EVO-LYZER: Social Media Mining System for Evolving Communication Behavior Analytics to Aid Climate Change Programs

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Abstract

Climate change has become a significant threat to our society. Researchers in climate change communication often rely on specific program-based interventions to train public communicators, such as journalists, to raise awareness about critical issues and events. However, researchers face challenges in analyzing the change in communication behavior of participants in the programs over time since using traditional social science research methods alone, such as surveys and interviews, for analyses could be resource-intensive and costly. Social media mining provides an opportunity for such communication researchers. In this paper, we propose a social media mining system called *Evo-Lyzer* to measure and analyze evolving communication behavior on social media. *Evo-Lyzer* employs topic modeling and novel measures of communication divergence and consistency, which are informed by prior research of communication sciences, to evaluate an intervention program for climate change communication. We showcase *Evo-Lyzer*'s capability in analyzing real-world data and assessing the effectiveness of a climate change communication program aimed at journalists and weathercasters. The application of our social media mining system could empower communication researchers to conduct large-scale studies on evolving communication behavior in program-specific interventions across different domains for sustainability and social good beyond communication about climate change.

1 Introduction

It is essential to keep the public informed about climate change with the latest and most reliable information to minimize the spread of misinformation and to take action to prevent and mitigate future disasters. One approach to keeping the public informed is through communication by journalists and television weathercasters (weather presenters).

Social media is a key source of information for many. Journalists, and weathercasters use it to share news with the public (Jurkowitz and Gottfried 2021). People can subscribe to journalists' social media accounts instead of relying on traditional news sources (Shearer and Mitchell 2021). Studying journalists' climate change communication patterns on social media can help understand how their behavior reaches public audiences.

In this study, we developed a system to automate data collection and analysis of social media posts by journalists to study their climate change communication behaviors and assess the impact of communication intervention programs. Such assessment benefits institutions overseeing communication training programs to improve their initiatives. Program-based communication interventions aim to improve the ability of participants to communicate about a particular topic (e.g., climate change) through activities such as workshops and weekly informational newsletters. This study supports the evaluation of one particular climate change reporting resource program called *Climate Matters*[1], which conducts training workshops to help television weathercasters and journalists report climate change-related stories. This program seeks to bridge the gap between attitudes and behaviors, meaning just because a television weathercaster or journalist sees climate reporting as desirable and self-selects to participate in a training workshop does not mean they will change their communication behavior. It is because other factors such as lack of time and training may stand in their way (Schäfer and Painter 2020).

Measuring communication behavior is crucial for evaluating the success of the program. More specifically, a key goal of the communication intervention program is to help weathercasters and journalists overcome barriers to reporting on climate change, so they could increase their reporting frequency . The program's success can be measured by the increased frequency of climate change-related social media posts from participating TV weathercasters and journalists.

In this paper, we develop a system called *Evo-Lyzer* (referring to *Evo*lving communication behavior ana*lyzer*) relying on social media mining techniques that help assess the effect of a program-based communication intervention on the target population of participants . The proposed system aims to operationalize two key components to measure the outcomes of a program-based communication intervention using social media mining techniques.

The *first* component to operationalize is a computational measure of communication behavior through posting on significant topics of a domain using guided-topic modeling algorithms (Li et al. 2018). Our rationale is that this is an approach to thoughtfully automate what communication re-

[1] https://www.climatecentral.org/climate-matters

searchers would typically do by hand for topic domains that are complex and nuanced, like climate change. In a traditional approach, researchers would generally code social media posts manually before and after a communication intervention and compare the results of that coding process to examine if a change occurs. However, collecting such vast amounts of data for several participants in a program and manually coding them is often infeasible. Our operationalization makes this process feasible with guided-topic modeling so that researchers can measure the discussion of specific domain topics from participants' posts on social media before and after intervention rapidly on a large scale.

The *second* component to operationalize is the longitudinal designs that are undoubtedly essential for measuring changes in communication behavior resulting from an intervention. This is because longitudinal data allows evaluators to see if behavior changes occur after participating in a communication intervention program and if those changes last over time (Yagatich et al. 2022a). However, when measuring posting frequency, these measurements are usually taken at only one or a few points in time. This measure is useful, but lacks the ability to track nuanced changes in posting frequency or implicit patterns in communication behavior shifts. It is particularly relevant for domains such as climate change, where reporting frequencies may be sensitive to local and global events such as hotter summers or international agreements. Therefore, our system seeks to assess the dynamic shifts in post frequency of participants that may occur before and after a program-based intervention through two measures of communication behavior: *divergence* (defined as a group-level communication shift between two periods) and *consistency* (defined as an individual-level communication shift across a sequence of periods).

Automated measures of divergence and consistency are valuable for evaluating communication intervention programs, such as the case in this study, for four reasons. First, directly observable behavior is crucial to measure to determine the success of an intervention, as expressed earlier. Observation of weathercasters' and reporters' social media posting is a directly observable measure of changes in climate reporting after involvement in the communication intervention program, and the traditional approaches of self-reported measures often come with more complex validity issues (Furr 2021). Second, *Evo-Lyzer* automates what typically is an extremely time and resource-intensive process for communication intervention evaluators. Conducting large scale qualitative analysis of communications before and after an intervention would be time, capital, and labor-intensive. Ultimately, manually analyzing social media data to study communication behavior patterns is cumbersome due to the volume and velocity of content generation. Meaning this communication intervention program outcome may, and often does, go unmeasured due to a lack of access to rapid measurement tools. *Evo-Lyzer* is an automated system to help overcome these challenges. Third, *Evo-Lyzer* offers two of many measures for evaluating communication intervention programs: a measure of topically relevant social media posts and a measure of these posts over time. This is important because evaluations of communication interventions require multiple data sources and collection methods. Using multiple data sources and collection methods , is valuable because it enhances the credibility of the findings by painting a more complete picture of the program's impact (Mertens and Wilson 2018). Therefore, divergence and consistency are two of many valuable measures for evaluating a communication intervention program. Finally, evaluations of communication intervention programs are seldom well documented. Our study presents an approach to browse through the participants' data back and forth at scale and enables documentation of insights on participant behavior at the individual and aggregated/group level for an intervention program with the help of *Evo-lyzer*, which can support future communication intervention evaluations.

Ultimately, this paper seeks to empower communication researchers and practitioners to address the methodological challenges of traditional analysis approach using social media mining, which could discover and illuminate insights into communication behavior rapidly at a large scale. The social media mining methodology provides a process to represent, analyze, and extract interesting patterns from social media data that lead to novel insights and scalable analysis of user behavior (Zafarani, Abbasi, and Liu 2014). Further, we develop a web-based interactive tool for the *Evo-Lyzer* system design to efficiently and effectively capture the evolution of communication behavior to paint a multi-dimensional picture of such behavior for helping communication scientists and practitioners.

Main Results and Contribution: In this study, we propose a novel approach to analyze evolving communication behavior due to communication intervention programs using the online social media data of participants. Furthermore, we apply our proposed approach for conducting a case study to analyze participants' communication behavior of a reputed climate-reporting resource program. Specifically:

1. We present an innovative application of social media mining to create a novel system to measure and analyze evolving communication behavior of users to aid assessment processes of communication-intervention programs in the domain of climate change and sustainability.
2. We introduce and operationalize two measures of divergence and consistency to evaluate evolving communication behavior at the group and individual levels.
3. We develop the system called *Evo-Lyzer* based on the above approach, which can assist communication researchers and practitioners in different areas in evaluating evolving communication behavior.
4. We validate the efficiency of *Evo-Lyzer* with a case study to help analyze a communication-intervention program for climate change.

Paper Organization: The remainder of this paper is organized as follows. Section 2 provides the background related to this study. Section 3 describes the problem formulation in detail. The approach is described in Section 4. The experimental details using the data for the case study are provided in Section 5. Sections 6 and 7 provide the results and the discussion of the case study as well as the system's features. Finally, Section 8 will conclude this paper.

2 Related Work

It is essential to identify the theoretical background in the communications literature for measuring the thematic change in discussions caused by a program-based communication intervention. Moreover, we present prior work on approaches for analyzing communication behavior.

2.1 Traditional methods for studying behavioral change

Traditional methods for observing the impact of a communication intervention on an individual's behavior are either done (1) directly or (2) indirectly. Direct observations take place in a laboratory setting where the environment can be controlled to examine people's behavior–to the extent possible–free of influence from factors aside from the intervention (Allen 2017). Both in the case of laboratory experiments and real-world observations of communication behavior, such as the manual content analyses of social media posts as mentioned in the Introduction, these observations tend to be at a small scale to be manageable for researchers. Other methods measure communication behavior indirectly through self-reports of such behavior or indicators of the behavior. Self-reports typically entail survey or interview questions that ask participants exposed to a communication intervention to report on their behavior (Allen 2017). Aside from self-reports, the Theory of Planned Behavior (TPB) shows that one's intention to enact a behavior is a predictor of actual behavior (Ajzen 1991). Therefore, if direct observation of behavior is not possible, behavioral intent can be measured indirectly through surveys or interviews. Considering those traditional methods for studying behavior change due to communication intervention and their limitations for scalable and rapid analysis, we identify an opportunity to design complementary computational methods guided from these traditional approaches.

2.2 Social media for climate change communication

Social media is a widely used communication tool for many institutions to share knowledge with the public. Specifically, journalists have widely adopted it to quickly reach the audience with the most relevant information (Alejandro 2010). Social media has also been widely used to communicate about climate change to the general public to engage them and raise awareness of climate change effects as well as educate them on the consequences of energy policies (Loureiro and Alló 2020). An abundance of research has focused on studying the use of the Twitter platform to communicate climate change (Becken et al. 2022; Uldam and Askanius 2022). Thus, analyzing the data from such social media platforms to understand the change in the communication behavior of participants in communication intervention programs related to climate change can provide meaningful insights to communication researchers. Recently, Falkenberg et al. (2022) studied the political polarization around climate change on social media. The authors used an approach that utilizes topic modeling for analyzing different climate change themes discussed on Twitter during the United Nations Conference of the Parties on Climate Change (COP). In their study, Dahal, Kumar, and Li (2019) conducted an analysis of global climate change tweets, employing topic modeling and sentiment analysis techniques. Their research aimed to examine and compare the characteristics of climate change discussions across various countries and over time.

2.3 Behavioral analysis

Previous studies have used social media discussions as a proxy to study the online behavior of social media users. For instance, several studies used discussions in social media to study user behavior before, during, and after disaster events (Niles et al. 2019; Purohit et al. 2014). Moreover, Niles et al. (2019) proposed a keyword-based approach for visualizing and quantifying the frequency of Twitter posts (tweets) for comparing different periods during a disaster. However, the authors focused only on identifying the important keywords in each period to describe online discussions without a quantifiable metric. In comparison, the study by (Purohit et al. 2014) presented an approach to analyze and measure the divergence in communication to quantify and explain the change in user discussion over time across disaster phases. Specifically, they first identified the topics in Twitter data during disaster events. They then used the average probability distribution over topics for the set of tweets published by groups of Twitter users to calculate the Jensen-Shannon (JS) divergence. However, the authors did not attempt to identify the consistency of communication about topics in discussions by users during each period of the disaster events. In addition, Solvik (2020) proposed a method to utilize topic modeling and KL-Divergence measure to compare the topic contents of online social media posts and emergency management reports across various time points during wildfires. The author found similarities in the topic distributions between the two types of reporting in the early stages of the event and diverging topics in the later stages. Moreover, Ito et al. (2015) used topic modeling and Jensen-Shannon Divergence (JSD) measure to identify a bot or a biased user compared to an average user through differences in topic distributions of content. Brodersen et al. proposed a Bayesian centric approach to infer the causal impact of designed market intervention on an output metric over time (Brodersen et al. 2015). However, using such approach would require us to assume that the intervention happened at the same time for all participants. In this study, we attempt to analyze and measure the change in communication behavior using a system design that allows communication researchers flexibility to conduct the desired analysis with different metrics, data representation, and levels from individual users to a group of users.

3 Domain Goal and Problem Formulation

In this study, our goal is to investigate the evolving communication behavior of participants of an intervention program using the data of social media posts generated by the participants.

Preliminaries: Assume each participant in a communication intervention program as a subject (s) of this study. There are two main features of a subject, a unique identifier for the subject (s_{id}) and a social media username ($s_{twitter}$). For each subject, there can be one or more associated events organized by the communication intervention program where the subject participated. Let us represent an event as e. An event in our study has two main properties: event id (e_{id}), and event time (e_{time}). Consider the notation s_d to represent a social media post (document) shared by a subject.

We define the *relevancy* (r) as the probability indicating the degree a social media post (s_d) is relevant to a topic of interest. In our specific case study, the relevant communications will be the ones related to climate change behavior, e.g., awareness of the climate impact of fossil fuels and alternative fuels. Moreover, we represent the relevancy of a collection of documents authored by the same subject (s) during a provided period (p) by $r_{s,p}$. We will further discuss our approach to identifying the relevant behavior in Section 4.

Given the goal of analyzing a communication intervention program's effectiveness in changing the subject's social media communication behavior, the technical objective is to compare the relevancy of posts published by the subjects within different time intervals. Thus, we define two separate forms of measures for this task of assessing the effectiveness: 1) Divergence and 2) Consistency as follows:

- **Divergence**. We define divergence as a measurement of evolving communication behavior that compares the difference in communication behavior between two groups of subjects. We can define the groups based on the time relative to an event. The mean of relevancy ($\bar{r}_p$) of a group of subjects (S) for a given period (p) is defined by the Equation 1. We calculate the percentage increment in the mean values of relevancy (δ_r) for each group of subjects before ($p = b$) and after ($p = a$) an event to calculate the divergence as shown in Equation 2.

$$\bar{r}_p = \frac{\sum_{s \in S} r_{s,p}}{|S|} \tag{1}$$

$$\delta_r = \frac{(\bar{r}_a - \bar{r}_b) \times 100}{\bar{r}_b}\% \tag{2}$$

- **Consistency**. We define consistency as a measurement of evolving communication behavior of an individual subject to compare the variance of related communications in social media (or general communications) across time intervals. We can compare the consistency distributions across two groups (across time intervals) to assess the effectiveness of the communication intervention program. Let the period of analysis p be divided into n smaller equal-length periods (p^i) (e.g., months). The consistency (c) of a subject (s) during a given period (p) is calculated by the following equation:

$$\sigma_{s,p} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (r_{s,p^i} - \mu_{s,p})^2} \tag{3}$$

$$c_{s,p} = \frac{\mu_{s,p}}{\sigma_{s,p}}; \text{ where } \mu_{s,p} = \frac{\sum_{i=1}^{n} r_{s,p^i}}{n}; \tag{4}$$

The average consistency (c) of subjects (S) across time periods before ($p = b$) and after ($p = a$) events are compared to analyze the effectiveness of the program. Specifically, we calculate the percentage increment in consistency (δ_c) as illustrated in the following equation:

$$\delta_c = \frac{(c_a - c_b)}{c_b} \times 100\%; \text{ where } c_p = \frac{\sum_{s \in S} c_{s,p}}{|S|} \tag{5}$$

For this study, we consider the social media timeline of a participant s with two distinct intervals before and after an event e at time e_{time}. Here, a time interval length (Δt) is selected based on the analysis requirements. Our goals are to measure 1) the divergence and 2) the change in consistency between periods before and after an event.

Problem: Given a set of participant subjects s in an event e of a communication-intervention program, the set of their social media posts N_1 and N_2 in a defined interval Δt before and after e_{time}, assess the program effectiveness within the set of participants by examining whether the statistical significance is above the practitioner-defined threshold ϵ for the difference in the *divergence* and *consistency* measures of participants' communication behavior before and after e.

It is important to highlight that within a communication intervention program, researchers in the field can determine the participant subjects, categorize them based on desired criteria, and select the specific event for analysis, thus allowing for a tailored approach to conducting the study.

4 Approach: *Evo-Lyzer* System Design

This section describes the proposed approach as *Evo-Lyzer* system design and the implementation of divergence and consistency measurements with the help of Twitter as a reference to a social media platform. Twitter was selected because of its data availability. The proposed system consists of the following components: *Data Collection*, *Topic Modeling*, and *Communication Behavior Evaluation*.

The initial inputs of the system are the information on participant subjects and the time of events of the communication-intervention program. The output of the data processing through our system is the divergence and consistency measurements and relevant visualizations. The following subsections will describe each component of the system in detail.

4.1 Data Collection

This data collection process considers the subjects and events provided by the communication researchers. We collected the tweet timelines of subjects considered in this study and filtered users' timelines for collecting data from only the relevant periods, given the possibility of a large volume of posts for a journalist user. Therefore, the proposed approach uses the Twitter API [2] with appropriate filters to collect the Twitter timelines of the subjects for the relevant periods. Specifically, we collected tweets of a participant subject during the eleven months before the month of the event and

[2] https://developer.twitter.com/en/docs/twitter-api

the eleven months after the month of the event. We chose eleven months as the time period for user timelines since it could allow us to capture all seasons in the pre and post-event equally. The API provides the data in $JSON$ format for a tweet object. After collecting tweet objects and meta-data of time of posting, author information, content, etc., we store them in files per participant user. Those stored files are used in the later stages for the analysis after pre-processing as needed.

4.2 Pre-processing

We perform a series of pre-processing steps to process the text attribute of a tweet post before providing the input to the topic modeling process. In this study, we focused specifically on utilizing the textual content of a social media post as a representation of the document for data processing. However, it is worth noting that the approach can be readily expanded to incorporate data from other metadata fields within the document. These additional fields can be presented as a set of tokens alongside the tweet text, enabling a more comprehensive representation that takes into account multiple types of interactions with the platform. Furthermore, this approach can be extended to represent the textual content using alternative encoding methods, such as zero-shot learners that could generate weakly supervised labels (Pourpanah et al. 2022). The sequence of pre-processing steps can be listed as follows: First, we converted the input text to the lowercase form. Next, we removed any user mentions, URLs, punctuation, stopwords, numbers, and words less than three characters. Then we tokenized the resulting text by splitting it by spaces. Finally, we added phrases as additional tokens by inspecting the input sequence of tokens. We identify phrases from the training dataset using the $Gensim$ library (Rehurek and Sojka 2011). We used phrases that were present at least ten times in our corpus.

4.3 Topic Modeling: *Author Topic Model*

We need to identify the social media posts relevant to the communication program before any meaningful analysis of the effectiveness of the communication-intervention program. One can compute the social media posts' relevancy using supervised and unsupervised machine learning techniques (Zafarani, Abbasi, and Liu 2014). However, supervised learning requires a large amount of labeled data to build a high-quality relevancy classification model to identify relevant posts. Moreover, defining relevant topics of interest is application specific and requires a significant manual effort than identifying the labels of a cluster/topic obtained through unsupervised learning methods such as topic modeling or clustering. Therefore, in this study, we propose an unsupervised learning technique of topic modeling to extract the latent topics of tweets. While it does not require the data labeling apriori, it can leverage large scale unlabeled data to discover relevant thematic categories automatically and, thus, can be easily applied to different application domains. Specifically, topic modeling is a Natural Language Processing (NLP) technique for identifying latent topics in a collection of documents (Blei, Ng, and Jordan 2003; Lin and He 2009). Latent Dirichlet Allocation (LDA) is a popular approach based on probabilistic generative statistical method (Blei, Ng, and Jordan 2003) for topic modeling. However, the basic LDA technique cannot model the topics of a collection of documents while considering their authorship. Author-Topic Model (ATM) (Rosen-Zvi et al. 2004) extends the LDA model with the ability to model author information. Furthermore, ATM can infer the topic distribution of a collection of documents aside from individual documents. The ATM extends LDA by associating an author with a multinomial distribution over topics. In this study, we use ATM to build a topic model for inferring topic probabilities of a collection of documents, such that an author is associated with a multinomial distribution over topics and a topic is associated with a multinomial distribution over words.

It is required to train and model the effectiveness of the topic model before inferring topic probabilities. We refer the reader to the Author-Topic Model implementation provided by the $Gensim$ (Rehurek and Sojka 2011) python library for our approach to train the topic model and to infer the topic distributions for tweet posts. $Gensim$ library utilizes the Variational Bayes (VB) when training the author-topic model to make the training process tractable (Mortensen 2017; Hoffman, Bach, and Blei 2010). We set the number of topics to 6, which is one topic more than the number of topical themes of seed-keywords (described below) (Lu et al. 2011). We rely upon the following strategies explored in the prior literature to improve modeling performance to infer coherent topics for topic modeling with ATM: 1) mapping seed-keyword list to desired topic categories, 2) random under-sampling, and 3) model priors.

Seed-Keywords List and Mapping: Keyword list facilitates a prior mapping of words/phrases of interest to their relevant topics (Lin and He 2009; Lu et al. 2011). In our study, it is a mapping of common terms used in climate change communication to their relevant topic categories as assigned by climate communication experts (through a partnership with the Climate Matters program).

Random Under-sampling: We randomly under-sample the posts that do not contain at least one of the keywords from the seed-keywords list before building the model. This strategy prevents the model from biasing towards topics that are less important to our analysis (Liu and Forss 2015).

Model Priors: In addition to filtering the posts by the seed-keywords list, we provide topic priors for each word in the keyword list while training. Authors in (Lin and He 2009) utilized a similar strategy to influence the topic model for better performance. It helps align the model to a set of expected topics by setting the model priors.

4.4 Measurement of Evolving Communication Behavior

The final key component of the proposed system first filters the relevant posts from a subject's timeline based on inferred topic probabilities for the posts. We then compute the divergence and consistency measures (as defined in Section 3) across periods using the identified relevant posts for each subject. We selected the threshold value (ϵ) for statistical significance (p value) as 0.05. We note that this component is easily extendable to incorporate additional measures for studying communication behavior patterns for helping applications in diverse domains. Lastly, the proposed system is implemented to provide analytical insights through the visual analytics dashboard of *Evo-Lyzer*.

5 Experiments: Case Study for a Climate-reporting Resource Program

We tested our proposed approach for evaluating communication behavior with a case study. The case study was developed in collaboration with a nationwide program dedicated in providing climate change communication resources for American broadcasters. This study utilized data from communication-intervention training events offered by the aforementioned program, which encompassed weekly newsletters and workshop-style training programs. The workshops were designed to help participants better understand climate science, local implications, and potential solutions. They also aimed to boost their confidence in reporting on local aspects of climate change and advance their local climate reporting skills. The climate change communication researchers that conducted previous evaluations of this training program were interested in supplementing their traditional methods for evaluating behavior change with new methods to comprehensively capture the suite of impacts this program may have on its participants and broader conversations about climate change (Myers et al. 2020; Yagatich et al. 2022b). Specifically, we employ the proposed *Evo-Lyzer* system to collect, process, and evaluate Twitter social media data for events relating to the communication-intervention program.

Communication professionals who are part of the program find value in such evaluations because of the attitude-behavior gap mentioned in the introduction of this study. Put simply; it cannot be assumed that just because a television weathercaster or journalist is motivated to communicate about climate change, they will do so since there are other factors that can impact whether their motivations lead to action. It is well documented in social science literature on behavior that attitudes do predict behaviors, but not always directly (Ajzen 1991; O'Keefe 2016). The Theory of Planned Behavior draws a link between attitudes and behaviors, but other factors also influence this relationship, like other's approval of the behavior, one's belief that they can preform the behavior, and, subsequently, intent to perform the behavior (Ajzen 1991). While the Theory of Planned Behavior is meant to be generalized across context, literature has also investigated context-specific reasons for the attitude-behavior gap in, for example, taking maintainable behavior (Claudy, Peterson, and O'Driscoll 2013; Schäufele and Janssesn 2021). The discussion with domain experts from the Climate Matters program indicates that there are context-specific reasons that limit television weathercasters' and journalists' ability to report on climate change, such as changes in the organizational structure of news media, lack of time for field reporting, lack of training in climate science, and many others (Schäfer and Painter 2020; Maibach et al. 2020). Communication interventions like those facilitated by *Climate Matters* are designed to support television weathercasters and journalists in overcoming such barriers; however, evaluation is necessary to determine if a program indeed supports participants in a way that leads to more frequent climate reporting.

Topical Theme	Keyword Examples
Causes	nitrous oxides, carbon dioxide emissions, hydrochlorofluorocarbons, aerosol, power plant
Problem	invasive species, gaining ice, climate shift, melting glaciers, record high temperatures
Solution	recycle, climate change preparedness, biodiesel, renewable sources of energy, carbon credit
Description	epa, world weather attribution, oxford, ipcc, fredi otto, climate central
Analysis	forecast, science, weather attribution, weather model, scientist

Table 1: Exemplar keywords for climate change communication provided by the partner program, used as priors in the topic modeling.

Dataset: We obtained data for our case study from two sources. First, we curated the list of subjects and training events based on data available from the program. Then, we collected social media data from Twitter API for analysis as described in Section 4.

- **Program Data**. We curated a list of journalists who participate in the Climate Matters program as our subjects. Each subject was identified by their first and last name, resulting in a total of 738 participants. These individuals were attendees of the training events (in the form of workshops) or/and had subscribed to the program's newsletter by "joining" the subscription.
- **Twitter Data**. Using Twitter API for user timelines, we collected publicly available tweets posted by each participant subject from the period of 11 months before an event to 11 months after the event, as described previously in Section 4. In case there are multiple events of the same subject, we select the (temporally) first event in the program. The resulting dataset contained $496,742$ tweets and was used for topic modeling and analyzing evolving communication behavior.

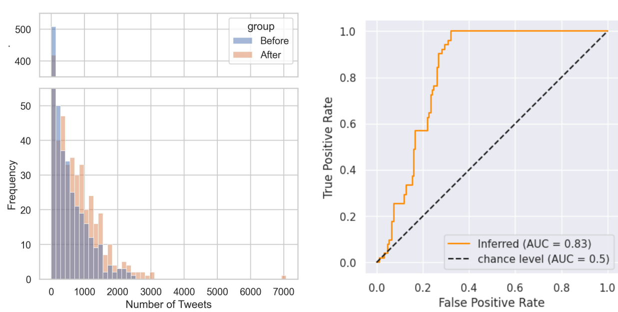
Topic Model:

To initialize the topic modeling process, we used a list of seed keywords mapped to 5 climate-related topics to apply performance improvement strategies (under-sampling, model priors) described earlier. The domain experts at the *Climate Matters* program curated the seed-keywords list. Table 1 shows a sample of keywords for the expected topics.

We used a multi-iteration approach to select a good topic model while qualitatively assessing the goodness of the word vocabularies representing topics at the end of each iteration with the help of an experienced communication researcher who is involved in *Climate Matters* program (Mimno et al. 2011). The assessments by the experts were valuable due to the quality enhancements they brought to the topics. To judge the relevance of topics, we first randomly selected 20 examples relevant to each topic. Next, we

Topic	Terms
Topic 1	gas, emissions, amp, greenhouse, plants, goes, methane, ash, greenhouse_gas, covid
Topic 2	oil, coal, new, carbon, climate, science, says, trump, fossil, energy
Topic 3	forecast, snow, rain, day, showers, amp, morning, weather, tonight, night
Topic 4	forecast, epa, morning, today, santa, day, rain, goes, afternoon, weekend
Topic 5	storm, weather, hurricane, forecast, severe, storms, tropical, update, winds, area
Topic 6	year, county, record, new, time, air, state, years, today, know

Table 2: Top terms representing the topics generated by topic model and the relevance of each topic to the task based on manual evaluation of tweet examples per topic.



(a) Distribution of tweeting frequency before and after event.

(b) ROC curve of topics 1, 2 (climate related tweets) vs the rest.

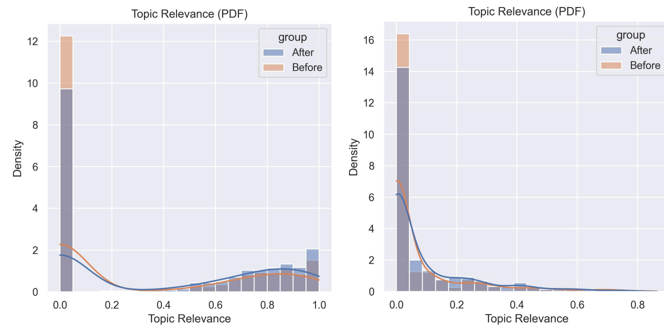
Figure 1: Descriptive analysis results.

manually annotated them to classify a resultant topic as relevant to the case study (i.e., discussing climate change issues) or irrelevant to the case study.

Based on our experiments, we found that setting the number of training iterations of the ATM to 20 and the number of passes to one provides the topics that are most aligned with our interests. Table 2 shows top words representing the six latent topics discovered from the Twitter dataset after the topic modeling process. The first two topics represent the core issues of climate change reporting, i.e., alternative and fossil fuels, followed by Topics 3, 4, and 5 representing the relevant issues for climatic events. Lastly, we identified Topic 6 to be less relevant to our interest.

6 Result Analysis for Case Study

In this section, we will discuss the results of our case study using the proposed approach.



(a) All topics *except* Topic 6.

(b) Core climate-issue topics.

Figure 2: Distribution of probability for Tweeting by subjects.

6.1 Descriptive Analysis

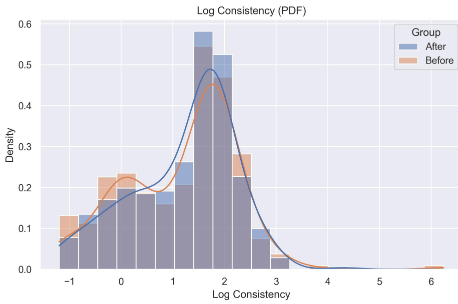
This section will first look at the Twitter dataset to analyze data distribution. Figure 1a shows the distribution of the number of tweet posts of subjects before and after an event. The observed distribution appears zero-inflated distribution with a high number of events corresponding to zero tweets in both cases before and after an event, possibly due to lack of activity by subjects for that period. Additionally, it is observed that the number of tweets after an event is higher than the number of tweets before an event. However, in our divergence analysis, this difference would have minimal influence since the proposed approach relies on relevancy measurement (using the probability of posting relevant tweet content) instead of the actual number of tweets.

In order to determine the effectiveness of identifying climate change-related tweets, we conducted an annotation process on a sample of 200 tweets. Given that a substantial portion of the tweets are likely to be unrelated to climate change, we ensured an equal number of tweets with the highest and lowest probabilities for topics 1 and 2 were included for annotation. The annotation process involved a single annotator. The results revealed a receiver operating characteristic area under the curve (AUC) of 83%, indicating a commendable performance in distinguishing between climate change-related and non-related tweets. The related Receiver Operating Characteristic (ROC) curve is depicted in Figure 1b.

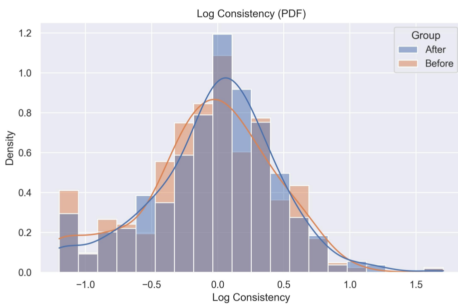
6.2 Divergence Measure Analysis

Divergence measures the change in the probability distribution of tweeting relevant posts from before the event to after the event. Figure 2a and 2b show the distribution of the tweet relevancy when considering the relevant topics as Topic 1 to Topic 5 and also when considering only the core climate issues-related topics for relevancy, i.e., Topic 1 and 2.

Figure 2a shows the plots for the relevancy of posting tweets, considering Topics 1 to Topic 5 as the relevant topics. We see an increase of $31.16\%(p = 1.48 \times 10^{-11})$ from 0.31 relevancy probability of posting tweets before the event to 0.41 relevancy probability after the event. We further note an interesting pattern that the density of relevancy probabil-



(a) All topics *except* Topic 6.



(b) Topics relevant to core climate-issue topics.

Figure 3: Distribution of consistency for posting tweets by subjects.

ity for near-zero topic relevance has a higher number of users *before* an event than those *after* the event. This pattern indicates that some participant subjects might have started more engagement after a communication-intervention program.

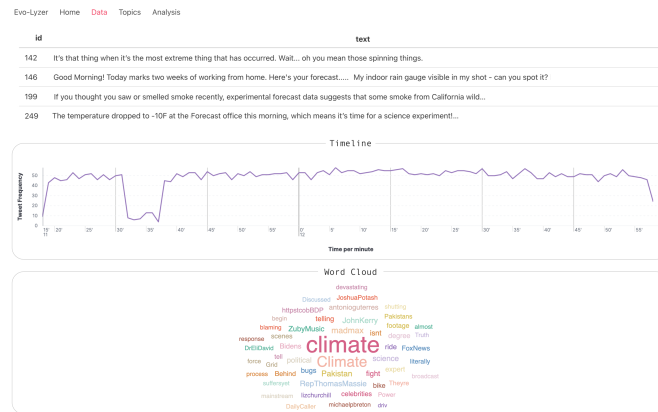
From Figure 2b, we can further observe that the relevancy probability of posting tweets, when considering core climate topics of Topic 1 and Topic 2, improves after an event compared with before the event by observing the plot where the probability density is high for the period after the event, compared with the period before the event. The average probability of posting relevant tweets by subjects before and after an event is 0.074 and 0.090. This represents a significant increase of 21.65% ($p = 8.0 \times 10^{-4}$) of average probability of posting relevant tweets. However, we observe that the average relevancy is low in both situations, which could be the result of the case where subjects would not be posting relevant tweets in periods before and after an event.

6.3 Consistency Measure Analysis

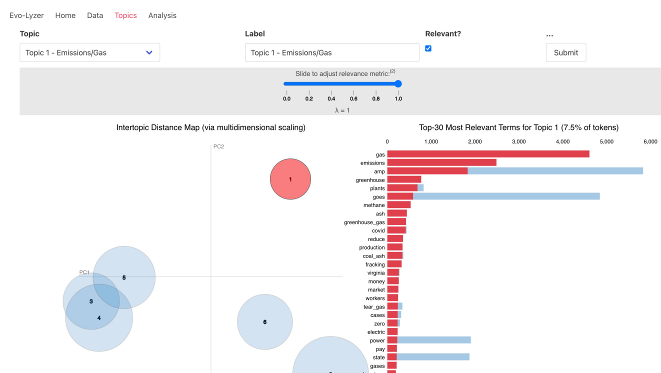
Similar to the divergence analysis, we performed an analysis of the consistency when considering the case of relevancy defined broadly with Topic 1 to Topic 5 captured together as relevant topics, as well as the case of considering only the core climate-issues topics of Topic 1 and Topic 2.

Figure 3a shows the distribution of the log consistency. Similar to our previous experiments, we observe that the consistency of posting relevant tweets has been improved after an event (2.63) compared with before an event (2.58). This indicates an improvement of $2.13\% (p = 8.9 \times 10^{-07})$ in consistency.

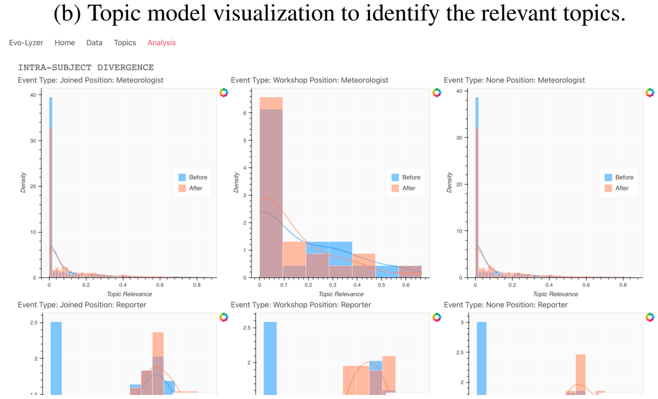
Furthermore, figure 3b shows the distribution of the log-consistency for all subjects. Here, we observe an improvement in consistency of posting relevant tweets after an event compared with before an event. The average consistency before and after an event is 0.41 and 0.55 accordingly. This represents a significant improvement of 36.24% ($p = 6.55 \times 10^{-7}$) in consistency.



(a) Summary of collected tweet data: a tweet table, a timeline of tweets, and a word cloud.



(b) Topic model visualization to identify the relevant topics.



(c) Interface showing different analyses of the collected tweet posts.

Figure 4: *Evo-Lyzer* dashboard interfaces.

7 Discussion and Applications for *Evo-Lyzer* System

Evo-Lyzer provides a novel contribution and powerful support of a complementary analytical tool to assist communication scientists and practitioners interested in evaluating potential changes in individual and group behavior due to a communication intervention. It provides a cost-effective and timely solution to some of the methodological challenges communication scientists and practitioners routinely face for conducting analyses of communication behavior rapidly at scale. *Evo-Lyzer* achieves this capability by creatively using social media mining techniques to capture and analyze large sets of user-generated data, which, otherwise, would be at minimum challenging and at maximum impossible for researchers to collect and analyze manually. Further, it employs the topic modeling method to thoughtfully automate what would typically be a manual coding process of complex domain topics like climate change while providing strategies to improve topic modeling performance using the domain knowledge of the experts for generating meaningful topics. And finally, it offers insights into both group-level (divergence) and individual-level (consistency) measures for the evolving communication behavior of users, which empowers the organizers of communication-intervention programs. Using the case study of a climate change reporting training program, this study demonstrates a valuable application of *Evo-Lyzer* and makes a case for applying it to new domains in the future for social good.

***Evo-Lyzer* System**: It provides web-based dashboard tool that can be adapted to various application domains for providing complementary analysis to aid the evaluation of program-based communication interventions. In this paper, we discussed a specific use case that has been applied to help evaluate a climate change communication program. We demonstrate the system's features using the resulting dashboard views for analyses conducted to aid the organizers of the communication-intervention program in the case study.

The web-based dashboard tool can take input from communication experts using spreadsheet that specifies the participants of an event. Then it utilizes the Twitter API to gather tweet timelines of those participants, following the methodology outlined in this study. The collected data is then subjected to inference using an author topic model and stored in a database. Subsequently, divergence and consistency metrics are calculated using this information. Finally, the interface is updated for the newly analyzed events indicating its effectiveness.

The system comprises of primarily three key functionalities: *Data* tables for browsing un/filtered posts of the participants in the program and other program data, *Topics* analysis for discovering and interpreting themes from data, and *Analysis* for faceted browsing and analysis of communication behavior-related measures for filtered data related to specific topics and user types. The topic labeling interface is shown in Figure 4b. This interface can show topics identified with the most salient terms of the topic and the inter-topic distance map (Sievert and Shirley 2014). Here, we used a modified version of pyLDAvis [3] for the author-topic model visualization. Moreover, the topics are supported by an example data table for tweets with relevancy filtering to aid a communication researcher or program analyst in investigating topics, as shown in Figure 4a. Finally, the dashboard can display the analysis results in plots as shown in Figure 4c and illustrate the divergence.

In practice, this dashboard can be used as a reporting tool that automatically analyzes and presents the effectiveness of the training event using the proposed metrics, which could be further extended with additional measurements . Furthermore, the dashboard can be used as an exploratory analysis tool for social media-based communication and the trained author topic models.

7.1 Lessons Learned

The proposed *Evo-Lyzer* system serves as an analysis tool for providing a complementary capability to traditional methods (e.g., surveys, assessments) for the evaluation of the impact of intervention programs, and thus, supports communication experts in assessing their effectiveness. Although this research focused specifically on climate change-related intervention programs, the system has the potential to be applied to a wide range of event-based interventions in various domains. The versatility of the proposed approach stems from the elimination of the need for extremely labor-intensive effort required from experts to manually identify different topical categories within a given domain, as topic modeling facilitates the discovery of all relevant topics. However, it is important to highlight that this method is not entirely automated for ensuring quality of topics. Human experts are required to review the topic models at times and identify the relevant topics for their analysis in order for the system to measure divergence and consistency of communication behavior accurately.

The field of natural language processing has experienced substantial advancements in recent years that could be leveraged to enhance the performance of *Evo-lyzer* system. Our approach introduced a minimal system design that comprised of components to operationalize measurements learned from traditional evaluation approaches for program-based communication interventions by creatively leveraging social media mining techniques. Nevertheless, the proposed system can be further enhanced by incorporating newer techniques and employing diverse document representation methods, as detailed in the Section 4.2. A possible progression of this study is to adopt state-of-the-art methods in natural language processing such as BERT (Devlin et al. 2019; Egger and Yu 2022; Falkenberg et al. 2022) for document representation in the form of processed tokens as the input to the author topic modeling process.

The output generated by *Evo-lyzer* system plays a crucial role in analyzing the divergence and consistency measures of each participant in an intervention program's event. These measurements can be further analyzed at the user level, enabling communication researchers to identify participating individuals who exhibit lower levels of engagement on

[3] https://pyldavis.readthedocs.io/

social media regarding climate change topics. This valuable information could allow communication researchers to closely collaborate with these participants, employing strategies such as surveys and assessment questionnaires to enhance the effectiveness of the intervention program. This complementary analytical capability could effectively reduce the cost of performing surveys at large scale since it enables performing flexible analyses from group to individual levels rapidly to ultimately help communication researchers and practitioners involved in those programs.

Looking ahead, communication researchers and practitioners at our partnering program Climate Matters have identified an alternative form of training that can be more cost-effective when considering per person trained. This approach involves an online, self-paced course known as the "Climate Reporting Master Class". Given the increasing number of participants involved, evaluating such programs can become more intricate. However, the *Evo-Lyzer* system presents a valuable opportunity to enhance the efficiency of evaluating large-scale interventions. By leveraging the capabilities of the *Evo-Lyzer* system, the evaluation process can be streamlined, resulting in improved effectiveness and efficacy when assessing the impact of these programs.

8 Conclusion

In this paper, we introduced a social media mining system called *Evo-Lyzer* to analyze evolving communication behavior of participants of a communication-intervention program. The proposed system is for processing social media communications that incorporate inputs from domain experts and analyze the social media posts of participant users in a communication program. It produces measurements that help evaluate the effectiveness of a communication-intervention program facilitated by a reputed climate change reporting resource program called Climate Matters. It provides an extensible and efficient approach to the alternative, i.e., the traditional method of manual processing of social media posts for deeper analysis of communication behavior. The *Evo-Lyzer* system relies on the foundation of author-topic models to facilitate the evolving communication behavior analysis via measures proposed in the paper: 1) divergence and 2) consistency for changes in both individual and group-level behavior for a set of participants in a communication-intervention program. We show the effectiveness of the proposed system by applying it to a real-world use case based on events of a reputed climate change communication intervention program. In the case study, we found that the divergence and consistency of the subjects participating in the studied communication program have improved. The source code for this study can be found in the following repository https://github.com/climate-matters/evo-lyzer.

Limitations and Future Work. We note the limitations of additional human involvement (e.g., curating the keywords list, identifying the topic models, and labeling the topics) in the process of assessing the evolving communication behavior effectively. Nevertheless, we can build upon this study to explore a system design with minimal human involvement once the initial input is provided. In this study, we did not include a control group or evaluate alternative metrics. Instead, our analysis focused on examining changes over time within the participants of the program. However, as a part of future work, the inclusion of a control group would provide valuable insights and a more robust framework for assessing the effectiveness of these programs. Furthermore, we will explore the possibility of gathering data from less restrictive online spaces, such as analyzing online articles published by the participating subjects. We also note that the X API (formally Twitter API) is no longer free, however, the system proposed in this paper would work with alternative social media (e.g., Mastodon) with some modifications. Finally, the *Evo-lyzer* system has the potential to be extended into a comprehensive system capable of performing in-depth exploratory analysis, providing a more detailed and comprehensive understanding of the collected data and event analysis using a variety of measures to study communication behavior.

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