singular "I" Pronouns
  ○ First-Person Plural "We" Pronouns
  ○ Second Person "You" Pronouns
  ○ Third-Person Singular "He/She" Pronouns
  ○ Third-Person Singular "They" Pronouns
• Impersonal Pronouns
	Average percentages of words (float)

In addition to the fields for the contacts table listed in Table 3.2.2, the following fields contribute to calculation checks:

- Number of custom messages (int)
- Number of not personal or custom messages (int)

The Contact ID field is a unique ID necessary to relate contacts and messages. The Member field is a Boolean field indicating if the contact has ever sent a message during the study time period while having an active membership status, where a contact's membership status is active for a year after paying membership dues for it. The two number of message fields (personal, total) are group summaries of message data described in the message table (Table 3.2.1). Like the number of message fields, average LIWC rates are summaries of data from the contact table. The number of message fields and the average LIWC rate fields speed up analysis, especially for large sets of messages (>100,000), but may be replaced with SQL queries to join message table data to contact data.

3.2.4.3.Additional Fields

Beyond the essential fields listed above, other fields were available in the messages table from the data that were not used. They could be used in future work as segments, drivers, and measures of engagement: message type (e.g. petition), message issue (e.g. energy policy, ivory, plastic straws, whales), contact gender, contact device (mobile or not), advocacy system (e.g. CQ, Convio, etc.), membership level (e.g. student, limited income, standard, big donor). Note that most contacts in this study's data were classified at the standard membership level. (See the introduction to Chapter 5 for more information about membership levels.)

3.2.5. Database Construction: Creating Message and Contact Tables

As described above, this study did not begin with the ideal messages tables and contact tables needed to test hypotheses showing the relationship between message attributes and the number of messages that contacts send as a measure of organizational engagement; original data were composed of message records, with contact metadata inefficiently attached to these message records. Further, data were split across several files and fields were untyped[1] in comma-separated-value (CSV) text files. The first step this study took was to combine files with similar fields in a database. In doing so, it assigned types and

---

[1] That is, initial data were not composed of structured data formats with types (e.g. integers, dates, text, etc.), like they are in a database.

keys to database fields. To do this, Excel and the following Python packages were used: Sys, Os, Pandas, Numpy, Datetime, Pymysql, Sqlalchemy, and Scipy.

First, ten CSV files containing personal (PM) and custom message (CM) records and four files containing other (NOTCORP) tables were manually converted into standard Excel XLSX format by opening the CSV files in Excel, removing extraneous summary text at the end of each file, and cleaning up the first row of each spreadsheet to make sure each first-row cell was correctly labeled as a field name with respect to its column's rows. During this process, Excel automatically guessed and saved the type of each field. It correctly recognized and typed most dates, numbers, and text. As expected, it did not assign more specific information to fields, like floating point precision values to numbers or character sizes to text.

Next, this study imported data into Python Pandas objects for exploration and conversion to MySQL tables via the Sqlalchemy Python package. (For comparison, creating Pandas objects directly from CSV files with the Pandas read_csv module worked, but did not automatically type data as well as preprocessing the data in Excel.) A Python script iterated through each Excel file and added each message record into one of two MySQL tables – one for personal and custom messages (coded CMPM) and one for other messages (NOTCORP). MySQL was then used to confirm the uniqueness of message IDs. Queries to count unique message and contact IDs revealed that IDs from some sources were case sensitive, so this study set the collation[2] of these keys

[2] For an introduction to database collations, see Chapter 10 of the MySQL manual: "Character Sets, Collations, Unicode" (https://dev.mysql.com/doc/refman/8.0/en/charset.html).

accordingly. Additional database instructions then set primary and unique indices on both the message and contact ID fields of these message tables.

This study then grouped messages by Contact ID across both CMPM and NOTCORP message tables with the MySQL GROUP BY command to create a unique contact table with summary contact fields. It used MySQL functions COUNT, AVG, SUM, and IFNULL to calculate summary metrics like the sums of all messages, personal messages, and customized messages in the contact table. For each contact, this study set contact gender to the last value of gender reported by the message table. A concatenation function created a field of all personal message text for each contact, which acted later as a calculation check throughout the analysis (e.g. double-checking pronoun use rates among message words for contact outliers using high and low rates of pronouns).

After this study created the contact table, this study used LIWC to assign word count rate scores (i.e. percentage pronoun words per message) and summary scores (e.g. total word count, words per sentence) to each individual personal message. To do this, Python scripts were used to tabulate message IDs and corresponding message text from the database into an Excel file for LIWC. LIWC made a copy of this table and appended its linguistic scores to each record. Python was then used in a reverse operation, to import the scores into a new database table. JOIN and GROUP BY functions were then used to calculate the average and standard deviation of scores for each unique contact. In retrospect, LIWC scores could have been calculated before contact tables were created to shorten the procedure described thus far, but isolating the linguistic analysis both limited potential memory problems and avoided any problems of inputting irrelevant data into the LIWC program (e.g. contact id, contact metadata, message topic, etc.).

3.2.6. Example Database Construction

Meet Lisander Snodgrass, Bowser Lemans, Guybrush Gilbert, and “Whale Lover” Gene. They are four fictitious environmental advocates who have sent messages to their congressional representatives in two different campaigns, reported by two different advocacy systems in Table 3.2.3 and Table 3.2.4. Using their messages, this section provides a simplified example of preparing data for analysis through the construction of a database containing a combined messages table and containing a derived contacts table (Table 3.2.5, Table 3.2.6). Throughout this example, table rows related to Lisander Snodgrass have been highlighted to emphasize database operations and calculations.

While the non-fictitious study in this dissertation began with a message table already prepared, containing unique message IDs, unique contact IDs, and personally identifiable information removed, researchers repeating this study with their own data may need to prepare data themselves and make assumptions to distinguish unique contacts. In this example, source Table 3.2.3 contains fields for message ID (ID), message, contact ID (CID), email, and member. Source Table 3.2.4 only contains message, email, and member fields.

Table 3.2.3 Example Source Messages
ID is message ID; CID is Contact ID

ID	Message	CID	Email	Member
1	Thank you for your support	1	Lisander.Snodgrass22@example.com	Yes
2	NULL	2	Bowser.LeMans@thimbleweed.pl	Yes
3	NULL	1	Lisander.Snodgrass22@example.com	No
4	We are affected by this issue	3	Guybrush.Gilbert@mymonkeytownusa.me	Yes

Table 3.2.4 Example Source Messages

Message	Email Address	Member
Save the whales!	Lisander Snodgrass	No
I love whales!	Whale Lover Gene	No

Future studies may be forced to use contact identifiers like email, phone number, full name, and address to distinguish individuals and eliminate duplicate contact records. In this example, Table 3.2.4 contains no contact ID field, so email is the best contact identifier for these two tables. Even if unique contact IDs are given, if one other unique identifier is given, COUNT and DISTINCT commands should be used to check table consistency between the contact identifiers. Database operations on these tables yield a combined messages table (Table 3.2.5).

Table 3.2.5 Example Combined Messages Table
This message table, along with contact Table 3.2.6, are the results of combining message source tables (Table 3.2.3 and Table 3.2.4).

ID	Message	Type	CID	Source Table	Name
1	Thank you for your support	Personal	1	1	Lisander Snodgrass
2	NULL	Not Personal	2	1	Bowser LeMans
3	NULL	Not Personal	1	1	Lisander Snodgrass
4	We are affected by this issue	Personal	3	1	Guybrush Gilbert
5	Save the whales!	Personal	1	2	Lisander Snodgrass
6	I love whales!	Personal	4	2	Whale Lover Gene

Table 3.2.6 Example Derived Contacts Table
This contacts table, along with messages Table 3.2.5, are the results of combining message source tables (Table 3.2.3 and Table 3.2.4).

ID	Messages	Not Personal Messages	Personal Messages	Member	Name
1	3	1	2	1	Lisander Snodgrass
2	1	1	0	1	Bowser LeMans
3	1	0	1	1	Guybrush Gilbert
4	1	0	1	0	Whale Lover Gene

In this database construction example, note that there are no customized messages (CM) and that “not personal messages” are similar to NOTCORP messages found in this study’s actual data (Table 3.2.5). Also notice that the resulting contacts table (Table 3.2.6) categorizes Lisander Snodgrass as a member because the original message tables report him as paying for membership dues at least one time, even though it also reports him as a non-member one time. (This study categorizes contacts among the actual, non-fictitious data in this same way – labeling a contact as a member means that the contact has been a member at least once during the study period.)

After this study constructs message and contact tables similar to example tables (Table 3.2.5 and Table 3.2.6), it is ready to continue analysis by calculating and storing LIWC, VADER, and Flesch scores as message fields in the database. Once this is complete, contacts and groups of contacts are ready to be queried by predictor variables and the two measures of engagement ("messages" and "members" fields) in the contacts table. The following sections, describing Objective One, continue this example.

3.3. Objective One Methods: Relationships Between Messages and the Number of Messages that Groups of Contacts Send

Objective One focuses on relating three message metrics (pronoun use rates, personal message rates, and the average message length) to the number of messages that contacts send. This section describes the methods that this study uses, considerations for lumping text metrics for contacts and groups of contacts, and example calculations. It contains the following subsections:

1. Hypothesis One: Personal Pronouns (Section 3.3.1)
2. Hypothesis Two: Personal Messages (Section 3.3.2)
3. Hypothesis Three: Message Length (Section 3.3.3)
4. Example Objective One Calculations (Section 3.3.4)

3.3.1. Hypothesis One: Personal Pronouns

3.3.1.1. Procedure

To begin relating pronoun use rates with the number of messages that contacts send, using the database of message and contact tables described above, this study first counts the use of personal pronouns in every personal message. It then counts the total number of words in every personal message. To do this, this study,

1. Creates message table fields for each of the eight LIWC pronoun rate dimensions
    a. All pronouns
    b. All personal pronouns
    c. First-person singular “I” pronouns (e.g. “I,” “I’ve,” “me”)
    d. First-person plural “we” pronouns
    e. Second person “you” pronouns
    f. Third-person “she/he” pronouns
    g. Third-person “they” pronouns
    h. All impersonal pronouns (e.g. “it,” “that,” “there”)
2. Creates a message table field for word count
3. For each message record, and for each of the eight LIWC pronoun dimensions, counts and stores pronoun use rates (words per message) and all words in the fields created in step one and two in this list, above

Note: During this process, for exploratory purposes not necessary for answering Hypothesis One, this study creates fields and records scores for all other LIWC dimensions (e.g. rates of swear words, positive-sentiment words, punctuation, etc.). See Pennebaker et al. (2015) for a complete list of LIWC dimensions.

This study aims to understand relationships between the use of pronouns by contacts with the number of messages that these contacts send. To this end, it,

1. Creates contact table fields for, and calculates values for, lumped pronoun metrics and lumped word counts metrics with database join and math statements

   a. Average contact LIWC rate, weighted by message
   b. Contact LIWC rate, for all contact messages
   c. Average message word count, weighted by message
   d. Total word count of all contact messages
2. Groups contacts by the number of messages that they have sent and calculates, for each of these groups, average, minimum, and maximum LIWC rates and word counts
3. Top-codes groups of contacts who have sent more than 20 messages
4. Plots lumped contact group LIWC rates calculated in step five of this procedure against the number of messages contacts all sent in each group
5. Calculates Pearson correlations between the lumped contact group LIWC rates and the number of messages contacts all sent in each group

Finally, this study compares the resulting relationships and correlations between group average LIWC rates and the number of messages groups of contacts send.

3.3.1.2.Lumping Text Metrics: Details and Rationale

This study lumps pronoun and word count text metrics by groups of contacts for contacts who have all sent the same number of messages. It first averages text metrics in 491,027 personal messages for each of the 194,409 contacts who have sent at least one personal message. Second, this study groups these contacts by the total number of messages that they have sent. It top-codes contacts who have sent more than 20 messages into a single group. In this second grouping, text-metrics are once again averaged, this time by contact. Top-coding contacts mitigates problems of high pronoun rate variability in small groups of contacts when calculating averages, viewing plots, and calculating correlations described in Section 3.3.1.

Top-coding contacts to test all three hypotheses in objective one, and explore membership in objective two, consists of grouping contacts who have sent more than 21 messages into a single group and calculating lumped message and text messages for them. Results reported in Section 4.1.2.3 show the importance of top-coding contacts.

Table 3.3.1 compares this method to two other methods. Instead of observing relationships between groups of contacts (Column C), this study could have observed relationships for either the series of personal messages (Column A) or the series of contacts who sent personal messages (Column B).

Table 3.3.1 Three Methods to Relate Text Metrics to the Number of Messages that Contacts Send

Method	A. Message Based	B. Contact Based	C. Group Based
Series Length and Unit	491,027 Messages	194,409 Contacts	21 Groups of Contacts
Predictor Fields	Pronoun rate, word count	Contact-lumped pronoun rate	Group-lumped pronoun rate
Engagement Variable	Total number of messages sent by related contacts	Total number of messages sent	Total number of messages sent

The message-based method described in Table 3.3.1 would entail creating a message table field for, and assigning values to each message record for, the total number of messages sent by each message’s author identified by contact ID. Then, this study could compare personal message text metrics (pronoun rate and word counts) to the total number of messages sent by personal message authors for each of the 491,027 personal messages. This message-based method is problematic in addressing Hypothesis One of Objective One. Objective One is interested in the linguistic styles of individual contacts and this message-based method does not equally consider the linguistic styles of individual contacts. Instead, it equally considers the linguistic styles of individual *messages*. Moreover, this message-based method considers very short messages and very long messages be equally reflective of individual contact linguistic styles, while longer messages are in fact better indicators of linguistic styles.

The contact-based method described in Table 3.3.1 addresses the problems of the message-based method by computing average text metrics per contact. Using this method, this study can compare lumped text metrics for each of the 194,409 contacts to the total number of messages that they have sent. The quantity of contacts and potentially high ranges of pronoun rates in this method, however, could yield hard to read, densely covered, plots of average linguistic scores for each contact vs. the number of messages each contact has sent. (Section 5.2 further explores this case.) The group-based method that this study used, described in Table 3.3.1, addresses the problems with the contact-based method by summarizing text metrics for each group of contacts with average text metrics. Trends are easier to identify in plots of 21 group pronoun rates than in plots of 194,409 individual contact pronoun rates. (Section 5.2, along with membership data, explores trends for ungrouped contacts.)

3.3.1.3.Short Example for Calculating Average Pronoun Rates for Groups

In a hypothetical sample of two contacts, for the category of all personal pronouns, if the first contact sent five messages, two personal and three petition-style messages, with the two personal messages having 3% and 5% rates of personal pronouns, that first contact has an average personal pronoun rate of 4%. If the second contact also sent five messages, but all personal, and with the rates of personal pronouns of 4%, 5%, 6%, 7%, and 8%, that contact has an average personal pronoun rate of 6%. Given these are the only two contacts in this short example, an example figure of group pronoun rates would show a single point at 5% personal pronouns (ordinate) for contacts who have sent five messages (abscissa): ((3% + 5%) / 2 + (4% + 5% + 6% + 7% + 8%) / 5) / 2 = 5%. Averaging message metrics weighted by contact gives each contact an equal influence over a contact group average regardless of the number of messages that they send. An unweighted average across all messages, alternatively, gives contacts who send more personal messages more influence on the average. The unweighted average of all messages in this example would be influenced more by the second contact, who sent five personal messages, than the first contact, who sent two messages. The unweighted average of 3%, 5%, 4%, 5%, 6%, 7%, and 8% is 5.4%. While this unweighted average can summarize messages of a group of contacts, it does not directly address the objective of this research to study individual contacts. Contact-weighted averages, conversely, both directly describe contacts and can be compared to values in literature that also do so. These contact-weighted averages also soften the effects of outlying contacts who may send a high ratio of personal messages to other messages, with an unusually high or low percentage of words in a particular category.

3.3.1.4. Hypothesis One Method Development: Spreadsheet Limitations, Top-Coding, and Software

This study initially used Excel spreadsheet pivot tables to pilot the processes of grouping contacts by the total number of messages sent, and plotting LIWC group average rates against this metric. This worked, but slowly, and due to software constraints, only for the set of personal messages (vs. all messages) and only for summarizing a partial number of

LIWC scores per database sheet. Results from this precursory analysis showed the personal pronouns “we” and “you” were related with the number of personal messages sent, but did not account for all messages (NOTCORP messages) sent. This spreadsheet process required creating new pivot tables for each pronoun metric to avoid spreadsheet software and memory limits. (Rendering computation results as spreadsheet views is slower and requires more memory than storing values in a database result objects.) In addition to looking at personal pronouns, average LIWC dimensions were plotted against the groups of contacts who have sent the same number of messages. These plots showed a potential negative relationship between perceptual words (“see,” “hear,” and “feel”) and the number of messages sent by contacts. Although no other trends were found, spreadsheet plots revealed some high ranges of text metrics for groups of contacts who sent high numbers of messages. The spreadsheets showed the number of contacts in groups of contacts who sent high numbers of messages are low, and this inspired the top-coding methods that this study ultimately used.

To more efficiently test Hypothesis One, to check the initial spreadsheet observations, and to begin exploration into the correlations between the number of messages contacts sent and all LIWC dimensions, this study used Anaconda, a collection of data science Python packages. It used Spyder to create a Python script to rapidly plot LIWC dimensions against groups of contacts who have sent the same number of messages. This script relied on Pandas, a data analysis library, and Matplotlib, a plotting library. Next, this study used Orange3 to review summaries of these data in several ways: Orange3 automated initiating Python scripts and SQL queries. Orange3 filtered results by group size; specifically, before this study ultimately top-coded groups of contacts who sent more than 20 messages, it used Orange3 to filter our groups of contacts with small numbers of contacts in them. Orange3 plotted correlations and calculated correlation coefficients for each LIWC dimension and for each group of contacts who have sent the same number of messages to their policymakers. Orange3 tabulated the correlation coefficients for every group average LIWC dimension and the number of messages sent by each group. Both the graphs created in Spyder with Pandas and Matplotlib, and the graphs created in Oranage3, confirmed the preliminary results from the spreadsheet analysis for personal messages only, and for the larger sets of NOTCORP messages. The following chapter reports results. This study used the same tools that were used to test Hypothesis One test Hypothesis Two and Hypothesis Three. Section 3.5 lists all tools and their website addresses.

3.3.2. Hypothesis Two: Personal Messages

The originally proposed procedures for testing Hypothesis Two prescribed

1. Calculating, for each contact who sent at least one personal message
    a. The number personal messages that they sent
    b. The ratio of the number of personal messages that they sent to the number of messages that they sent that did not have a personal message attached to them
2. Plotting the number of messages sent by each contact against the two potential predictor metrics calculated in step one

This procedure produced plots that hinted at relationships, but revising the procedure to average the number of personal messages sent and average the ratio of personal messages sent for groups of contacts who have sent the same number of messages, with the same groups used to test Hypothesis One, revealed a clearer picture. Following final procedures to test Hypothesis Two, this study

1. For each contact, calculates
    a. The number of personal messages sent by the contact
    b. The number of total messages sent by the contact
    c. The rate of personal messages sent by the contact (the ratio of the two previous calculations)
2. For groups of contacts who have sent the same number of messages, calculates
    a. The average number of personal messages sent for all group contacts
    b. The average rate of personal messages sent for all group contacts
3. Plots the two, group metrics calculated in step two, above, against the number of messages sent by contacts in each group
4. Compares the average rate plots with consideration to the number of contacts in each group

3.3.3. Hypothesis Three: Message Length

To test Hypothesis Three, the relationship between the length of each message and the number of messages sent, this study uses the same groups used for testing hypotheses one and two. This study

1. Uses word count as a measure of message length
2. Plots average word counts for groups of contacts against the number of messages sent by contacts in each group (both variables calculated during the test for Hypothesis One)

3. Compares average word count points in the plot created in step two with consideration to the number of contacts in each group of contacts who have sent the same number of messages

3.3.4. Example Objective One Calculations

Given example message and contact tables (Table 3.2.5 and Table 3.2.6), derived from source message tables (Table 3.2.3 and Table 3.2.4) at the end of Section 3.2, methods to test Hypothesis One for the example data, with no top-coding, for the count of all pronouns (a single, example LIWC dimension), yield the example message and contact tables, Table 3.3.2 and Table 3.3.3. Table 3.3.2 shows the field for the count of all pronouns for example calculation purposes only. The non-fictitious study database does not contain this field, but it can be back-calculated from the word count field and the LIWC pronoun rate field.

Table 3.3.2 Example Message Table with Pronoun Rate and Word Count Fields
The rows for Lisander Snodgrass are highlighted to emphasize the calculation of lumped metric rates.

ID	Message	Type	CID	Source Table	Count of All Pronouns (pronouns)	Word Count (words)	LIWC Pronoun Rate (% pronouns)	Example Name
1	Thank you for your support	Personal	1	1	2 (you, your)	4	50% (2/4)	Lisander Snodgrass
2	NULL	NOTCORP	2	1	NULL	NULL	NULL	Bowser LeMans
3	NULL	NOTCORP	1	1	NULL	NULL	NULL	Lisander Snodgrass
4	We are affected by this issue	Personal	3	1	1 (we)	6	16.66% (1/6)	Guybrush Gilbert
5	Save the whales!	Personal	1	2	0	3	0% (0/3)	Lisander Snodgrass
6	I love whales!	Personal	4	2	1 (I)	3	33.33% (1/3)	Whale Lover Gene

Table 3.3.3 Example Contact Table with Lumped LIWC and Word Count Fields
The row for Lisander Snodgrass is highlighted to emphasize the calculation of lumped metric rates.

ID	Messages	Not Personal Messages	Personal Messages	Member	Average Pronoun Rate Weighted By Message	Average Pronoun Rate for All Messages	Average Word Count	Total Word Count for All Messages	Example Name
1	3	1	2	1	25% avg(50%, NULL, 0%)	28.57%*	3.5 = avg(4, NULL, 3)	7 (4 + NULL +3)	Lisander Snodgrass
2	1	1	0	1	NULL	NULL	NULL	NULL	Bowser LeMans
3	1	0	1	1	16.66%	16.66%	6	6	Guybrush Gilbert
4	1	0	1	0	33.33%	33.33%	3	3	Whale Lover Gene

* Lisander Snodgrass's average pronoun rate for all messages, weighted by messages length, is equal to the sum of all pronouns that Lisander used divided by the sum of all messages words that he wrote, calculated for this example as (2+NULL+0) / (4+NULL+3) = 2/7 = 28.57%, or, as calculated in the non-fictitious study database with total word counts and pronoun rates, as (4 words * 50% pronouns / word + NULL + 3 words * 0% pronouns / word) / (4 words + NULL + 3 words) = (4*0.5 + 3*0.0) /(3+4) = 2/7 = 28.57%.

Table 3.3.4 show the four contacts from Table 3.3.3 lumped into groups of contacts who have sent the same total number of messages. Notice the null values are ignored in average functions, effectively summarizing the group average pronoun rates and group average word count rates for contacts who have sent personal messages (Guybrush Gilbert and Whale Lover Gene).

Table 3.3.4 Example Contact Groups

Group ID	Group Size (Contacts)	Number of Messages Sent by Each Contact	Personal Message Rate	Group Average Pronoun Rate for Contacts who have Sent at Least one Personal Message	Group Average Word Count for Contacts who have Sent at Least on Personal Message
1	1 (Just Lisander)	3	66.66% 2/3	25%	3.5 = avg(4, NULL, 3)
2	3 (Bowser, Guybrush, and Gene)	1	66.66% (0+1+1)/3	25% avg(NULL, 16.66%,33.33%)	4.5 avg(NULL,6,3)

In this example, for Hypothesis One, Table 3.3.4 reveals that there is no difference between the number of messages sent by contacts who have sent at least one personal message and the rate that these contacts use pronouns; the single contact who sent three messages (Lisander) used pronouns at the same rate as the two contacts who have sent one personal messages (Guybrush, and Gene): 25%. For Hypothesis Two, there is also no difference between the personal message rate of the single contact (Lisander Snodgrass) who sent three messages (2/3 personal) and the three other contacts who sent one message each (2/3 personal). Finally for Hypothesis Three, groups of contacts who only sent one message in this example sent them with one word, on average, longer than the "group" of one contact that sent three messages (4.5 - 3.5 = 1).

3.4. Objective Two Methods: Membership Exploration

Objective Two explores relationships between message and text metrics with a second measure of engagement, membership. Methods and results of these explorations are written together, in the Chapter 5. Objective Two begins by reviewing relationships between membership and the message and text metrics used in testing objective one hypotheses (Section 5.1.1). Next, for ungrouped contacts, Objective Two calculates correlations between the use of LIWC dimension words and (a) membership, (b) the number of messages that contacts have sent, and (c) the number of personal messages that contacts have sent (Section 5.1.2). Finally, it reports membership rates for contacts grouped by conditions defined by terms used to search for personal stories (Section 5.3), writing complexity defined by the Flesch reading ease test (Section 5.4), sentiment defined by the VADER sentiment classifier (Section 5.5), popular words among all personal messages in this study (Section 5.6), and words in all LIWC Dimensions (Section 5.7).

Appendix B, Appendix C, and Appendix D support reproducing procedures and building on these methods. Appendix B describes and lists MySQL search queries and regular expressions used by this study in attempts to find personal stories in messages. Appendix C reports methods and results of validating VADER for advocacy messages. Appendix D suggests methods for validating the classifying personal stories in messages.

3.5. Tools

Table 3.5.1 lists the analysis tools, development environments, and Python libraries that this study uses to develop databases, code methods, analyze data, and visualize data. Table 3.5.2 lists software platforms and node (https://nodejs.org/en/) packages that this study uses to collect data during the validation of VADER with human reviewers, described in Appendix C. These platforms and packages may also be used in future work to prototype advocacy services. Table 3.5.3 lists the programming languages that this study uses to accomplish these tasks.

Table 3.5.1 Analysis Tools, Development Environments, and Python Libraries

Tool	Website Address
Analysis Tools and Development Environments	
Anaconda	https://www.anaconda.com
Atom	https://atom.io/
Excel	https://products.office.com/en-us/excel
Google Sheets	https://www.google.com/sheets
Linguistic Inquiry and Word Count (LIWC)	http://liwc.net/
MySQL Workbench	https://www.mysql.com/products/workbench/
Orange3	https://orange.biolab.si/
SPSS	https://www.ibm.com/products/spss-statistics
Spyder	https://www.spyder-ide.org/
VS Code	https://code.visualstudio.com/
Python 3 Libraries	
Matplotlib	https://matplotlib.org/
NLTK	https://www.nltk.org/
NumPy	https://numpy.org/
Pandas	https://pandas.pydata.org/
PyMySQL	https://github.com/PyMySQL/PyMySQL
Scipy	https://www.scipy.org/
Seaborn	https://seaborn.pydata.org/
SQLAlchemy	https://www.sqlalchemy.org/
textstat	https://github.com/shivam5992/textstat
Python Core Libraries	
sys	https://docs.python.org/3/library/sys.html
os	https://docs.python.org/3/library/os.html
datetime	https://docs.python.org/3/library/datetime.html
difflib	docs.python.org/2/library/difflib.html

Table 3.5.2 Platforms and Node Packages for Validating VADER Sentiment and Prototyping Services

Tool	Website Address
Platform	
Apache	https://www.apache.org/
Debian	https://www.debian.org/
WordPress	https://wordpress.org/
Node Packages	
create-react-app	https://www.npmjs.com/package/create-react-app
flesch	https://www.npmjs.com/package/flesch
flesch-kincaid	https://www.npmjs.com/package/flesch-kincaid
gender-detection	https://www.npmjs.com/package/gender-detection
react	https://www.npmjs.com/package/react
sentence-splitter	https://www.npmjs.com/package/sentence-splitter
syllable	https://www.npmjs.com/package/syllable
vader-sentiment	https://www.npmjs.com/package/vader-sentiment
wordcount	https://www.npmjs.com/package/wordcount

Table 3.5.3 Study Programming Languages

Tool	Website Address
ECMAScript 6	https://www.ecma-international.org
MySQL 8	https://www.mysql.com/
PHP 8	https://www.php.net/
Python 3	https://www.python.org/
SCSS 1.24	https://sass-lang.com/

CHAPTER 4. RESULTS FOR OBJECTIVE ONE: NUMBER OF MESSAGES

Results from testing Hypothesis One show that relationships exist between the number of messages contacts have sent their policymakers and the average use of all pronouns (negative relationship), the average use of first-person plural “we” pronouns (negative relationship), and the average use of third-person singular “you” pronouns (positive relationship) (Section 4.1). Hypothesis Two test results show that the average rate of personal messages to general messages for groups of contacts who have sent more than one message is higher than the average rate of personal messages for the group of contacts who only sent a single message (Section 4.2). Hypothesis Three test results show that most groups of contacts send the same number of messages (Section 4.3). The following three sections of this chapter report these findings along with intermediary calculation results that inspire Objective Two explorations (Chapter 5). Each section contains plots of predictor variables (LIWC rates, personal messages rates, and average message length) along ordinate axes and the number of messages that contacts have sent along abscissa axes.

4.1. Hypothesis One: Relationships Between Pronouns and the Number of Messages that Contacts Send

4.1.1. Hypothesis One Test Results

LIWC reports word counts of (1) all pronouns (2) all personal pronouns, (3) first-person singular “I” pronouns (e.g. “I,” “I’ve,” “me”), (4) first-person plural “we” pronouns, (5) second-person “you” pronouns, (6) third-person singular “she/he” pronouns, (7) third-person plural “they” pronouns, and (8) all impersonal pronouns (e.g. “it,” “that,” “there”). Table 4.1.1 and Figure 4.1.1 through Figure 4.1.7 summarize the relationships between the use of each of these categories of pronouns and groups of contacts who have sent the same number of messages (personal or otherwise). Each figure plots the use of pronouns as a percentage of words used in personal messages (LIWC score), averaged per contact, and then averaged per group of contacts who have sent the same number of messages (personal or otherwise). See Section 3.3 for example calculations.

Table 4.1.1 labels correlations strong for $R^2 \in [0.7,1]$, moderate for $R^2 \in [0.3,0.7)$, and weak for $R^2 \in [0.2,0.3)$. For the three LIWC dimensions of all pronouns, all personal pronouns, and “she/he” pronouns, the linear-logarithmic relationships listed in Table 4.1.1 and plotted in Figure 4.1.1, Figure 4.1.2, and Figure 4.1.6, compensate for a positive bias in the linear relationship for large groups of contacts that have sent small numbers of messages (one, two, and three messages).

Table 4.1.1 Relationships Between Group Average Pronoun Use Rates and The Number of Messages Sent by Contacts

		Correlation		Range (%)		
	LIWC Dimension	R^2	Pronoun Use Rate (%)	Min	Max	Summary
1	All Pronouns	0.77	-0.18 ln [Messages] + 14.1	13.6	14.4	A strong, negative, linear-log correlation with a small (0.8%) range exists
2	Personal Pronouns	0.51	-0.107 ln [Messages] + 8.9	8.5	9.1	A moderate, negative, linear-log correlation with a small (0.6%) range exists
3	I	0.03	2.3e-3 [Messages] + 1.53	1.4	1.8	No obvious correlation exists. The rate of first-person singular “I” pronouns decreases for the bulk of the contacts sending between one and four messages from 1.7% to 1.5%, and then increases slowly to 1.6% for the smaller groups of contacts sending more messages
4	We	0.87	-0.0311 [Messages] + 4.05	4.0	3.3	A very strong, negative, linear correlation with a small (0.7) range exists
5	You	0.70	0.016 [Messages] + 2.26	2.2	2.8	A moderately strong, positive, linear correlation with a small (0.6) range exists
6	She/He	0.29	-0.0234 ln [Messages] + 0.371	0.3	0.5	Over all messages, a weak, negative, linear-log correlation exists. The rate decreases from 0.5% to 0.3% from one to five messages before remaining at 0.3% for all numbers of messages (except at 18 messages, where the rate returns briefly to 0.4%).
7	They	Not calculated; close to constant		0.6	0.7	The rate remains close to constant between a very small 0.6% to 0.7% range
8	Impersonal Pronouns	0.55	-0.0118 [Messages] + 0.553	4.9	5.3	A moderate, negative, correlation with a very small (0.4%) range exists

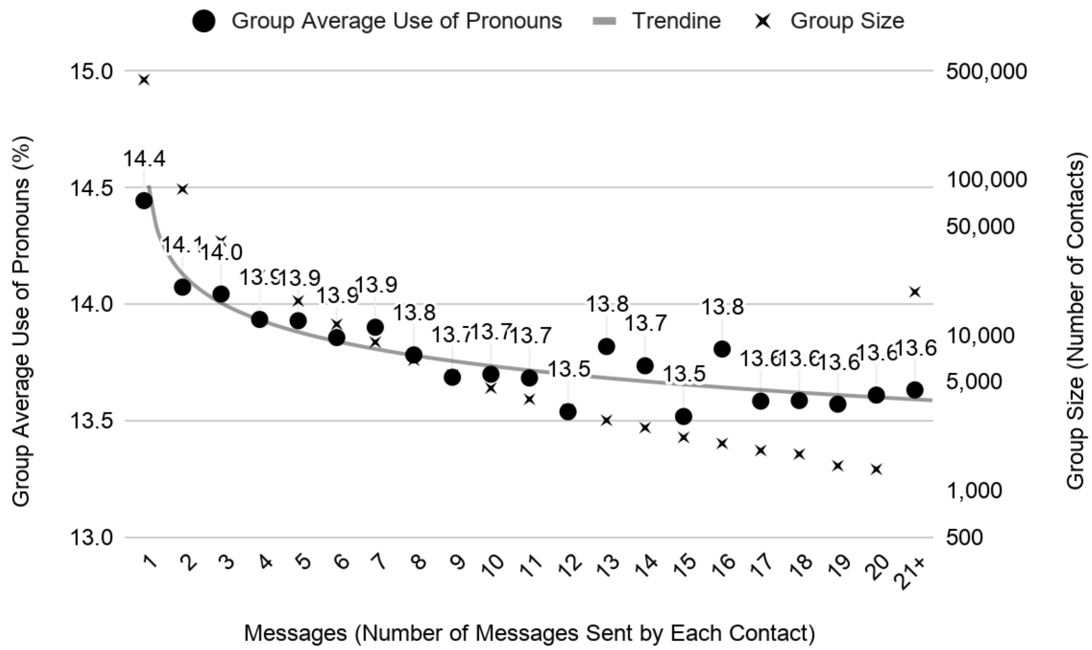


Figure 4.1.1 Group Average Use of Pronouns (%) vs. Messages Sent
Trendline: R^2 = 0.765 for [Group Average Use Pronouns] = -0.18 ln [Messages] + 14.1

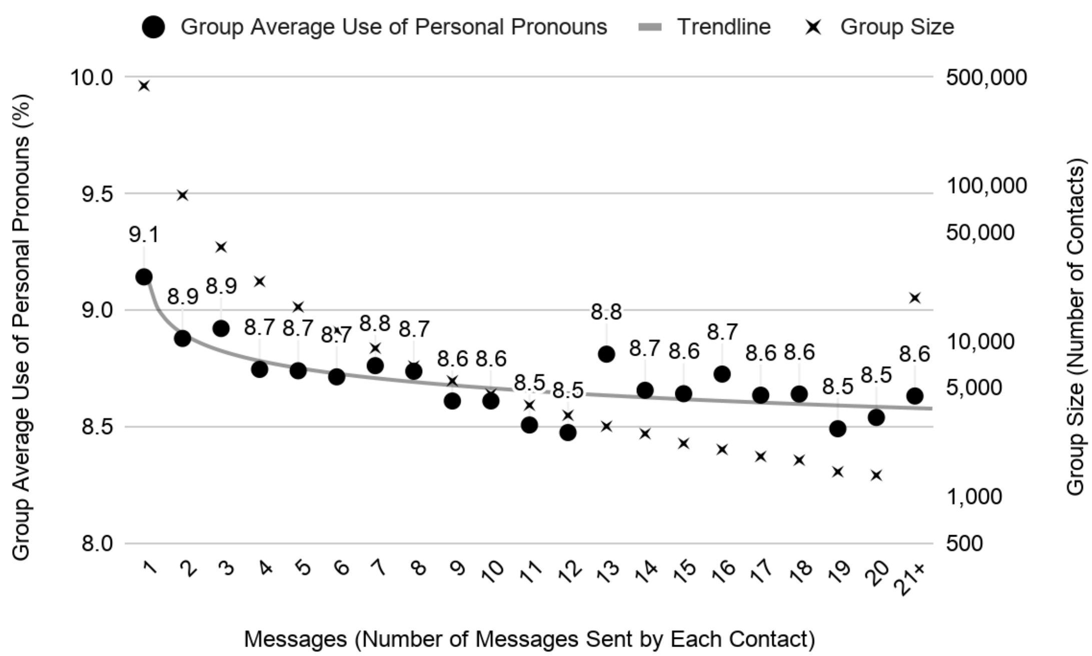


Figure 4.1.2 Group Average Use of Personal Pronouns (%) vs. Messages Sent
Trendline: R^2 = 0.51 for [Group Average Use of Personal Pronouns] = -0.107 ln [Messages] + 8.9

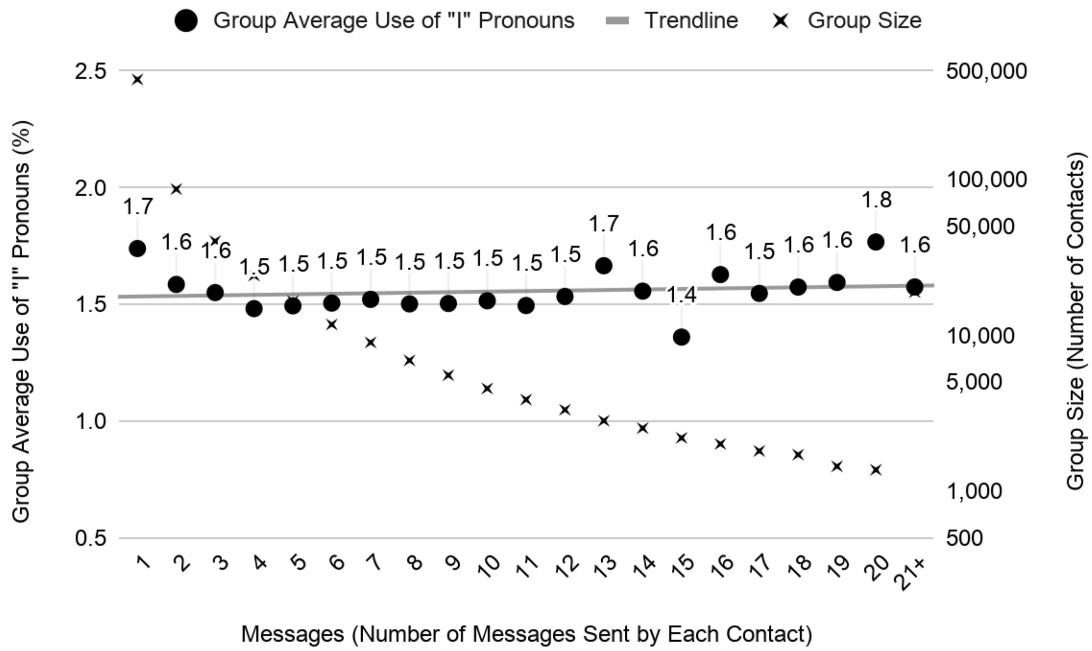


Figure 4.1.3 Group Average Use of “I” Pronouns (%) vs. Messages Sent
Trendline: R^2 = 0.025 for [Group Average Use of “I” Pronouns] = 2.3e-3 [Messages] + 1.53
The rate of first-person singular “I” pronouns decreases for the bulk of the contacts sending between one and four messages. Over all messages, no obvious correlation exists.

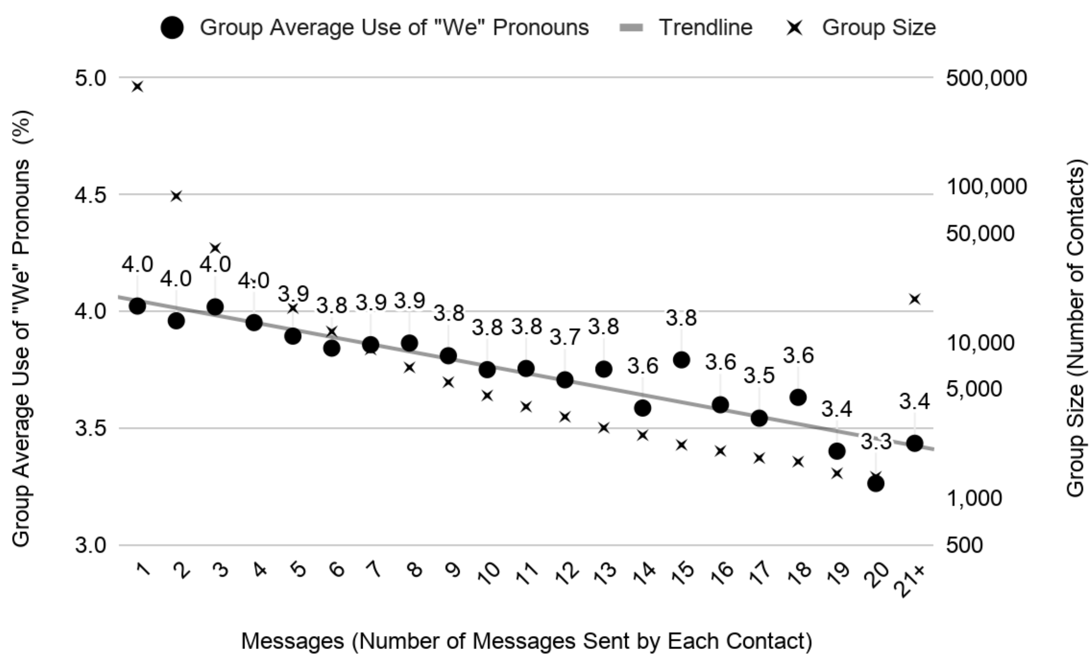


Figure 4.1.4 Group Average Use of “We” Pronouns (%) vs. Messages Sent
Trendline: R^2 = 0.871 for [Group Average Use of “We” Pronouns] = -0.0311 [Messages] + 4.05
A strong, linear, negative correlation exists.

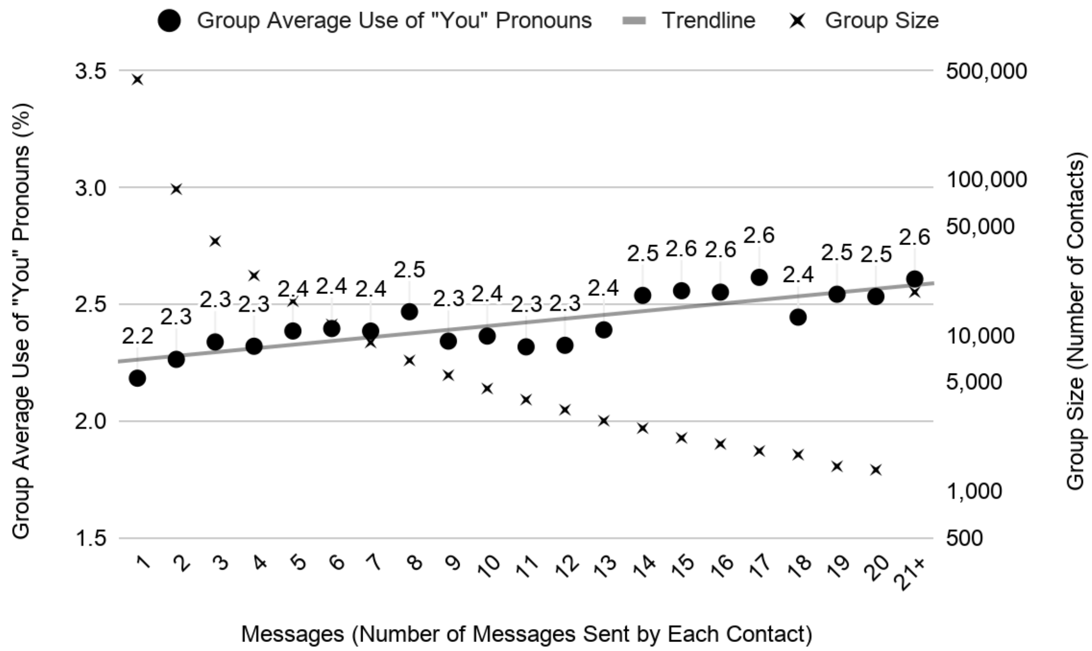


Figure 4.1.5 Group Average Use of "You" Pronouns (%) vs. Messages Sent
Trendline: R^2 = 0.691 for [Group Average Use of "You" Pronouns] = 0.016 [Messages] + 2.26
A moderate, linear, positive, correlation exists.

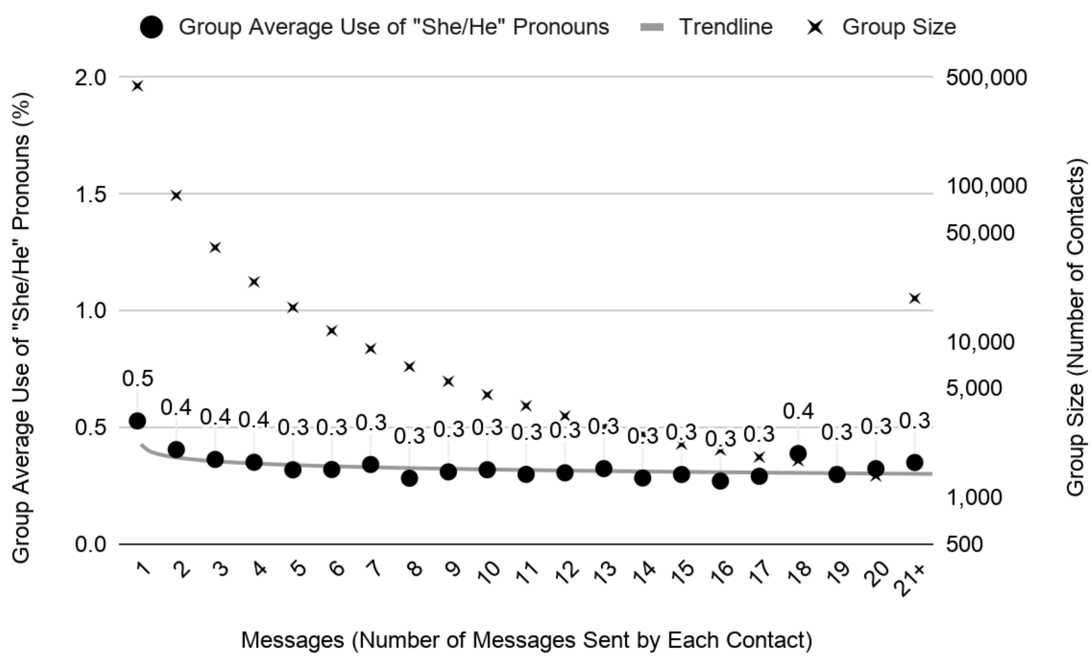


Figure 4.1.6 Group Average Use of "She/He" Pronouns (%) vs. Messages Sent
Trendline: R^2 = 0.288 for [Group Average Use of "She/He" Pronouns] = -0.0234 ln [Messages] + 0.371. The LIWC rate decreases from 0.5 to 0.3 from one to five messages before remaining at 0.3 for the remaining numbers of messages (except at 18 messages, where the rate returns briefly to 0.4).

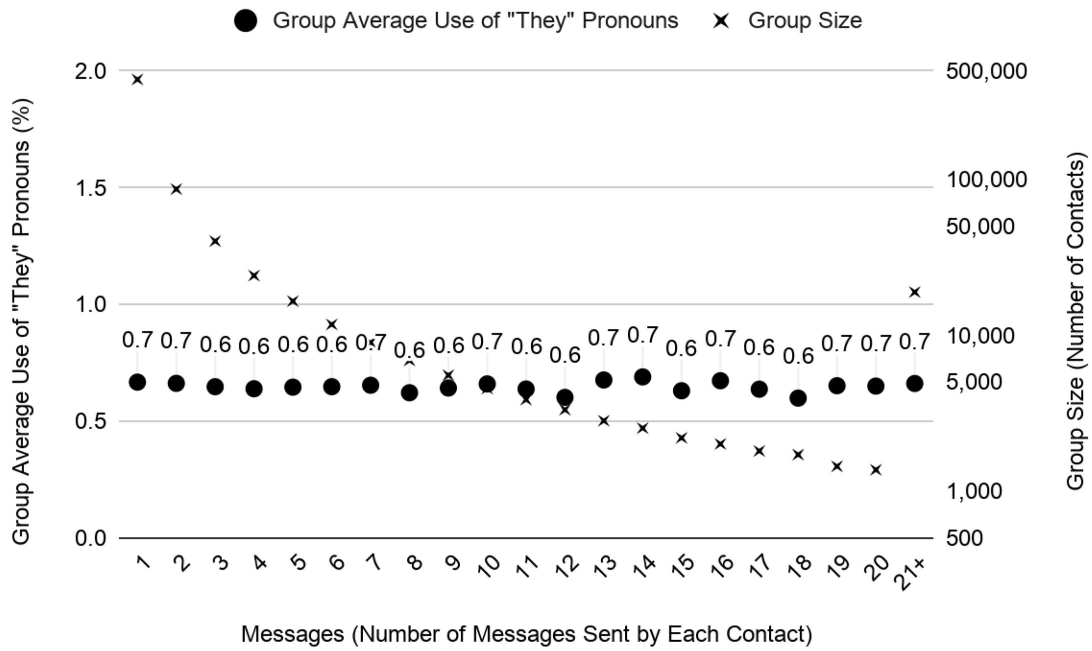


Figure 4.1.7 Group Average Use of “They” Pronouns (%) vs. Messages Sent
The rate remains constant between 0.6% and 0.7%

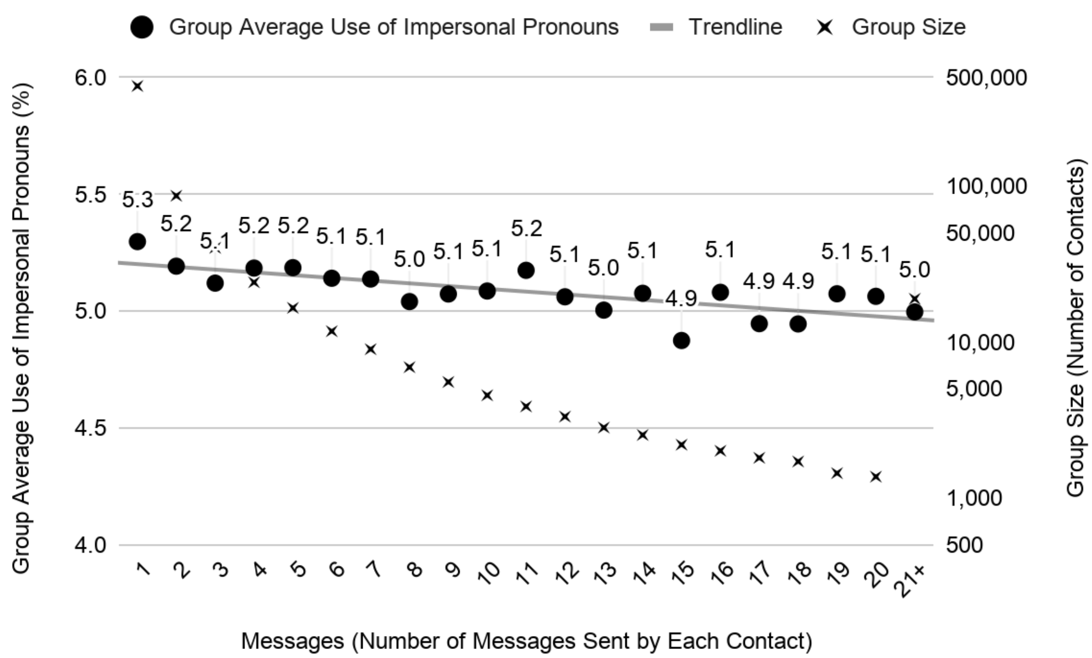


Figure 4.1.8 Group Average Use of Impersonal Pronouns (%) vs. Messages Sent
Trendline: $R^2 = 0.553$ for [Group Average Use of “She/He” Pronouns] = -0.0118 [Messages] + 0.553

4.1.2. Additional Observations and Calculation Checks for Hypothesis One

Chapter 6 discusses the results of testing Hypothesis One reported in the previous section (Section 4.1.1). This section reports results of additional observations, calculation checks, and variations of the test for Hypothesis One. It includes the following sections:

1. Use of Pronouns: Contact Averages vs. Message Averages vs. Other Corpuses

   This section compares the average pronoun use rates in the study data calculated in two different ways (over all messages, weighted message author, and equally and over all messages). It then compares these rates to rates in literature.

2. Minimum, Average, and Maximum Pronoun Rates for Groups and Contacts

   This section discusses testing the use of minimum, average, and maximum pronoun rates for (a) groups of contacts and for (b) messages that contacts have sent to describe groups of contacts.

3. Group Sizes

   This section shows the importance of top-coding contacts who sent more than 20 messages into a single group.

4. Sensitivity of Word Count on First-Person Plural ("We") Pronouns: Do pronoun relationships hold true or vary for contacts who write longer messages?

   This section shows the effect of limiting study message data to increasingly longer messages (from a minimum of 0 words to a minimum of 100 words in steps of 10 words) on relationships between the use of "we" words and the number of messages that contacts have sent.

5. First-Person Plural "We" Group Averages Weighted By Word Count vs. Contact

   This section compares weighting individual messages that contacts write equally to weighting these messages by message length.

6. Limiting "Our" Time Period

   This section shows the effects on the relationship between the use of "we" words and the number of messages that contacts have sent in the two cases of (a) limiting study message data to the four months for which NOTCORP data was collected and (b) analyzing only personal messages by removing all NOTCORP messages and custom messages from the study data.

4.1.2.1.Contact Averages vs. Message Averages and Other Corpuses

The results to Hypothesis One are found by calculating the LIWC group average rates for contacts who have written at least one personal message. (See detailed methods in Section 3.3.1.) Table 4.1.2 and Figure 4.1.9 compare the overall, average, personal message LIWC pronoun rates weighted by contact (Table 4.1.2 column two) against overall, unweighted, average, personal message rates (Table 4.1.2 column three). Both of these rates are calculated irrespective of the groups of contacts who sent the same number of messages that were used to test Hypothesis One, and the overall unweighted, average, message rates are calculated irrespective of contacts. The two overall rates are similar.

Table 4.1.2 and Figure 4.1.9 also compares these overall, average rates against average rates supplied in "The Development and Psychometric Properties of LIWC2015" (Pennebaker et al. 2015) for Twitter messages and the grand mean of six other text categories: blogs, expressive writing, novels, natural speech, the New York Times, and Twitter. Table 4.1.2 and Figure 4.1.9 report Twitter messages outside the grand mean of all six LIWC text categories to emphasize the comparison between advocacy messages and Twitter messages. Among the six LIWC text categories, Twitter messages most closely resemble personal advocacy messages in length. In fact, nonprofit organizations often encourage constituents to share their advocacy messages on Twitter.

Comparing study text to the other text categories, Table 4.1.2 and Figure 4.1.9 show, first, that contact average pronoun rates are similar to message average pronoun rates. Second, in comparison to general writers of Twitter messages and general writers of text in the six LIWC text categories, environmental advocates use fewer “I” pronouns and more “we” pronouns. They use “he/she” pronouns at similar rates to those found in the Twitter messages, and less than those found in the six LIWC text categories.

Results from the test of Hypothesis One (4.1.1) showed the use of “we” pronouns, among all LIWC pronoun dimensions, has the strongest correlation with the number of messages that contacts have sent. While the overall use of “we” pronouns used per message is low (3.9%), comparing the use of this dimension to its use in the six other LIWC text categories in Table 4.1.2, its rate of use is more than four times each of the values found in blogs (0.91%), expressive writing (0.81%), novels (0.61%), natural speech (87%), the New York Times (38%), and on Twitter (0.74%). The percentage is closer to that of positive and negative emotional words, which range from 2.1 to 5.5 percent in these same LIWC categories, have much larger LIWC dimension dictionaries (620 for positive emotions and 720 for negative emotions), and are frequently used in sentiment analysis studies such as Kouloumpis (2011), for Twitter messages, H Wang (2012, 2012), for presidential candidates’ Twitter messages, and Luxon, E.M. (2019), for environmental policy news coverage.

Table 4.1.2 Pronoun Rate Comparison
This table lists average pronoun rates for study data calculated in two different ways and for Twitter messages and six text categories of reported by Pennebaker et al. (2015): blogs, expressive writing, novels, natural speech, NY Times, and Twitter

	Average Pronoun Rate (%)				
	Study Data		Pennebaker et al. (2015)		
LIWC Pronoun Category	Contacts' Message Average	Messages	LIWC Twitter Messages	Average of Six LIWC Text Categories	Dictionary Size (words)
All	14.12	13.85	13.62	15.22	143.00
Personal	8.92	8.72	9.02	9.95	93.00
I	1.62	1.48	4.75	4.99	24.00
We	3.92	3.83	0.74	0.72	12.00
You	2.30	2.39	2.41	1.70	30.00
She/He	0.42	0.36	0.64	1.88	17.00
They	0.66	0.66	0.47	0.66	11.00
Impersonal	5.19	5.12	4.60	5.26	59.00

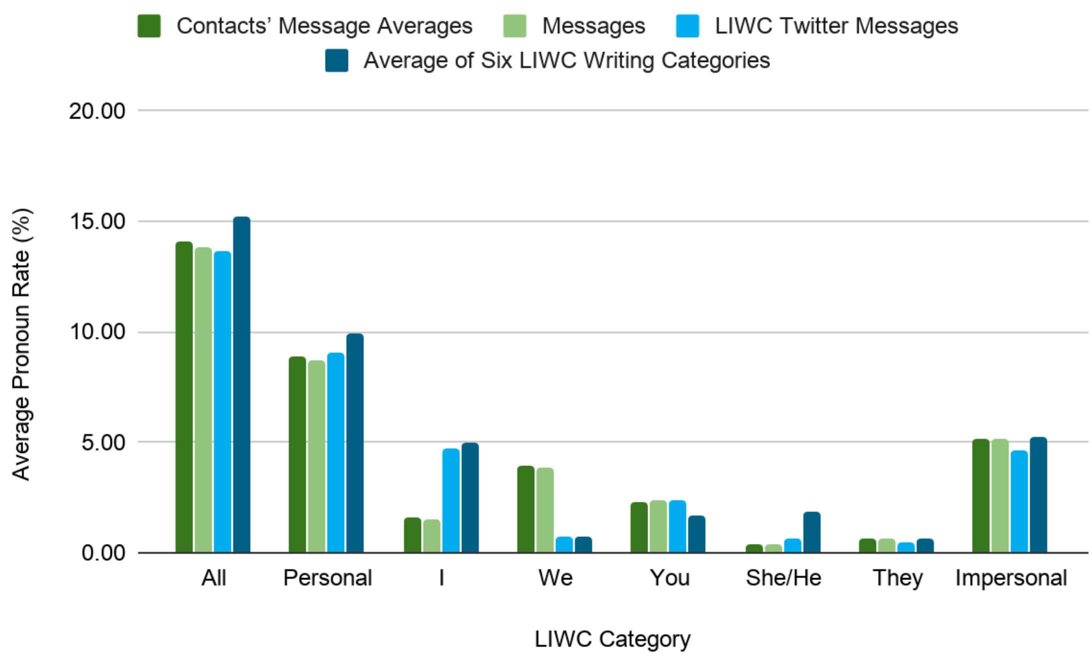


Figure 4.1.9 Plot of Table 4.1.2. Comparing the Use of Pronouns in Personal Message Data with the Use of Pronouns in LIWC Twitter and General Data Sets

4.1.2.2.Minimums, Averages, and Maximums for Groups and Contacts

This study calculated additional series of LIWC values, not reported above, while calculating group averages of contact averages. It calculated minimums and maximums for both groups and contacts, yielding a total of 9 series (including the average series) for each of the LIWC pronoun dimensions. Group minimums were the least practical metric, as the minimum use of each dimension was, as expected, zero for this case. A single message that does not contain a word in a particular LIWC dimension makes the minimum zero for its author and its author's group. Group maximum rates were also not very useful. They contain regular ratio values for the minimum, average, and maximum rates (e.g. 100%, 50%, 66%) of contacts. For example, a single contact sending a single message with 50% pronouns (e.g. "love you") might define the maximum "you" rate for their group (50%). Finally, group minimums of contact average rates and group maximums for contact average rates were calculated. These two series show minimums and maximums approaching upper and lower average contact rates. These rates express the distributions minimum and maximum contact rates. Figure 4.1.10 and Figure 4.1.11 show, as examples, the group maximum and group average rate series. While less pertinent to answering the research questions than the group averages of the contact averages, the group minimum and maximum diverging lines in Figure 4.1.11 confirm what is expected — that rate ranges are greater for contacts who send more messages.

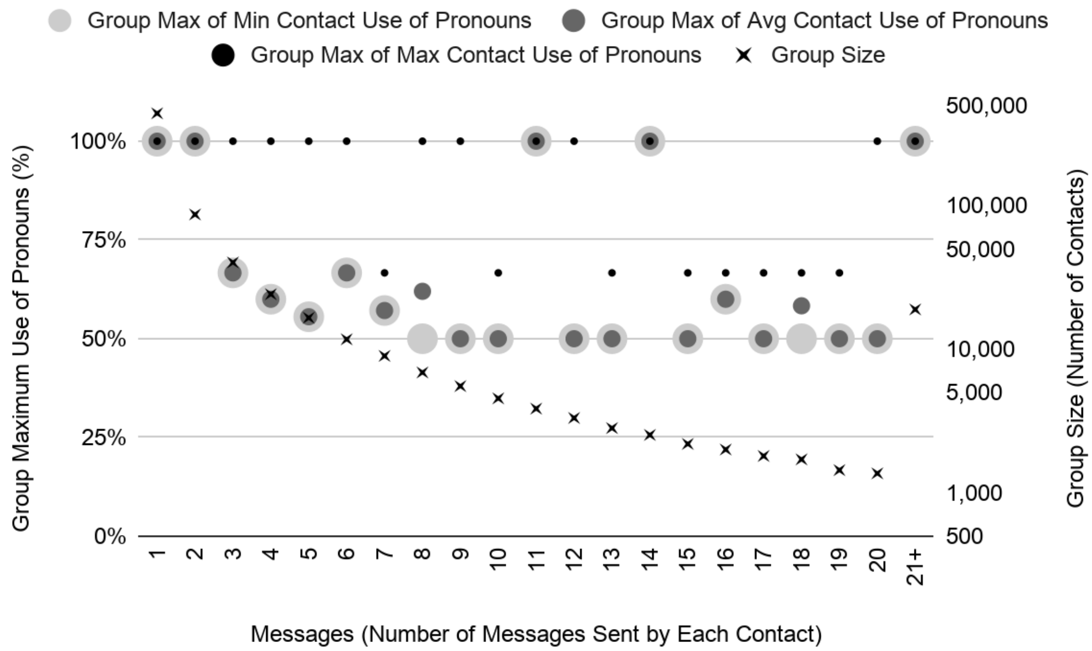


Figure 4.1.10 Average Use of Pronouns (%) vs. Messages Sent Expressed by Group Maximums of (a) Contact Minimums, (b) Contact Averages, and (c) Contact Maximums
Values are regular numerical ratios (e.g. 50%, 66.66%)

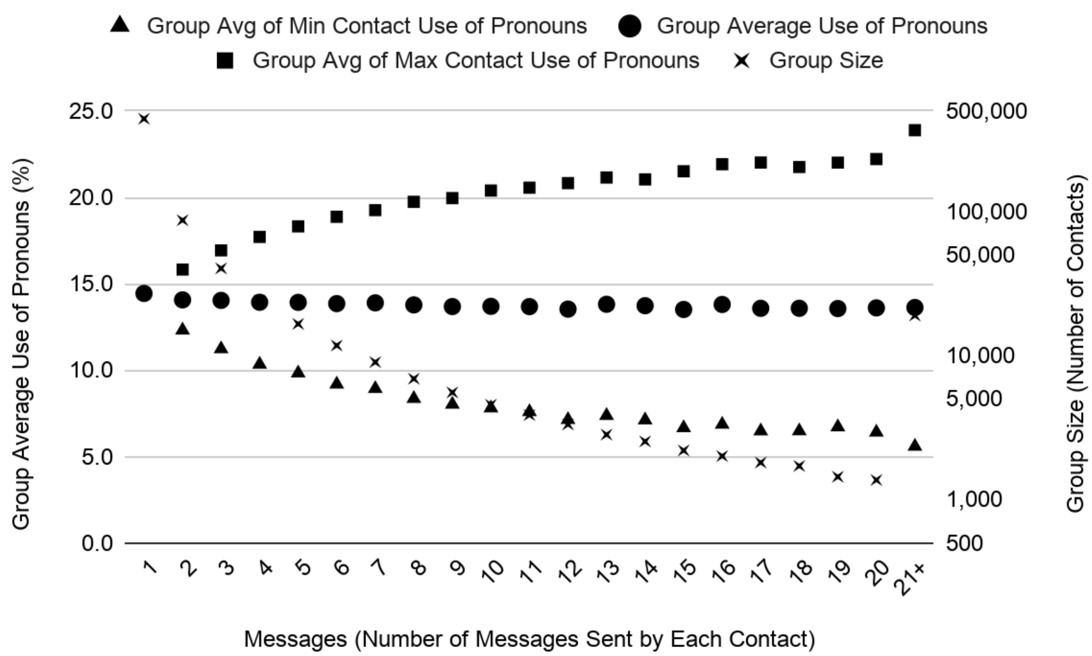


Figure 4.1.11 Use of All Pronouns vs. Number of Messages Sent Expressed by Group Averages of (a) Contact Minimums, (b) Contact Averages, and (c) Contact Maximums
The group averages of contact minimums and maximums express the range of pronoun usage for each group of contacts who have sent the same number of messages.

4.1.2.3.Group Sizes

Contacts have sent between one and 238 personal messages. For the group of contacts who have sent exactly one message, 78,334 out of 442,079 (18%) of these contacts wrote a personal message. The group that sent the highest number of personal messages, in comparison, is not a group at all: it's a single contact that sent 238 messages, nine of which were personal messages. Figure 4.1.12 and Figure 4.1.13, in comparison to top-coded Figure 4.1.4, show the effect of group size (number of contacts) on the LIWC group average calculations for first-person plural ("we") pronouns. As the number of messages sent by each contact in each group increases along the abscissa, the group size (right axis) decreases. On a semi-log plot, Figure 4.1.13 shows that this decrease is exponential until the group size starts to dip below 1,000 contacts, at which point it starts decreasing more rapidly. As group size decreases, the variability of LIWC group means increase, and overall relationships become visually less apparent.

Figure 4.1.14 shows this effect of decreasing group size on all LIWC pronoun attributes. Outliers in Figure 4.1.14 are more common for groups where group size is small. For example, the extreme outlier visible in the upper right of Figure 4.1.14 for the "group" that sent 147 messages per contact is, like the "group" that sent 238 messages, actually a single contact. This contact has written, in a single personal message, "thank you for your consideration." Compared to other messages, this short message contains an extremely high percentage of "you" words (40%), that is over 15 times the average "you" rate for all messages shown in Table 4.1.2 (2.39%) and for the group average rates shown in Figure 4.1.5 (ranging from 2.2% to 2.6%). This message uses no other pronouns. The "group of one" sending 140 total messages is another outlier. This contact sent 138 messages, but only two of them were personal — and the two that he or she sent were comprised of random characters like "asdlkfhalfjd." (While the author of these characters might have been using them to express an emotion or an exclamation, it is impossible to tell for sure.) To avoid small group problems, like these two, this study top-coded groups of contacts (19,017 of them; 2.75%) who sent more than 20 messages. This top-coding resulted in a minimum group size of 1,371 contacts for the group of contact that each sent a total of 20 messages. Figure 4.1.15 shows that top-coding the results in this manner accounts for most contacts (671,614/690,631; 97.25%) and messages (70% general messages; 71% personal messages) in the groups of contacts who sent 20 or less messages. (Winsorizing or eliminating values would produce similar effects in explaining correlation variations.)

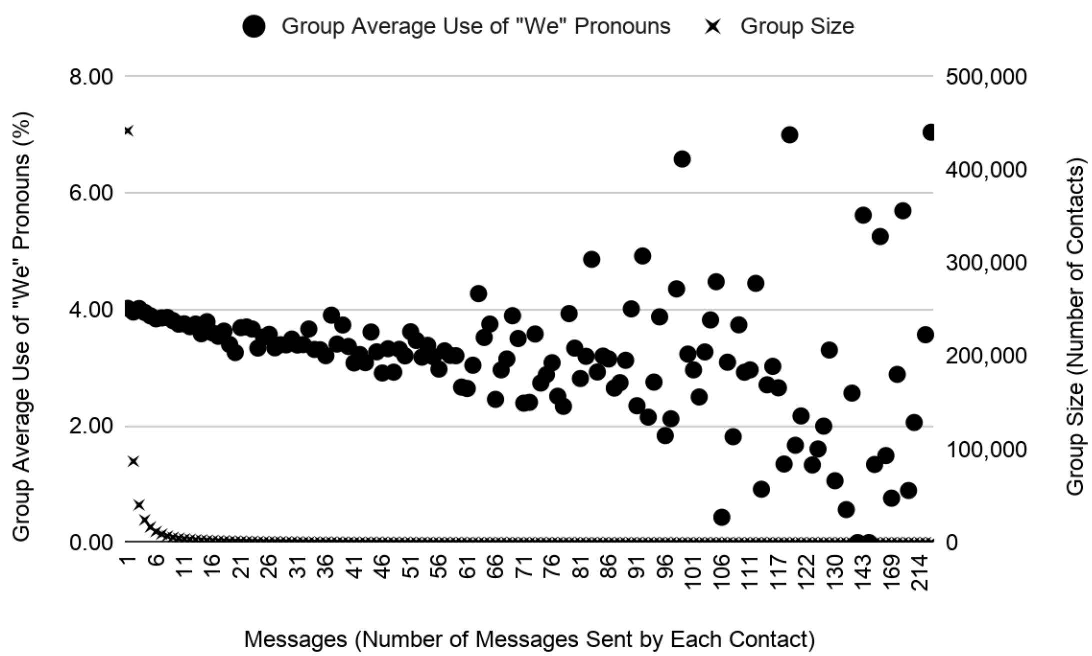


Figure 4.1.12 Group Average Use of "We" Pronouns (%) (left axis) and Group Size (right linear axis) vs. Messages Sent
Compare to Figure 4.1.4, this figure does not top-code contacts who sent more than 20 messages into a single group. This shows the variability in "we" percentages increases as group size decreases.

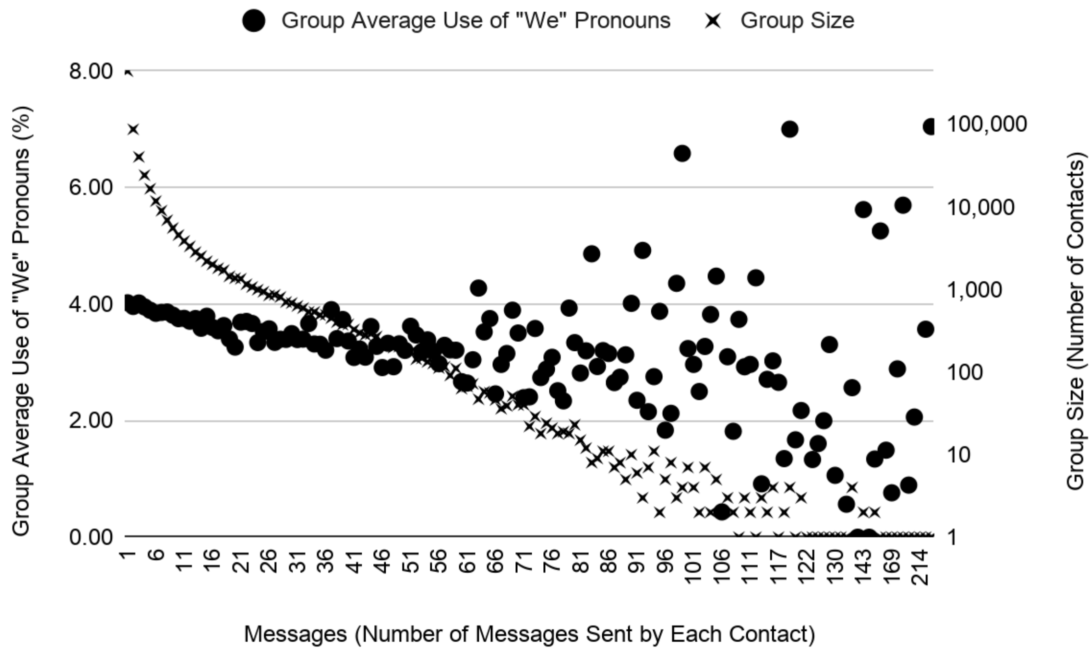


Figure 4.1.13 Group Average Use of “We” Pronouns (%) (left axis) and Group Size (right log axis) vs. Messages Sent.
Compared to Figure 4.1.12, the log scale for group size emphasizes the relationship between the use of the “we” words and the engagement factor, messages per contact, for the bulk of the contacts who sent a low number of messages. The log scale for group size also reveals the high number of “groups” with only a single contact in them for contacts who have sent over 100 messages (bottom right of this figure).

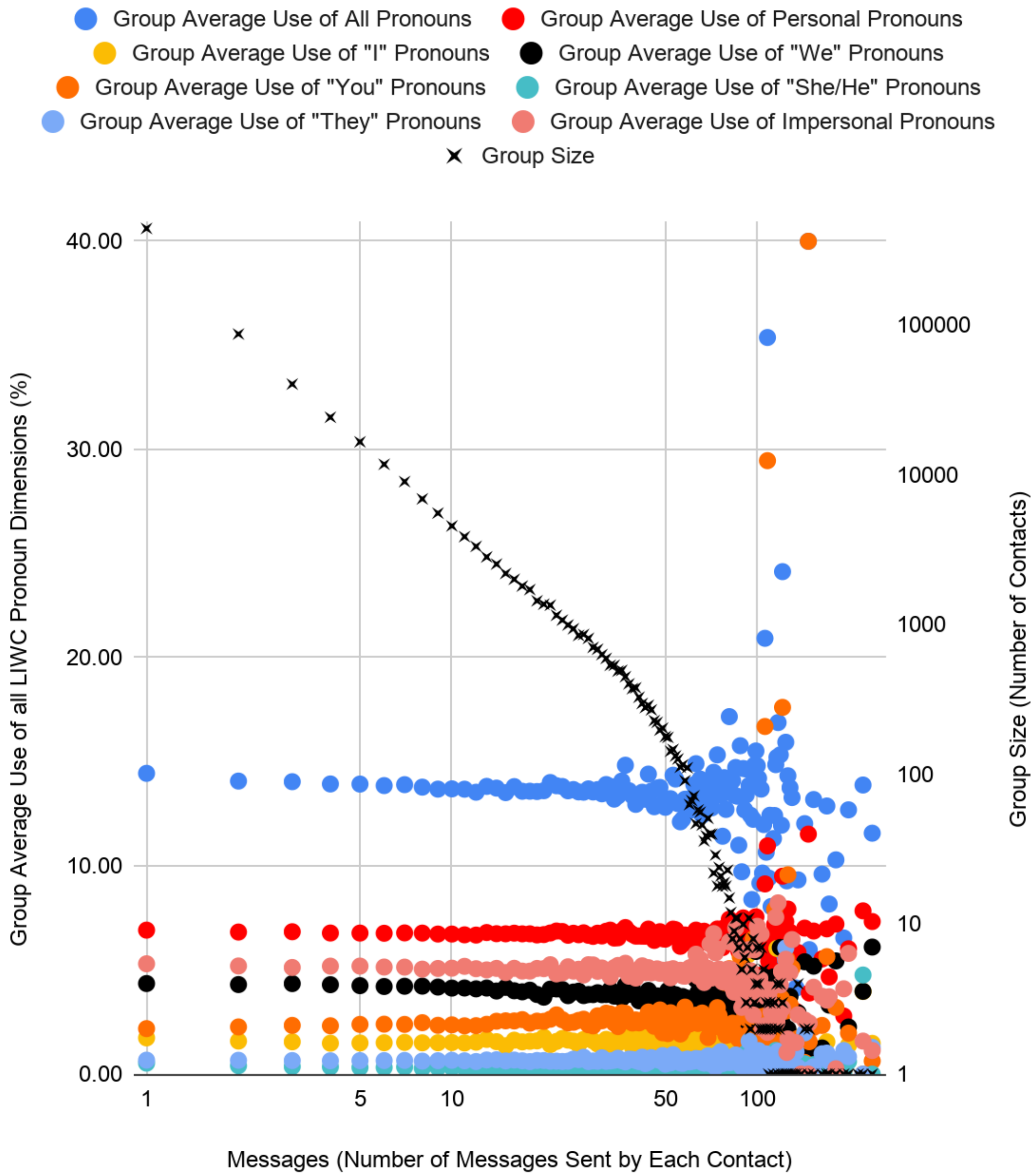


Figure 4.1.14 Group Average Use of all LIWC Pronouns Dimensions (%) (left axis) And Group Size (right log axis) vs. Messages Sent.
This plot shows the variability all LIWC pronoun attributes increases as group size (contacts) decrease.

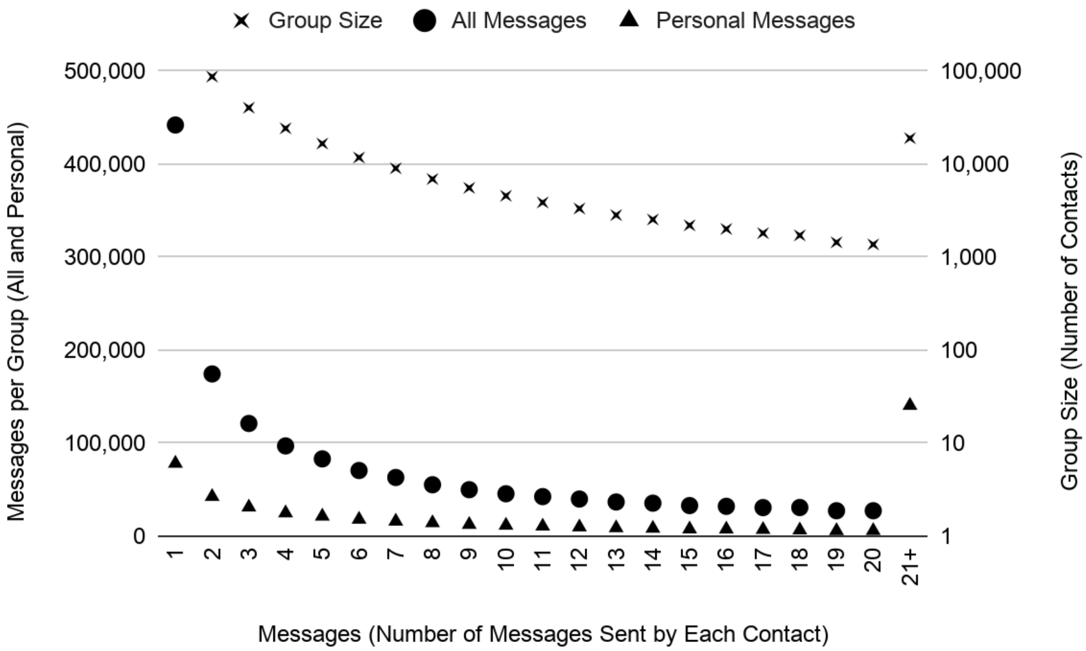


Figure 4.1.15 Number of All Messages and Number of Personal Messages (left axis) and Group Size (right axis) vs. Messages Sent

4.1.2.4.Sensitivity of Word Count on First-Person Plural ("we") Pronouns: Do Pronoun Relationships Hold True or Vary for Contacts who Write Longer Messages?

Although a clear, strong negative relationship exists between the number of messages that contacts send and first-person plural "we" pronouns, R^2 = 0.87 (Table 4.1.1, Figure 4.1.4), the practical use of "we" pronouns to predict organizational engagement from a single message is limited by (a) the low percentage of "we" pronouns in each message and (b) by the low regular word count for a personal messages. Figure 4.1.5 shows the frequency distribution of word count is positively skewed with an average of 29 words per message and a mode of 11 words per message.

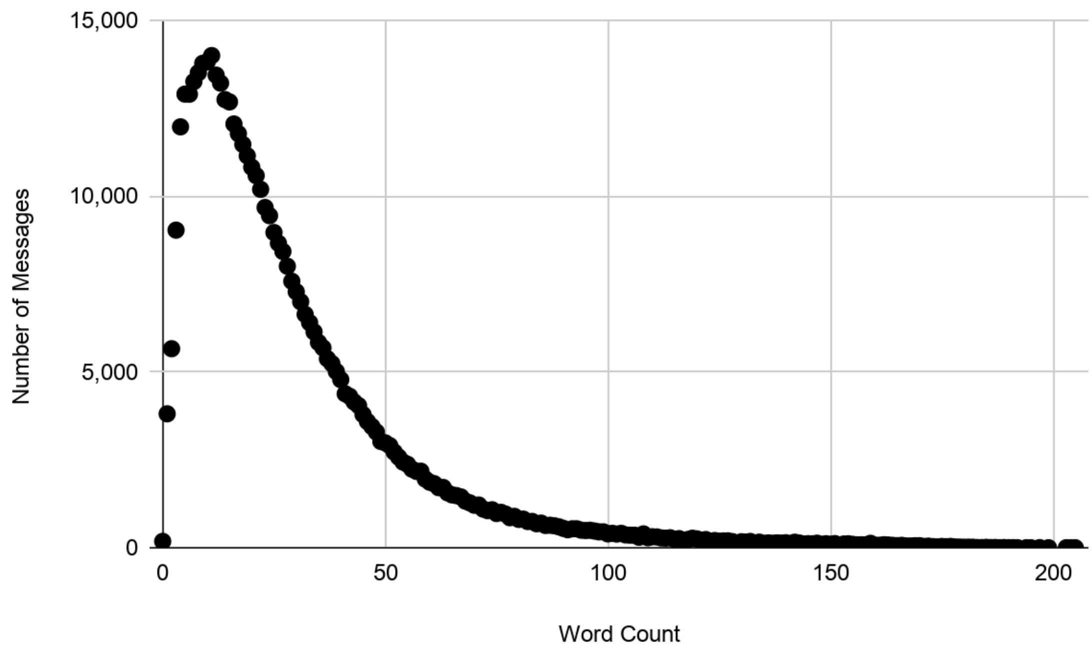


Figure 4.1.16 Positively Skewed Distribution of Word Count
Average = 29 Words; Mode = 11 Words

While many studies do review linguistic attributes that are used in low frequencies (like the studies referenced in Section 4.1.2.1), determining the difference of using 3% or 4% of "we" pronouns in a *single* personal message, given word count, is unrealistic.

These observations inspire a message length (word count) sensitivity analysis on the relationship between "we" pronouns and the number of messages that contacts send. This analysis should answer the question: Is it easier to predict the number of messages that contacts send from the use of "we" pronouns for contacts who write longer messages? Repeating the test of the relationship between "we" pronouns on the number of messages sent in Hypothesis One, and limiting the group size in this test for contacts who write messages with a minimum average word count in the range of zero to 100 shows, at first, that the correlation decreases with word count. A weaker, but still strong correlation (R^2=0.74) exists at a 20 word minimum limit. A moderate correlation exists (R^2=0.52) for a 30 word minimum limit. Results are shown in Table 4.1.3 and Figure

4.1.17. The decreasing correlation may be due to decreasing group size (also tabulated in Table 4.1.3; less contacts send longer messages), but the wavering tail correlation increase shown in Figure 4.1.6 may be due to word count. Future work could investigate these relationships further.

Table 4.1.3 Effects of Limiting Data by Minimum Word Count (WC) on the Correlation Between the Use of First-Person Plural "we" Pronouns and Groups of Contacts Who Have Sent the Same Number of Messages.

Minimum WC	R^2	Group Size (Contacts)
0	0.87	690,631
10	0.85	248,552
20	0.74	162,666
30	0.52	123,411
40	0.35	100,210
50	0.25	84,574
60	0.20	73,736
70	0.15	65,559
80	0.23	59,500
90	0.35	54,752
100	0.09	50,892

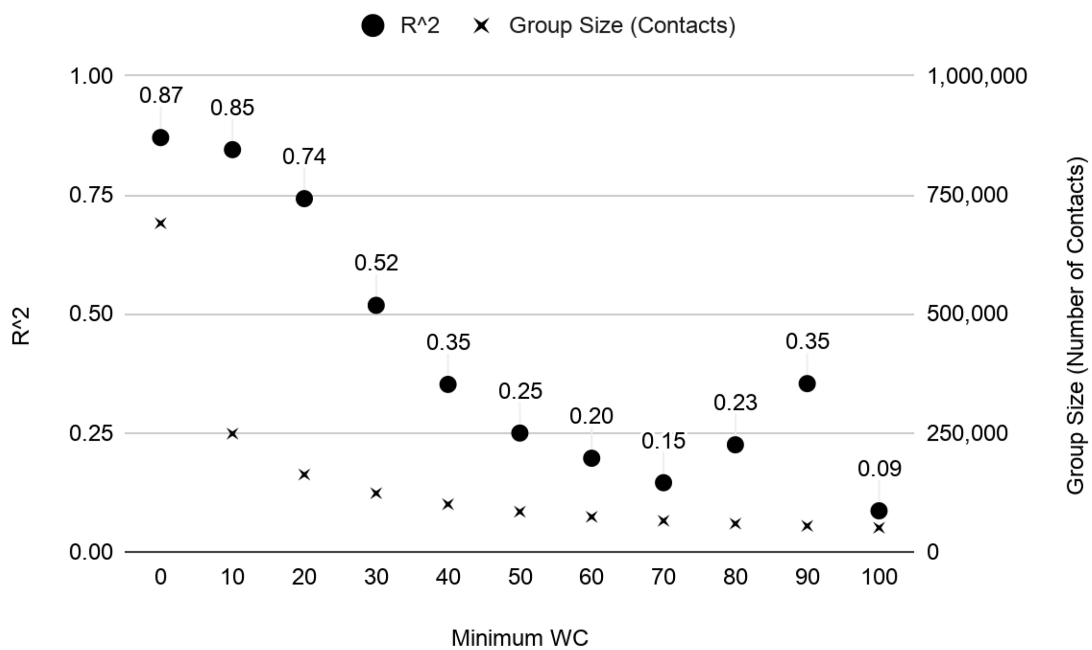


Figure 4.1.17 Effects of Limiting Data by Minimum Word Count (WC) on the Correlation Between the Use of First-Person Plural "we" Pronouns and Groups of Contacts Who Have Sent the Same Number of Messages.

4.1.2.5. First-Person Plural "We" Group Averages Weighted By Word Count vs. Contact

Objective One methods describe two procedures to lump pronoun rates for groups in Section 3.3.1. The first procedure calculates average contact LIWC rates, weighted equally messages (step 4a in Section 3.3.1). Results reported in Section 4.4.1 at the beginning of this chapter follows this procedure. The second procedure (step 4b in Section 3.3.1) calculates contact LIWC rates for all contact messages. This is equivalent to weighting messages by message length in the calculation of each contact rate, or concatenating the personal messages that each individual contact wrote, and calculating an overall, single, contact LIWC score.

In weighting messages equally to calculate average contact pronoun use rates, short messages could lead to contact rates that misrepresent the linguistic styles of their authors expressed in any long messages also written by them. For example, a contact who sends one very short message, "I love you," uses zero words in the LIWC "we" pronoun dimension. If that same contact sends a longer message using "we" words at a rate of 10%, following the procedure in step 4a in section 3.1, the test for Hypothesis One would give the contact an overall 5% rate (0%+10%)/2 = 5%). Repeating Hypothesis One "we" words, but with word count averages instead of contact averages, yields results similar to the original results. Results from this "we" pronoun test are shown in Figure 4.1.7.

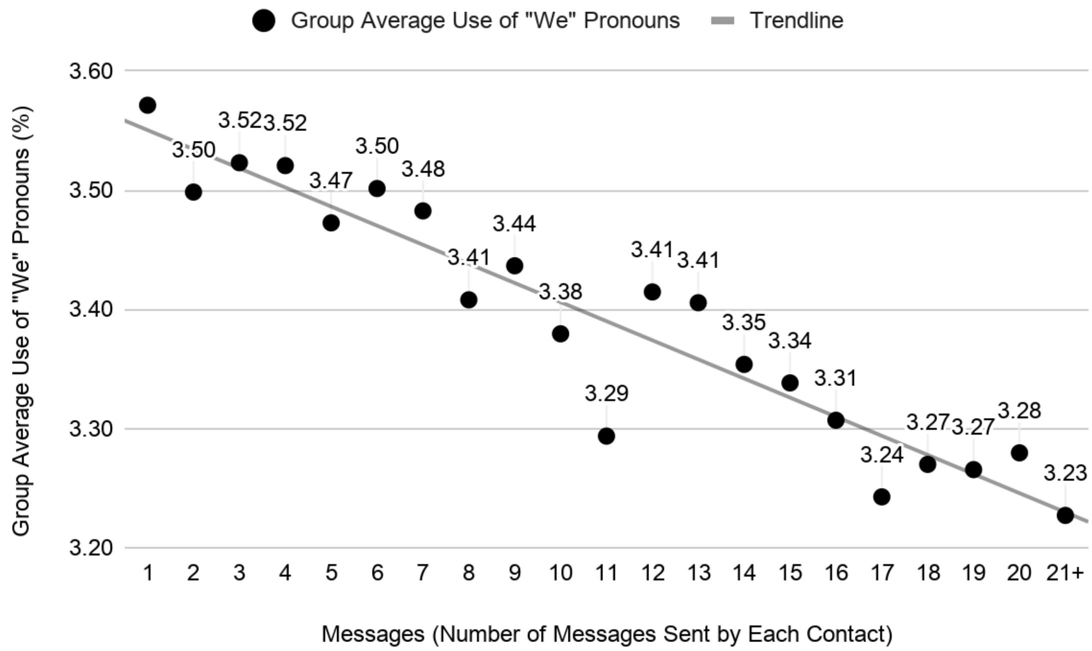


Figure 4.1.18 Group Average Use of "We" Pronouns Weighted by Message Length and then by Contact (%) vs. Messages Sent
Trendline: R^2 = 0.895 for [Group Average Use of "She/He" Pronouns] = -0.016 [Messages] + 3.55
Results are similar to those found by equally weighting "we" rates by message,
where R^2 = 0.895, shown in Figure 4.1.4.

4.1.2.6.Limiting "Our" Time Period

As described in the data section, messages that were not customized and were not personalized (NOTCORP) were only available between July 1, 2018 through October 31, 2018 (four months), while personal messages and customized messages were available between July 1, 2017 and October 10, 2018 (16 months). This difference in periods presented two main options for testing the three initial hypotheses: (1) using all data to calculate the number of messages and the average linguistic rates for each contact, and (2) constraining the data to the limited set of four months. A third, intermediate option, is to (3) remove the NOTCORP data. The advantage of the first option is that it considers a longer history for each contact and therefore a larger sample of messages. The disadvantage of the first option is that it increases the variability of the average number of messages sent per contact when contacts are individually more or less active before and after July 1, 2017. The advantage of the first option – the longer time period and greater number of messages used to describe a contact – can also be considered a disadvantage. Advertising companies like Google, for example, place less value on older data. In fact, Google even allows users to have their data usage purged automatically after three or eighteen months (Google 2019) – but no less. The second option could be, therefore, considered advantageous in that only linguistic rates calculated from recent months would be considered. (A future temporal analysis could test the sensitivity of time ranges on relationships, provided new data.) The third option, like the first option, considers the longer 16-month time period, but it eliminates the NOTCORP data, and its limited timeframe, completely. This third option still considers messages without personal messages — the customized messages for which linguistic scores were not computed for.

While the results chapter reports findings from selecting the first option as the primary method of conducting the study, results from testing the second and third option were similar. Figure 4.1.19 demonstrates the effect of limiting the study time period on the test of first-person plural "we" pronouns as a predictor of engagement. Even though the number of contacts in each group has been reduced, a strong, negative, linear correlation remains (R^2 = 0.827). Figure 4.1.20 shows the third analysis option — eliminating the NOTCORP data. It yields a correlation of R^2 = 0.717. These figures indicate that considering both the petition-style messages, and the messages that contacts choose not to customize, alongside the messages that they do customize, strengthen observed correlations.

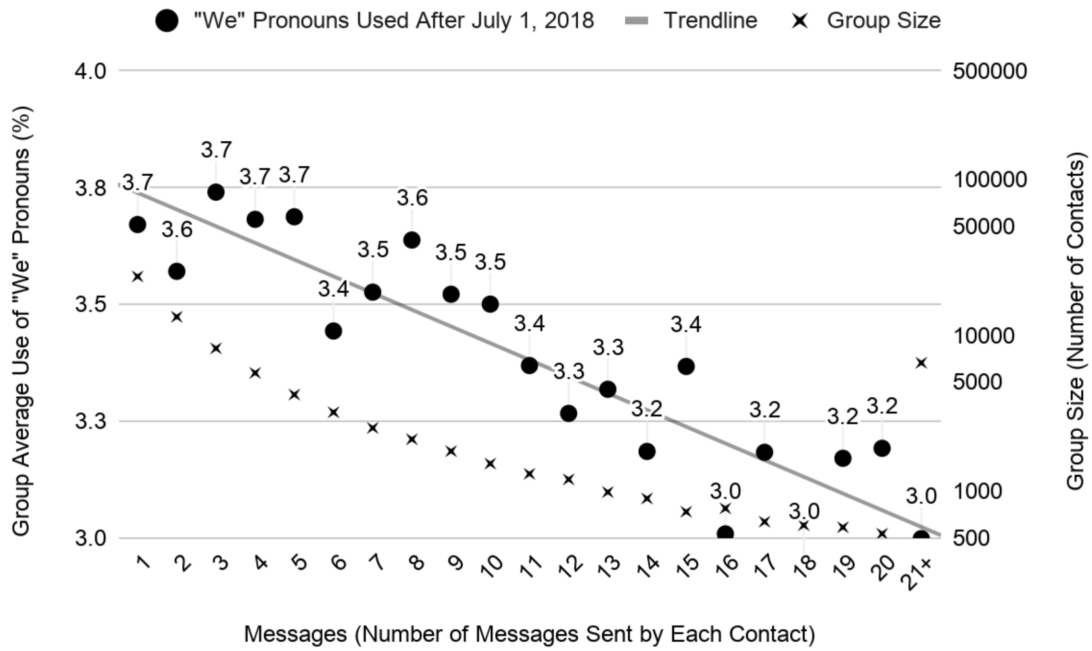


Figure 4.1.19 Group Average Use of “We” Pronouns (%) vs. Message Sent After July 1, 2018
Trendline: $R^2 = 0.827$ for [Group Average Use of “We” Pronouns] = -0.0358 [Messages] + 3.74

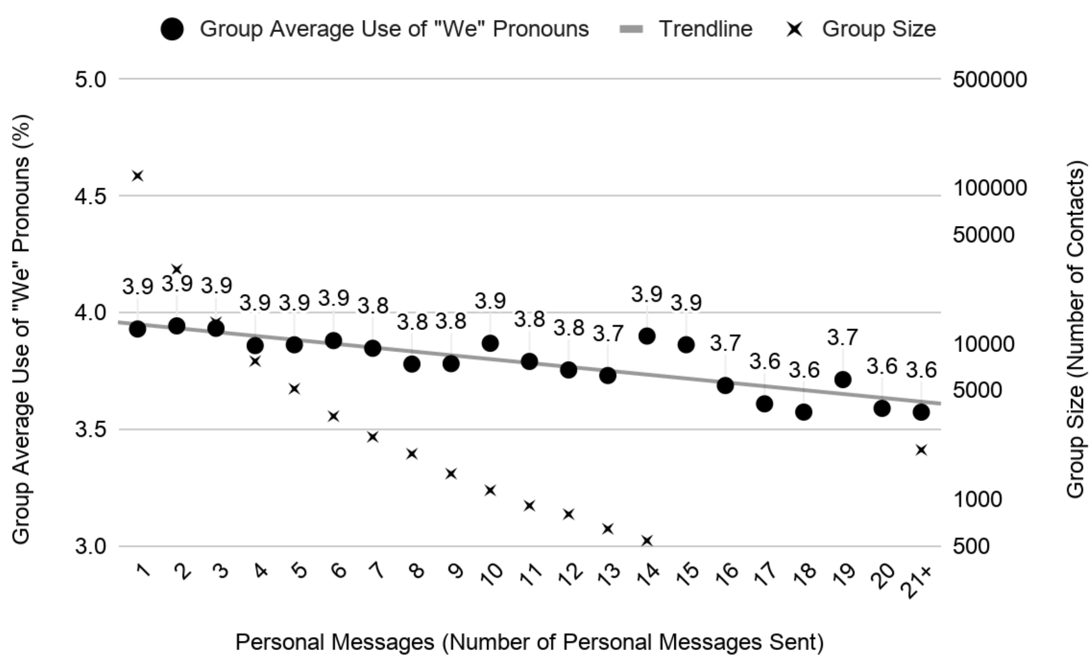


Figure 4.1.20 Group Average Use of “We” Pronouns (%) vs. Personal Message Sent
Trendline: $R^2 = 0.717$ for [Group Average Use of “We” Pronouns] = -0.0166 [Messages] + 3.95

4.2. Hypothesis Two: Relationships Between Personal Messages and the Number of Messages that Contacts Send

Figure 4.2.1 shows results from the methods to test Hypothesis Two for groups of contacts who sent the same number of messages. The average personal message rate increases from 18% to 24% to 26% between groups of contacts who sent one, two, and three messages. The rate stays at 26% personal messages before slowly decreasing to a minimum of 15% for contacts who sent 35 messages. It then increases to rates approaching 50% for small groups of contacts who sent a lot of messages (>40).

Given the group size discussion in the results for the test of Hypothesis One (section 4.1.2.3), most contacts who have sent two or more messages are more likely to have sent personal messages at a higher rate than contacts who sent a single message. Additionally, the small number of contacts who sent many messages (>40), sent personal messages at an increasing rate. Figure 4.2.2 shows a simpler plot of the average number of personal messages sent instead of the rate.

Contacts who write more messages also send personal messages at a higher rate. Inversely, and directly answering the research question, contacts who send personal messages at high rates also send more messages. For the bulk of the contacts (671,614 among 690,631; 97%) sending under 20 messages: groups of contacts who send messages at the average rate of 18%, send only send one message. The group of contacts sending two to twenty messages, send them at an average rate of 25%.

A final, simpler way to understand the relationship between the use of personal messages and the use of all messages is by reviewing the plot of the total number of each of these categories of messages as shown in Figure 4.1.15, above, and isolated in Figure

4.2.3, below. The figure shows the ratio of personal messages to all messages increasing as the number of messages that contacts send increases from one message to two messages.

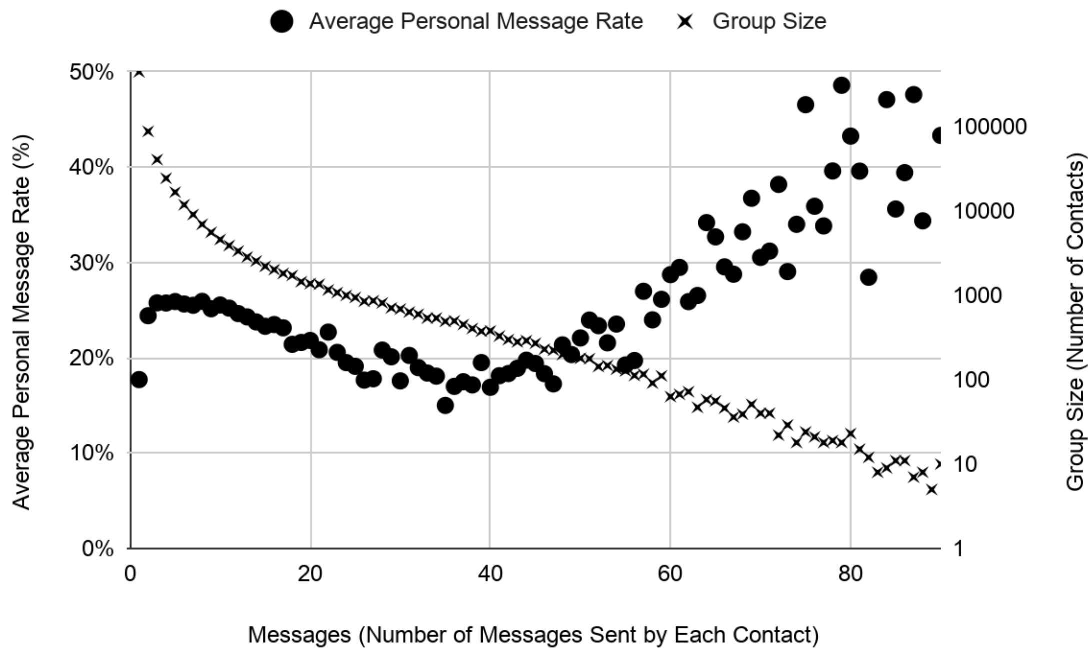


Figure 4.2.1 Average Personal Message Rate vs. Messages Sent per Contact

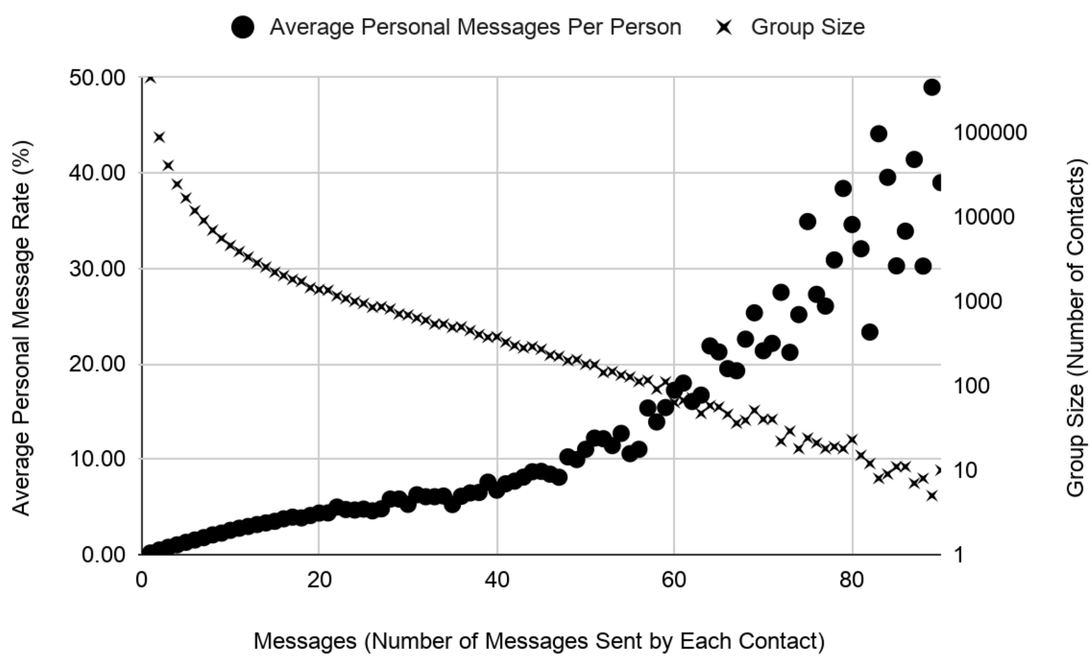


Figure 4.2.2 Average Personal Messages vs. Messages Sent per Contact

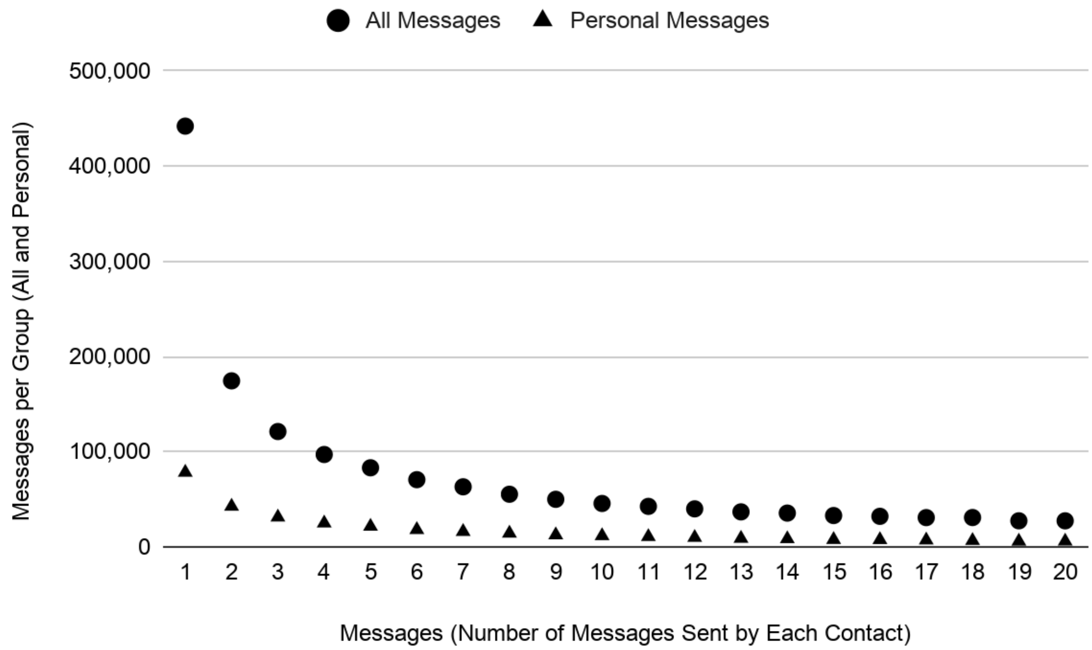


Figure 4.2.3 Number of All Messages and Number of Personal Messages for Groups of Contacts Who Have Sent the Same Number of Messages from One to Twenty

4.3. Hypothesis Three: Relationships Between Message Length and the Number of Messages that Contacts Send

Figure 4.3.1 shows that, on average, most contacts write messages one word longer (28 to 29 words) when they write more than a single message. The number of messages then begins to drop by a slight 1/10 of a word per message with a moderate strength correlation (R^2=0.694). The average message length for the group sending more than one message, however, is 29 words, and the average message length for all messages is also 29 words. In summary, groups of contacts who send only one message send very slightly shorter messages (1 word). (Interestingly, as shown in Chapter 5 explorations, most contacts who send more messages are also more likely to contribute membership dues to the organization.)

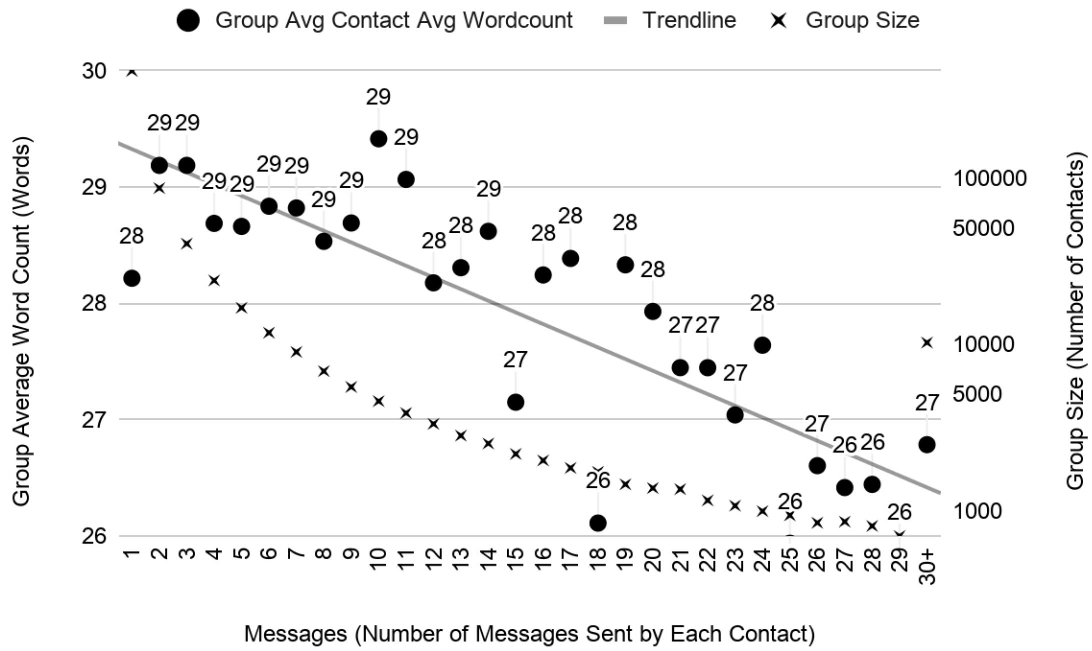


Figure 4.3.1 Word Count vs. Number of Messages Sent
Trendline: R^2 = 0.694 for [Word Count] = -0.01 [Messages] + 29.3
After two messages, contacts who sent more messages, sent slightly shorter messages.

CHAPTER 5. RESULTS FOR OBJECTIVE TWO: MEMBERSHIP EXPLORATION

This chapter both details methods and reports relationships between message and text metrics with a second measure of engagement, membership. It labels contacts as members if they have paid any amount of membership dues to their organization within the past year of any message that they have sent, or have been designated as a lifetime member by their organization for a large contribution during or before the study period. It refers to the percentage of members in different groups of contacts as a membership rate for that group.

The first section of this chapter, Section 5.1, reports relationship between membership and the message and text metrics used in testing Objective One hypotheses:

1. Number of messages and personal messages (Section 5.1.1)
2. Use of pronouns (Section 5.1.2)
3. Message length (Section 5.1.3)

Next, Section 5.2 reports correlations between the use of LIWC dimension words and membership for ungrouped contacts. It also reports correlations between the use of LIWC dimension words and the measure of engagement from Objective One, the number of messages that contacts send, as well as the number of personal messages that contacts send – but for individual, ungrouped contacts vs. the groups of contacts.

Section 5.3 through Section 5.7, finally, reports membership rates for contacts grouped by conditions defined by the following text metrics:

1. Terms used to search for personal stories (Section 5.3)
2. Writing complexity defined by the Flesch reading ease test (Section 5.4)

3. Sentiment defined by the VADER sentiment classifier (Section 5.5)
4. Popular words among all personal messages in this study (Section 5.6)
5. Words in all LIWC Dimensions (Section 5.7)

Among the 690,631 total contacts who have sent any type or number of messages, 90,698 are members (13% membership rate), 194,409 have authored personal messages (28%), and 52,323 are members who have sent personal messages (7.6%). Compared to the overall 13% membership rate (90,698/690,631), the membership rate for those sending personal messages is 27% (52,323/194,409). Section 5.3 through Section 5.7 compares conditional membership rates to alternative conditions and these baseline membership rates (13% and 27%).

Contacts labeled as members in this study gave a minimum of $15/year. Most contacts gave suggested amounts, or more. For reference, Table 4.3.1 shows minimum, suggested, and maximum membership rates for large, prominent U.S.-based nonprofit environmental organizations that actively host online advocacy systems to send petitions and letters to policymakers. The average, regular, annual membership or one-time donation rate for these organizations is $52/person/year. Study data did not come from all these organizations.

Table 4.3.1 Membership Rates for Large, National Environmental Nonprofit Organizations with Online Petition or Letter-Writing Campaigns.
Data comes from organization websites, ProPublica (2019) and the Internal Revenue Service (2019) for 501c3 and 501c4 organizations. Organization form 990 revenue comes from several sources, including, but not exclusively from membership dues. Study data did not come from all of these organizations.

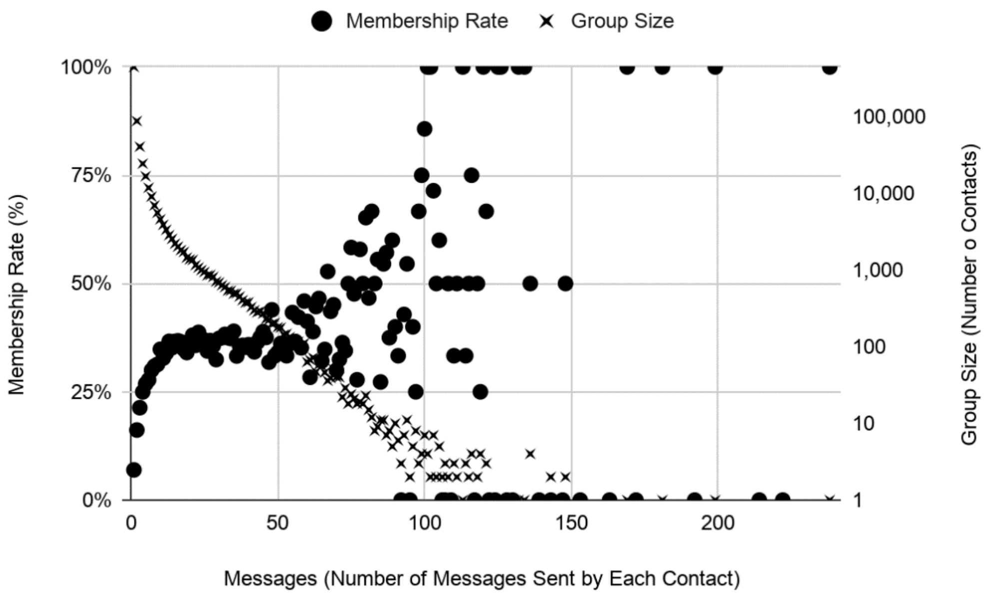
	Monthly			Annual or One Time			
Advocacy Organization	Min	Suggested	Max	Min	Suggested	Max	Form 990 Revenue (M)
Earthjustice	$35	-	$1,000	$35	$30	$1,000	$80
Environmental Defense Fund	$15	$25	$75	$35	$50	$1,000	$211
Greenpeace	$15	$25	$55	$30	$50	$120	$17
National Audubon Society	$20	$50	$500	$20	$50	$500	$134
National Wildlife Federation	$8	$50	$50	30	50	1000	$83
Natural Resources Defense Fund	$15	$20	$100	$35	$50	$200	$182
Nature Conservancy	$15	$100	$10,000	$15	$100	$10,000	$1,185
Sierra Club	$15	$20	$85	$25	$39	$75	$141
Wildlife Conservation Society	$10	$20	$100	$25	$50	$500	$279
World Wildlife Fund (WWF)	$10	$15	$50	$25	$50	$5,000	$257
Average	*$16*	*$36*	*$1,202*	*$28*	*$52*	*$1,940*	*$257*

5.1. Exploration One: Membership as a Measure of Organizational Engagement

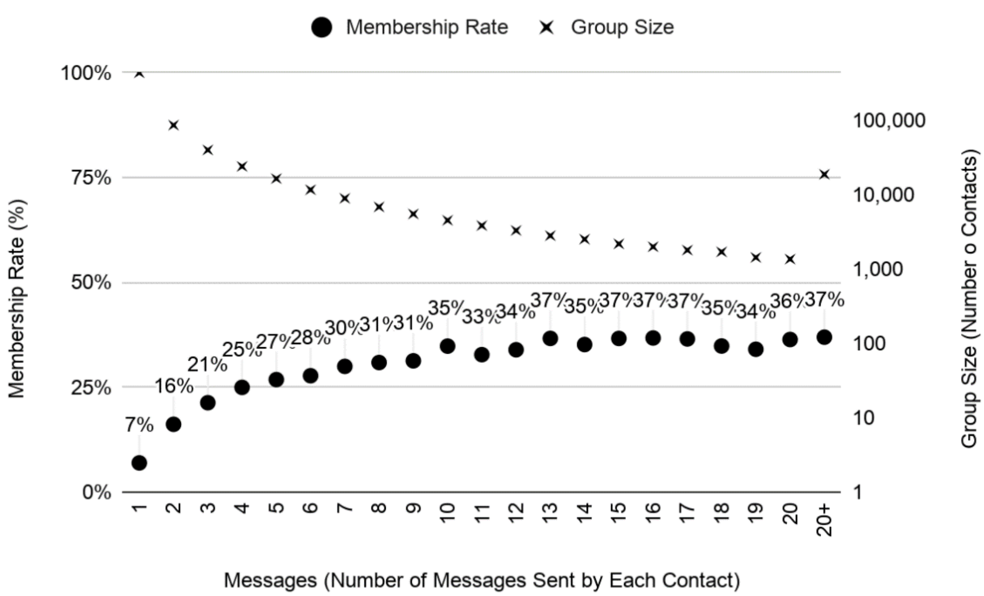
This section reports test results of relating three types of predictor metrics to membership. These three types of predictor metrics are similar to the three types of predictor metrics in the three initial hypotheses in Objective One; they are: the number of messages and the number of personal messages a contact has sent (Section 5.1.1), pronoun use (Section 5.1.2), and message length (Section 5.1.3).

5.1.1. Membership and The Number of Messages Sent

This exploration begins by testing relationships between the number of messages that contacts have sent, the measure of engagement of Objective One, to membership, the measure of engagement of Objective Two. Figure 5.1.1 shows positive relationships between the number of messages that contacts have sent as a predictor of membership. Similar to Figure 4.1.13 and Figure 4.1.14 in Section 4.1.2.3, Figure 5.1.1a shows the effects of groups of contacts with low numbers of contacts, who have sent high numbers of messages, on the variability of membership rates. As the number of messages that groups send increases, group size rapidly decreases to one or two contacts, and the variability of membership rates increases. For example, the average size of groups of contacts sending 100 or messages is equal to two. This example explains the points that could form a horizontal line at the 50% membership rate in Figure 5.1.1a. Connected, other points in Figure 5.1.1a would form other horizontal lines at other regular membership rates for small groups of contacts (e.g. 0%, 25%, 33%, 66%, 75%, and 100% membership rates). As addressed in the results for Hypothesis One, Figure 5.1.1b top-codes groups of contacts sending more than 20 messages into a group of 19,017 contacts. (See Section 3.3.1.2 for a description of how this study top-codes contacts and Section 4.1.2.3 for the importance of top-coding contacts who have all sent high numbers of messages, over 20.)



(a) All Groups of Contacts who Sent the Same Number of Messages
Membership rates are percentages of members for groups of contacts.



(b) Groups of Contacts who Sent the Same Number of Messages, Top-Coded for Contacts who Sent More than 20 Messages

Figure 5.1.1 Membership Rate (%) vs. Number of Messages Sent
Membership rates range from 7%, for the group of contacts who sent one message, to 37%, for the groups of contacts who sent 13, 15, 16, 17, and 21+ messages. Membership rates are percentages of members for groups of contacts.

Figure 5.1.2 flips looking at average membership rates as a function of groups of contacts who sent the same number of messages, to looking at the average number of messages sent as a function of membership. The figure shows a total of four groups of two averages. The first two groups show that members send more messages than non-members. They send, on average, 3.753 more messages (6.445 - 2.692 = 3.753; a 139.4% increase) and 1.478 more personal messages (1.995 - 0.517 = 1.478; a 285.9% increase).

The second two groups in Figure 5.1.2 represent contacts who have sent at least one personal message. These groups are interesting to this study because the contacts' personal messages in these groups permit this study to perform text analysis on them. These two groups show, in general, similar results to the first two groups: members send messages at higher rates than non-members. Specifically, for contacts who have sent at least one personal message, average overall message rates increase by 3.061 messages (7.938 - 4.877 = 3.061; a 62.76% increase) and personal message rates increase by 1.277 (3.459 - 2.182 = 1.277; a 58.52% increase). Comparing the first two groups to the second two groups, for each group, contacts who have sent at least one personal message are also more likely to send more messages overall.

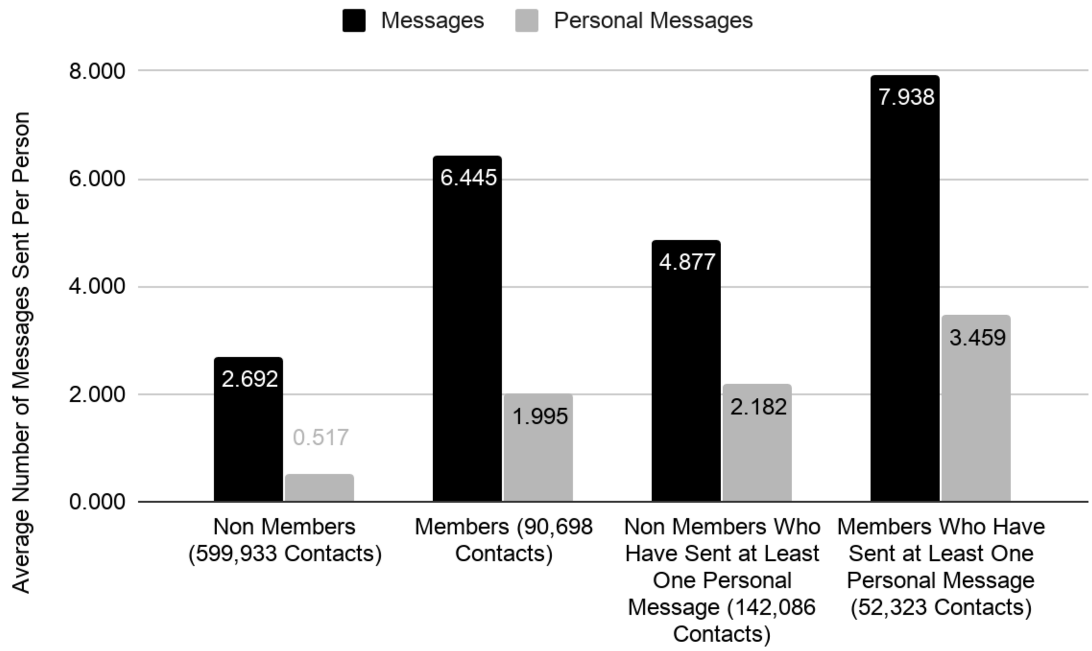


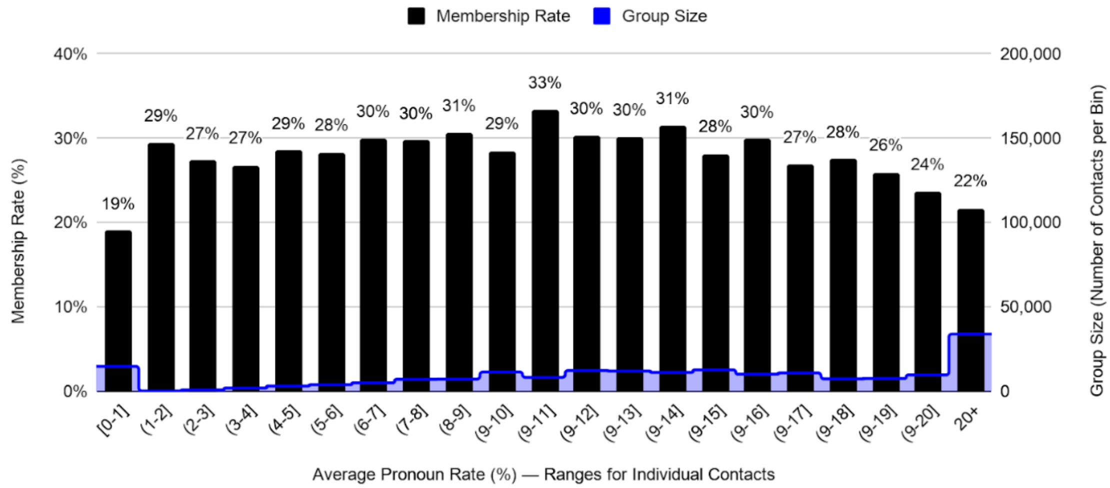
Figure 5.1.2 Average Number of Messages and Personal Messages Sent Per Contact Organized by Conditions of Membership and Whether a Contact has Sent a Personal Message

5.1.2. Membership and LIWC Pronoun Rates

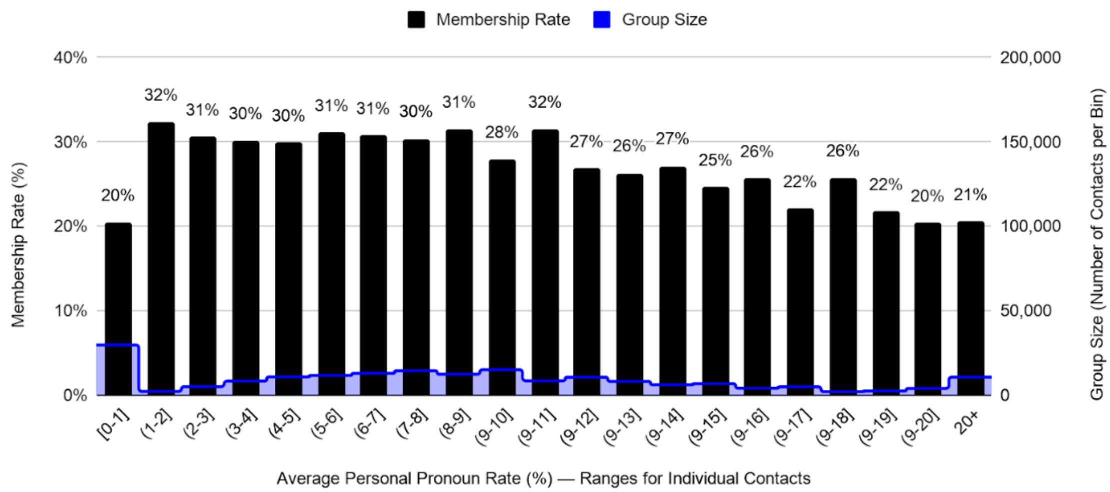
Figure 5.1.3 shows that most contacts use no or low rates (≤ 1%) of pronouns from each individual “i,” “we,” “you,” “she/he” and “they” pronoun dimension. These contacts have membership rates equal to or slightly lower than the baseline membership rate for all contacts who write personal messages (27%). The contacts who use pronouns from each individual “i,” “we,” “you,” “she/he” and “they” dimension at a rate of 1% or lower have respective membership rates of 25%, 23%, 25%, 27%, and 26%. The contacts who use pronouns from each individual “i,” “we,” “you,” “she/he” and “they” dimension at rates between 1% and 2% have much higher respective membership rates of 36%, 35%, 36%, 31%, and 35%, but much fewer contacts use pronouns in these dimensions at rates higher than 1%. For the contacts that do use pronouns at rates higher than 1% for “i,” “we,” "you," "she/he" and "they" pronoun dimensions, Figure 5.1.3 shows a negative relationship between these pronouns and membership.

Membership rates are all lower for contacts that use no or low rates (≤ 1%) of pronouns from the all pronoun, all personal pronoun, and impersonal pronoun dimensions (19%, 20%, and 22%) compared to the membership rates for "i," "we," "you," "she/he" and "they" dimensions. Additionally, Figure 5.1.3 does not show clear trends between membership and the use of all pronouns and all personal pronouns for pronoun use rates greater than 1%. These observations illustrate the parent-child category relationships between pronoun dimensions in LIWC (2018) and show that contacts do not use all types of pronouns in all messages.[3]

[3] Given message time stamps, these plots could inspire future tests of relationships between membership, pronoun diversity, and changing perspectives of authors. See Pennebaker (2011) for a discussion of the importance of analyzing changing perspectives in text.

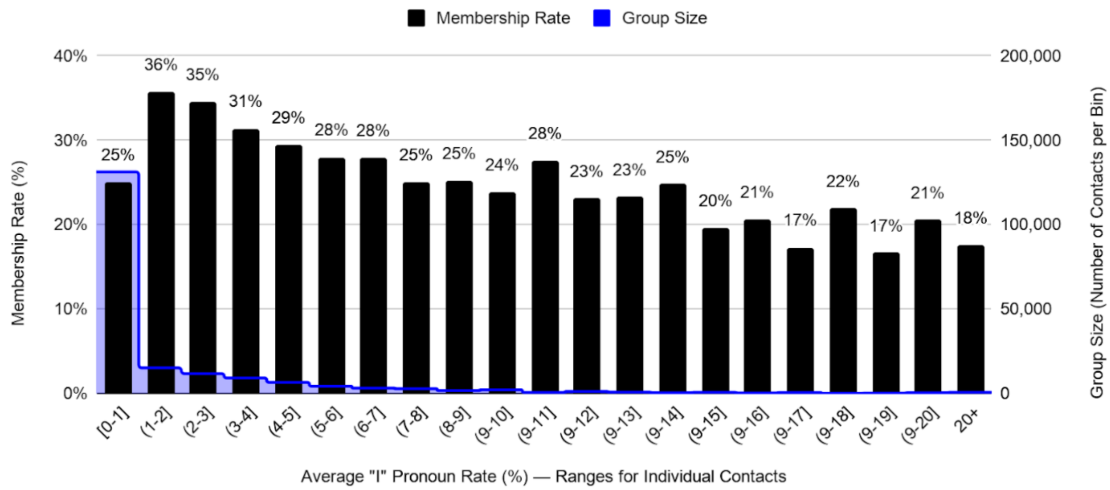


a. All Pronouns

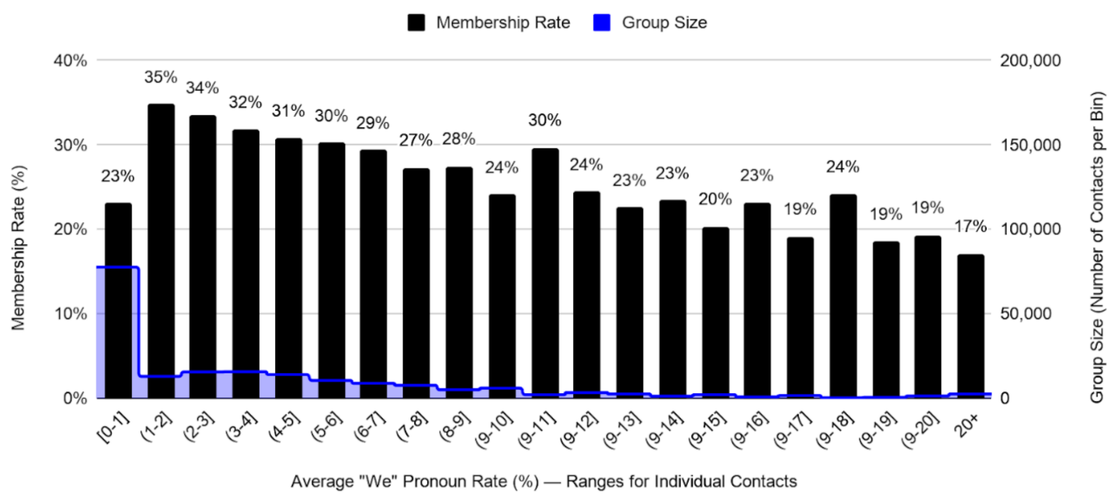


b. All Personal Pronouns

Figure 5.1.3 Membership Rate (%) vs. LWIC Pronoun Dimensions Rates (%)
For (a) All Pronouns, (b) All Personal Pronouns, (c) “I” Pronouns, (d) “We” Pronouns, (e) “You” Pronouns, (f) “They” Pronouns, (g) “She/He” Pronouns, (h) and Impersonal Pronouns Contacts are grouped into bins by their individual average message LIWC rates. Membership rates are percentages of members for groups of contacts.

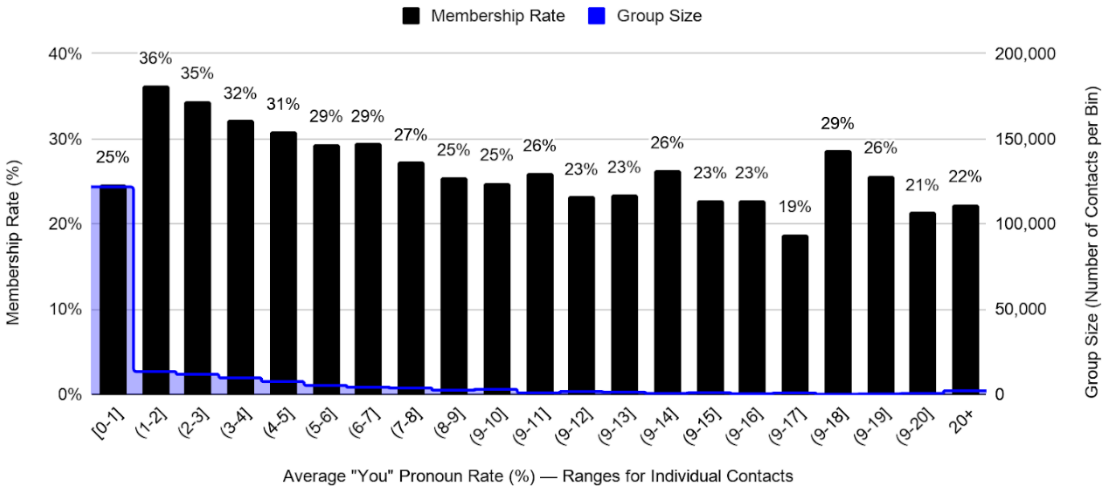


c. “I” Pronouns

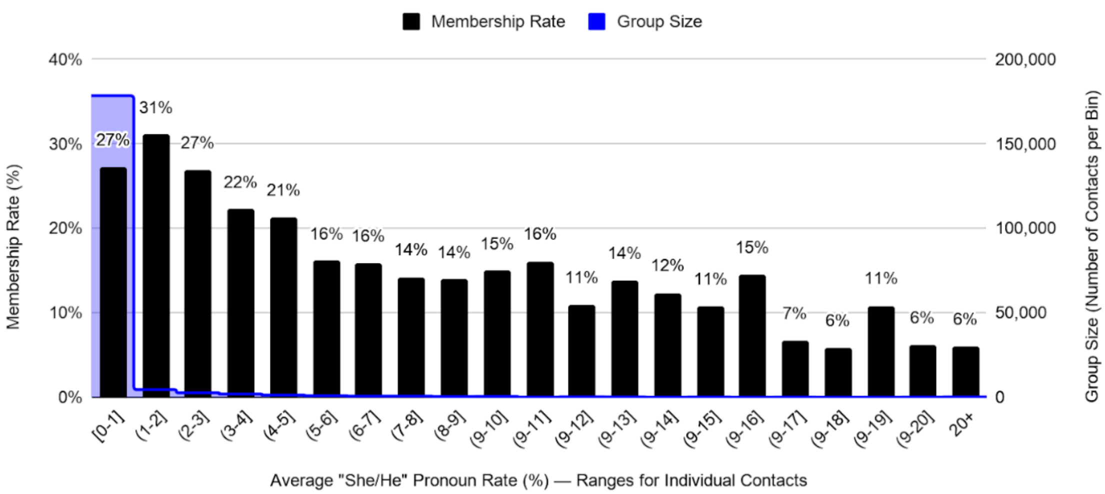


d. “We” Pronouns

Figure 5.1.1 Continued. Membership Rate (%) vs. LWIC Pronoun Dimensions Rates (%)
For (a) All Pronouns, (b) All Personal Pronouns, (c) “I” Pronouns, (d) “We” Pronouns, (e) “You” Pronouns, (f) “They” Pronouns, (g) “She/He” Pronouns, (h) and Impersonal Pronouns Contacts are grouped into bins by their individual average message LIWC rates. Membership rates are percentages of members for groups of contacts.

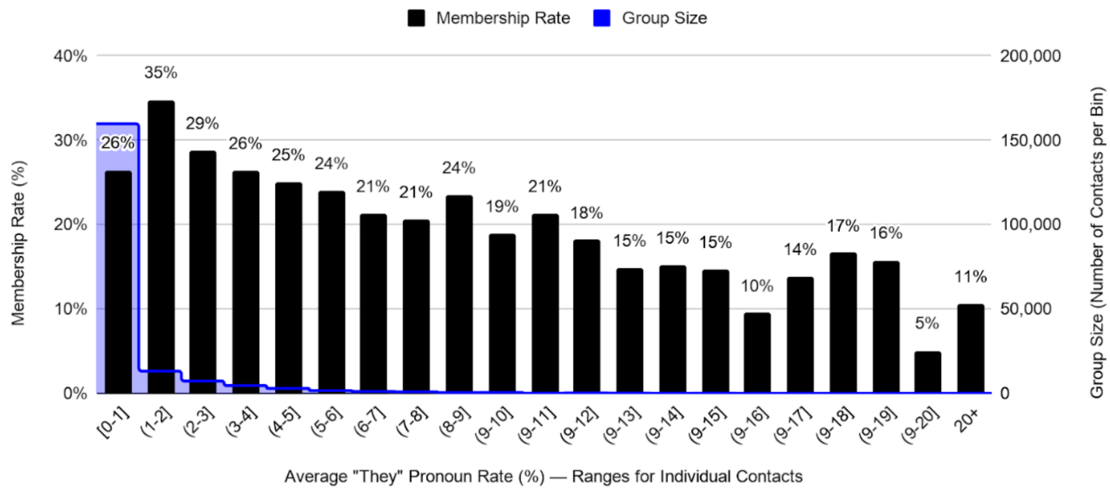


e. “You” Pronouns

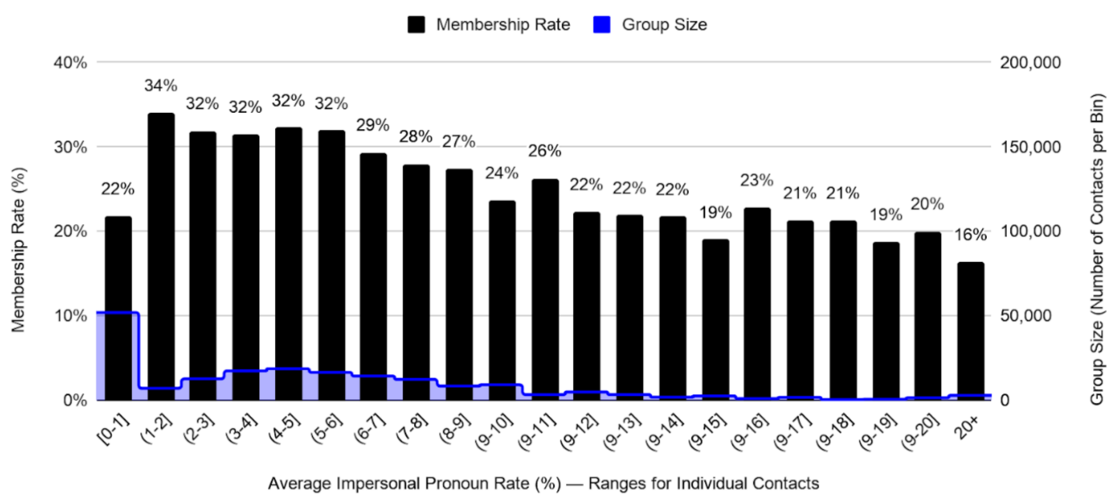


f. “She/He” Pronouns

Figure 5.1.1 Continued. Membership Rate (%) vs. LWIC Pronoun Dimensions Rates (%)
For (a) All Pronouns, (b) All Personal Pronouns, (c) “I” Pronouns, (d) “We” Pronouns, (e) “You” Pronouns, (f) “They” Pronouns, (g) “She/He” Pronouns, (h) and Impersonal Pronouns Contacts are grouped into bins by their individual average message LIWC rates. Membership rates are percentages of members for groups of contacts.



g. “They” Pronouns



h. Impersonal Pronouns

Figure 5.1.1 Continued. Membership Rate (%) vs. LWIC Pronoun Dimensions Rates (%) For (a) All Pronouns, (b) All Personal Pronouns, (c) “I” Pronouns, (d) “We” Pronouns, (e) “You” Pronouns, (f) “They” Pronouns, (g) “She/He” Pronouns, (h) and Impersonal Pronouns Contacts are grouped into bins by their individual average message LIWC rates. Membership rates are percentages of members for groups of contacts.

5.1.3. Membership and Message Length

Figure 5.1.4 shows that for average word count bins, membership rates quickly increase from 17% to 30% as average word counts for individual contacts increase between 1 to 40 words long. Then, membership rates begin to slowly decrease with increasing average word counts and decreasing numbers of contacts. The contacts who sent messages with average word counts less than or equal to 40 account for most of the contacts who sent personal messages (79%; 152,712 out of 194,409 contacts). The contacts who have sent messages with an average word count greater than 40 words have an average membership rate of 28%, which is close to the baseline membership rate for all contacts who write personal messages (27%).

The membership rate for the group of contacts that includes contacts who sent messages with an average word count equal to the mode word count of all personal messages (13 words) is 26%, which is close to the baseline membership rate for all contacts who write personal messages (27%). The membership rate for the group of contacts that includes contacts who sent messages with an average word count equal to the average word count of all personal messages (29 words) is 30%, which is only slightly higher than the baseline membership rate (27%).

Overall, membership rates (left axis) and the positively skewed distribution of word count (right axis) show that for most contacts, average word counts between one and the overall average word count (29) are better predictors of membership rate differences than higher average word counts are. For example, Figure 5.1.4 groups contacts who write messages 25 words shorter than the average message (29 - 25 = 4 words) with contacts that have a 17% membership rate (17% - 30% = -13%; a strong difference). Alternatively, Figure 5.1.4 groups contacts who write messages 25 words longer than the average message (29 + 25 = 54 words) with contacts that have a 29% membership rate (29% - 30% = -1%; a slight difference).

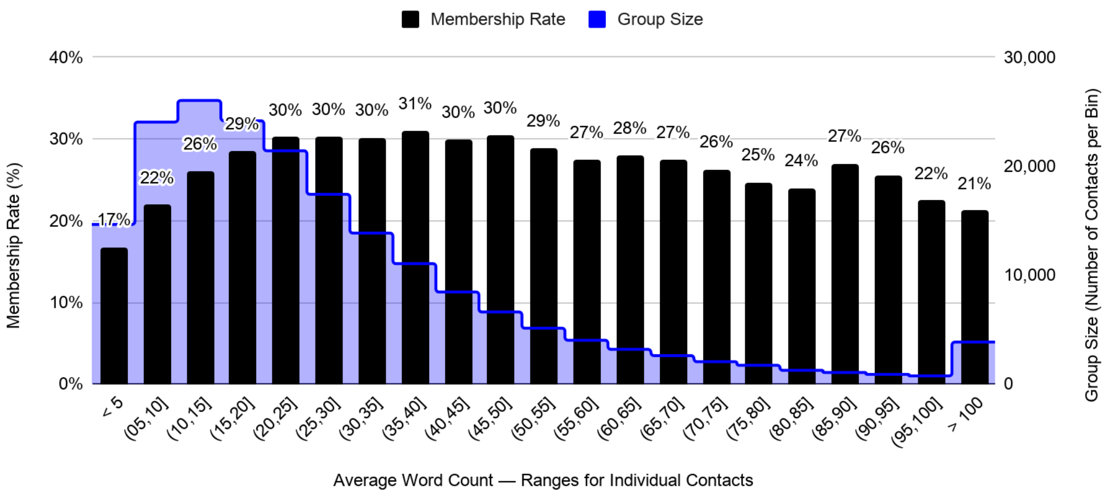


Figure 5.1.4 Membership Rate vs. Average Word Count
Contacts are grouped into bins by their individual average message word counts. Membership rates are percentages of members for groups of contacts.

5.2. Exploration Two: Ungrouped Correlations

While the results from Hypothesis One show correlations between pronoun usage and the average number of messages that *groups of contacts* send, correlations between pronoun usage and the number (not average) of messages that *individual* contacts send approach zero for all contacts. This makes sense: groups of thousands of contacts sending tens of thousands of messages reveal more information than single contacts sending a few messages — the bulk of the data. By limiting the test of individual correlations to more prolific writers (as identified by minimum word counts and minimum numbers of messages sent), correlations begin to appear. In summary, it is easier to distinguish correlations among contacts who write longer and more messages. Figure 5.2.1 shows these correlations for contacts sending a minimum number of personal messages equal to

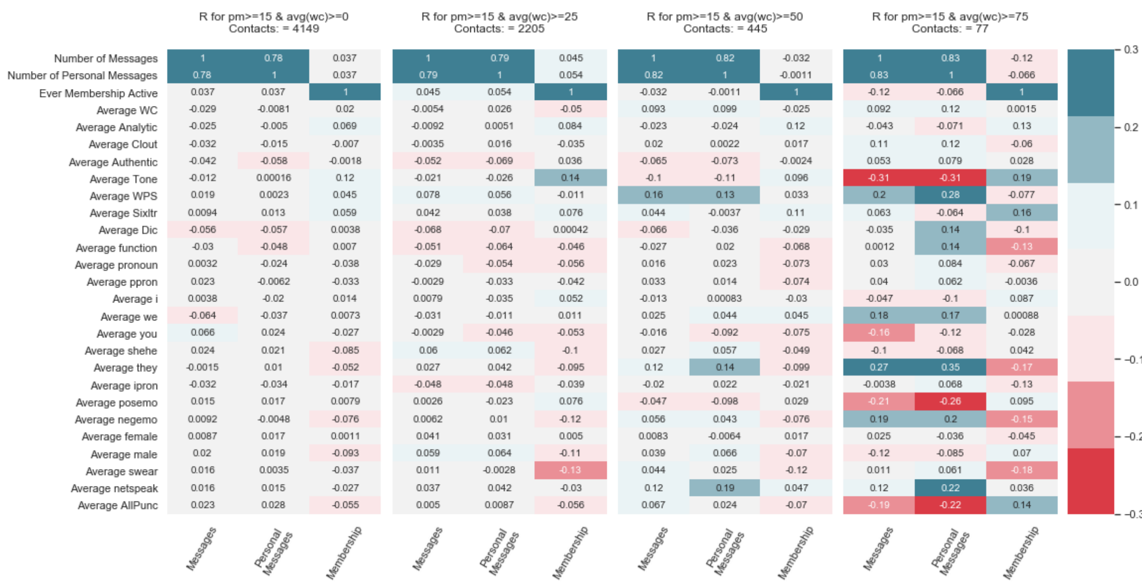
1, 2, 10, 15, and 20 (rows of plots) with minimum word counts of 0, 25, and 75 (columns of plots). Pronoun dimension correlations are plotted alongside other LIWC dimensions described in LIWC 2018. Notice that, while practically nonexistent, when the data are less restricted, the correlation coefficients between “we” and “you” words are respectively negative and positive as seen in the group test results of Hypothesis One. As the minimum number of messages per contact increases, and the minimum average word count per contact increases, the trend becomes slightly reversed: For example, the very small groups of prolific writers (e.g. the 77 contacts who wrote an average of 75 words per message — three times the average — among at least 15 messages — five times the average) tend to use “we” words somewhat more often (R=0.18), and “you” words slightly less often (R=-0.16) for greater numbers of messages.

(a) Contacts sending at least one personal messages (pm ≥ 1)

(b) Contacts sending at least two personal messages (pm ≥ 2)

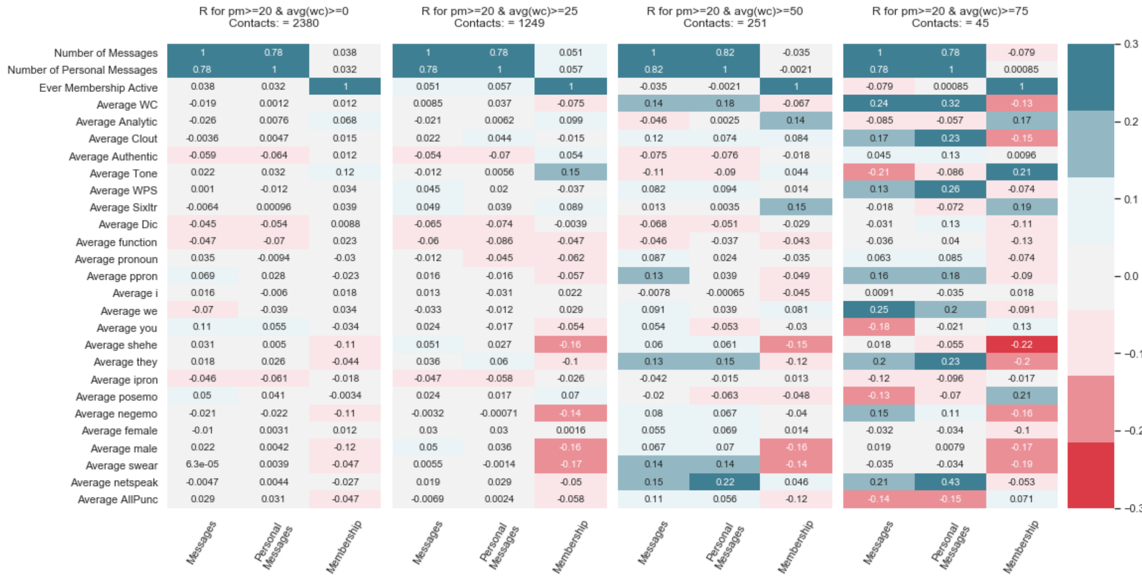
Figure 5.2.1 Continued. Relationships (R) between Individual Contact Linguistic Score Averages and Engagement (Messages, Personal Messages, and Membership) for Minimum Average Word Counts – avg(pm) – of 0, 25, 50, and 75.

(c) Contacts sending at least ten personal messages (pm ≥ 10)



(d) Contacts sending at least three personal messages (pm ≥ 3)

Figure 5.2.1 Continued. Relationships (R) between Individual Contact Linguistic Score Averages and Engagement (Messages, Personal Messages, and Membership) for Minimum Average Word Counts – avg(pm) – of 0, 25, 50, and 75.



(e) Contacts sending at least 20 personal messages (pm ≥ 20)

Figure 5.2.1 Continued. Relationships (R) between Individual Contact Linguistic Score Averages and Engagement (Messages, Personal Messages, and Membership) for Minimum Average Word Counts – avg(pm) – of 0, 25, 50, and 75.

5.3. Exploration Three: Personal Stories

As described in the introduction, research bodies and practitioners encourage nonprofits to look for personal stories among personal messages (Karpf 2016, Congressional Management Foundation 2017, Social Change Agency 2017a, 2017b, Long 2018) to create "groundbreaking" (Social Change Agency 2018b) digital campaigns. These researchers have shown that contacts who share stories about how they have been affected by campaign issues have a greater potential to contribute to nonprofits as participants and organizers. In fact, an original proposal for this dissertation considered training a naive Bayes classifier to attempt to identify personal stories for advocacy campaigns. While a machine learning classification model could be developed in the future, work on Objective Two begins by using key-phrase searches to identify messages with personal stories. It then tests whether specific phrases are related to membership.

This exploration developed phrases from a collection of words already used by an employee of one nonprofit advocacy organization to look for personal stories. This employee noticed that the following phrases help identify personal stories for their team:

1. As a
2. I am a
3. I live
4. In my state/district
5. My family
6. My husband
7. My wife
8. My children

While some letter-writing campaigns may elicit many personal stories of lived experiences, permitting organizations' legal teams to pick and choose testimonials, many campaigns do not, and sets of small numbers of identified stories lead to statistically insignificant findings about membership even if those stories may be practically applied. Categorical chi-squared tests comparing small groups of contacts who have sent personal stories to those who have not sent personal stories, on the basis of membership, yield high, insignificant, p-values.

To address this problem of small groups matching conditions, inspired by LIWC pronoun dictionaries and work by Gordon et al. (2009), who looks for stories in longer passages of text, the study casts a net to catch personal stories by expanding the original list of personal story phrases (above) to include subject pronoun variations (first-person, second-person, third-person, singular, plural; e.g. "I" and "we"), verb tenses (past, present, future) and endings (e.g. "ed" and "ing"), object single and plural ending variations (e.g. child vs. children), and limited consideration to imperfect tense (e.g. was vs. had) and some associated hedge phrases (e.g. have been living, had lived, go to, going to).

It tests for the presence of phrases (a) starting a message, (a) anywhere, and (c) at the beginning of sentences and prepositions, qualified by patterns of punctuation and spaces. Searching for phrases at the beginning of a message automatically finds messages that begin with sentences that begin with the phrases, e.g., "as a scientist…," but does not find messages that contain later sentences that begin with the phrases, e.g., "stop the pipeline. As a scientist…." Searching anywhere finds both types of messages, increasing the number of results. Qualifying messages actually limits the number of search results returned by queries, but in many cases, aligns results closer to their queries' intent. For example, an unrestricted search for "as a" returns unintentional results for any message with a word ending in "as" and a following word beginning with "a," like, "The department has already accepted the contract…," where "h*as a*lready" contains the matching phrase. A regular expression to search for this particular unintended result (MySQL expression "[a-z]as a[a-z]") returns 7,588 similar messages. Most of these messages do not tell personal stories like those found by the more complex pattern matching for "as a" at the beginning of sentences and prepositions (MySQL expression "(([:punct:][:space:](As a))|(^As a))[:space:]"). (Note: Despite the capital letter "A" shown in the pattern of this example, expressions in this study were matched against fields with a case insensitive collation to pick up prepositional phrases, e.g. "after witnessing the dissemination of African Elephants from my family home village over the last 20 years, as an African, I hope that you will support the U.S. program to….")

Reading messages resulting from the initial queries reveals most regular expressions describing these phrases do, indeed, reveal what an advocacy organization might call "personal stories" — but not necessarily "lived experiences" (Sandhu 2017, Social Change Agency 2017a). Many resulting messages independently convey other meanings, such as volition to act and threats, e.g. "I will vote against every conservative politician I can and switch my party affiliation if Bears Ears National Monument is reduced by even one square foot"; family support, e.g. "my husband and I urge you to do this"; specific occupation, e.g. "I am a carpenter and, therefore…support…sustainable logging. The Giant Sequoias are too important…"; education and income, e.g. "I am an undergrad who with student loans. I try my best every single month to save energy in every way possible….”

Contacts describing battles with asthma near sources of pollution convey personal stories. A search for sentences beginning with “I’ve had” and “I live” return results such as,

> *I’ve had asthma my whole life. I grew up in LA in the 50s and this issue matters to me. I want a world where my grandchildren can breathe easy,*

and

> *I live along the interstate outside this operation. My family and friends are getting sick with asthma and are being forced to exercise indoors since fracking began. Methane and VOCs need to be regulated in every way possible*

These messages have subjectively “more” personal stories in them than results from other queries for “my daughter” and “I have:”

> *My child and I have asthma. Do your job. Protect our air!*

and

> *I have asthma and need clean air to breathe.*

While this review exposes varying degrees of personal stories and intents of messages found with different expression patterns, this exploration did not rank messages by degrees of personal story. This work might be better suited for a machine learning in the future. This exploration does, however, evaluate several categories of searches and, additionally, tests LIWC dimensions and the most popular words used in messages. It reports findings for searching for personal stories with references to family, gender, residence, education, activism, volunteering, voting, spending, suffering, and swear words. Appendix B lists the SQL queries and regular expressions used by this study to conduct these searches.

5.3.1. Personal Stories and Family

The study began exploration with a search recommended by a nonprofit organization to test for the presence of “my husband” or “my wife” at the beginning of a message to find personal stories. The search found some personal stories — but more interestingly, successfully identified high membership rates. Table 5.3.1. shows that authors who have begun their messages with “my wife” or “my husband” (n=608, coded in MySQL as “LIKE ‘my husband%’”) have almost double the membership rate of those who did not (49% vs. 27%). A chi-square test shows the relationship is significant, X^2 (k=1, n=194,409) = 154, $p < 0.01$. Table 5.3.2 shows the calculation of expected values for this statistic. Authors who have used these terms anywhere in their messages (n=1,219, e.g. "%my husband%") have a 45% membership rate compared to a 27% membership rate for those that do not (also $p<0.01$). Limiting this test to the group of contacts who have sent longer-than average messages has little effect on the test results: The number of results decreases to 438 contacts and the membership rate increases by one percent, to 50% — producing a 23% increase over the 27% membership rate of the alternative results ($p < 0.01$).

Table 5.3.3 shows results for variations for husband and wife queries tested independently along with other family conditions. The chi-squared tests for second-person and third-person husband and wife search conditions, such as searches for “your wife,” have low enough conditional group sizes that their p-values exceed 0.1; their relationships therefore are not significant. Table 5.3.3 also shows that groups of contacts who begin messages with search terms, despite their lower group sizes, generally have one or two percent higher membership rates compared to contacts who use the search terms anywhere in their messages. Further, the groups of contacts matching alternative conditions have membership rates close to the general membership rate of contacts sending personal messages (27% to two significant figures).

Contacts who discuss children have the highest numbers of matching contacts and significant 36% and 37% membership levels compared to the average 27% membership rate. Queries that find these contacts match “my children” and “our children” in addition to singular “child” expressions. Figure 5.3.1. shows these membership rates.

In summary, contacts who discuss their family members are more likely to be members, and contacts discuss their children more than their spouses. An expansion study could test membership against references to grandchildren and other types of family members and friends not tested here: sons, daughters, mothers, fathers, etc.

Table 5.3.1 Husband and Wife Personal Story Observation Contingency Table and Calculations

A "personal story" condition in this table is defined by the case where a contact has written a message beginning with "my husband" or "my wife." X^2 (k=1, n=194,409) = 154, $p < 0.01$

Observed	Began a message with "my husband" or "my wife"	Did not begin message with "my husband" or "my wife"	Sum	Total Proportion
Member	299	52,024	52,323	0.269 (52,323/194,409)
Not a Member	309	141,777	142,086	0.731 (142,086/194,409)
Sum	608	193,801	194,409	1
Membership Rate	49% (100%*299/608)	27% (100%*52,024 /193,801)	27% (100% *52,323 /194,409)	

Table 5.3.2 Husband and Wife Personal Story Expected Values Contingency Table and Calculations

Along with observations from Table 5.3.2, this table shows expected values and sub-calculations to calculate the chi-squared statistic and the chi-squared test p-value. These two tables serve as examples for additional chi-squared tests in Chapter 5.

Expected	Began a message with "my husband" or "my wife"	Did not begin message with "my husband" or "my wife"
Member	164 (608*0.269)	52,157 (194,409*0.269)
Not a Member	444 (608*0.731)	141,642 (194,409*0.731)
Sum	608	193,801

Table 5.3.3 Membership Rates (m), Sizes (contacts, n), and Chi-Squared Test P-Values for Family Conditions (true, c, and not true, ~c)

condition	term	n|c	n|~c	m|c	m|~c	m|c-m|~c	m|c-m	p
starts with	my family	586	193,823	38%	27%	12%	11%	0.00
contains	my family	2,258	192,151	38%	27%	11%	11%	0.00
phrase starts with	my family	873	193,536	37%	27%	11%	11%	0.00
starts with	our family	155	194,254	40%	27%	13%	13%	0.00
contains	our family	1,496	192,913	36%	27%	9%	9%	0.00
phrase starts with	our family	219	194,190	39%	27%	12%	12%	0.00
starts with	my child	166	194,243	38%	27%	11%	11%	0.00
contains	my child	2,060	192,349	37%	27%	10%	10%	0.00
phrase starts with	my child	337	194,072	38%	27%	11%	11%	0.00
starts with	our child	578	193,831	38%	27%	11%	11%	0.00
contains	our child	14,005	180,404	36%	26%	10%	9%	0.00
phrase starts with	our child	1,579	192,830	36%	27%	9%	9%	0.00
starts with	my husband	384	194,025	47%	27%	21%	20%	0.00
contains	my husband	811	193,598	41%	27%	15%	15%	0.00
phrase starts with	my husband	528	193,881	45%	27%	18%	18%	0.00
starts with	my wife	224	194,185	52%	27%	25%	25%	0.00
contains	my wife	410	193,999	51%	27%	24%	24%	0.00
phrase starts with	my wife	273	194,136	52%	27%	26%	25%	0.00
starts with	my wife or my husband	608	193,801	49%	27%	22%	22%	0.00
contains	my wife or my husband	1,219	193,190	45%	27%	18%	18%	0.00
contains	your wife or your husband	62	194,347	24%	27%	-3%	-3%	0.63
contains	his wife or her husband	53	194,356	26%	27%	0%	0%	0.93

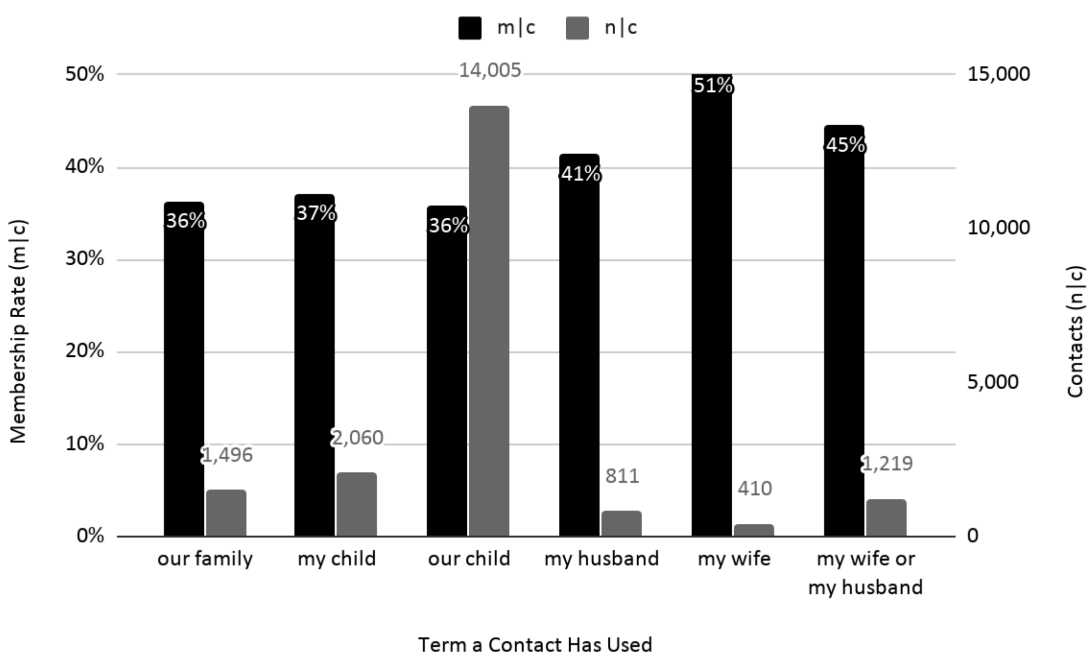


Figure 5.3.1 Family Words and Membership
37% membership rate for 20,001 total contacts
Membership rates are percentages of members for groups of contacts.

5.3.2. *Self-Identification Predictors for Personal Stories and Membership*

As describing one's husband or wife may be indicative of a personal story (and perhaps money spent on membership; Figure 5.3.1, above), categorizing one's self is by definition personal, and results from the search for terms like "as a," "I am," and "I live," reveal more than just the stories of "lived experiences" (Sandhu 2017, Social Change Agency 2017a) that this exploration set out to look for. Results of these types of searches answer questions that advertising companies and banks traditionally asked consumers to judge consumer income and make credit determinations. Without taking a survey, some writers identify their own family membership, gender, occupations, affiliations, and education, writing "I am a mom," "I am a doctor," "I am a college student," "I am a teacher," or "I am a Marylander." Table 5.3.4 shows membership rates for these types of queries.

5.3.2.1.General Self-Identification

For general self-identification conditions, Table 5.3.4 shows that contacts who identify themselves have above-average membership rates. Contacts who use begin phrases with "as a" are the most relevant, with membership levels 13% above the average 27% rate. Figure 5.3.2 highlights contacts identifying themselves in first person have 6-7% higher membership rates than those identifying themselves in second person. See Appendix B, personal story reference Table 1 for regular expressions used to identify these conditions.

Table 5.3.4 Self-Identification and Membership

condition	term	n|c	n|~c	m|c	m|~c	m|c-m|~c	m|c-m	p
starts with	As a	6,266	188,143	40%	26%	14%	13%	0.00
contains	As a	23,230	171,179	37%	26%	11%	10%	0.00
phrase starts with	As a	6,749	187,660	40%	26%	13%	13%	0.00
starts with	I am a	3,338	191,071	38%	27%	12%	11%	0.00
contains	I am a	5,692	188,717	38%	27%	11%	11%	0.00
phrase starts with	I am a	2,323	192,086	38%	27%	12%	11%	0.00
starts with	We are	3,110	191,299	35%	27%	8%	8%	0.00
contains	We are	13,271	181,138	34%	26%	8%	7%	0.00
phrase starts with	We are	6,754	187,655	33%	27%	7%	6%	0.00
starts with	We are a	591	193,818	36%	27%	9%	9%	0.00
contains	We are a	2,598	191,811	37%	27%	10%	10%	0.00
phrase starts with	We are a	250	194,159	32%	27%	5%	5%	0.09

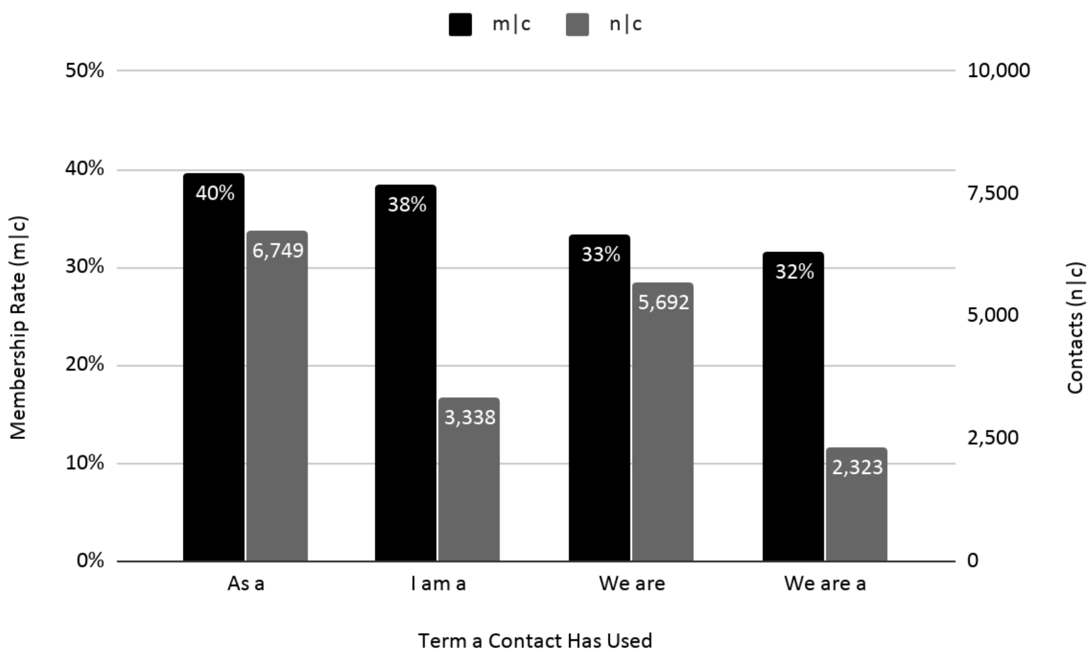


Figure 5.3.2 Self-Identification and Membership
This plot shows data from Table 5.3.4 for “phrase starts with” conditions.
37% membership rate for 15,779 total contacts (15,779 = 6,749 + 3,338 + 5,692, where all 2,323 messages containing “we are a” also contain “we are.”) Membership rates are percentages of members for groups of contacts.

5.3.2.2.Gender Self-Identification

For gender, Figure 5.3.3 shows small numbers of contacts identify with male terms (56) and female terms (150). The low difference between the observed and expected membership rates for females along with the low number of contacts yields a more modestly significant chi-squared test p-value of 0.05 compared to the male p-value, 0.01. Contacts who state their gender have higher than average membership rates (45% males and 34% females), but not many contacts do so (150 + 56 = 256). See Appendix B, personal story reference Table 2 for the regular expressions used to find contacts who identify themselves as male or female.

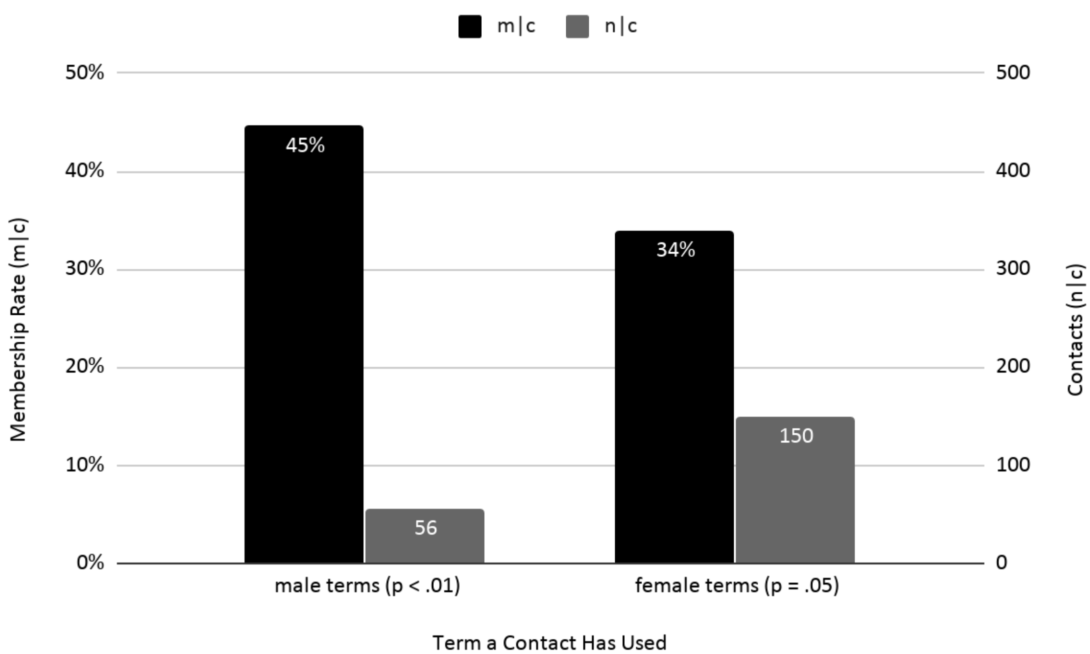


Figure 5.3.3 Self Gender Identification and Membership
Membership rates are percentages of members for groups of contacts.

5.3.2.3.Residence Self-Identification

For self-identification of residency, Table 5.3.5 shows higher than average membership rates, up to 41%, for contacts stating they live in a place in the first-person, with a good number of results for phrases that contain “I live” (2,819), start with “I live” (1,784), contain “I live in” (1,465) and start with “I live in” (1,131). “We call home” phrases were not detected enough to call membership rate differences significant. The last row of the table tests a more complex condition for several identifications of “living” by the MySQL expression, “REGEXP '(I(went| went to| am|\'m| will| will be| was| have| have been|)(go to| going| going to|)) (live|living)',” which looks for several first-person singular patterns described in the introduction of this chapter, successfully increasing the number of matching results while limited false positive detection rates. Figure 5.3.4. plots data in Table 5.3.5 for “phrase starts with” conditions and the complex expression for first-person singular identification of living. See Appendix B, personal story reference Table 3 for regular expressions used to find contacts who identify themselves as living in a place.

Table 5.3.5 Residence and Membership

condition	Term	n|c	n|~c	m|c	m|~c	m|c-m|~c	m|c-m	p
contains	I live	2,819	191,590	39%	27%	12%	12%	0.00
phrase starts with	I live	1,784	192,625	39%	27%	12%	12%	0.00
contains	I live in	1,465	192,944	41%	27%	14%	14%	0.00
phrase starts with	I live in	1,131	193,278	40%	27%	13%	13%	0.00
contains	We live	1,445	192,964	32%	27%	5%	5%	0.00
phrase starts with	We live	359	194,050	36%	27%	10%	10%	0.00
contains	We live in	639	193,770	34%	27%	7%	7%	0.00
phrase starts with	We live in	206	194,203	39%	27%	12%	12%	0.00
contains	We call home	100	194,309	31%	27%	4%	4%	0.36
phrase starts with	We call home	2	194,407	0%	27%	-27%	-27%	0.39
complex	First-Person Singular Live/Lived/Living	3,178	191,231	39%	27%	12%	12%	0.00

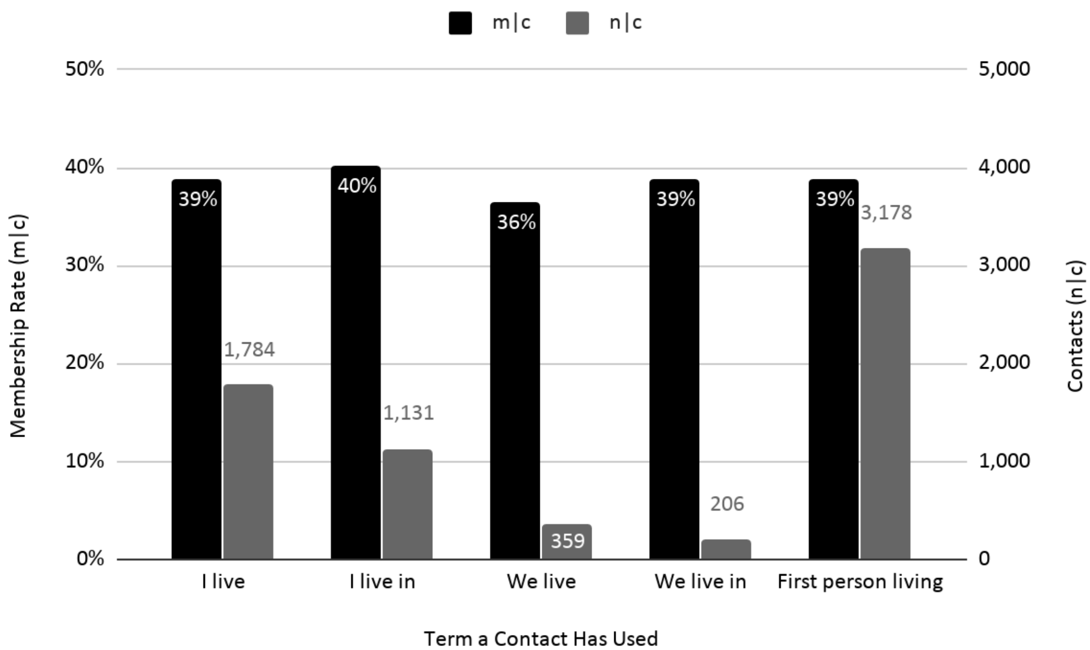


Figure 5.3.4 Residence and Membership
This plot shows data from Table 5.3.5 for “phrase starts with” conditions.
39% membership rate for 3,737 total contacts
Membership rates are percentages of members for groups of contacts.

5.3.2.4.Family Role Self-Identification

Contacts identifying themselves as spouses, parents, grandparents, children, siblings, aunts, and uncles, identified with several, long MySQL expressions, like, “REGEXP '(I am|I\'m|I was|I have been|I will be) (a|an|the) ([a-z]+ |)(grandma|grandmother|grandpa|grandfather)'” return good membership results, but low conditional group sizes. All chi-squared test p-values for these searches are relatively high compared to other tests in this exploration, with the exception of the test for self-identification as a “son, daughter, child, or kid.” That test returns 216 matching contacts with a 44% membership rate ($X^2 = 34$ for k=1 and n=216; $p < 0.01$). See Appendix B, personal story reference Table 2 for regular expressions used to identify these conditions.

5.3.2.5.Education Self-Identification

The test for contacts identifying themselves as students, graduates, or teachers — found with the MySQL expression, “REGEXP '(I am|I\'m|I was|I have been|I will be) (a|an|the) ([a-z]+ |)(college|student|phd|master\'s|master of|doctor of|graduate|professor|ta|teacher|highschool|elementary school|preschool|pre-school|higher education|research)” — yield only 193 results, a membership rate of 28%, only one percent greater than the average, and a chi-squared test p-value of 0.74 indicating an insignificant relationship. Alternatively contacts who identify themselves as teachers, not through declaration such as “I am” and “I’m,” but through verbs such as “teach” and variations of “teach,” return a higher membership of 38%, but a similarly low number of results (185 contacts). The chi-squared test p-value for the verb test is significant ($X^2 = 12$ for k=1 and n=185; $p < 0.01$). See Appendix B, personal story reference Tables 2 and 3 for regular expressions used to identify these conditions.

5.3.2.6.Working and Occupation Self-Identification

Table 5.3.6 show results from looking for contacts who explicitly name themselves with specific words in a similar way that family roles were identified, above. It also shows results for identifying contacts through verb use, in a similar way that teachers were identified with “teach” verbs, above. Although the words ending in “ist” and “tor” generally find contacts working in professional fields, this analysis is in no way comprehensive. The occupation taxonomy from the Bureau of Labor Statistics could greatly improve this exploration in future work (https://www.bls.gov/oes/current/oes_stru.htm). See Appendix B, personal story reference Tables 2 and 3 for regular expressions used to identify these conditions.

Combined with a taxonomy of occupations, work and occupation searches could aid organizations in immediately organizing letter-writing campaign participants. For example, a chatbot interacting with a person who self-describes themselves in a message, "I'm a hydrologist at … and I support expanding the Rainscapes program in Montgomery County," could ask that person whether the bot's controlling organization could send the author's message with other scientists' messages to representatives together. With a positive reply, the bot could then ask if the person would like to join an online group of concerned scientists who have written to support the Rainscapes program, or flag the person for a follow-up call with a legal action team looking for testimony.

Table 5.3.6 Work, Occupation, and Membership

identification	root-term	n|c	n|~c	m|c	m|~c	m|c-m|~c	m|c-m	p
self	*ist, doctor, nurse	386	194,023	41%	27%	14%	14%	0.00
self	*ist	345	194,064	41%	27%	14%	14%	0.00
self	*tor	85	194,324	47%	27%	20%	20%	0.00
self	*or	749	193,660	39%	27%	12%	12%	0.00
self	*er	2,076	192,333	39%	27%	13%	12%	0.00
self	doctor, nurse	61	194,348	49%	27%	22%	22%	0.00
self	lawyer, judge	7	194,402	29%	27%	2%	2%	0.92
self	engineer	34	194,375	26%	27%	0%	0%	0.95
verb	work	898	193,511	38%	27%	11%	11%	0.00
verb	program	6	194,403	67%	27%	40%	40%	0.03
verb	analyz	3	194,406	0%	27%	-27%	-27%	0.29

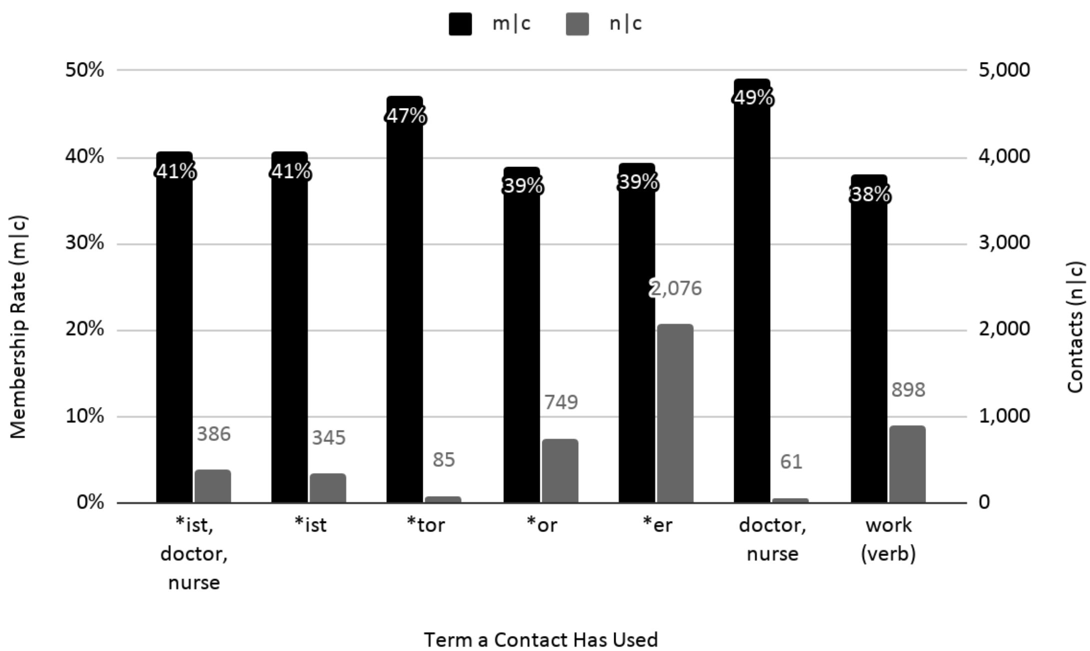


Figure 5.3.5 Work, Occupation, and Membership
Membership rates are percentages of members for groups of contacts.

5.3.2.7.Activism, Volunteering, Voting, and Spending Self-Identification

In addition to the key phrases that identify personal stories listed at the beginning of this exploration section, nonprofit organizations are interested in voters and contributors to causes. Reading through search results for personal stories reveals evidence of past activism in addition to personal stories. Table 5.3.7 shows membership rates for contacts who have used verbs “volunteer,” “join,” “protect,” “guard,” “save,” “fight,” and “spend” with first-person singular “I” words, tested with expressions like those used for tests of “teaching,” explained above. Results show limited numbers of matching results and modestly significant p-values. Even though contacts discuss “spending” in higher numbers then contacts discuss “volunteering” and “joining” combined, the latter two metrics reveal much higher, and significant membership rates (52% and 44%). See Appendix B, personal story reference Table 3 for regular expressions used to identify these conditions.

Table 5.3.7 Activism Verbs Used in the First-Person

root term(s)	n|c	n|~c	m|c	m|~c	m|c-m|~c	m|c-m	p
volunteer	66	194,343	52%	27%	25%	25%	0.00
join	63	194,346	44%	27%	18%	18%	0.00
protect, guard, save, saving, fight, fought	217	194,192	35.02%	26.90%	8.12%	8.11%	0.01
spend	114	194,295	32%	27%	5%	5%	0.26

5.3.2.8.Outdoor Appreciation Self-Identification

Advocacy organizations like The Audubon Society, the Sierra Club, and other organizations give their members access to outdoor program and events with membership. Table 5.3.8 shows that a limited search for outdoor verbs shows campers, hikers, and walkers have significantly higher levels of membership than the average despite their moderately low regular expression matching rates. See Appendix B, personal story reference Table 3 for regular expressions used to identify these conditions.

Table 5.3.8 Outdoor Verbs
49% membership rate for 682 total contacts

root term(s)	n|c	n|~c	m|c	m|~c	m|c-m|~c	m|c-m	p
camp	54	194,355	44%	27%	18%	18%	0.00
hike, hiking	218	194,191	54%	27%	27%	27%	0.00
trek	1	194,408	0%	27%	-27%	-27%	0.54
climb	8	194,401	63%	27%	36%	36%	0.02
ski	4	194,405	25%	27%	-2%	-2%	0.93
hunt, fish	25	194,384	32%	27%	5%	5%	0.57
bike, biking, cycl	6	194,403	50%	27%	23%	23%	0.20
hike, hiking, walk	325	194,084	48%	27%	21%	21%	0.00
swim, swam	19	194,390	47%	27%	20%	20%	0.04
ride, riding, rode	22	194,387	41%	27%	14%	14%	0.14

5.3.2.9.Suffering Self-Identification

Words of suffering surfaced in reading through personal stories identified by the previous searches. They uncover lived experiences that negatively impact message writers' lives. Stem verbs, including "suffer," depriv," "die," "dying," "hurt," "curs," "broke," "break," "lost," "lose," "endur," and "I will go through," all return small numbers of results with p-values greater than 0.01 (mostly insignificant). The test for the presence of base "suffer" verbs has the greatest matching number of results among these tests (138 contacts) with 34% membership rate (a small 7% above the average). The test for "endur" yields only five contacts, but three of them are members (60% membership rate, p=0.10). See Appendix B, personal story reference Table 3 for regular expressions used to identify these conditions.

5.3.2.10. Swear Words

While phrases derived from searches of personal stories find higher membership rates, swear words find lower membership rates. Looking purely for the presence of three four-letter swear words, along with the presence of any swear word reported by the LIWC "swear" dimension, reveals contacts who swear are less likely to pay for membership. Table 5.3.9 shows the results. The 260 contacts who begin messages with the first swear word have very low membership rates (11%). Individual swear word conditions yield chi-square test result p-values lower than 0.01, and all exhibit membership rates lower than those found by the LIWC swear word test (23%). See Appendix B, personal story reference Table 4 for regular expressions used to identify these conditions.

Table 5.3.9 Swear Words and Membership

Condition	Term	n|c	n|~c	m|c	m|~c	m|c-m|~c	m|c-m	p
Starts with	F Swear Word	260	194,149	11%	27%	-16%	-16%	0.00
Contains	F Swear Word	946	193,463	15%	27%	-12%	-12%	0.00
Starts with	D Swear Word	30	194,379	20%	27%	-7%	-7%	0.39
Contains	D Swear Word	925	193,484	26%	27%	-1%	-1%	0.37
Starts with	S Swear Word	8	194,401	25%	27%	-2%	-2%	0.90
Contains	S Swear Word	728	193,681	20%	27%	-7%	-7%	0.00
Contains a	LIWC Swear Word	8667	185,742	23%	27%	-4%	-4%	0.00

Appendix B describes all personal story queries and includes a reference of all the database LIKE and REGEX conditions that this chapter uses.

5.4. Exploration Four: Flesch Reading Ease

Exploration Four tests if members that write more words per sentence and more syllables per word, according to the Flesch reading ease score (206.835 - 1.035 * words/sentences - 84.6 * syllables/words), have significantly different membership levels than the 27% average membership rate for contacts who sent personal messages. Tests consider minimum (Figure 5.4.1 and Figure 5.4.2), average (Figure 5.4.3 and Figure 5.4.4), and maximum (Figure 5.4.5 and Figure 5.4.6) Flesch scores per contact. The tests of minimum Flesch reading ease scores highlight the most difficult-to-read messages that each contact has written. The tests of maximum Flesch reading scores highlight the opposite — the simplest-to-read messages that contacts have written. The tests of minimum scores show significant differences in membership rates. The tests of maximum scores show no differences.

Figure 5.4.1 (membership rate) and Figure 5.4.2 (conditional group size) show that membership rates increase with minimum Flesch ease of reading scores from a below average membership rate of 16% (minimum Flesch score > 100; 4th grade and lower reading level; <10% below the overall average score of 27%) to an above average score of 37% (minimum Flesch score ≥ 30; college graduate reading level; >10% above the overall average score of 27%). All categorical chi-squared tests for these minimum Flesch score conditions have p-values of less than 0.001; they are significant.

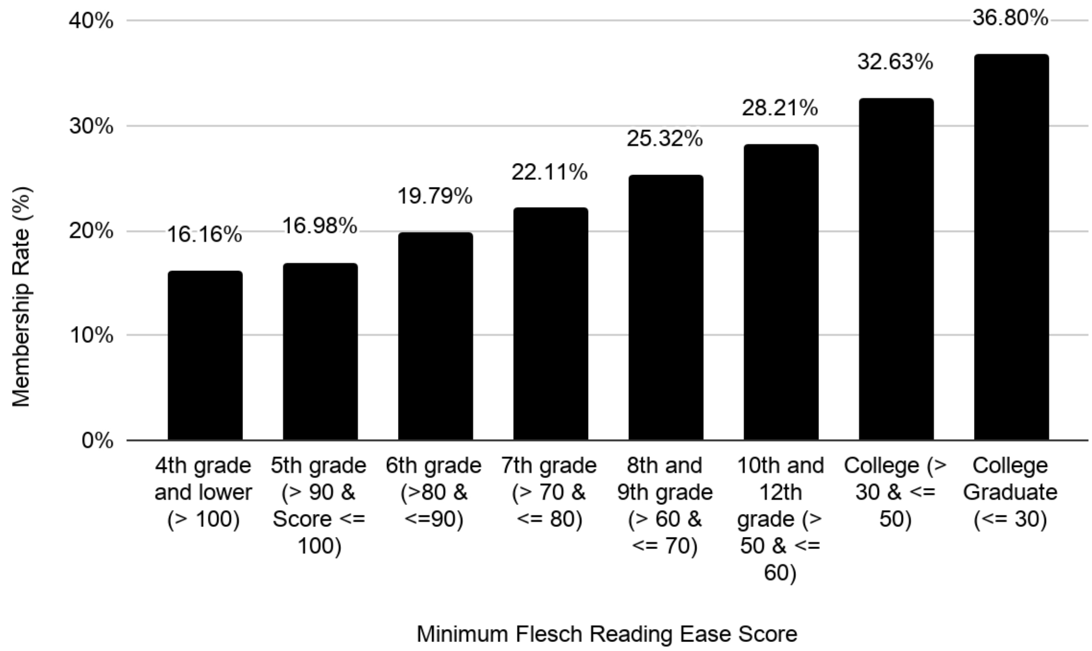


Figure 5.4.1 Membership Rates for Groups of Contacts with Minimum Flesch Reading Ease Scores
Membership rates are percentages of members for groups of contacts.

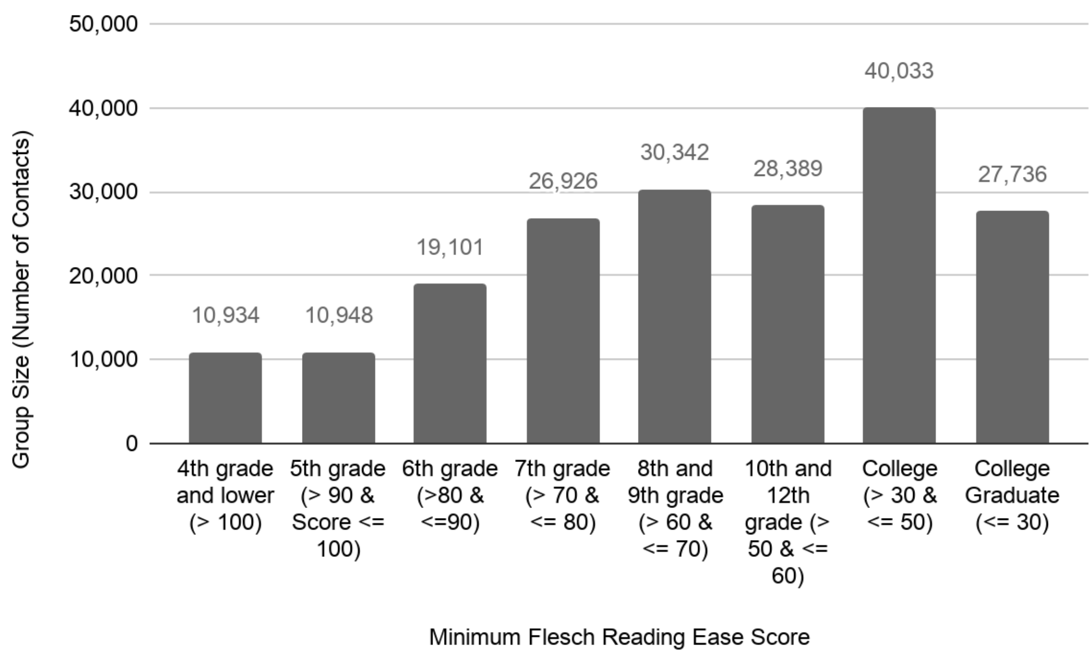


Figure 5.4.2 Group Size (Number of Contacts) for Groups of Contacts with Minimum Flesch Reading Ease Scores

Figure 5.4.3 (membership rate) and Figure 5.4.4 (conditional group size) show that the membership rates increase with average Flesch ease of reading scores from a below average membership rate of 17.2% (average Flesch score > 100; 4th grade and lower ease of reading level) to a slightly above average score of 31% (average Flesch score ≥ 30 & ≤ 50; college reading level). All categorical chi-squared tests for average Flesch score conditions have p-values of less than 0.01 except for the test where the score is greater than 70 and less than or equal to 80 (7th grade reading level). The p-value for that test is 0.01. All tests, therefore, are significant, and contacts who write text at the two lowest reading levels (highest scores) have differences in membership rates from their alternative conditions of -10.36% and -7.70%.

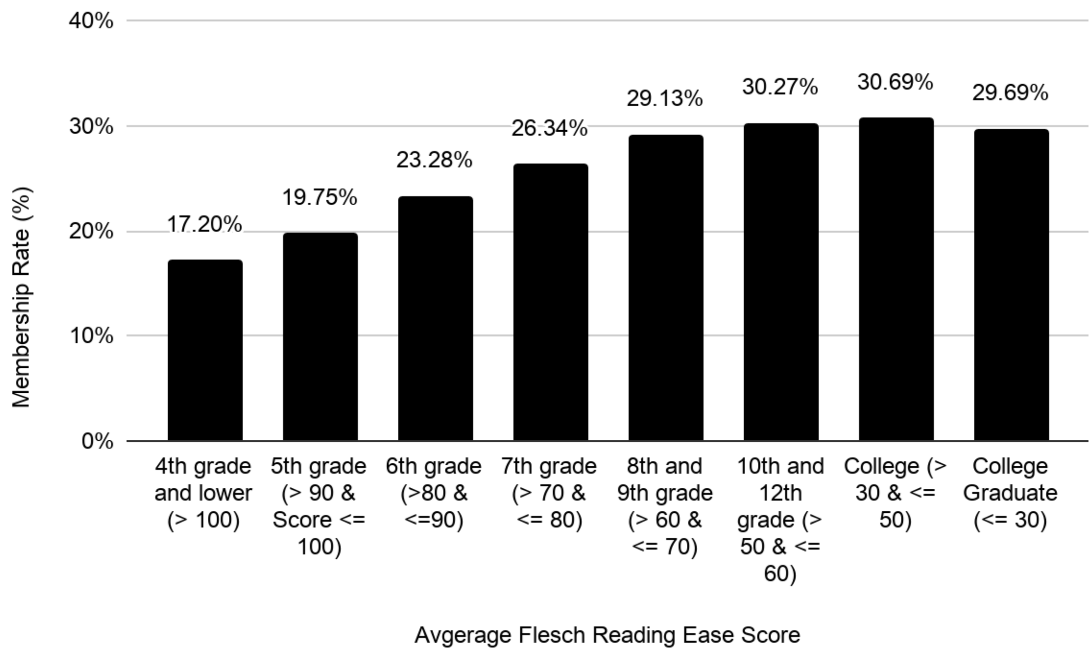


Figure 5.4.3 Membership Rates for Groups of Contacts with Average Flesch Reading Ease Scores
Membership rates are percentages of members for groups of contacts.

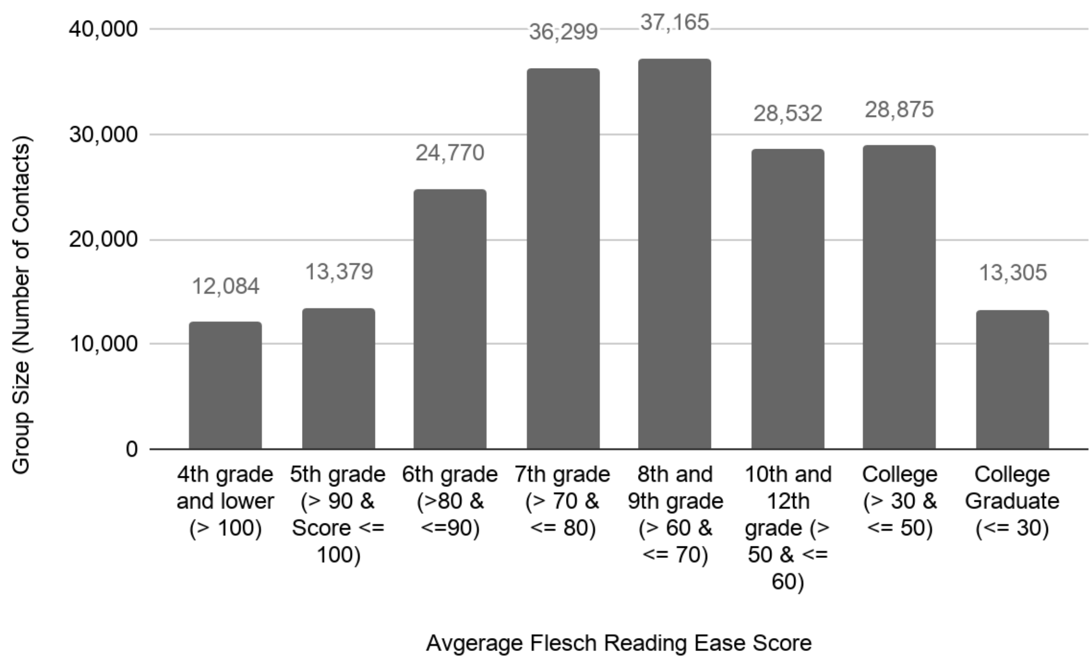


Figure 5.4.4 Group Size (Number of Contacts) for Groups of Contacts with Average Flesch Reading Ease Scores

Figure 5.4.5 (membership rate) and Figure 5.4.6 (conditional group size) show that the maximum membership rates between groups of contacts defined by their maximum Flesch scores (the simplest messages that contacts have written) are almost indistinguishable from each other, and very close to the average total membership rate for contacts who sent personal messages: 27% membership. Categorical chi-squared tests for Flesch score conditional scores of >100, >90 and ≤ 100, >80 and ≤ 90, >60 and ≤ 70, >30 and ≤ 50, and ≤ 30 have respective p-values of 0.00, 0.10, 0.65, 0.02, 0.16, 0.03, 0.73, 0.16 and respective membership rate differences from opposite conditions of 1.22%, 0.47%, 0.10%, -0.52%, -0.34%, -0.63%, 0.10%, -0.60%. Differences are, therefore, small or insignificant — and most of the time both — for this test.

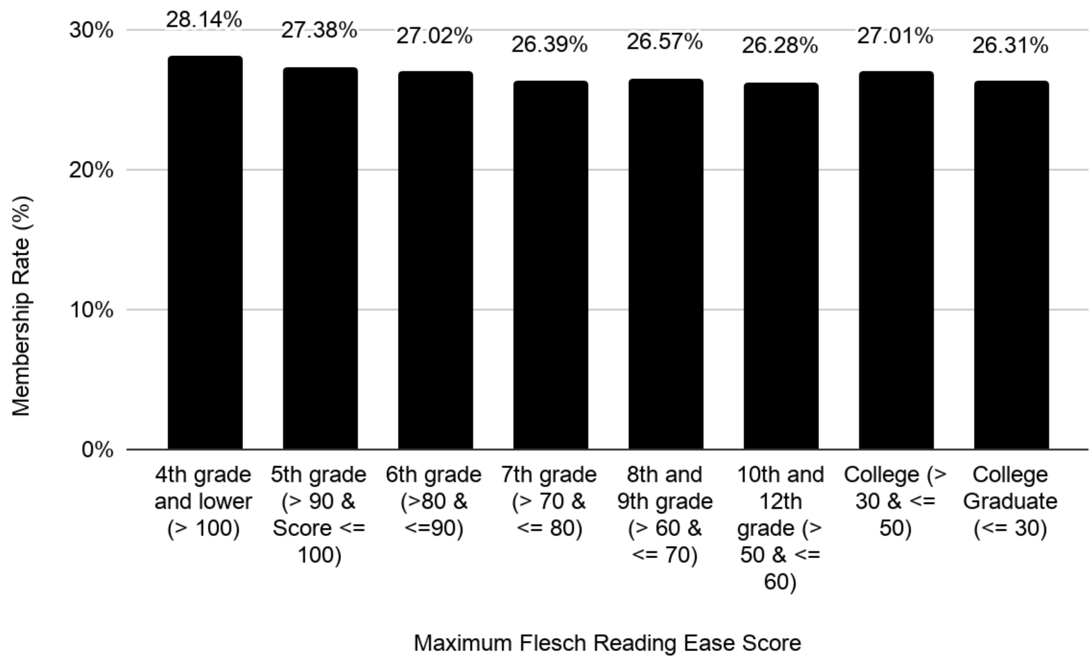


Figure 5.4.5 Membership Rates for Groups of Contacts with Maximum Flesch Reading Ease Scores
Membership rates are percentages of members for groups of contacts.

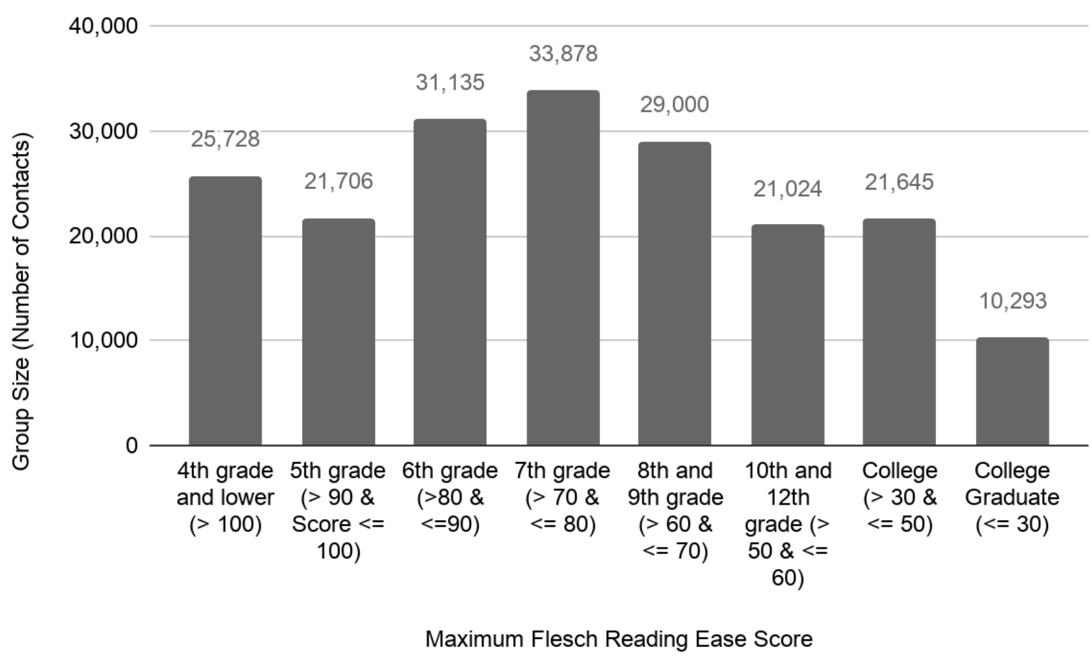


Figure 5.4.6 Group Size (Number of Contacts) for Groups of Contacts with Average Flesch Reading Ease Scores

In summary, minimum score Flesch tests are more revealing than maximum score Flesch tests. They expose the most difficult-to-read (high grade level) passages that a single contact has ever written. Those scores impact membership. Maximum scores, and therefore average scores to a lesser extent, are less revealing. If a contact writes two messages and one is short and sweet (easy to understand), but the other is complex, the complex message can tell an organization more about its author's potential to pay membership dues than the simple message.

5.5. Exploration Five: Sentiment

The compilation of all LIWC scores revealed, by accident, relationships between membership and swear words, positive words, and negative words in long messages and for contacts who sent many messages. This exploration checks for relationships between membership and sentiment. It calculates VADER sentiment scores for each message, and then calculates lumped average, minimum, and maximum scores for each person. It then calculates membership rates for VADER sentiment scores below the range of [0,-0.95] and above the range of [0,0.95] where scores below -0.05 are considered negative and scores above 0.05 are considered positive (Hutto and Gilbert 2014; https://github.com/cjhutto/vaderSentiment#about-the-scoring). Results are shown for the minimum, average, and maximum lumped scores per contact in Figure 5.5.1, Figure 5.5.2, and Figure 5.5.3. Figure 5.5.4 compares the results in a single plot.

In chi-square tests for two-by-two contingency tables of members and non-members for each VADER condition tested, p-values were all less than 0.01 except when the average compound VADER score was less than or equal to 0.6, 0.65, 0.7, 0.8, and 0.95 and the minimum VADER score was greater than 0.95. For maximum compound VADER scores, group sizes ranged from 651 to 147,540 as shown in Figure 5.5.5. Figure 5.5.6 shows the difference between the membership rates for maximum compound VADER score conditions and their alternatives conditions.

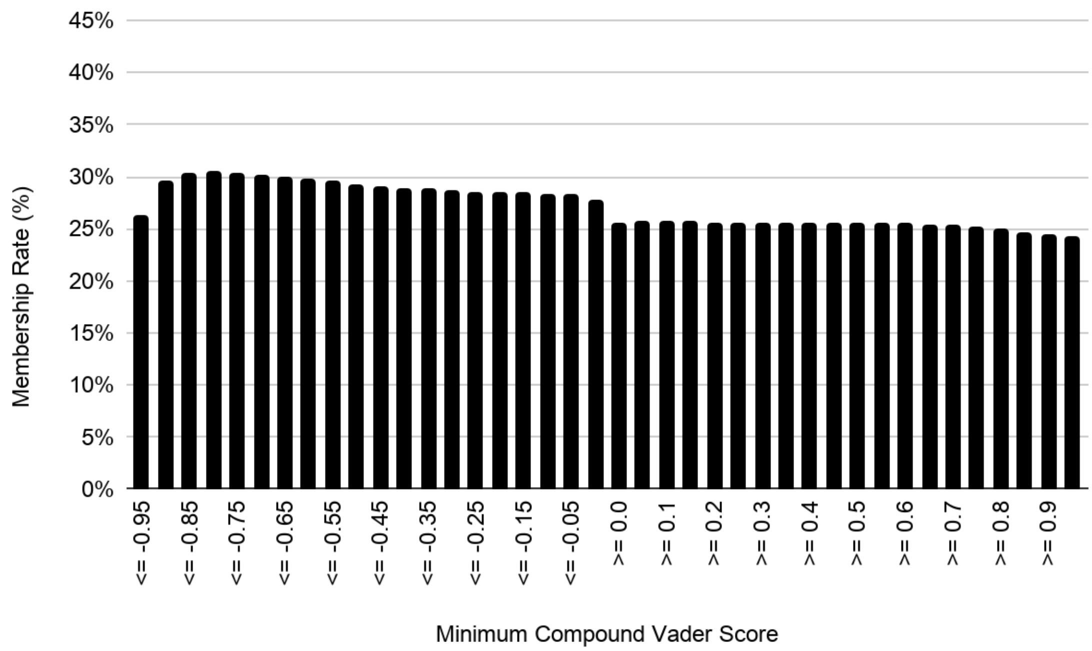


Figure 5.5.1 Membership Rates for Contact Minimum VADER Scores
Membership rates are percentages of members for groups of contacts.

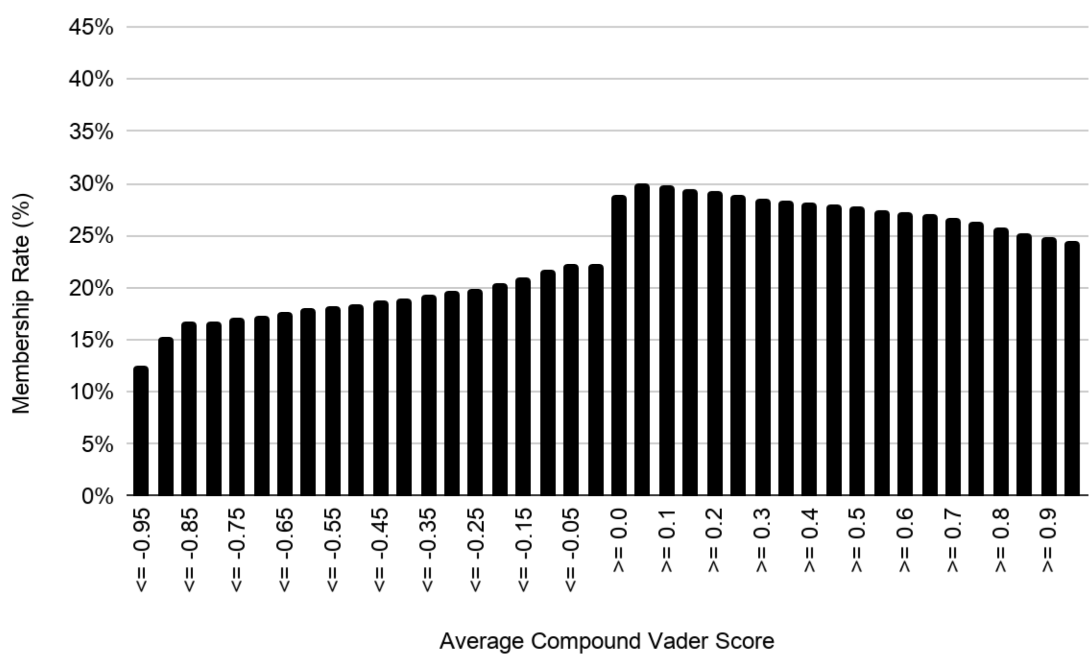


Figure 5.5.2 Membership Rates for Contact Average VADER Scores
Membership rates are percentages of members for groups of contacts.

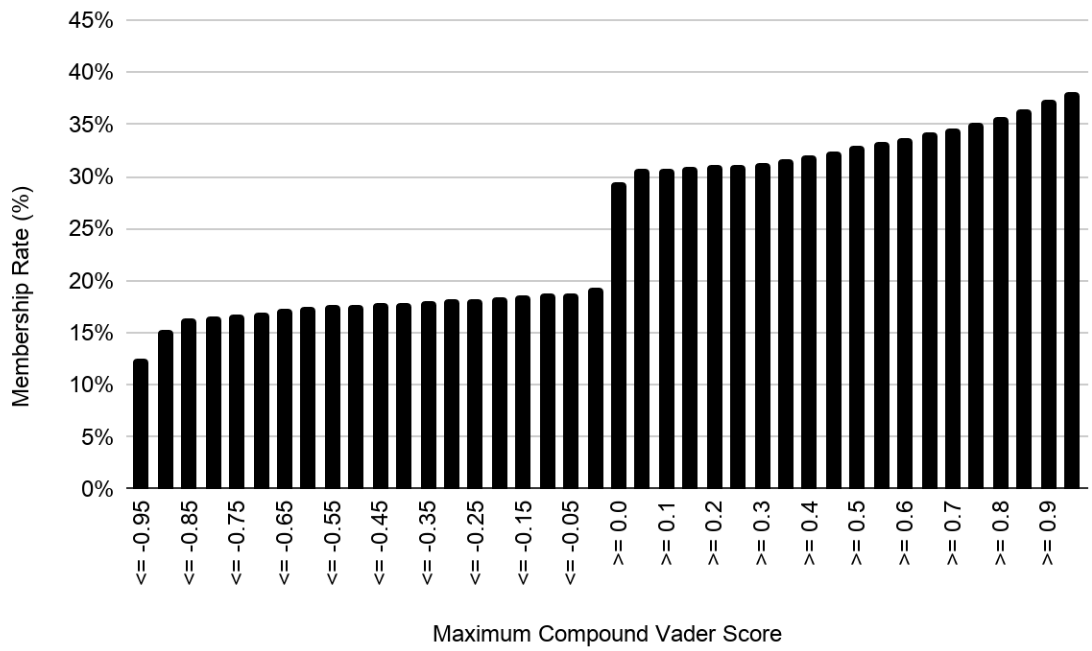


Figure 5.5.3 Membership Rates for Contact Average VADER Scores
(Min 12%; Max 38%; 18% for score ≤ 0.05; 33% for score ≥ 0.05)
Membership rates are percentages of members for groups of contacts.

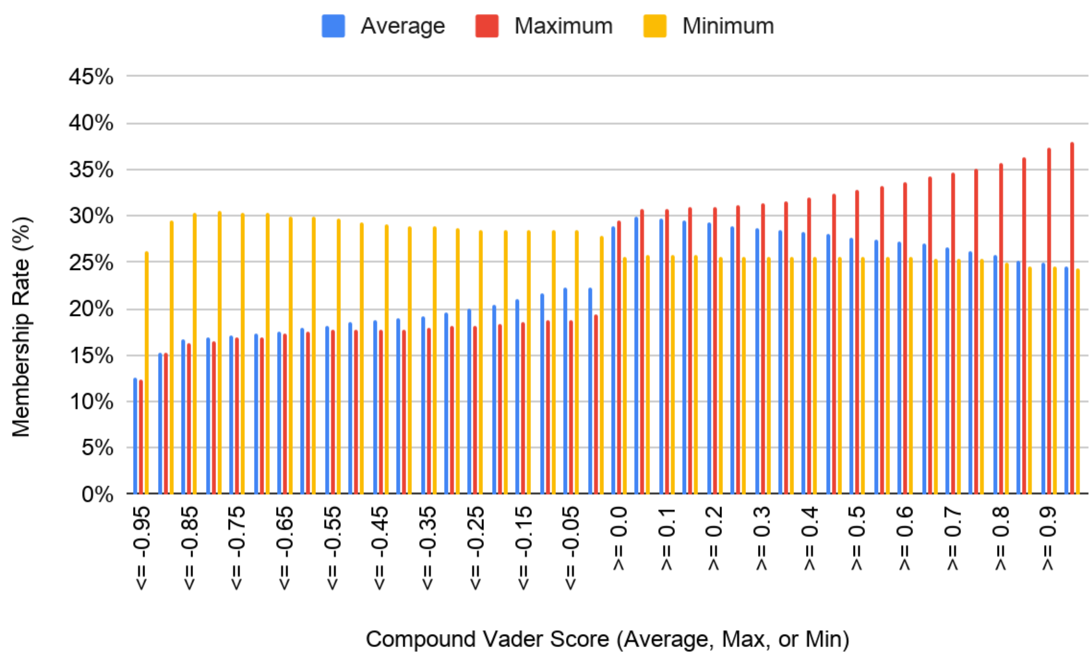


Figure 5.5.4 Membership Rates for VADER Scores (Average, Min, and Max)
Membership rates are percentages of members for groups of contacts.

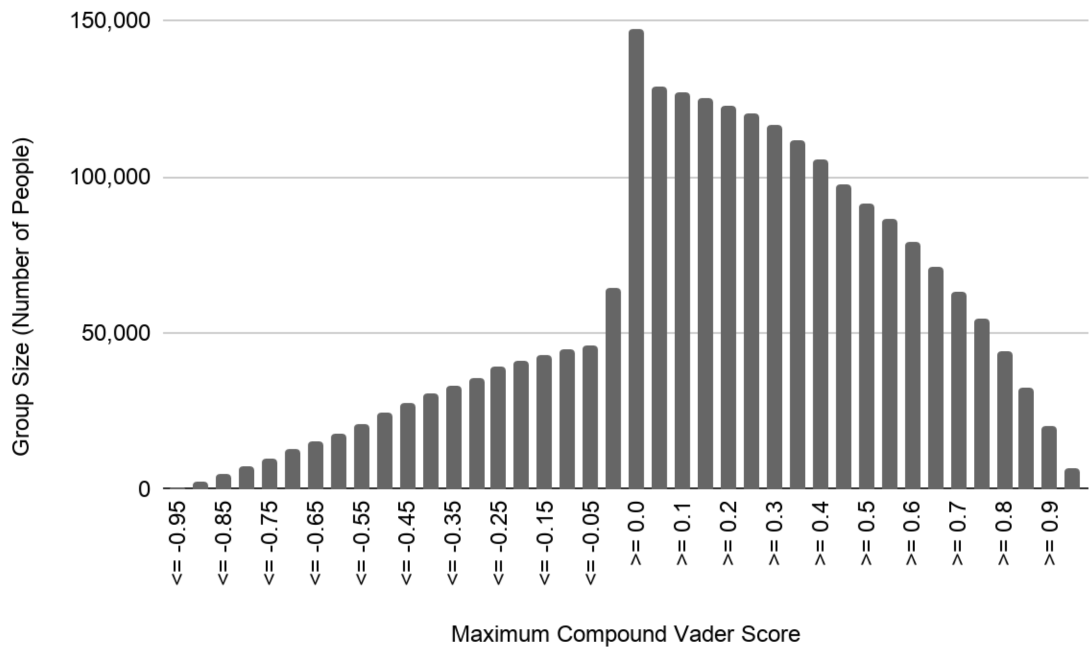


Figure 5.5.5 Group Sizes for Max Compound VADER Score Conditions
(n | total = 194,409)

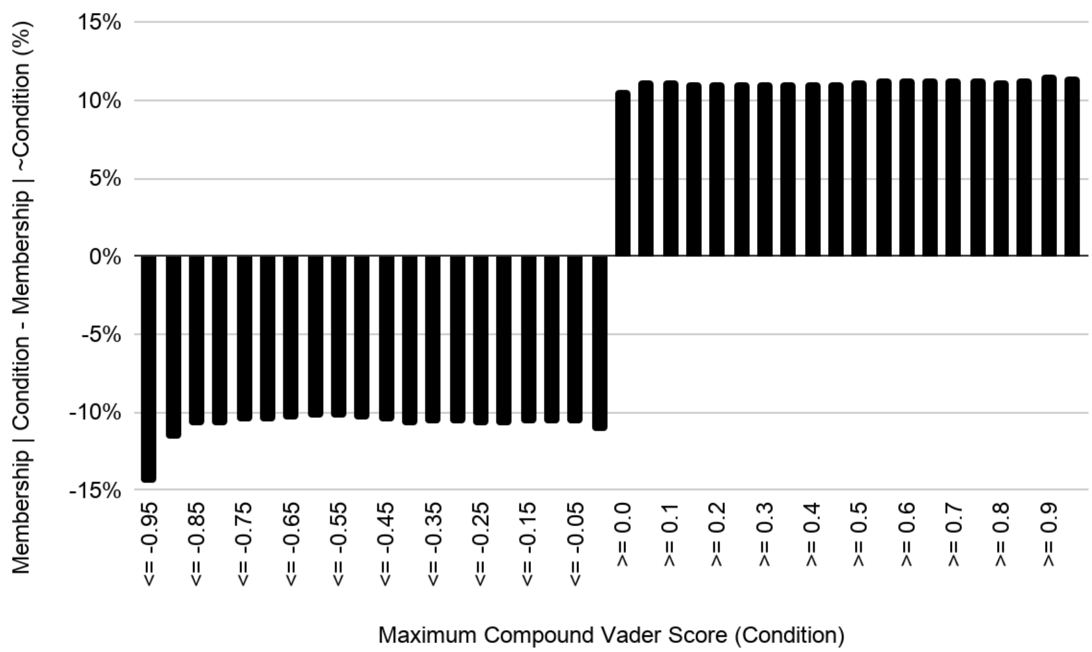


Figure 5.5.6 The Difference Between the Membership Rates for Maximum Compound VADER Score Conditions and Their Alternative Conditions
Membership rates are percentages of members for groups of contacts.

Table 5.5.1 compares members and non-members for average compound VADER scores. It shows that average membership rate for contacts who write messages with positive sentiment is close to the average membership rate overall. The membership rate for contacts who write with increasingly negative average sentiment (lower compound sentiment scores), however, decreases. Table 5.5.2 shows messages from six contacts, selected at random, for positive and negative average scores (within 0.1 of the negative and positive sentiment ratings equal to -0.80, -0.5, -0.05, 0.05, 0.50, and 0.80).

Table 5.5.1 Membership Rates and Group Sizes for Contacts Grouped by VADER Sentiment Scores

Average VADER Compound Score	Group Size	Membership Rate
≥0.05	109,765	30%
≥ 0.10	104,939	30%
≥ 0.50	53,700	28%
≥ 0.80	18,525	26%
≤ -0.05	61,999	22%
≤ -0.10	57,830	22%
≤ -0.50	26,399	18%
≤ -0.80	74,444	17%

Table 5.5.2 Example Messages with Positive and Negative Sentiment

Contact	Average VADER Compound Score	Messages
A	0.889	Message 1/1: I will be going green and buying clean energy for my family this year. Please don't pollute our environment further than you have. Be smart, and invest in our future, not wall-street. (Member)
B	0.516	Message 1/2: Our world should not be sacrificed for higher profits for the fossil fuel industry. Let’s put Virginia's people first! Our children's future can't be for sale - for any amount of money! Message 2/2: Do the correct thing! Forests are irreplaceable. North American forests are one of those forests. These lands need to be protected for all humanity. (Non-Member)
C	0.05	Message 1/1: Close down businesses like Monsanto who are helping to destroy our land. (Non-Member)
D	-0.06	Message 1/1: Any nonrenewable project here would be fool hardy when we know about the emissions that would be released. (Non-Member)
E	-0.54	Message 1/1: Fracking is hazardous and dangerous to the water we drink and the air we breathe. Gas is no longer a sustainable option. We must switch to wind power and safe energy sources or we will suffer great these bad choices! (Non-Member)
F	-0.80	Message 1/2: You've f***ed up our world with your dishonesty and greed Message 2/3: When will it stop? It is tragic that life, plants, animals, seabirds, and the source of life to millions of global citizens are vanishing. We are done with your greed in enacting this destructive legislation. Please start caring. (Non-Member; words censored for this table)

5.6. Exploration Six: Top Words

A purely exploratory test shows the 50 most popular words among all messages, scrubbed for stop words (NLTK) and American Standard Code for Information Interchange (ASCII) punctuation characters, have greater than average membership rates ranging from 29% to 40%, with an average membership rate of 30%. These rates are comparable to some of the best rates found from more-rationally searching for terms related to personal stories in Exploration Three, above. The words detect contact group sizes satisfying their conditions of between 16,215 and 61,594 contacts. With high group sizes, chi-square test p-values are all lower than 0.01 for each test (significant). Table 5.6.1 shows results from testing the top 50 words on membership rates.

Looking individually at the top 5,000 most-used words, the highest membership rate, for searches returning more than 1,000 results and significant chi squared test p-values greater than 0.01 is 50% for both the words “greenhouse” (1,059th most popular word) and “efficiency” (868th most popular word). Both are subject matter words. The alternative membership rates for these conditions (m|~c) are both equal to the average membership rate (27%). Conversely, the lowest significant ($p<0.01$, $n>1,000$) membership rate is 17%, for contacts who have used the word “impeach” (1,692). Interestingly, the four letter swear words and other negative words appear alongside this term.

Finally, note that an early miscalculation revealed the mis-spelling for the word “don’t’” as “dont” without an apostrophe has a negative, significantly below-average membership rate of 19% ($X^2 = 28$ for $k=1$ and $n=869$; $p < 0.01$). Future work might study misspelled words as a negative predictor of engagement.

Table 5.6.1 Popular Words and Membership

Term	n|c	n|~c	m|c	m|~c	m|c-m|~c	m|c-m	p
please	61,594	132,815	33%	24%	9%	6%	0.00
people	35,540	158,869	33%	26%	7%	6%	0.00
need	42,658	151,751	33%	25%	8%	6%	0.00
protect	47,671	146,738	35%	24%	11%	8%	0.00
clean	34,123	160,286	36%	25%	11%	9%	0.00
us	96,674	97,735	31%	23%	8%	4%	0.00
stop	31,377	163,032	30%	26%	3%	3%	0.00
don't	29,748	164,661	32%	26%	7%	6%	0.00
future	31,986	162,423	36%	25%	10%	9%	0.00
environment	38,524	155,885	36%	25%	11%	9%	0.00
energy	25,979	168,430	37%	25%	12%	10%	0.00
planet	23,449	170,960	31%	26%	5%	5%	0.00
water	26,025	168,384	34%	26%	9%	7%	0.00
oil	23,057	171,352	37%	26%	11%	10%	0.00
thank	24,754	169,655	37%	25%	12%	10%	0.00
air	24,813	169,596	37%	25%	12%	11%	0.00
would	22,253	172,156	35%	26%	9%	8%	0.00
trump	21,345	173,064	29%	27%	2%	2%	0.00
right	25,732	168,677	34%	26%	8%	7%	0.00
children	25,370	169,039	36%	26%	10%	9%	0.00
want	23,091	171,318	34%	26%	8%	7%	0.00
must	19,557	174,852	36%	26%	10%	9%	0.00
country	21,164	173,245	34%	26%	8%	7%	0.00
public	23,580	170,829	38%	25%	13%	11%	0.00
lands	20,700	173,709	39%	26%	13%	12%	0.00
health	24,041	170,368	39%	25%	14%	12%	0.00
make	23,925	170,484	35%	26%	9%	8%	0.00
time	22,309	172,100	36%	26%	10%	9%	0.00
money	17,087	177,322	32%	26%	6%	5%	0.00
world	18,485	175,924	33%	26%	7%	6%	0.00
keep	20,832	173,577	35%	26%	10%	9%	0.00
one	52,777	141,632	31%	25%	6%	4%	0.00
earth	16,042	178,367	31%	27%	4%	4%	0.00
national	17,270	177,139	40%	26%	14%	13%	0.00
land	33,693	160,716	35%	25%	10%	9%	0.00
generations	17,183	177,226	36%	26%	10%	9%	0.00
like	16,511	177,898	34%	26%	7%	7%	0.00
drilling	15,391	179,018	37%	26%	11%	10%	0.00
life	26,682	167,727	33%	26%	7%	6%	0.00
take	21,673	172,736	33%	26%	7%	6%	0.00
climate	14,845	179,564	39%	26%	13%	12%	0.00
many	15,687	178,722	36%	26%	10%	9%	0.00
get	21,532	172,877	33%	26%	7%	6%	0.00
know	17,732	176,677	35%	26%	9%	8%	0.00
wildlife	13,146	181,263	34%	26%	8%	7%	0.00
change	16,311	178,098	38%	26%	12%	11%	0.00
thing	33,600	160,809	32%	26%	6%	5%	0.00
think	16,596	177,813	34%	26%	8%	7%	0.00
american	20,656	173,753	36%	26%	10%	9%	0.00
care	16,215	178,194	33%	26%	6%	6%	0.00

5.7. Exploration Seven: LIWC Scores and Membership

This exploration reviews relationships between membership and LIWC scores for pronouns and other LIWC dimensions.

5.7.1. Pronoun Exceedance Tests

Exceedance tests identify contacts who have ever written a message with a score exceeding (i.e. above) a threshold. Alternative tests identify contacts who have never written a message that has exceeded a threshold. Contacts, however, can send more than one message, so alternative exceedance tests are not the same as non-exceedance tests. They may hint at results to them with increasing thresholds and linguistic consistency between messages written by the same contact. Non-exceedance tests identify contacts who have ever written a message not exceeding (i.e. below) a threshold. For example, a contact who writes two messages with scores of one and three satisfies an exceedance test for a threshold of two; three is greater than two. Because they satisfy the exceedance test, they do not satisfy the alternative exceedance test: They have not never sent messages with scores above two. They satisfy, however, the non-exceedance test; one is less than two. As the threshold increases, in this case to four, alternative exceedance and non-exceedance test results match; one and three are both less than four.

5.7.2. Pronoun Exceedance Test Results

Membership rates shown in Figure 5.7.1 change in small amounts as LIWC pronoun score exceedance thresholds increase from 0% to 10%. Membership rate ranges equal 0%, 1%, 2%, 2%, 1%, 3%, 5%, 3%, and 2% for respective pronoun, personal pronoun, “I,” “we,” “you,” “she/he,” “they,” and impersonal pronoun conditions. Membership rates change the most (5% from 29% to 23%) as “she/he” rates increase. Some membership rates for she/he pronoun conditions, however, are insignificant in comparison to alternative conditions due to the low use of the she/he pronouns. Chi-squared tests comparing observed and expected values of groups of members satisfying minimum LIWC score exceedance conditions yield p-values less than 0.01 (significant) except for tests of membership for “he/she” pronoun rates >4%, >5%, and >6%. Tests of membership rates for “he/she” pronoun rates >7%, >8%, >9%, and >10% are all significant, but catch low numbers of members (2% to 4% of all message writers). Overall, membership rate differences are small compared to those found in prior analysis.

The alternative exceedance tests shown in Figure 5.7.2 shows the presence of any pronoun (from the pronoun LIWC dimension) is more revealing than the use of any particular pronoun (e.g. from the “I” dimensions) in two ways: (a) comparing Figure 5.7.1 to Figure 5.7.2, membership rates are higher for groups who have ever exceeded thresholds and (b) membership rates drop from 28% to 19% for those who have not used any pronouns at all. The non-exceedance test (not shown) is not able to show this drop; contacts that send messages with no pronouns (pronoun rate = 0) still send messages. Membership rate ranges, like those shown in the exceedance tests, are all small for component pronoun tests. They approach the average personal message membership rate of 27% as test conditions identify increasing numbers of contacts that never send messages with scores above increasing thresholds. Word count tests show similar results to rate tests (Figure 5.7.3 and Figure 5.7.4). They highlight the effects of less frequently used pronouns (e.g. they).

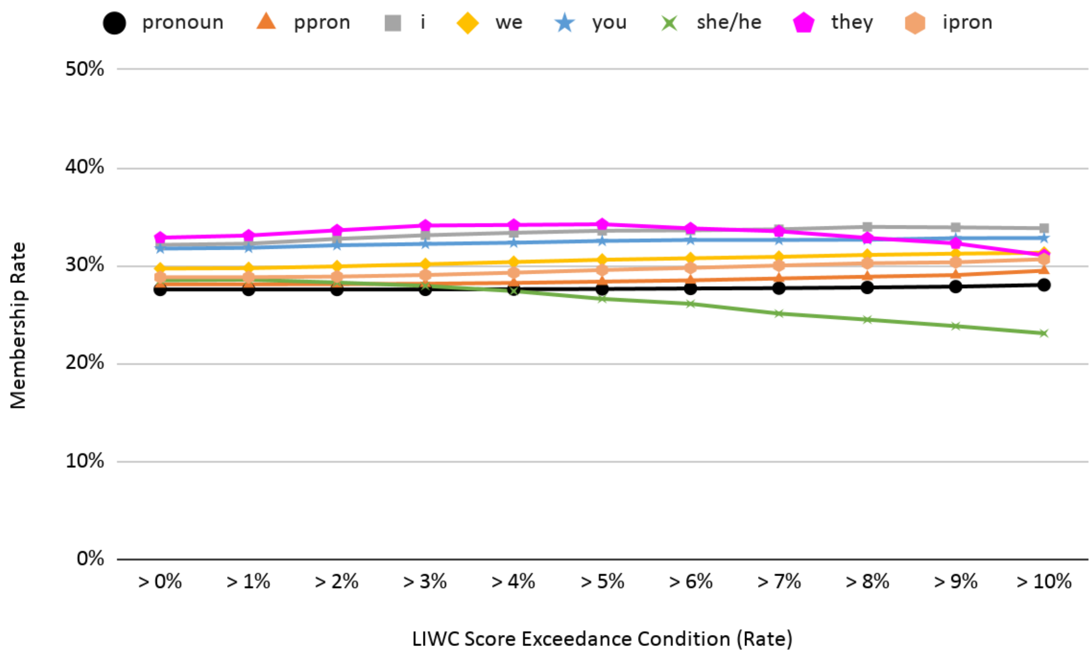


Figure 5.7.1 Membership Rates for Exceedance Conditions
Membership rates change in small amounts.
Membership rates are percentages of members for groups of contacts.

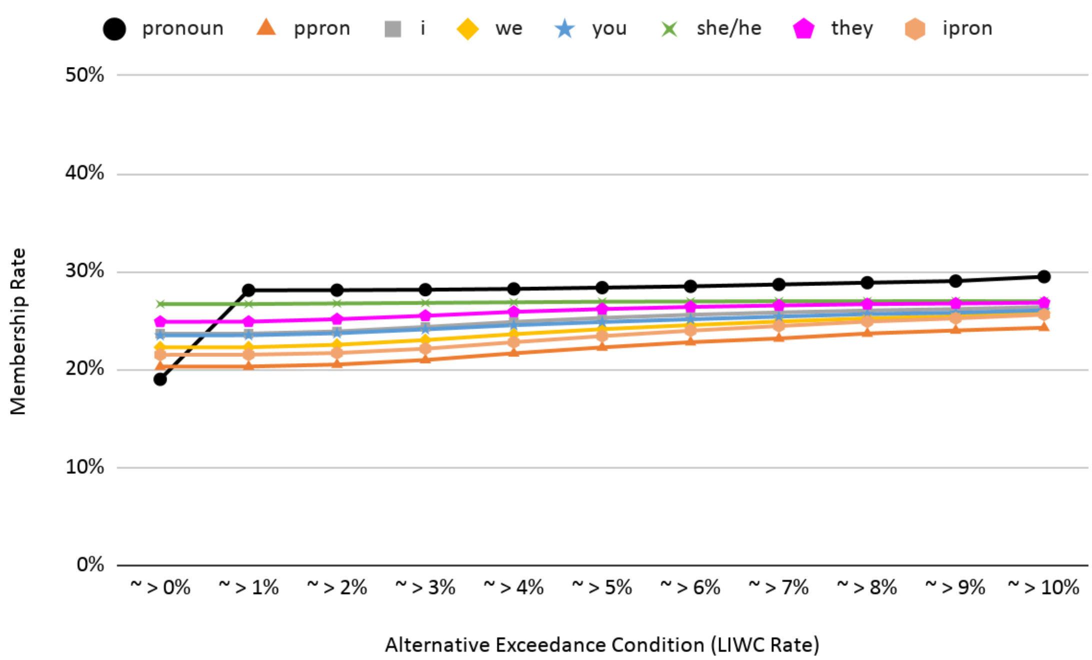


Figure 5.7.2 Membership Rates for Alternative Exceedance Conditions
Membership rates are percentages of members for groups of contacts.

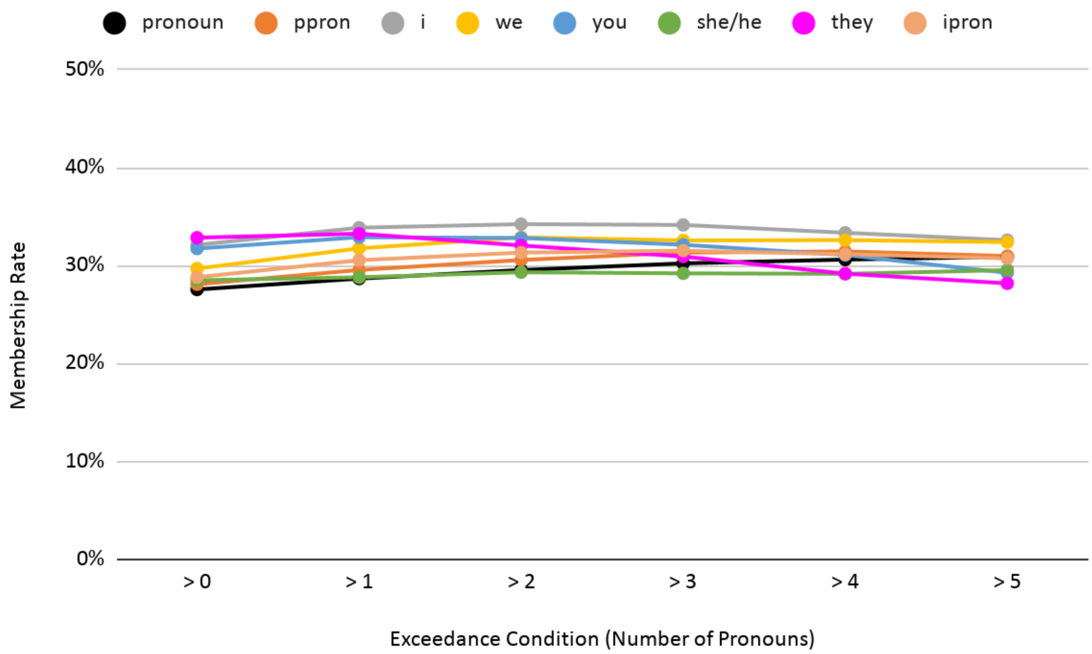


Figure 5.7.3 Membership Rates for Minimum LIWC Scores
Membership rates are percentages of members for groups of contacts.

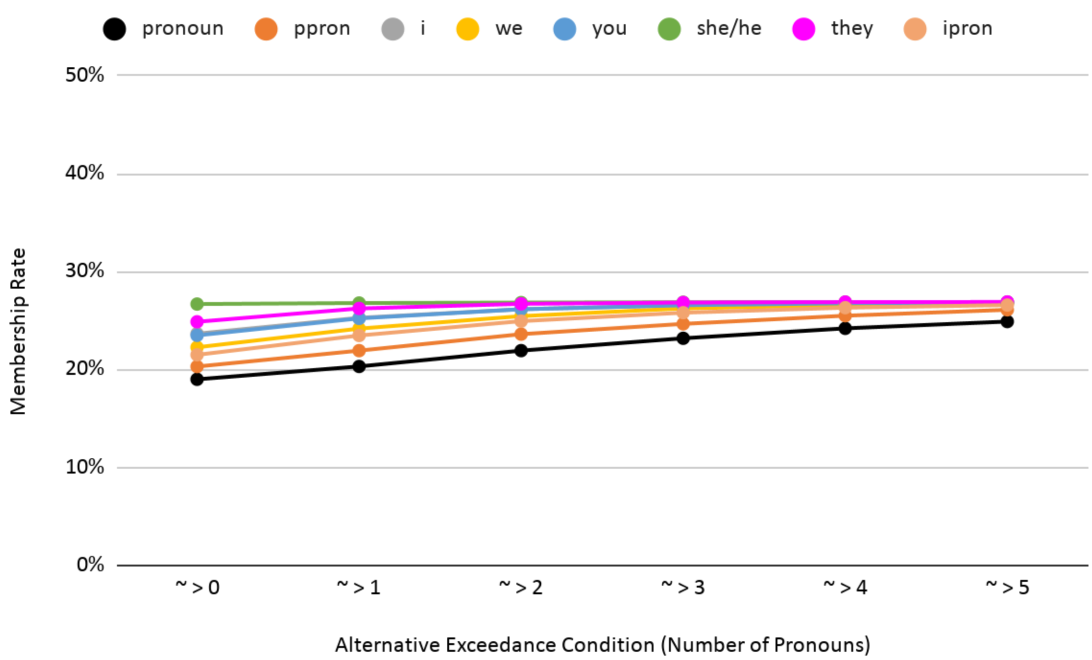


Figure 5.7.4 Membership Rates for Alternative Minimum LIWC Scores (Maximums)
Membership rates are percentages of members for groups of contacts.

5.7.3. Other Notable LIWC Dimensions: Swear Words, Punctuation, Nonfluencies, Family, and Friends

Among membership tests for each LIWC dimension, only the test for swear words, as shown in exploration three, yields a below-average membership rate (23%). The membership rate for contacts who do not use swear words equals the average membership rate for contacts who write personal messages (27%).

The presence of five LIWC dimensions yield membership rates 10% or greater than the average rate. Contacts who use nonfluencies (written out as “err,” “hrm,” “eh,” etc.), parentheses, dashes, semicolons, and colons have respective membership rates of 37%, 37%, 37%, 37%, and 39%. The tests for the alternative conditions yield slightly below average and average membership rates (26%, 26%, 25%, 27%, and 27%, respectively). Contacts who use the more common punctuation (periods, commas, question marks, and exclamation marks) all have above-average membership rates, but only by a 2 to 5% increase (3% average increase). The test for quotes yields a 36% membership rate. Members use more punctuation than non-members.

LIWC categorizes swear words and nonfluencies as informal speech dimensions. There are three more categories in the informal speech group, and they show moderate to high membership rates: netspeak (e.g. btw, lol; 31%, n=6286), assent words (agree, OK, yes; 34%, n=8,222), and filler words (e.g. Imean, youknow; 35%, n=740).

Finally, supporting results found in looking for personal stories with family phrases, two dimensions among the LIWC social sub-processes have 35% membership rates: family (e.g. husband, daughter; 27,185 matches) and friends (e.g. buddy, neighbor; 11,334 matches). Compared to the combined test for first-person references to specific family members (Figure 4.3.1; 37% membership for 20,001 contacts), the LIWC family test returns more contacts, slightly lower membership rates, and fewer personal stories.

In a random sample of ten messages that include LIWC family words, three of the messages are personal stories and seven are not. All of the personal stories contain family words prefixed the possessive first-person plural pronoun, “my:”

1. The base of the Berryessa Snow Mountains was my home for many years and I want this monument preserved for *my children* and grandchildren. It is a majestic….
2. *My family* used to swim and fish along the Anacostia River in the 50s. Please….
3. *My husband* and I are both employed by wind energy providers and….

The regular expression search for first-person pronouns followed by family words is more specific than the identification of LIWC family words, but it would not miss any of the stories found by the LIWC search in the random sample of ten messages. Three of the messages in this sample do not contain stories (false positives). The regular expression would correctly classify them as not stories. The three messages contain references to (1) “big brother,” (2) “mother earth,” and (3) “your children” but do not describe any lived experiences.

CHAPTER 6. DISCUSSION

6.1. Objective One Discussion: Messages per Contact as a Measure of Organizational Engagement

6.1.1. Pronouns and Messages per Person

Consistent with prior studies (e.g. Pennebaker 2017, pp 63, 118; Lenard 2016), small differences (<1%) in the use of pronouns yield significant findings. Results show that groups of contacts who send personal messages with lower rates of pronouns overall, lower rates of personal pronouns overall, lower rates of first-person plural “we” pronouns, and moderately greater rates of “you” pronouns, also send more messages (Table 4.1.1). The decreasing use of “we” words is the clearest individual pronoun predictor of increasing numbers of messages that groups of contacts send ($R^2 = 0.87$). This could indicate contacts with positive, personal association (Pennebaker 2011) with their state or country (e.g. “our country...” vs. “make America...”) send fewer messages. A sentiment test on all messages moderately supports this theory. Messages with a high use words “we” words exhibit a higher degree of positive sentiment (>5% “we” words; 0.21 VADER compound sentiment) than messages with a low rate of “we” words (<3% “we” words; 0.09 VADER compound sentiment).

While clear relationships exist between the central tendencies of LIWC pronoun rates for *groups* of contacts, they cannot be used to predict the number of messages that most *individual* contacts will send based on their first message. The observations and calculation checks made in the report of results for testing Hypothesis One (Section 4.1.2) shows this is true for averaging rates in different ways and for different sets of messages. Further, Section 5.2 shows Hypothesis One cannot be accepted for individual contacts, ungrouped, because most contacts do not send enough long messages. Like most social media posts, personally authored advocacy messages are short (Figure 4.1.16). Unlike social media posts, many contacts write just one or two through systems controlled by a specific organization. This study looked briefly at these two properties — length and quantity — in calculating the correlation between the use of first-person plural "we" pronouns and the number of messages that contacts send: Table 4.1.3 and Figure 4.1.17 show that the number of contacts sending messages is more important than the length of their messages in establishing correlations. (Future work could test if this relationship holds true for other LIWC dimensions.) In simpler terms, ranges of three to four percent usage of "we" of pronouns, 13.6% to 14.4% usage for all pronouns, and 2% to 3% usage of "you" words are small considering the average length of a personal messages is 29 words, and the mode length is 11 words (Figure 4.1.16). Four percent of 11 is zero whole words.

6.1.2. The Pronouns of Environmental Advocacy

Given the relevance of groups of messages compared to individual messages, a comparison between the biggest group of messages in this study — all messages — with summaries of other corpuses of text provided by the LIWC manual defines a language of environmental advocacy. The other corpuses include tweets, blog posts, essays, news articles, and novels. Environmental activists use "I" words at much lower rates (1.62% compared to 4.99%) and "we" words at much higher rates (3.92% compared to 0.72%) than authors of text among the other corpuses (Figure 4.1.9). They use similar rates of "she/he" words as those found in tweets, which are much less than those found in longer passages of text. Like a parent talking to a child, this low use of "I" words and high use of “we” words indicate environmental activists write to their policymakers from a seemingly higher social status (Pennebaker 2011, pp. 174). Supporting this theory, nine out of ten randomly selected messages that begin with the word “we” use the word “we” as the word “you,” a policy maker, or as the words “me and you.” In the message, “we must avoid being the country responsible for unleashing the beast of climate change by monstrous policies that only benefit big oil and agriculture companies” the word “we” refers first to the U.S. and then directly to the message recipient who, assumedly, can enact “monstrous policies” or not. The low use of “I” words and low use of “she/he” words that all environmental advocates use do not indicate anything about social status, but may help explain the less clear trends for these pronouns identified in the test of Hypothesis One.

Finally, the overall high use of “we” words and the low use of “I” indicates that either (a) there are more male contacts (Pennebaker 2011), or (b) female activists use a typically “masculine” political vocabulary of personal pronouns — also more typical of the language of modern female politicians — when writing policymakers (Jones 2017). Interestingly, two out of three contacts are female, supporting the latter of these two theories. Future work could investigate what this means for the two engagement factors given males have higher overall membership rates (37%) compared to females (29%).

6.1.3. Personal Messages Rates and Word Counts

Hypothesis Two test results show that both the number of personal messages and the number of all messages decrease for groups of contacts sending increasingly large numbers of messages per contact. The number of messages sent also increases from 1 to 10 (the bulk of the data) as the average *rate* of personal messages increases from 20% to

25% (left side of Figure 4.2.1). As the number of messages sent continues to increase, the rate decreases to 15% at the group that sent 40 messages, and then steadily increases to 50% for groups of contacts who sent 90 messages (left side of Figure 4.2.1).

In summary, groups of contacts who send personal messages at rates of 18% (one personal message for every five messages) are less likely to send a second message. Groups of contacts who do send more than one message usually send them with a personal message rate of 25% (one personal message for every four sent). These groups, however, will be smaller than the groups with lower personal message rates (Figure 4.2.3). Advocacy organizations and policymakers evaluating an initial wave of messages from a specific group, therefore, can expect both continued action (a second message) and higher rates of personal messages if this initial wave of messages has a personal message rate of 25% or more.

Advocacy campaign managers who value greater numbers of personal messages to look for personal stories in, and building relationships with contacts who send more of them, therefore, should not be discouraged by an overall lower number of messages in the response from a specific campaign compared to similar campaigns if the rate of personal messages returned from the campaign is high (25% vs. 18%). Results emphasize the importance of asking contacts to write personal messages, if not to help amplify their voices and identify personal stories, to at least help predict future engagement.

Hypothesis Three test results show that while the number of messages sent roughly increases with slightly decreasing word counts for groups of contacts (29 to 26 words; $R^2 = 0.69$; data top-coded at 30+ messages), contacts sending more than one message send them at the overall average word count of 29 words compared to 28 words for those who send a single message. This difference is small and insignificant for low numbers of messages. For large numbers of messages, it will be easier to discern one in five personal messages from one in four personal messages as shown above in comparison to discerning 28 words per message to 29 words per message. This one-word difference could also easily be affected the language of a specific campaign. Message analysts should not, therefore, use this metric to predict the number of messages a group may send in the future without testing the metric across high rates of similar campaigns.

6.2. Objective Two Discussion: Exploring Membership, Personal Stories, Sentiment, and Writing Simplicity

The results from the three initial hypotheses inspired an exploration into membership as a measure of organizational engagement. Results show that the number of messages written, the use of pronouns, the identification of personal stories, sentiment, writing simplicity, the use of swear words, the use of punctuation, the use of popular words, and potentially the use of misspelled words can all help organizations identify membership rates. If the 90,698 contacts categorized as members pay an average of $52/year, campaigns receive $5.7M/year. If all 690,631 contacts paid this amount, campaigns would receive $35,912,812, more than double the budget of Greenpeace, the smallest environmental advocacy organization listed in Table 4.3.1.

The membership rate for all contacts is 13%. The membership rate for contacts sending personal messages is 27%. As described in the introduction to Objective One, this study describes 5%, 10%, and 15% membership rate differences from the average 27% rate, as moderate, strong, and very strong differences, respectively. Tests show:

1. Membership rates increase with message rates.

   Relating the two rates of engagement (messages and membership), membership rates more than double, from 16% to 35% for groups sending one to ten messages, before leveling off. Groups sending 20 or more messages have an average membership rate of 37%.

2. Membership rates increase with average word count.

   Membership rates increase from 17% to 30% for the contacts who sent messages between one and 40 words long, before leveling off. Contacts who have sent messages with an average word count greater than 40 words have an average membership rate of 28%.

3. Membership rates increase with certain words and phrases.

   Regular expression searches for personal stories with pronouns, verb variations, and LIWC scores return some stories of lived experiences, but they also identify authors in other ways. Membership rates increase with first-person pronouns and

   a. References to wives, e.g. "my wife" (51%; 410 contacts)
   b. References to family members, overall (37%; 2,001 contacts)
   c. Identification with phrases that begin with "As a," (40%; 6,749 contacts) "I am a," (38%; 3,338 contacts) "We are" (33%; 5,692 contacts) and "We are a" (32%; 2,323 contacts).
   d. Self-identification with the male gender, e.g. "I am a father…" (45%, 56 contacts)
   e. Self-identification with the female gender, e.g. "I am a mother…;" (34%, 150 contacts)

f. Self-identification of residence, e.g. “I live…” (39%; 3,737 contacts)

g. Self-identification as a family member, e.g. “I will be a grandma…” (44%; 216 contacts)

h. Self-identification as a teacher with verbs, e.g. “I teach” (38%; 185 contacts), but not with titles (e.g. “I’m a school teacher”)

i. Self-identification with “ist” roles, like “scientist or biologist” (41%; 386 contacts) and “er” roles, like “carpenter” or “driver” (39%; 2,076 contacts)

j. Volunteering verbs (52% membership rate; but only 66 matches; $p < .01$)

k. Outdoor activity verbs, e.g. “I have hiked” (49%; 682 contacts)

5. Membership rates decreased with the use of swear words.

   Membership rates did not significantly increase or decrease for most words describing suffering, but they significantly and very strongly decreased for members using swear words, as low as 11% for 260 contacts beginning their messages with a word beginning with the letter “F” and 15% for 946 contacts using that word in their message. Membership rates for the group of contacts using any LIWC swear word (swear rate > 0) decreased to 23%.

6. Membership rates increase with writing grade-level (i.e. message complexity).

   Membership rates steadily increase from 16% (4th grade level) to 37% (college graduate) with decreasing minimum Flesch ease of reading scores (21% range).

7. Membership rates increase with sentiment.

   Maximum compound VADER scores describe the most positive message a contact has sent. They are good indicator of membership (Figure 5.5.3; 12% to 38%). Minimum and average VADER scores are less descriptive. Contacts with negative maximum VADER scores (<-0.05) have an average membership rate of 18%. Contacts with positive scores (>0.05) have 33% membership rates (15% range).

8. Membership rates increase with popular, on-topic words like “efficiency” and “greenhouse” and decrease with negative words.

   Among the top 5,000 subject words used in messages, the two words (a tie) used by at least 1,000 contacts with the highest levels of membership (50%) are “efficiency” and “greenhouse.” The word used by at least 1,000 contacts with the lowest membership level (17%; n=1,692) is “impeach” and is found among swear words not tested earlier with similarly low membership rates.

9. Membership rates increase with the presence of any pronoun compared to no pronouns.

   Contacts who do not use pronouns at all have low membership rates (19%). For contacts who do you use them, individual pronouns rate increases reflect only small changes in membership rates.

10. Membership rates increases with the use of nonfluencies (37%) and less used punctuation (38% for colons).

11. The membership rate is low for contacts who misspell “don’t” as “dont” (19%).

Results sketch a picture of a stereotypical member: An outdoorsy parent with a job and spouse that talks about their children. They write for an educated audience and use positive, issue-related words in sentences delineated with punctuation. They do not complain about impeachment or use swear words, but may informally write nonfluencies into their messages.

For one analyst, identifying personal stories in advocacy messages will help their organization “be better set up to recognize what kinds of personal messages we are getting, and which have the best value for continued/increased engagement.” This study used regular expressions inspired by keywords that campaign managers use. It used first-person phrases and looked for references to family, home, suffering, and personal interests. Matches showed that what makes a personal story “personal” and a “story” is subjective and a framework that could categorize and measure story attributes in short advocacy messages could be helpful. In conducting these searches, matches also revealed information about contacts that an advocacy organization or policy office might collect in a survey. Contacts reveal personal interests, professions, and family information in there stories. Self-written levels of education were only found in small numbers, but the writing complexity score and found occupations may hint at these levels.

6.3. Limitations and Two Database Gotchas

This study found that compared to predictors of membership investigated in the exploration (Objective Two), pronoun predictors for the number of messages a contact sends has limited practical application for the initial problem that inspired this research — rapid response to a new contact with limited information. The length of most messages are too short to be studied individually with pronouns only. Additionally, this study (a) was not segmented by location or topic, (b) did not have access to a complete contact demographics, but it could have used state as a proxy indicator, (c) did not have exact location data so it did not address an originally proposed objective to test engagement and personal stories with the proximity to sources of pollution, and (d) did not have access to political affiliation for any contacts. Future work and case studies could address these limitations.

There are two database problems that all data analysts should watch out for and were found in this study: (1) Some raw database IDs for some campaigns were alphanumeric case-sensitive strings. In creating a contact table, a new auto increment primary key may be created to avoid this problem. This study used a case-sensitive field collation to address the problem. (2) Data from different organizations and different for different campaigns used different character encodings. A few points of data had quotes replaced by questions marks. After correction, LIWC analysis trends became slightly more definite.

CHAPTER 7. CONCLUSIONS AND FUTURE WORK

7.1. Text Analysis for Online Advocacy Organizations

> *We stand now where two roads diverge. But unlike the roads in Robert Frost's familiar poem, they are not equally fair. The road we have long been traveling is deceptively easy, a smooth superhighway on which we progress with great speed, but at its end lies disaster. The other fork of the road — the one less traveled by — offers our last, our only chance to reach a destination that assures the preservation of the earth.*
>
> — Rachael Carson, Silent Spring, 1962

> *My message is that we'll be watching you. This is all wrong. I shouldn't be up here. I should be back in school on the other side of the ocean. Yet you all come to us young people for hope. How dare you. You have stolen my dreams and my childhood with your empty words. Yet I am one of the lucky ones. People are suffering.*
>
> — Greta Thunberg, United Nations Climate Action Summit, 2019

Carson paints a picture and provides efficacy to her readers to think and make decisions — readers without the internet and policymakers without fax machines. Thunberg is direct and angry, speaking like a hero in the golden age of distraction. VADER sentiment scores rate their respective quotes negative (-0.2) and more negative (-0.4) and Flesch scores rate them readable to 7th grade students (Flesch score of 77) and low-grade-level students (Flesch score of 98).

Jones (2017), Lenard (2016), and Pennebaker (2011) would contend that Carson's high use of first-person plural inclusive "we" words represent a high social status and a "masculine," authoritative linguistic style that female politicians have recently begun to adopt. They would say Thunberg's high use of pronouns (one or more in almost every sentence), and especially her high use of the word "I" reflect a female speaker, self-focused and aware of the suffering of her generation.

These researchers have shown that the words and public speeches of leaders, candidates, and officials who people elect to represent their families and vote for their children's future, are well studied, and a joy to analyze and read about. Philosophers, bloggers, and reporters study how these leaders speak to their constituents and each other and archive their words as history. What can researchers now learn about the words that activists speak back to power? How will organizations use this knowledge to empathize, ally, or manage them?

⁂

This dissertation was inspired by the successful development of an online advocacy system created for a small nonprofit organization in Maryland in the early 2000s. It helped the group of faith-based and union-backed organizers win living wage and healthcare legislation by filling state legislators' inboxes with customized form letters, properly addressed via a GIS-based zip code matching system. As petitions do, it also helped the organization recruit members and grow. "Slacktivism" worked! But this form of activism turned from influencing policymakers to disengaging them (Miler 2014, Social Change Agency, 2017a, Congressional Management Foundation 2017) and the term "slacktivism" was coined as such by Morozov in 2009. White, at this time, decried the "ideology of marketing" in activism as "clicktivism" (2010). Even so, this study and advocacy organizations listen to Karpf (2017, 2018), resolutely looking for the potential of analyzing and A/B testing everything. Results from this research show that environmental advocacy organizations should solicit and analyze personal messages from their constituents to both limit slacktivism — that is, limit disengaging policymakers with impersonal messages — and bolster their understanding of their contacts. In soliciting personally written messages, in combination with services like Communicating with Congress (CWC, 2017), advocacy organizations can help keep policymakers from being inundated with form-letters. In analyzing personal messages, organizations can exploit and improve on the metrics reviewed in this study.

At minimum, organizations need to continue giving individuals the option of writing a personal message in online advocacy campaigns. If they are not already doing so, by starting they can begin to predict future behavior from their contacts' messages. Results show that the membership rate for those sending a personal message in this study's data is 27%, compared to the overall 13% membership rate for those sending any type of message, personal or otherwise: more than double. Results also show that groups of most contacts who write personal messages at rates of higher than 18% (one in five), also send more than one message. Simply asking for and counting personal messages can help organizations establish baseline engagement predictions without any text analysis. Additionally, given that impersonal messages can disengage policymakers and bury the personal messages, organizations should also stop sending impersonal letters along with personal ones, or flag them in a way that systems like CWC can recognize them as petitions. Without a system like CWC that mitigates the risk of losing personal messages among others, organizations should hand-deliver signatures in batches or at strategic times to avoid disengagement with policy makers.

Once advocacy organizations are collecting personal messages, they should analyze their text to help them further predict the number of messages that groups of constituents will send and future payments for membership. Results from this study show analysts and algorithms can use text in two situations: (a) in analyzing and engaging large groups of individuals, and (b) in response to a contact immediately after they have sent a message (i.e. the chatbot predicament). Results show that, in analyzing groups of contacts, low pronoun rates overall and low first-person plural “we” pronoun rates indicate a group will be more likely to send more messages. For either analyzing groups of contacts or rapidly responding to a single contact online, the results also show that organizations should be able to more readily ask for membership contributions from contacts who have sent increasing numbers of messages and word counts approaching a threshold. The threshold for this study was 30 words — one word above the average. It may vary between organizations and campaigns.

From within the text, to further identify potential members, advocacy organizations should look for messages written for higher reading levels (low reading ease scores), and use of positive sentiments, self-references, references to family and friends, punctuation, and informal speech aside from swear words. Organizations and campaigns are unique, so campaign managers should pilot the relevant engagement factors discussed above for their own data in order to reveal other trends. They may begin doing this by identifying and testing popular words. Message reviewers may use regular expressions or future machine learning models to help them identify personal stories, but these methods should not replace timely, human review of messages. Text metrics are not perfect, and they can be misused.

7.2. Test Analysis for Policymakers, Service Providers, and Stakeholder Managers

In the same way that online advocacy organizations learn from electoral campaigns, but should not mimic them (Karpf 2017), policymakers should conduct the analysis recommended above for advocacy organizations but adjust them to fit their situations. Given term limits in public offices, policymakers may not start their terms with large histories of constituent engagement. With smaller databases, they will not be able to run the pronoun use tests to anticipate future message frequencies.

As policymakers build their CRM databases, they will also find themselves in the unique situation where they are receiving messages couriered by several advocacy organizations about a single policy or project. In this case, they will be able to use text metrics to spot and judge power differences between organizations. For advocacy organizations, Karpf (2018) emphasizes that data, in general, needs to be delivered in ways that decision makers can interact with. This is equally true for policymakers. To support policy makers and advocacy organizations alike, online advocacy service providers (e.g. CWC) need to build text metrics into their reports.

Stakeholder management researchers, Kahn et al. 2017, have developed psychological attributes that they recommend civil and environmental project managers to look for in managing stakeholders: motivation and concern, expectation and perception, and attitude and behavior. These researchers share best practices for managing supportive, indifferent, and adversarial stakeholders (Kahn et al. 2019). In summarizing Petro-Canada's website, their research praises Petro-Canada's "highly-rated . . . 'win-win' policy" of "innovative and diverse strategy execution measures" for its "fair, ethical and professional approach in its dealings with its secondary stakeholders in all its projects and operations inside and outside Canada." They highlight an example, originally shared by Petro-Canada, of how this fossil fuel company put a local fishing community at ease during exploration of drilling sites offshore of the Caribbean islands of Trinidad and Tobago. The company conducted courses for the fishers on how they could learn new “survival techniques” and safely continue using their equipment during the offshore exploration. At the courses, they gave away reflectors and GPS devices. They also installed “fish aggregating devices” to keep fish away from their exploration. The researchers also show how Petro-Canada paid for First Nation social programs, like a daycare facility, before mining their land in Fort McMurray, Canada. Future studies could investigate if psychological attributes described by these researchers could be identified through text analysis of constituent messages. If so, in promoting environmentally sustainable technologies or not, policymakers could share findings with civil and environmental project managers, and they, together, could judge the power of influence that the stakeholders have over their projects and researchers could test the management frameworks introduced by Kahn et al. For example, stakeholder managers and policymakers working with (or for) companies like Petro-Canada, who implement education programs, hazard mitigation infrastructure, and social services to ensure safety and public acceptance of their projects, could benefit from analyzing advocacy messages. Opposition letters to offshore drilling and mining in communities written with relatively high rates of pronouns, high writing grade levels, and high numbers of personal stories about “my” or “our” children could help these managers plan increases to their community engagement budgets. If messages come from more than one environmental advocacy organization, text analyses could further aid stakeholder managers to determine which groups have the highest numbers of dues-paying members and could best fund putting the personal stories they are collecting into community forums, legal testimony, and advertisements.

7.3. Future Work

7.3.1. Engagement Framework and Investigating Relationships of Messages and Time Use Profiles

Future work should consider past research to develop a social cognitive theory to describe what a regular dues-paying member is, what a person with a lived experience is, and what a volunteer is — three roles that describe people that environmental advocacy organizations seek to engage. To start, it could use an online implementation of Arnstien's "ladder of citizen participation" (1969) as an engagement dimension. Next, it could use the Bureau of Labor Statistics (BLS) American Time Use Survey (2019) data to determine a dimension for volunteering.

It should then see if relationships between text analysis metrics found in this study and additional data, like more granular membership contribution data and constituent event participation histories, can help explain the roles defined by the theory. A multivariate model could help predict how well contacts fit into these three roles. Given BLS data, for example, occupations reported by contacts in messages could help rate a contact along dimensions for volunteering and giving without asking contacts questions directly; BLS reports unemployed people volunteer twice as much (0.44 hrs/day) as employed people (0.21 hrs/day). Flesch scores, if tied to education and income, could help place a contact along a dimension for giving.

This theory-based approach of making educated guesses of engagement predictors and then piloting them contrasts machine-learning approaches and the approach employed by Exploration Six in this study. Without any social or behavioral *a priori* observations or theory (or "bias," depending on how relevant observations and theories are to specific situations), Exploration Six brutally tests thousands of the most popular words in this study in an attempt to find words that contacts use with minimum frequencies indicative of high and low membership rates. Model development should use both theoretical and exploratory approaches. Machine learning and unbiased exploration might confirm theories, or it may inspire additional theories and tests. Exploration Six and Exploration Seven in this study, for example, confirmed the relationships between negative words and membership studied in Exploration Three, exposed the relationships between nonfluencies and punctuation with membership, and inspired the review of all informal word dimensions categorized by LIWC.

7.3.2. Doing What You Love or Marginalizing "Lost Voices"

In the development of any engagement model, as described above, advocacy organizations should be wary of focusing on any one measure of engagement at the expense of others. During the November 2019 Virginia state elections, non-partisan Get Out The Vote (GOTV) canvassers working with Virginians Organized for Interfaith Community Engagement (VOICE) were rewarded with more smiles, more residents willing to take publicity photos, fewer slammed doors, and fewer guard dogs, when canvassing in more affluent neighborhoods where more people were excited to vote or could be encouraged to register (pers. exper. 2019). Nall (2018) explores these behaviors, investigating situations where on-foot canvassers stay in the neighborhoods where they receive positive responses and where they have smaller social distances from residence (e.g. language). In response to these perceived successes, canvassers could inadvertently marginalize the people that are directly affected by issues that their organizations are addressing. Canvassers may miss testimony, miss the opportunities to ally with people directly affected by issues, and miss opportunities to expand their campaign with new leaders. VOICE mitigated these pitfalls by pairing canvassers from different backgrounds and targeting districts with low voter turnouts. Future work could investigate if similar problems are present in online advocacy campaigns. Nall states "online mobilization presents one challenge to our way of describing the canvass." Results from this study show higher rates of membership contributions from contacts who write at higher grade levels with positive sentiments. Future work should investigate if targeting these contacts, in particular, hides testimony from potential future campaign leaders personally affected by campaign issues.

7.3.3. Improving Online Advocacy Services

An early proposal for this dissertation described testing ways to improve online advocacy services instead of proposing to study constituent messages passed through them. It focused on testing methods to lower transaction costs for constituents to take action online and keep them engaged. The problems identified in the original proposal did not disappear:

> *Citizens need effective ways to regularly engage in policy decisions that impact them – whether these decisions shape civil and environmental projects, or other projects. Research shows that both social media and online advocacy software services, public and private, have simplified and increased access to policymakers in the last two decades, but the efficacy for, sustainability of, and timeliness of interactions that they provoke needs improvement (Bimber 2001, Boulianne 2009, Karpf 2010, Kenski 2010, Bakker, T.P. et al. 2011, Kim et al. 2017). Even with the new ease of access to policymakers that online tools give*

citizens, it's hard for citizens to stay informed on multiple issues and strategically time their actions. Adserà et al. 2003 and Castells 2007 show that many citizens are disenfranchised with this process and that they feel powerless to corrupt governments. policymakers in corporations and in government have access to advisory boards and cabinets to research different issues and propose issue-specific solutions at key times. Average citizens do not have these teams. They, by default, only have their elected representatives.

Without time for their own research and without their own issue-matter experts to advise them, many citizens become disengaged with policies that affect them and do not follow-up with their representatives, trust them (Castells 2007), vote (File 2015, U.S. Elections Project 2016, Pew 2017, U.S. Census Bureau 2018), or even know who their lawmakers are. Lawmakers, in turn, are left out of touch with their constituents' positions, and rely on their own heuristics (accurate and representative or not), research (peer reviewed or not), advisors (at least they can have them – official or not), and biases (Broockman and Ryan 2016, Broockman and Skovron 2017, Butler and Broockman 2011, Haynes et al. 2011, 2011, 2012, Tversky and Kahneman 1973, 1974, Kahneman 2011). They have also long been susceptible to special interest lobbying and campaign contributions (Snyder 1990, Claessens et al. 2008). Further, spikes of communication on popularized issues leave policy offices unprepared to summarize and respond to public comments and questions. Citizens, similarly, become fatigued with the effort and timeliness necessary to respond to proposed policy revisions.

Researchers and policy campaign managers from public, academic, community, and nonprofit organizations strive to limit this disengagement. They know that political participation and perceptions of democracy reinforce each other (Oni et al. 2017) and that, along with money, continuous and timely contact can persuade policymakers (Miler 2014), even with template-driven letters and petitions as part of a larger lobbying plan (Karpf 2010). Campaign managers, in particular, rely on software services to educate and enlist citizens to engage policymakers, often elected, on issues that affect the citizens. They are always looking for ways to provoke timely and sustained action and improvements to the status quo in advocacy services could directly benefit them.

While this dissertation, the study of relationships between constituent messages and organizational engagement, does not directly address these problems, findings may support the development of new services that do. This effort may continue as a follow-up to the results of this dissertation.

APPENDIX A. STATES AND TERRITORIES

The 2,199,624 messages in this study were sent from campaigns that targeted environmental advocacy issues in either (a) all U.S. states and territories, (b) no state or territory, or (c) an individual state or territory. The following is a list of each of these location targets and, in parentheses, the number of messages generated from these target's associated campaigns, sorted from the greatest number of messages to the least number of messages. Note: messages were sent from campaigns targeted at all 50 states except Kansas, North Dakota, and South Dakota.

All (1,193,389)
None (877,493)
MN (21,948)
CA (10,006)
VA (9,626)
PA (8,593)
OH (8,445)
WA (8,411)
NC (7,203)
CO (6,259)
NY (5,483)
MI (3,965)
AZ (3,526)
FL (3,511)
MD (3,433)
IL (2,859)
OR (2,851)
TN (2,470)
MA (2,235)
UT (1,815)
IN (1,712)
WY (1,709)
WV (1,554)
NM (1,490)
TX (1,312)
MO (898)
OK (801)
WI (777)
NV (770)
KY (729)
GA (596)
LA (472)
CT (450)
ID (386)
PR (367)
MS (348)
AL (299)
DE (219)
DC (205)
NH (188)
MT (187)
NE (165)
VT (165)
ME (87)
SC (70)
IA (66)
NJ (62)
HI (11)
RI (7)
ND (1)

APPENDIX B. PERSONAL STORY QUERIES

Exploration three explains how attempts to find lived experiences, as defined by Sandhu (2017), in messages began with text searches for “as a,” “i am a,” “i live,” “my family,” “my husband,” “my wife,” and “my children.” This appendix lists these searches. All searches are case insensitive. For background, please see the MySQL 8.0 reference manual, especially documentation on searches and regular expressions: https://dev.mysql.com/doc/refman/8.0/en/regexp.html#operator_regex

B.1. Simple MySQL Searches for Personal Stories

Basic MySQL searches that identify terms anywhere in a message take the form of,

- `SELECT * FROM table WHERE message LIKE "%Term%"`

Where the following words replace “Term”:

```
1.     As a
2.     I am a
3.     We are
4.     We are a
5.     I live
6.     I live in
7.     We live
8.     We live in
9.     We call home
10.    My family
11.    My husband
12.    My wife
13.    My child
14.    My husband
15.    My wife
```

Some of these searches can return unintended results when looking for personal stories. For example, the first search for “as a” can return a message containing the words “h*as* *a*lready.” Removing the first percentage sign around the term in the “as a” query helps. In this case, the modified search looks for the term at the beginning of a sentence. For example:

- `SELECT * FROM table WHERE message LIKE "Term%"`

The modified searches for terms at the beginning for messages eliminate unintended results like the "has already" result for the “as a” query. They also eliminate, however, terms that begin sentences and phrases in the middle of messages. While this study still uses and reports results from these modified queries, to find terms that begin sentences and phrases in the middle of messages, this study uses regular expressions. Personal Story Reference Table 1, at the end of this appendix, includes a complete list of these basic MySQL search conditions.

B.2. Regular Expression Searches for Personal Stories

Simple searches returned some unintended results, like the "has already" result. The following regular expressions to find the simple search terms at the start of messages, sentences, and prepositions eliminate problems like these.

```
1.    (([:punct:][:space:](As a))|(^As a))[:space:]
2.    (([:punct:][:space:](I am a))|(^I am a))[:space:]
3.    (([:punct:][:space:](We are))|(^We are))[:space:]
4.    (([:punct:][:space:](We are a))|(^We are a))[:space:]
5.    (([:punct:][:space:](I live))|(^I live))[:space:]
6.    (([:punct:][:space:](I live in))|(^I live in))[:space:]
7.    (([:punct:][:space:](We live))|(^We live))[:space:]
8.    (([:punct:][:space:](We live in))|(^We live in))[:space:]
9.    (([:punct:][:space:](We call home))|(^We call home))[:space:]
10.   (([:punct:][:space:](My family))|(^My family))[:space:]
11.   (([:punct:][:space:](Our family))|(^My family))[:space:]
12.   (([:punct:][:space:](My Child))|(^My Child))[:space:]
13.   (([:punct:][:space:](Our Child))|(^My Child))[:space:]
14.   (([:punct:][:space:](My husband))|(^My husband))[:space:]
15.   (([:punct:][:space:](My wife))|(^My wife))[:space:]
```

Personal Story Reference Table 1, at the end of this appendix, includes a complete list of these basic MySQL search conditions. As an example of a complete MySQL search using one of the patterns above, the search for “I am a” at the beginning of a sentence or preposition looks like this:

- `SELECT * FROM table WHERE message`
- `REGEXP '(([:punct:][:space:](I am a))|(^I am a))([:space:])'`

B.3. Self-Identification with Nouns

The search for "as a" and "I am a" return messages written by contacts who label themselves with specific terms. They identify themselves as belonging to groups such as gender categories, family roles (e.g. "father"), organizations ("member"), occupation categories (e.g. "carpenter"), and contacts living in specific locations (e.g. "Marylander"). The following regular expression expands the "I am" search to include variations such as "I'm a," "I have been a," and ""'I will be the."

- ```
  REGEXP '(I am|I\'m|I was|I have been|I will be) (a|an|the) [a-z]+'
  ```

Suffixes to this pattern narrow results to specific labels that contacts call themselves and also account for a single, optional label modifier ([a-z]+ |). For example, the following regular expression identify self-descriptions of male and female family roles:

- ```
  REGEXP '(I am|I\'m|I was|I have been|I will be) (a|an|the) ([a-z]+ |)(male|boy|man|guy|husband|father|dad|papa|grandpa|grandfather|granddad|son|brother|uncle)([:alpha:]|[:space:])'
  ```
- ```
  REGEXP '(I am|I\'m|I was|I have been|I will be) (a|an|the) ([a-z]+ |)(female|girl|lady|wife|mother|mom|mama|momma|grandma|grandmother|grandmom|daughter|sister|aunt)([:alpha:]|[:space:])'
  ```

Personal Story Reference Table 2, at the end of this appendix, includes a complete list of patterns that identify self-descriptions of family role, gender, some occupations (e.g. "doctor," "carpenter") and places of living (e.g. "Marylander").

B.4. Activity Self-Identification with Verbs

Self-identification can also be found in verbs. While above searches expect sentence objects to suffix them, past, present, and future tense verbs can also identify specific task and occupation specific verbs. This study uses the following expression to search for a generic verb action:
  ```

- `REGEXP '(I( went| went to| am|\'m| will| will be| was| have| have been)( go to| going| going to|))'`

Notice the lack of the pipe ("|") after the words "have been" in this generic verb action expression that more specific queries use ("have been|"). The pipe makes the verb modifiers (e.g. " will") optional. Without a specific verb in this generic query, the modifiers are necessary. A more sophisticated program could identify verbs with a dictionary to improve this generic query. It would identify any verb followed by the word "I."

Personal Story Reference Table 3, at the end of this appendix, includes a complete list of patterns that identify, with verbs, more specific content related to self-identification, job identification, outdoor activities, suffering, pain, and experience. For example, the following expressions were used to search for people who camp and hike:

- `REGEXP '(I( went| went to| am|\'m| will| will be| was| have| have been|)( go to| going| going to|)) camp'`
- `REGEXP '(I( went| went to| am|\'m| will| will be| was| have| have been|)( go to| going| going to|)) (hike|hiking)'`

B.5. Swear Words

This study looked for three swear words at the beginning and anywhere in sentences, and compared membership rates of contacts who have used those words to those using any of the LIWC swear words with the following MySQL query parts (words censured with "**"):

- ``` `Message` LIKE 'f**k%%' ```
- ``` `Message` LIKE '%%f**k%%' ```
- ``` `Message` LIKE 'd**n%%' ```
- ``` `Message` LIKE '%%d**n%%' ```
- ``` `Message` LIKE 's**t%%' ```
- ``` `Message` LIKE '%%s**t%%' ```
- ``` `swear` > 0 ```

The patterns are listed in Personal Story Reference Table 4.

B.6. Finding Members With Matching Messages

The following MySQL query, defined in Python, describes how this study searched for contacts who used messages matching the searches and expressions described above, in the variable “search condition” below:

```
command ="""
SELECT COUNT(*) as 'Contacts'
FROM (
	SELECT DISTINCT CID
		FROM messages
	WHERE
		"""+search_condition+"""
	) AS a
LEFT JOIN contacts b
ON a.CID = b.CID
WHERE b.`ever member` = """+str(membership)+""";
""";
```

Where “messages” is a table of personal messages, “cid” is a unique contact id, “contacts” is a table of contacts, and “member” is a field that contains either one or zero, determining if a contact has ever been a member within a year of one of their messages in the study period. This query is in the loop

```
for membership in [0,1]
```

For the calculation of membership rates for conditions and alternative conditions.

B.7. Personal Story Search Reference Tables

The following tables provide a reference of all of the MySQL LIKE and REGEX condition patterns that Exploration Three uses to search for personal stories.

1. Basic MySQL searches for personal stories
2. First-Person Singular Self-Identification with Nouns
3. First-Person Singular Self-Identification with Verbs
4. Swear Words

B.8. Personal Story Reference Table 1. Basic MySQL Searches for Personal Stories (LIKE and REGEX)

Note: The word “basic” in the title of this section refer to basic words and phrases developed from those that one nonprofit advocacy organization uses to manually, ad hoc search for personal stories in advocacy messages.

Condition	Term	MySQL Pattern
Message contains	As a	`LIKE “%As a%”`
Message starts with	As a	`LIKE “As a%”`
Phrase starts with	As a	`REGEX “(([:punct:][:space:](As a))|(^As a))[:space:]”`
Message contains	I am a	`LIKE “%I am a%”`
Message starts with	I am a	`LIKE “I am a%”`
Phrase starts with	I am a	`REGEX “(([:punct:][:space:](I am a))|(^I am a))[:space:]”`
Message contains	We are	`LIKE “%We are%”`
Message starts with	We are	`LIKE “We are%”`
Phrase starts with	We are	`REGEX “(([:punct:][:space:](We are))|(^We are))[:space:]”`
Message contains	We are a	`LIKE “%We are a%”`
Message starts with	We are a	`LIKE “We are a%”`
Phrase starts with	We are a	`REGEX “(([:punct:][:space:](We are))|(^We are))[:space:]”`
Message contains	I live	`LIKE “%I live%”`
Message starts with	I live	`LIKE “I live%”`
Phrase starts with	I live	`REGEX “(([:punct:][:space:](I live))|(^I live))[:space:]”`
Message contains	I live in	`LIKE “%I live in%”`
Message starts with	I live in	`LIKE “I live in%”`
Phrase starts with	I live in	`REGEX “(([:punct:][:space:](I live in))|(^I live in))[:space:]”`
Message contains	We live	`LIKE “%We live%”`

Message starts with	We live	`LIKE “We live%”`
Phrase starts with	We live	`REGEX “(([:punct:][:space:](We live))|(^We live))[:space:]”`
Message contains	We live in	`LIKE “%We live in%”`
Message starts with	We live in	`LIKE “We live in%”`
Phrase starts with	We live in	`REGEX “(([:punct:][:space:](We live in))|(^We live in))[:space:]”`
Message contains	We call home	`LIKE “%We call home%”`
Message starts with	We call home	`LIKE “We call home%”`
Phrase starts with	We call home	`REGEX “(([:punct:][:space:](We call home))|(^We call home))[:space:]”`
Message contains	My family	`LIKE “%My family%”`
Message starts with	My family	`LIKE “My family%”`
Phrase starts with	My family	`REGEX “(([:punct:][:space:](My family))|(^My family))[:space:]”`
Message contains	Our family	`LIKE “%Our family%”`
Message starts with	Our family	`LIKE “Our family%”`
Phrase starts with	Our family	`REGEX “(([:punct:][:space:](Our family))|(^Our family))[:space:]”`
Message contains	My child or my children	`LIKE “%My child%”`
Message starts with	My child or my children	`LIKE “My child%”`
Phrase starts with	My child or my children	`REGEXP '(([:punct:][:space:](My child))|(^My child))(ren|)([:punct:]|[:space:])`
Message contains	Our child or our children	`LIKE “%Our child%”`
Message starts with	Our child or our children	`LIKE “Our child%”`
Phrase starts with	Our child or our children	`REGEXP '(([:punct:][:space:](Our child))|(^Our child))(ren|)([:punct:]|[:space:])`
Message contains	My husband	`LIKE “%My husband%”`
Message starts with	My husband	`LIKE “My husband%”`

Phrase starts with	My husband	REGEX "(([:punct:][:space:](My husband))|(^My husband))[:space:]"
Message contains	My wife	LIKE "%My child%"
Message starts with	My wife	LIKE "My child%"
Phrase starts with	My wife	REGEX "(([:punct:][:space:](My husband))|(^My husband))[:space:]"

B.9. Personal Story Reference Table 2. First-Person Singular Self-Identification with Nouns

Condition	MySQL Pattern
Male	'(I am|I\'m|I was|I have been|I will be) (a|an|the) ([a-z]+ |)(male|boy|man|guy|husband|father|dad|papa|grandpa| grandfather|granddad|son|brother|uncle)([:alpha:]|[:space:])'
Female	REGEXP '(I am|I\'m|I was|I have been|I will be) (a|an|the) ([a-z]+ |)(female|girl|lady|wife|mother|mom|mama|momma|grandma| grandmother|grandmom|daughter|sister|aunt)([:alpha:]|[:space:])'
Doctors, nurses, and words ending in "ist"	REGEXP '(I am|I\'m|I was|I have been|I will be) (a|an|the) ([a-z]+ |)([a-z]+ist|doctor|nurse)'
Words ending in "ist"	REGEXP '(I am|I\'m|I was|I have been|I will be) (a|an|the) ([a-z]+ |)([a-z]+ist)'
Words ending in "tor"	REGEXP '(I am|I\'m|I was|I have been|I will be) (a|an|the) ([a-z]+ |)([a-z]+tor)'
Words ending in "or"	REGEXP '(I am|I\'m|I was|I have been|I will be) (a|an|the) ([a-z]+ |)([a-z]+or)'
Words ending in "er"	REGEXP '(I am|I\'m|I was|I have been|I will be) (a|an|the) ([a-z]+ |)([a-z]+er)'
Doctors and nurses	REGEXP '(I am|I\'m|I was|I have been|I will be) (a|an|the) ([a-z]+ |)(doctor|nurse)'
Lawyers and judges	REGEXP '(I am|I\'m|I was|I have been|I will be) (a|an|the) ([a-z]+ |)(lawyer|judge)'
Note: Additional terms like "attorney" could expand this search	

<table>
<tr><td>Engineer</td><td>REGEXP '(I am|I\'m|I was|I have been|I will be) (a|an|the) ([a-z]+ |)engineer'</td></tr>
<tr><td>Husband or wife</td><td>REGEXP '(I am|I\'m|I was|I have been|I will be) (a|an|the) ([a-z]+ |)(husband|wife)'</td></tr>
<tr><td>Mother or father</td><td>REGEXP '(I am|I\'m|I was|I have been|I will be) (a|an|the) ([a-z]+ |)(mother|father|mom|dad|mama|papa)'</td></tr>
<tr><td>Grandmother or grandfather

Note: The word “grandparent” could expand this search</td><td>REGEXP '(I am|I\'m|I was|I have been|I will be) (a|an|the) ([a-z]+ |)(grandma|grandmother|grandpa|grandfather)'</td></tr>
<tr><td>Child</td><td>REGEXP '(I am|I\'m|I was|I have been|I will be) (a|an|the) ([a-z]+ |)(son|daughter|child|kid)'</td></tr>
<tr><td>Sister or brother</td><td>REGEXP '(I am|I\'m|I was|I have been|I will be) (a|an|the) ([a-z]+ |)(sister|brother)'</td></tr>
<tr><td>Uncle or aunt</td><td>REGEXP '(I am|I\'m|I was|I have been|I will be) (a|an|the) ([a-z]+ |)(uncle|aunt)'</td></tr>
<tr><td>Educator

(college, student, phd, mater’s, master of, doctor or, graduate, professor, ta, teacher, high school, elementary school, preschool, pre-school, higher education, research)</td><td>REGEXP '(I am|I\'m|I was|I have been|I will be) (a|an|the) ([a-z]+ |)(college|student|phd|master\'s|master of|doctor of|graduate|professor|ta|teacher|highschool|elementary school|preschool|pre-school|higher education|research)'</td></tr>
</table>

B.10. Personal Story Reference Table 3. First-Person Singular Self-Identification with Verbs

<table>
<tr><th>Condition</th><th>MySQL Pattern</th></tr>
<tr><td>Generic first-person singular actions</td><td>REGEXP '(I(went| went to| am|\'m| will| will be| was| have| have been)(go to| going| going to|))'</td></tr>
<tr><td colspan="2">Self/Job Identification</td></tr>
<tr><td>Mary</td><td>REGEXP '(I(went| went to| am|\'m| will| will be| was| have| have been|)(go to| going| going to|)) (married|mary)'</td></tr>
</table>

Teach	`REGEXP '(I( went| went to| am|\'m| will| will be| was| have| have been|)( go to| going| going to|)) (teach|taught)'`
Vote	`REGEXP '(I( went| went to| am|\'m| will| will be| was| have| have been|)( go to| going| going to|)) (vote|voting)'`
Work	`REGEXP '(I( went| went to| am|\'m| will| will be| was| have| have been|)( go to| going| going to|)) work'`
Live	`REGEXP '(I( went| went to| am|\'m| will| will be| was| have| have been|)( go to| going| going to|)) (live|living)'`
Program	`REGEXP '(I( went| went to| am|\'m| will| will be| was| have| have been|)( go to| going| going to|)) program'`
Analyze	`REGEXP '(I( went| went to| am|\'m| will| will be| was| have| have been|)( go to| going| going to|)) analyz'`
Volunteer	`REGEXP '(I( went| went to| am|\'m| will| will be| was| have| have been|)( go to| going| going to|)) volunteer'`
Join	`REGEXP '(I( went| went to| am|\'m| will| will be| was| have| have been|)( go to| going| going to|)) join'`
Protect, guard, save, fight	`REGEXP '(I( went| went to| am|\'m| will| will be| was| once was| used to|\'m used to| have| have been|)( go to| going| going to|)) (protect|guard|save|saving|fight|fought)'`
Spend	`REGEXP '(I( went| went to| am|\'m| will| will be| was| have| have been|)( go to| going| going to|)) spend'`
Outdoor Activities	
Camp	`REGEXP '(I( went| went to| am|\'m| will| will be| was| have| have been|)( go to| going| going to|)) camp'`
Hike	`REGEXP '(I( went| went to| am|\'m| will| will be| was| have| have been|)( go to| going| going to|)) (hike|hiking)'`
Trek	`REGEXP '(I( went| went to| am|\'m| will| will be| was| have| have been|)( go to| going| going to|)) trek'`

<table>
<tr><td>Climb</td><td>REGEXP '(I(went| went to| am|\'m| will| will be| was| have| have been|)(go to| going| going to|)) climb'</td></tr>
<tr><td>Ski</td><td>REGEXP '(I(went| went to| am|\'m| will| will be| was| have| have been|)(go to| going| going to|)) ski'</td></tr>
<tr><td>Hunt, fish</td><td>REGEXP '(I(went| went to| am|\'m| will| will be| was| have| have been|)(go to| going| going to|)) (hunt|fish)'</td></tr>
<tr><td>Bike, cylce</td><td>REGEXP '(I(went| went to| am|\'m| will| will be| was| have| have been|)(go to| going| going to|)) (bike|biking|cycl)'</td></tr>
<tr><td>Hike, walk</td><td>REGEXP '(I(went| went to| am|\'m| will| will be| was| have| have been|)(go to| going| going to|)) (hike|hiking|walk)'</td></tr>
<tr><td>Sim</td><td>REGEXP '(I(went| went to| am|\'m| will| will be| was| have| have been|)(go to| going| going to|)) (swim|swam)'</td></tr>
<tr><td>Ride</td><td>REGEXP '(I(went| went to| am|\'m| will| will be| was| have| have been|)(go to| going| going to|)) (ride|riding|rode)'</td></tr>
<tr><td colspan="2">Suffering, pain, and experience</td></tr>
<tr><td>Suffer</td><td>REGEXP '(I(went| went to| am|\'m| will| will be| was| have| have been|)(go to| going| going to|)) suffer'</td></tr>
<tr><td>Deprive</td><td>REGEXP '(I(went| went to| am|\'m| will| will be| was| have| have been|)(go to| going| going to|)) depriv'</td></tr>
<tr><td>Die</td><td>REGEXP '(I(went| went to| am|\'m| will| will be| was| have| have been|)(go to| going| going to|)) (die|dying)'</td></tr>
<tr><td>Hurt</td><td>REGEXP '(I(went| went to| am|\'m| will| will be| was| have| have been|)(go to| going| going to|)) hurt'</td></tr>
<tr><td>Curse</td><td>REGEXP '(I(went| went to| am|\'m| will| will be| was| have| have been|)(go to| going| going to|)) curs'</td></tr>
<tr><td>Break</td><td>REGEXP '(I(went| went to| am|\'m| will| will be| was| have| have been|)(go to| going| going to|)) (broke|break)'</td></tr>
<tr><td>Lose</td><td>REGEXP '(I(went| went to| am|\'m| will| will be| was| have| have been|)(go to| going| going to|)) (lost|lose)'</td></tr>
</table>

Endure	`REGEXP '(I( went| went to| am|\'m| will| will be| was| have| have been|)( go to| going| going to|)) endur'`
Bleed	`REGEXP '(I( went| went to| am|\'m| will| will be| was| have| have been|)( go to| going| going to|)) (bleed|bled)'`
Go through	`REGEXP 'I went through|I go through|I\'m going through|I will go through'`

B.11. Personal Story Reference Table 4. Swear Words

Words are censored in this table with asterisk.

Condition	Swear word	MySQL Pattern
Message contains	F**k	`` `Message` LIKE "%F**k%" ``
Message starts with	F**k	`` `Message` LIKE "F**k%" ``
Message contains	D**n	`` `Message` LIKE "%D**n%" ``
Message starts with	D**n	`` `Message` LIKE "D**n%" ``
Message contains	S**t	`` `Message` LIKE "%S**t%" ``
Message starts with	S**t	`` `Message` LIKE "S**t%" ``
Message contains	Any swear word in the LIWC swear dictionary dimension	`` `swear` > 0 ``

APPENDIX C. VALIDATION OF VADER FOR ENVIRONMENTAL ADVOCACY MESSAGES SENT TO POLICYMAKERS

C.1. Validation Summary and Introduction to Precision, Recall, and F-Score Measures

The VADER analysis for rating the sentiment of environmental advocacy messages addressed to policymakers was validated by comparing VADER ratings to corresponding human ratings of 400 randomly selected personal messages from 491,027 in the database.

Validation of VADER begins with a single human reviewer. It employs the same 9-point Likert scale that Hutto and Gilbert (2014) use in their validation of VADER for social media words: extremely negative, very negative, moderately negative, slightly negative, neutral, slightly positive, moderately positive, very positive, and extremely positive. It also asks the reviewers to rate messages in a way that reduced variations between reviewer scores for Hutto and Gilbert, by asking them to rate messages in a way they believe others would rate messages. While Hutto and Gilbert crowd-sourced reviewers and screened them with an English language test, this study selected an English-speaking reviewer with a college degree.

VADER identifies messages as either negative, neutral, and positive. It identifies messages in these categories with a 56% match rate with the human reviewer, where a match rate is the percentage of messages that VADER and the human reviewer rate the same.

Precision, recall, and F1 scores explain the ability of a classification model to correctly identify truth (in this case, judged by a human reviewer) in more detail than an overall match rate. For reference, precision is the number of correct classifications of items that a machine makes in that category divided by *all the classifications of items that the machine makes in that category*. Recall is the number of correct classifications of items that the machine makes in the category divided by *all items in the category* whether classified by the machine or not (Kent et al. 1955). If the primary goal of an application is to correctly classify a small number of items, and avoid incorrect classifications, a high degree of precision is more desirable than a high degree of recall. If the primary goal of an application is to correctly classify as many items as possible, and incorrectly classifying items is not important, a high degree of recall is more important than a high degree of precision. The F1 score is the harmonic mean of recall and precision: F1 = 2/(1/Recall + 1/Precision). The F1 score equally weights recall and precision, irrespective of the importance of one over the other. Precision, recall, and the F1 scores are measures typically used to validate machine models. Hutto and Gilbert use them in during the development of VADER (2014) and Ding uses them in assessing the effectiveness of customized sentiment analyzers (2018).

In this validation, VADER identifies messages with a moderate 0.51 negative sentiment F1 score, a low 0.13 neutral sentiment F1 score, and a moderately high 0.66 positive sentiment F1 score. It finds negative messages with a high precision of 0.71 but a moderately low recall of 0.47. It finds positive messages with moderate precision of 0.57 and a moderately high recall rate of 0.66. It finds neutral messages with low precision and recall rates of 0.13 and 0.14. While VADER poorly identifies neutral messages, the human reviewer only rated 11% of messages as neutral. They rated 49% of messages positive and 41% of messages negative.

C.2. Validation with a Single Human Reviewer

Validation of VADER with a single human reviewer begins by assessing the accuracy of VADER by comparing VADER sentiment ratings and human sentiment ratings in a contingency table (Table 1) for the sample of 400 random messages described above. The table directly reports the human reviewer responses to the Likert scale as human ratings. For VADER ratings, the table reports a classification of VADER compound sentiment scores (-1 to 1) into negative, neutral, and positive categories as recommended by Hutto and Gilbert (2014) and described in Chapter 2. VADER compound scores less than or equal to -0.05 indicate negative sentiment, VADER compound scores greater than or equal to 0.05 indicate positive sentiment, and other VADER compound indicate neutral sentiment. The match rate for each VADER category (negative, neutral, positive) is equal to the number of VADER ratings in a category that match human ratings, all divided by the total number of VADER ratings in that category. For example, the match rate for negative VADER ratings is equal to the count of all negative VADER ratings that match the human ratings for the four negative Likert scale categories (extremely negative, very negative, moderately negative, and slightly negative) divided by the total number of negative VADER ratings: (18 + 27 + 23 + 23)/129 = 0.71. This negative VADER match rate shows that 71% of the negative ratings that VADER makes also match negative human ratings. This is high compared to the 0.57 positive VADER match rate, and very high compared to the 0.13 neutral VADER match rate.[4] These match rates are measures

[4] VADER neutral sentiment ratings match the human reviewer neutral sentiment ratings with low rates when categorizing messages as neutral when their compound VADER scores are in the recommended neutral range, between -0.05 and 0.05 (Hutto and Gilbert 2014). Increasing this neutral range, increases the neutral match rate. The neutral match rate, similarly, increases if messages rated by the human reviewer as

of VADER precision. While VADER matches negative ratings more precisely than positive ratings, the human match rates shown in the last column of Table 1 indicate that VADER identifies positive human-rated messages at a higher rate than it identifies negative human-rated messages.

In other words, given just two messages identified by VADER, one negative and one positive, because VADER is more precise in identifying negative messages, the one negative message is more likely to be rated negative by the human reviewer than the one positive message is likely to be rated positive by the human reviewer. Alternatively, given all 400 VADER ratings, VADER identifies more of the positive human-rated messages than it identifies the negative human-rated messages. It does so, however, with a greater likelihood of producing false positive-sentiment ratings compared to false negative-sentiment ratings (vs. the human reviewer).

"slightly positive" and "slightly negative" are considered neutral ratings. Neutral sentiment rating match rates, because they are categorized as such in relatively narrow boundaries, are also more susceptible to positive or negative bias by either VADER or the human reviewer in comparison to negative sentiment and positive sentiment rating match rates. For example, as shown in Table 4, the human reviewer rated 19 messages as slightly negative and VADER rated them as neutral.

Table 1. VADER and Human Sentiment for 400 Advocacy Messages

	VADER Rating				
Human Rating	Negative	Neutral	Positive	Total	Human Match Rate
Extremely Negative	18	1	5	24	0.75
Very Negative	27	9	7	43	0.63
Moderately Negative	23	8	22	53	0.43
Slightly Negative	23	15	36	74	0.31
Neutral	11	6	26	43	0.14
Slightly Positive	14	4	37	55	0.67
Moderately Positive	4	2	34	40	0.85
Very Positive	4	1	29	34	0.85
Extremely Positive	5	1	28	34	0.82
Total	129	47	224	400	
VADER Match Rate (Precision)	0.71	0.13	0.57		

Table 2 lumps the scores shown in table one into a three by three confusion matrix in the same way that the VADER match rates are calculated in Table 1 — categorizing all positive human ratings as positive, all negative human ratings as negative, and the neutral ratings as neutral. For example, there are 91 messages that VADER and humans rated negative (18 + 27 + 23 + 23). The last column of table three contains VADER recall rates. These rates confirm observations of Table 1 that VADER identifies more positive human-rated messages than negative human-rated messages, but with relatively greater false positive (type one) errors.

Table 2. VADER and Human Sentiment Rating Confusion Matrix for 400 Advocacy Messages

	VADER Rating				
Human Rating	Negative	Neutral	Positive	Total	Recall
Negative	91	33	70	194	0.47
Neutral	11	6	26	43	0.14
Positive	27	8	128	163	0.79
Total	129	47	224	400	
Precision	0.71	0.13	0.57		

Table 3 summarizes the overall match rate, precision, recall, and F1 scores, for negative, neutral, and positive VADER ratings compared to the human ratings.

Table 3. Precision and Recall for VADER Sentiment Ratings

VADER Rating	Precision	Recall	F1
Negative	0.71	0.47	0.56
Neutral	0.13	0.14	0.13
Positive	0.57	0.79	0.66

The overall match rate with an individual human reviewer is 56%.

While Hutto and Gilbert (2014) recommend categorizing sentences into three ordinal categories with the VADER compound score at -0.05 and 0.05 thresholds, as calculated above, and while Likert scale questions are also ordinal, Table 4 reveals a level of match exists when in a confusion matrix with nine equally spaced bins for VADER ratings subjectively associated with the nine human ratings.

Table 4. Precision and Recall for VADER Sentiment Ratings

Human Rating	Subjective VADER Rating -4	-3	-2	-1	0	1	2	3	4	Total	Recall
-4	4	7	4	2	2	1	3	1	0	24	0.17
-3	3	10	6	6	11	2	1	0	4	43	0.23
-2	4	6	6	3	13	2	7	6	6	53	0.11
-1	4	8	7	3	19	5	11	10	7	74	0.4
0	1	2	6	2	8	5	7	8	4	43	0.19
1	1	6	2	5	5	6	10	14	6	55	0.11
2	1	0	1	1	4	4	8	11	10	40	0.20
3	1	1	1	1	1	1	9	11	8	34	0.32
4	0	1	3	0	2	4	5	6	13	34	0.38
Total	19	41	36	23	65	30	61	67	58	400	
Precision	0.21	0.24	0.17	0.13	0.12	0.20	0.13	0.16	0.22		

The subjective VADER scores in Table 4 (-4 to 4) are determined by the function:

```
IF( VADER>=0.7777, 4,
  IF( VADER>=0.5555, 3,
    IF( VADER>=0.3333, 2,
      IF( VADER>=.1111, 1,
        IF( VADER>=-0.1111, 0,
          IF( VADER>-0.3333, -1,
            IF( VADER>-0.5555, -2,
              IF( VADER>-0.7777, -3,-4)
            )
          )
        )
      )
    )
  )
)
```

C.3. Validation with a Multiple Human Reviewers

Table 5 shows match rates between VADER and six individual reviewers, x1 … x6, rating the same 400 messages and using the same Likert scale survey described for the single reviewer (x4) above. It also shows the match rates between VADER and the six reviewer's average ratings rounded to the nearest integer (57% match rate).

Table 5. VADER Sentiment Match Rates and Correlations

	Reviewer						
	x1	x2	x3	x4	x5	x6	round(avg(x))
VADER Match Rate	45%	56%	51%	56%	58%	55%	57%

The round(avg(x)) variable is the list of average reviewer sentiment scores from -4 to 4, rounded to the nearest integer.

While VADER ratings match those of the average group ratings at slightly higher rates than the ratings of most individual reviewers, reviewer scores should only be lumped together if their ratings are consistent with one another. This study uses Chonbach's alpha and factor analysis to check if reviewer scores are consistent with each other. Assuming an integer ratio scale for human reviewers from -4 to 4 corresponding to extremely negative to extremely positive ratings, as assumed in Table 4 for compound VADER scores, Chronbach's alpha of 0.90 for the six human reviewers indicates that reviewers are fairly consistent in their ratings and it is not unreasonable to take their average rating, rounded to the nearest integer, as a better measure of human judgement than using just one reviewer. In the calculation of Chronbach's alpha, the number of reviewers, k, equals six, the sum of the variances of each of the reviewer's scores is equal to 24.83 and the variance of all of the sums of the scores for each question is equal to 100.14. The sum of the variances of each of the reviewer's scores is comparatively low compared to the variance of all of the sums of the scores for each question. Chonbach's alpha equals 6/(6-1) (1 - 24.83/100.14) = 0.90. Factor analysis, furthermore, shows most of the variables have similar factor loading (x1=0.68, x2=0.87, x3=0.87, x4=0.84, x5=0.88, x6=0.81). Table six compares the precision and recall rates from table three for a single reviewer to those of the group of reviewers. Values are similar. The overall accuracy increases to 57%. Finally, compared to Table 4, for a single reviewer, Table 7 shows precision and recall rates for the lumped group score.

Table 6. Precision and Recall for VADER Sentiment Ratings
Against an Individual Reviewer and Against a Group of Reviewers

VADER Rating	Precision	Recall	F1
Individual Negative	0.71	0.47	0.56
Group Negative	0.65	0.53	0.58
Neutral Negative	0.13	0.14	0.13
Group Negative	0.17	0.12	0.14
Individual Positive	0.57	0.79	0.66
Group Positive	0.61	0.79	0.69

The overall match rate with an individual human reviewer is 56%.
The match rate with a group of six human reviewers is 57%.

Table 7. Precision and Recall for VADER Sentiment Ratings

Group Human Rating	Subjective VADER Rating										
	-4	-3	-2	-1	0	1	2	3	4	Total	Recall
-4	2	1	4	2	0	0	1	1	0	11	0.18
-3	4	11	4	1	6	0	3	0	2	31	0.35
-2	4	13	4	6	12	2	2	4	6	53	0.08
-1	4	5	8	4	16	8	9	6	4	64	0.06
0	4	5	9	3	11	3	14	11	7	67	0.16
1	1	6	5	6	16	14	17	24	14	103	0.14
2	0	0	1	1	3	2	11	16	11	45	0.24
3	0	0	1	0	1	1	4	5	13	25	0.20
4	0	0	0	0	0	0	0	0	1	1	1.00
Total	19	41	36	23	65	30	61	67	58	400	
Precision	0.11	0.27	0.11	0.17	0.17	0.47	0.18	0.07	0.02		

C.4. Validation Conclusion and Recommendation

In conclusion, the human validation of VADER shows that Section 5.5 of this study reasonably reports that relationships *between membership rates and VADER scores* are descriptive of relationships *between membership rates and sentiment*. Although neutral sentiment rating match rates are low between humans and VADER in this validation, neutral match rates increase with increasing neutral ranges as shown in Table 4 and Table 7.

In comparison to sentiment language classifiers reviewed and customized by Ding (2018), and validated for twitter messages about public infrastructure projects, VADER performs well for this study. Ding reports a 20% accuracy rate for the Aylien Text API classifier (Aylien 2019), a 50% accuracy rate for the SentiStrength classifier (Thelwall et al. 2012), and a 68% accuracy rate for a customized classifier based on a sentiment lexicon developed by Hu et al. (2014) and Ding's study data. These measures of accuracy are comparable to the 56% and 57% match rates identified in the human validation of VADER sentiment for advocacy messages reported in this Appendix. Given this study's results (Section 5.5, Chapter 6) that sentiment classification can help identify membership rates of authors of advocacy messages, future work should be done to investigate the ability of other classifiers to identify sentiment in advocacy messages. Also, given Ding's success in customizing a sentiment dictionary for Twitter data, future work should investigate the ability of customizing the dictionary of lexicon based classifiers like VADER for finding sentiment in advocacy messages. For example, in a review of falsely classified messages used to validate VADER in this study, changing a misspelled word in one message from "thenk" to "thank" in "thank you" would have increased the overall VADER match rate.

APPENDIX D. DEFINING AND VALIDATING A MODEL FOR CLASSIFICATION OF PERSONAL STORIES

As reported in Section 5.3, this dissertation did not develop and validate a model to find personal stories in messages because (a) it did not set out to do so and (b) results from searches for personal stories revealed other, related content in messages that was indicative of high and low membership rates. This dissertation prioritized reporting these results to achieve objective two over further developing a model to identify personal stories. Future work could be conducted to develop a personal story classifier model. Such a model could identify “lived experience” (Sandhu 2017) content in messages as well as and related content (e.g. family references) found by this dissertation in the search for lived experiences. It should also consider research from Gordon et al. (2009) who classified for personal stories in longer passages of text. This appendix suggests ways to validate a model in the future.

The validation of the classification of messages as personal stories by a model depends on the number of descriptive factors that a model classifies messages into, and these factors’ scales of measurement. This study suggests future work must first better define what a personal story is, and what supporting and useful, related factors should be reported by a model classifying messages as such. In the most basic case, (a) given a random sample of 400 messages, (b) given a single reviewer, and (c) given a model that classifies messages containing “lived experiences,” as defined by Sandhu (2017), or not, a person familiar with Sandhu’s work should ideally be consulted to judge if each of the 400 messages contains a personal story or not. Then, this study should describe the accuracy of the model with (a) the model’s match rate to the reviewers classifications, (b) precision, (c) recall, and (d) F1 scores. This section details these recommendations and considers more complex cases for validating multiple factors with multiple reviewers.

Research (Sandhu 2017) and campaign development guides from the Social Change Agency (2017a, 2017b) show advocacy organizations benefit from enlisting individuals who have lived experiences affected by campaign issues into organizer and leadership positions of campaigns. In comparison to online form-letters and petitions, which go unseen by policymakers (Miler 2014), leadership and rhetoric from those with lived experiences build trust between advocacy organizations, policymakers, and the public. The Congressional Management Foundation (2017) shows that, more generally, U.S. congressional representatives say that individualized letters from constituents help them take positions on issues. (Chapter 1 and Chapter 2 describe further the state of congressional communication.) For reference, as described in Section 3.2, this dissertation labels messages originally authored by users of online advocacy systems as personal messages. It labels personal messages that contain descriptions and references of lived experiences as personal stories.

This study searches for personal stories with regular expressions (Objective Two). In doing so, it exposes the subjective nature of the definition of what a lived experience is. It also finds that messages, whether describing experiences of how campaign issues directly affect authors, or simply describing an author's occupation or family status, are related to membership rates. For example, the following messages could all indicate different classifications and degrees of “lived experiences”:

1. I plan on moving to Flint, Michigan, but am worried about water contamination
2. My uncle died of black lung disease when I was five. Please phase out these coal mines in the next 10 years and provide assistance for those working in the industry to make the occupation transitions
3. As a proud Marylander, I support your proposal to make our city a safe place for climate refugees
4. I worry about climate change every day
5. I drive a car and I support stronger fuel emission standards
6. My wife and I don't want our children playing on toxic, synthetic turf proposed in the new Downtown Silver Spring update plans

Sandhu (2017) defines lived experiences as "the experience(s) of people on whom a social issue, or combination of issues, has had a direct personal impact." Some of these messages describe past experiences, some describe worrying about future experiences, some describe experiences of family members, some express common experiences, and some simply express family associations. Each message may be subjectively classified as a lived experience.

Before validating classification models (deterministic or probabilistic) of personal stories, therefore, more specific criteria of what a personal story is needs to be developed and incorporated into these models. From an applied point of view, supplementing the importance of lived experiences with exploration results from this study, advocacy organizations and policymakers may benefit from identification of self-described "direct personal impact" statements, that Sandhu describes, as well as identification of self-described occupations, places of living, family roles, family relationships, and outdoor activities. Both models and human judges may classify these factors on Likert scales, like VADER classifies sentiment, or in Boolean and null categories (present, not present, and undetermined).

The most general model, with the least number of classification factors, is the model that classifies a message describing or not describing lived experiences as defined by Sandhu (2017). It reports a single, Boolean classification factor for every message. The next most general model adds an undetermined category to this single classification factor. The next most general model reports this single classification factor on an ordinal scale, and the next most general model reports it on a ratio scale. After this, additional classification factors, such as those suggested above (occupation, places of living, family role, etc.), with different scales measurement, define more complex models.

To validate the most general model – the one with a single Boolean classification factor based on the definition of a lived experience – with only a single human judge of truth and a sample of 400 random messages, this study suggests building on lessons learned from this study's validation of VADER with a single reviewer. It suggests

1. Seeking a college educated, English-speaking expert well-acquainted with Sandhu's definition and research on lived experiences (2017), to classify messages as meeting or failing to meet Sandhu's definition as personal stories
2. Presenting the reviewer with an online survey that
    a. Shows messages one at a time and requires human interaction between messages

b. Asks the reviewer to rate messages as they think other experts might rate messages to increase reviewer consistency, as it did for Hutto and Gilbert (2014)
c. Shows the reviewer their progress and rewards the reviewer with positive thank you messages as they complete the survey
d. Shows Sandhu's definition of what a lived experience is alongside every question

3. Ensuring the reviewer has an environment where they agree that they can focus on the survey; if they say the online format doesn't work for them, the survey should be printed

In the case that multiple experts are able to review messages, validation design work should begin by consulting with at least one expert to construct example vignettes of what a lived experience is and what it is not in order to ground reviewer understanding of what a lived experience is and increase reviewer rating consistency. An odd number of reviewers should review messages, or a single expert should be available to break ties. Reviewer consistency should be evaluated with factor analysis or a statistic such as Greatest Lower Bound (GLB) or Kuder-Richardson Formula 20 (KR-20). If reviewer consistency is low, validation will require further investigation to understand why and possibly eliminate bad reviewers.

In the more complex cases, where reviewers are asked to report ordinal and ratio judgements for one or more metrics, this study recommends using Chronbach's alpha and factor analysis to check the consistency of reviewers, as this study does for checking the consistency of reviewers judging message sentiment. In these cases, where reviewers are asked to check messages for multiple factors, questions can be grouped by message or by factor. Grouping questions by factor would require the user to read each message multiple times (equal to the number of factors) and increase the time and effort required by reviewers to complete the review. Grouping questions by message, alternatively, would allow reviewers to keep a message in their short-term memory and then answer questions about each factor in it. In this second case, the survey could present factor questions all at once, on a single screen, in sets, or individually for each question. This study recommends presenting questions by message, and presenting no more than seven factor questions about a message on a single screen at a time. If factor questions could be confused with each other, the survey should present them on the same screen with distinctions between them highlighted.

After reviewer data has been collected, classifier validation can employ the same match rate, precision, recall, and F1 scores used by this study in validating VADER sentiment ratings to access model accuracy. In the more complex model situations, these scores should be calculated for each message factor that the model and humans classify.

GLOSSARY

Action Center. A trade name for an online advocacy service. See advocacy service

Advocacy Campaign. An effort, generally centrally managed by an advocacy organization, to support a specific issue. In this study, advocacy campaigns refer to online campaigns in which advocacy organization contacts and market targets are asked to send petitions and personal messages to their policymakers

Advocacy Organization. An organization that educates the public and lobbies policymakers to support projects and policies. Advocacy Organizations discussed in this dissertation are all nonprofit, membership-based organizations which collect annual membership dues and contributions to support environmentally sustainable policies and projects. Advocacy Organizations discussed in this dissertation all use online advocacy services among other methods to achieve their goals

Advocacy Service Provider. A software vendor that develops and provides advocacy services to advocacy organizations

Advocacy Service. A software service used by advocacy organizations to both recruit members and enable contacts to conveniently write their policymakers

Campaign Manager. A staff member or volunteer managing an advocacy campaign. This dissertation often refers to campaign managers as campaign organizers

Campaign Organizer. See campaign manager

Contact. A person with a relationship to an advocacy organization. Note: new contacts do not necessarily have information about them stored in an organizational contact relationship management database

Flesch Ease of Reading Test. A popular test that scores text on how easy it is to read by people with different levels of education. The Flesch score is a function of syllables, words, and sentences in text. See Flesch (1948)

Linguistic Inquiry and Word Count (LIWC). A software package that counts words in text matching collections of words. See LIWC (2018)

Linguistic Inquiry and Word Count (LIWC) Dimension. A labeled collection of words in the LIWC software package. E.g. pronouns, function words, positive emotions, etc.

Linguistic Inquiry and Word Count (LIWC) Score. A LIWC test-result that describes a text specimen. LIWC reports all word count rates as percentages matching a LIWC dimension (e.g. all pronouns). LIWC reports word count as the number of words in text, not a percentage

Message. Any message sent to a policymaker through an online advocacy system, including form letters, custom messages, and personal messages

Messages, Custom. Prewritten advocacy messages, edited and customized by contacts using online advocacy services

Message, Not Custom And Not Personal (NOTCORP). Messages that have specifically not been customized nor individually authored by contacts

Message, Personal. Individually authored text sent to a policymaker. Contacts compose personal messages into blank text area fields on websites and in messenger-application entry fields

Message, Personal Story. A message that describes a "lived experience" (Sandhu 2017); also used to describe messages found by searches for "lived experiences"

Policymaker. A primary target of online advocacy campaigns, many times being state and national elected officials or appointees that can vote or influence project and policy decisions

Valence Aware Dictionary for sEntiment Reasoning (VADER). A rule-based model that measures sentiment in text, specifically created for short social-media messages. See Hutto et al. (2014) and related code at https://github.com/cjhutto/vaderSentiment#about-the-scoring

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