Routledge
Taylor & Francis Group

Digital Journalism

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/rdij20

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DIGITAL JOURNALISM
https://doi.org/10.1080/21670811.2022.2031241

ARTICLE

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ABSTRACT

We propose a five-step computational framing analysis framework that researchers can use to analyze multilingual news data. The framework combines unsupervised and supervised machine learning and leverages a state-of-the-art multilingual deep learning model, which can significantly enhance frame prediction performance while requiring a considerably small sample of manual annotations. Most importantly, anyone can perform the proposed computational framing analysis using a free, open-sourced system, created by a team of communication scholars, computer scientists, web designers and web developers. Making advanced computational analysis available to researchers without a programming background to some degree bridges the digital divide within the communication research discipline in particular and the academic community in general.

KEYWORDS

Framing; machine learning; deep learning; BERT; topic modeling

With an incredible amount of data such as media data and digital trace data being created every day, the use of computational methods has become increasingly common in communication research. In particular, the abundance of online news content has prompted researchers to make extensive use of computational approaches in studying news texts (Boumans and Trilling 2016; Günther and Quandt 2016). This type of research has generated a significant impact on academic debates in fields including news diffusion (Bakir and McStay 2018), algorithmic journalism (Dörr and Hollnbuchner 2017), and news consumption patterns (Jacobi, van Atteveldt, and Welbers 2016).

Despite the rapid development of computational communication research, many challenges remain. This study focuses on four in particular. First, such research tends to be descriptive without contributing much in terms of theory building (e.g., Hilbert et al. 2019). Second, the black box problem—that the process of transforming input information into output is not transparent—is present in various applications of data science techniques in communication research (Guo 2018), hindering the open science movement in our field (van Atteveldt and Peng 2018). Third, despite the growing

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importance of understanding international information flow, most research tackles English-language text, leaving multilingual communication largely understudied. Fourth, the current ecosystem around "big data" creates new digital divides (Boyd and Crawford 2012). Among other barriers, the limited access to computational resources and skillsets prevents many communication scholars from taking advantage of a large number of unprecedented research opportunities.

To address these challenges, we—a team of communication scholars, computer scientists, web designers, and web developers—created a system Open Framing AI (OFAI; http://www.openframing.org) to facilitate computational research of digital media content that is theory-driven and open-sourced. Specifically, we propose a five-step analytical framework allowing users to identify *frames*—generally speaking, aspects of communication—in large-scale, multilingual media text by leveraging state-of-the-art computational research techniques. Our work is advantageous because, first, the framework is grounded in media framing theory, one of the most established theories in communication research (Reese, Gandy, and Grant 2001). Second, we provide a web-based, user-friendly graphic interface where researchers with little to no computational background can perform advanced data analysis through a click-and-run approach. Third, all algorithms are open to users, and the benefits and limitations of the algorithms are explained at each step. Fourth, our tool can be used to analyze media content in 23 languages based on a state-of-the-art multilingual deep learning model. Lastly, with the support of a research grant, we will make our tool free to the academic community.

In this article, we start with a review of the theoretical and methodological background from which our system OFAI was developed. We then detail the five-step framing analysis facilitated by the OFAI, accompanied by a case study that demonstrates the use of the system. The importance of bridging the digital divide and making efforts toward open science in the field of computational communication research will also be discussed.

Mapping the Field: Computational Framing Analysis

The field of computational communication research comprises work by scholars of various disciplinary backgrounds, research perspectives, and methodological approaches. One consistent criticism of this type of research is its lack of contributions to journalism and communication theories (e.g., Hilbert et al. 2019). Focusing on media framing theory, we propose an analytical framework that uses computational methods to analyze news frames in multiple languages. To situate our project in the existing literature, the following review includes the discussion of (1) framing theory and conventional news frame analysis, (2) computational methods that can be used in news frame analysis, (3) computational frame analysis focused on multilingual data, and (4) digital divides in computational communication research.

Framing Theory and News Frame Analysis

Framing theory is one of the most popular theoretical frameworks in communication research. Generally speaking, the theory considers how issues are presented in different types of communication and the resultant effects on audiences. Despite its wide use, what exactly constitutes framing remains unresolved. For example, scholars have analyzed the content of framing, causes of framing, and effects of framing. Explicating the diverse definitions and theoretical perspectives of framing is beyond the scope of this article (but see e.g., Cacciatore, Scheufele, and Iyengar 2016; Vliegenthart 2012; Vliegenthart and Van Zoonen 2011 for more discussion). Our project focuses on analyzing the content of framing such as news frames, and we recommend a specific theoretical approach detailed below. Researchers, however, may use the OFAI to identify frames in any text based on their desired theoretical framework.[1]

We suggest that a constructive, cultural approach is especially helpful in conceptualizing media framing in a cross-cultural, transnational context. Within this paradigm, Reese (2001) defines media frames as "organizing principles that are socially shared and persistent over time, that work symbolically to meaningfully structure the social world" (p. 11). In other words, one can frame an issue in multiple ways, but a frame must be shared by the target audience on some level for it to be communicable and effective (Reese 2001). Accordingly, news frame analysis should focus on frames that are "persistent over time" (Reese 2001, p. 11). These include *generic frames* that appear across issues, time, and space, such as *human interest*, *conflict*, and *economic consequences* (Neuman, Just, and Crigler 1992; Nisbet 2010; Semetko and Valkenburg 2000), and *issue-specific frames* that can be applied to a particular issue. For example, journalists often use *peace-* and *war-oriented* frames to help their audience understand the complexity of wars (Neumann and Fahmy 2012). For cross-national comparison, Guo and colleagues (2012) suggest that researchers should also consider *domestic frames*, or media frames that resonate with audiences in a specific social-cultural context but not others. For example, the *one-of-us* frame is more prominent in a collectivist than an individualistic society (Kwon and Moon 2009).

A cohesive approach to analyzing generic, issue-specific, and domestic frames is crucial to the advancement of media framing theory. However, the conceptualizations of frames are diverse in the existing literature. Some studies approach media framing by analyzing mainly themes or topics. From a constructive perspective, this approach is not appropriate because, again, news frame analysis should identify patterns that endure over time, which differs from thematic or topical analyses that describe themes or topics as instances reported in certain stories (Reese 2007). Additionally, themes and topics do not "organize" or "structure" as frames do.

Our proposed news frame analysis framework is based on this constructive tradition. Our goal is to detect generic, issue-specific, and domestic frames that persist over time in a given context. As "organizing principles" (Reese 2001, p. 11), frames conceptualized in this way tend to be abstract and less manifest. Therefore, compared with thematic or topical analysis, this type of frame analysis often requires a careful investigation of nuance in news coverage, which poses a challenge to computer automation when it comes to validity and reliability (Matthes and Kohring 2008). Our work incorporates a multi-step analytical framework and a state-of-the-art language model that can overcome this challenge to some extent. Before we introduce our approach, we first review the methods other researchers have used to automate the analysis of news frames.

Computational Approaches in News Frame Analysis

There are in general three computational approaches to text analysis: (1) lexical-based, (2) unsupervised machine learning, and (3) supervised machine learning. All of these approaches treat text as data: researchers convert text into features of data and analyze these features for patterns rather than interpret text directly (Benoit 2020; Grimmer and Stewart 2013). Two assumptions of treating text as data are worth noting. First, researchers often use manifest indicators, such as word frequencies, to infer latent characteristics such as topics and frames. Second, many of these analytical procedures are based on the bag-of-words model, representing text by counting how many times each word appears without considering the order or context of the words. We first introduce each methodological approach and then discuss its applicability in news frame analysis. To be consistent, the unit of analysis for all these approaches is called a document, which refers to a piece of text such as a news headline, news article, or tweet.

The lexical-based approach relies on predefined lists of words, known as lexicons or dictionaries, with each word associated with a certain semantic category. For example, words such as "happy," "growth," and "improve" can be used to indicate the category "positive" in sentiment analysis. Researchers either create custom lexicons tailored for specific projects (e.g., sentiment in U.S. economic news) or use off-the-shelf lexicons (e.g., sentiment in any documents). The lexical-based approach is one of the most commonly used computational methods in communication research because of its relative simplicity, but the validity of the approach—especially the off-the-shelf model—remains questionable (e.g., Boukes et al. 2020; Wilkinson and Thelwall 2012). When it comes to framing research, researchers must construct dictionaries to identify frames. For example, Lind et al. (2019) developed keywords to search for frames in the news coverage of immigration: *economy & budget*, *labor market*, *welfare*, and *security*. We contend that the lexical-based approach is not ideal for news frame analysis. Unlike the topic-like frames in Lind et al. (2019), many enduring media frames from a constructive perspective (e.g., *conflict, human interest*) are abstract and involve complex meanings, which cannot be easily captured by a list of words alone.

The second and third approaches are based on machine learning (ML), which focuses on building applications that learn from data and identify patterns. The main difference between the two is that supervised learning is done using a "ground truth." That is, the machine is trained by learning a sample of documents that are already labeled with the "correct" answer. In communication research, the "ground truth" often refers to labels provided by human coders through quantitative content analysis (Krippendorff 2004). Once a model is trained, it can be used to predict unlabeled documents. In contrast, unsupervised ML models work on their own to discover information and patterns from the unlabeled data. In short, unsupervised ML is inductive, whereas supervised is deductive.

Several existing news frame studies take an unsupervised ML approach. Compared to a supervised, deductive approach, unsupervised ML is advantageous in being able to quickly explore the entire dataset and potentially reveal new patterns not seen in previous literature. Among other unsupervised approaches (see Nicholls and Culpepper 2021), the Latent Dirichlet Allocation (LDA) based topic modeling is a

Table 1. The LDA topic modeling output based on five topics.

	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
KW 1	Time	Police	Student	Trump	Law
KW 2	Life	Officer	High	President	Firearm
KW 3	Mass	Shot	Florida	Nra	State
KW 4	Victim	Man	Parkland	House	Weapon
KW 5	Year	Told	Douglas	Republican	Rifle
KW 6	Family	County	Teacher	State	Violence
KW 7	Killed	Yearold	Stoneman	White	Company
KW 8	Friend	Suspect	Cruz	Democrat	Year
KW 9	Video	Report	March	Bill	Amendment
KW10	Day	Department	Marjory	Control	Ban

*KW = Keyword.

popular example. The LDA is a generative statistical model that detects unobserved groups from large corpora based on the similarities among parts of the whole text using a non-intrusive, probabilistic method (Blei, Ng, and Jordan 2003). In analyzing news content, the text is observed as a set of latent "topics" and these topics are distributed over words in a probabilistic order. The output of the LDA topic modeling is a "topic matrix" with a list of keywords representing each topic. Researchers review the top keywords and decide on a label to represent the meaning of each topic. See Table 1 for an example of the LDA topic matrix, which is a part of the analysis introduced later in the paper.

We maintain that an LDA topic is not equivalent to a frame as conceptualized in this article. Again, similar to topics and themes mentioned above, the LDA topics often—while not always—represent instances reported in certain stories (Reese 2007). Table 1 shows many topics include terms that specifically speak to the data under investigation and may not generalize beyond the study. Therefore, the LDA results are not used to directly indicate, but rather to infer frames (van Atteveldt et al. 2014). For example, Walter and Ophir (2019) approach begins by running an LDA analysis to examine all topics related to the issue under consideration, which they consider "frame elements." Then community detection techniques—methods to identify communities in complex networks—are applied to automatically group frame elements into "frame packages."[2] The approach is systematic and potentially replicable. However, because of the inductive nature of the approach, the generated "frames" do not necessarily correspond to those enduring frames—generic, issue-specific, and domestic—defined in the existing media framing literature. Without analyzing the predefined frames, the new analysis may contribute little to our prior knowledge of how the given issue is reported. Beyond news frame analysis, the implementation of the LDA method itself lacks standardization in our field, and therefore the reliability and validity of the results it yields are still questionable (Maier et al. 2018).[3]

Like unsupervised ML, supervised ML has become increasingly common in communication research (e.g., Colleoni, Rozza, and Arvidsson 2014; De Grove, Boghe, and De Marez 2020). In the context of news frames conceptualized in this article, supervised ML can be used to detect enduring frames, given a sample of ground truth data labeled with these frames. In practice, there are several supervised ML algorithms available. In performing a text analysis, the Support Vector Machine (SVM) has been found to outperform others (Collingwood and Wilkerson 2012) and thus frequently applied in communication research (e.g., Flaounas et al. 2013). Despite its popularity, using supervised ML in news frame analysis is rare, with a few exceptions (Burscher et al. 2014; Opperhuizen, Schouten, and Klijn 2019). Notably, Burscher et al. (2014) is a methodological exploration that applies supervised ML to automate the coding of four generic frames: *conflict*, *economic consequences*, *human interest*, and *morality*. Based on a series of experiments, they conclude that supervised ML is well-suited to automate frame coding, but the levels of the performance vary from frame to frame and depend on how ML is implemented. For example, the study suggests that increasing the number of positive cases of a frame (i.e., more documents that are labeled as a certain frame) in the training data can improve prediction accuracy. This observation is consistent with previous findings of other prediction tasks (e.g., Collingwood and Wilkerson 2012), but this strategy requires more manual annotations, which is labor-intensive. Burscher et al. (2014) also suggest that some frames are harder to predict, perhaps due to their semantic nature. Compared with unsupervised ML, supervised ML is also limited in identifying new information that emerges from the data. That is, it cannot detect categories not part of the training data.

Computational Approaches for Multilingual News Frame Analysis

Against the backdrop of continuing trends of globalization, researchers have begun to pay greater attention to news frames across national boundaries. For multilingual data, researchers often recruit coders who specialize in different languages to implement the multilingual news frame analysis (e.g., De Vreese, Peter, and Semetko 2001; Esser and Angelo 2006). This is not an easy task due to the difficulty of recruiting multilingual coders, the time to establish intercoder reliability between coders across teams, and the resulting cost (Reber 2019).

Given these challenges, communication researchers have applied the above-discussed lexical-based approach and topic modeling to identify frames in multilingual, cross-national text corpora (Heidenreich et al. 2019; Lind et al. 2019). Furthermore, newer methodological approaches such as machine translation and aligned word embeddings have been used to facilitate the comparative analysis of multilingual data while overcoming language barriers (Chan et al. 2020; Reber 2019). However, as argued above, the semantic constructs identified in this way are more similar to topics or themes than frames from a constructivist perspective. Additionally, when applying topic modeling to multilingual data, the topics that emerge in documents of different languages may not align, making comparison difficult.

The Digital Divides in Computational Communication Research

Implementation of computational models necessitates a high level of computational resources and skills. This is especially true for advanced language models, whose training may involve millions of parameters. Even fine-tuning models requires computers with the graphics processing unit (GPU) compute capability, which is expensive and not widely available. Some cloud services such as Google Colab provide free but limited access to GPUs (i.e., One GPU with limited memory of 12GB per user), which is not sufficient to train a deep learning model. In short, having unlimited access to GPUs at any time for running deep learning models is a privilege. Even within the field of computer science, the intensive computational requirements for running large ML models and the unequal access to these computing resources among researchers contribute to the digital and computational divides (Strubell, Ganesh, and McCallum 2019).

For communication researchers, the divide is exacerbated due to the shortage of computational research skills. Implementing and fine-tuning topic modeling or deep learning models requires a considerable degree of comprehension and comfort with a deep learning programming framework such as Pytorch or TensorFlow, machine learning libraries such as scikit-learn for the training and evaluation setup and analysis, natural language processing libraries such as the Natural Language Toolkit (NLTK) or spacy to clean and pre-process the text, and the Python programming required for all these frameworks and libraries. Users with little experience in computer science are likely to find it challenging to run computational analysis on their own.

Summary

Based on a review of the literature, we found several limitations of computational framing analysis in the current scholarship. First, the conceptualization of framing remains fuzzy. Second, the three popular computational analysis approaches—lexical-based, unsupervised ML, and supervised ML—each presents problems that affect the validity and efficiency of news frame analysis. Third, computational framing analysis of multilingual media content is underdeveloped. Fourth, implementing computational analysis requires extensive computational resources and skills, which are not widely accessible in the communication research community.

To address these issues, we first recommend a constructivist definition of news frames, focusing on the analysis of generic, issue-specific, and domestic frames that persist over time in a given context. Based on this theoretical perspective, we propose a multilingual framing analysis framework that combines unsupervised and supervised ML.[4] To reiterate, unsupervised ML can help develop a holistic picture of large-scale text corpora and can discover new patterns; a deductive, supervised approach can identify enduring frames in different cultural contexts, thus building on the existing framing literature. When it comes to multilingual framing analysis, combining unsupervised and supervised ML to determine an exhaustive set of frames for multiple datasets makes comparison possible. In addition, our proposed framework incorporates a state-of-the-art multilingual deep learning algorithm, which improves the detection of nuanced and complex news frames as defined in this article.

Lastly, with the support of a research grant and a cross-disciplinary team, our system aims to make computational framing analysis accessible to researchers with limited experience in computer science. Through a click-and-run web-based system, users can follow the guidance on the website and run advanced computational analysis step-by-step. We also make it our conscious effort to provide a user-friendly and interactive website so that users with different levels of expertise know where to start and how to interact with the system. Unlike many similar applications in the market, the

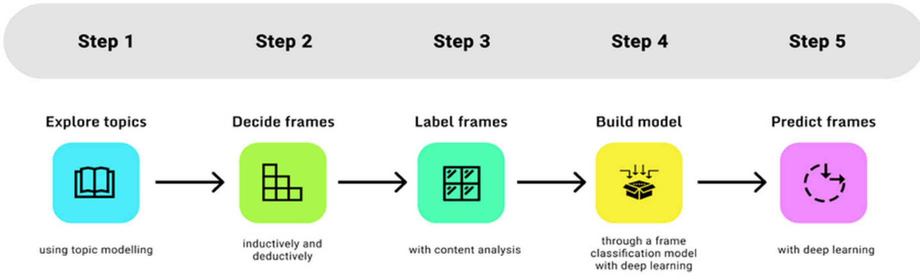

Figure 1. An illustration of the proposed five-step news frame analysis.

OFAI prioritizes transparency in data processing, algorithms, and limitations of machine-generated results. The tool is entirely open-sourced. We explicitly detail all the computational techniques used in the backend of the system, and users have access to the raw code on Github. The following section introduces our framing analysis framework and the online system.

Five-Step Multilingual Framing Analysis

Our framework involves five steps that researchers can take to conduct a computational framing analysis of multilingual text corpora (see Figure 1). To demonstrate the research procedure, the introduction will be accompanied by a case study that examines frames in the U.S. and German news coverage of the U.S. gun violence issue.

Before using the OFAI, researchers should first collect media data related to the issue under consideration. For the case study, we used Crimson Hexagon's ForSight platform (now Brandwatch) to retrieve relevant news articles both in English and in German. First, using the keyword combination (gun OR firearm OR nra OR "2nd amendment" OR "second amendment" OR AR15 OR "assault weapon" OR rifle OR "brady act" OR "brady bill" OR shooting), we collected a total of 42,917 English news articles from a list of U.S. traditional and emerging media outlets in 2018. The U.S. gun violence also attracts international news attention. Evaluating how foreign countries frame the issue will enrich our understanding of the U.S. soft power in particular and international relations in general. This demo uses German news coverage as an example for multilingual content in a corpus (see Akyürek et al. 2020 for frame analysis in other languages). We then translated these search terms into German with some adaptation and retrieved 1,523 articles from a list of German-language news organizations in 2018.[5]

To analyze how the news media frame an issue, we first suggest users come up with a list of specific "frames" that guide the discussion of the issue. This process of searching for frames should be both *inductive*—based on an observation of the data—and *deductive*—based on a review of the previous framing literature. Both steps are essential because the analysis of frames should not just aim for a full capture of the data (inductive), but also to build and further advance media framing theory (deductive).

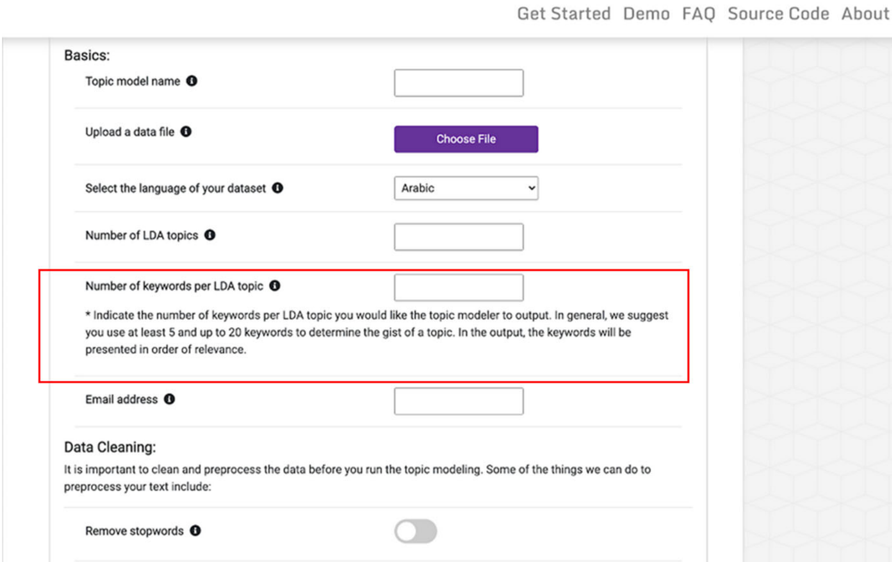

Figure 2. Screenshot of part of the Web page for running the LDA. *Note*. The highlighted part shows that, when the user clicks on the "i" button, more information about the selection will be shown.

Step 1: Explore Topics with Topic Modeling

Step one focuses on the inductive part of the research. Obtaining a quick, preliminary understanding of the data is crucial, especially when the dataset is large and may contain a wide range of information. As introduced above, the LDA topic modeling is a recommended method for researchers to explore prominent "topics" in the data. It is important to reiterate that an LDA "topic" is different from a frame, and the LDA topic modeling results will not be directly used to identify frames. The goal of this first step is to preliminarily examine the LDA "topic" information of the data, which helps researchers decide the final frames to be analyzed in Step 2.

Before the topic modeling analysis, it is essential to preprocess the data. Technically, the OFAI tool first cleans the user-uploaded dataset by providing a list of data cleaning options (see some of them in Figure 2; more preprocessing steps can be found from the system). In particular, we provide the option of running the analysis in multiple languages. The NLTK provides a library of stopwords available in 23 languages, which we use to remove stopwords in the language specified by the user. We also use the NLTK to tokenize the text, which means breaking sentences into words. The LDA topic modeling algorithm, which is language invariant, is then applied to generate topics from the cleaned text.

Although the LDA topic modeling is a computational method, its implementation involves a series of human reasoning. For instance, as mentioned above, researchers should decide the data cleaning procedures, the number of LDA topics, and the number of keywords associated with each topic. Any decision in this process will have an impact on the output (Guo 2018). Our tool OFAI not only allows users to specify their preferred settings, but also provides guidance and recommendations for each decision

Table 2. The LDA topic modeling output based on 10 topics.

	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
KW 1	Nra	Amendment	Student	Police	Trump
KW 2	Company	Weapon	High	Officer	President
KW 3	Rifle	Breitbart	Florida	Shot	House
KW 4	Group	Court	Cruz	Man	White
KW 5	National	Firearm	Teacher	Yearold	State
KW 6	Member	News	Parkland	Told	Campaign
KW 7	Firearm	State	Douglas	Department	Republican
KW 8	Association	Rifle	County	Video	Election
KW 9	Sale	Hawkins	Shooter	Chicago	Russian
KW10	Million	Awr	Sheriff	County	Donald
	Topic 6	Topic 7	Topic 8	Topic 9	Topic 10
KW 1	Gunman	Violence	Dont	Student	Trump
KW 2	Victim	Law	Time	March	Bill
KW 3	Killed	Firearm	Video	High	State
KW 4	Mass	State	Thing	Parkland	Republican
KW 5	Bar	Year	Make	Violence	Law
KW 6	Vega	Percent	Day	Florida	Check
KW 7	Attack	Health	Back	Control	Background
KW 8	Police	Mass	Child	Douglas	Control
KW 9	Shot	Death	Family	Stoneman	House
KW10	Fire	Mental	Life	Life	Florida

(see Figure 2). Consider the number of the LDA topics as an example. Researchers should decide the number of topics when performing the LDA topic modeling analysis. While statistical methods exist to help determine the number, the statistically estimated number does not necessarily lead to the most coherent topic matrices, that is, topics that are distinct from each other and semantically meaningful (Guo et al. 2016). Instead, researchers usually create LDA models across different topic numbers and then check the topic coherence for each. Following previous research (e.g., Guo et al. 2016; Hecking and Leydesdorff 2019; Jacobi, van Atteveldt, and Welbers 2016), we recommend users try different numbers of topics before making the final decision.

In the gun violence study, we first used the LDA to explore prominent topics in English and German news articles about the U.S. gun violence issue. For demonstration purposes, we tried 5, 10, and 15 topics in the English data. See Tables 1–3 for the LDA topic matrices.

Based on the five-topic LDA output, we can manually assign labels to these topics: (1) mass shootings, (2) police officers, (3) school shootings and demonstrations, (4) gun rights and gun control, and (5) the Second Amendment. We recommend at least two researchers independently review the topics and then decide the labels collectively.

Based on the 10-topic LDA output, we can manually assign labels to these topics: (1) gun rights groups and gun sales, (2) the Second Amendment, (3) school shootings, (4) police officers, (5) politics, (6), mass shootings, (7) mental health, (8) children and family, (9) student-led demonstrations, and (10) gun control. It is clear that when we increase the number of topics from five to 10, more information emerges, such as mental health.

Based on the 15-topic LDA output, we can manually assign labels to these topics: (1) politics, (2) gun rights groups and gun-related businesses, (3) gun control, (4) the second amendment and gun control, (5) politics and gun control, (6) N/A,[6] (7) politics

Table 3. The LDA topic modeling output based on 15 topics.

	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
KW 1	Trump	Nra	Weapon	Breitbart	Trump
KW 2	President	Company	Firearm	Hawkins	Bill
KW 3	House	National	Rifle	Awr	Check
KW 4	White	Rifle	Ban	News	House
KW 5	Russian	Group	Law	Amendment	President
KW 6	Fbi	Member	Assault	Range	Law
KW 7	Donald	Association	Handgun	Control	Background
KW 8	Russia	Million	Magazine	Armed	Florida
KW 9	Campaign	Business	Owner	American	State
KW10	Investigation	Bank	State	Host	Republican
	Topic 6	**Topic 7**	**Topic 8**	**Topic 9**	**Topic 10**
KW 1	Dont	Republican	Police	Police	Bar
KW 2	Thing	Control	Officer	Officer	Vega
KW 3	Time	State	Man	Shot	Mass
KW 4	Make	Democrat	Shot	Sheriff	Oak
KW 5	Cnn	Support	Chicago	Suspect	Thousand
KW 6	Video	Candidate	Video	Gunman	California
KW 7	Lot	Election	Charge	County	Gunman
KW 8	Theyre	Percent	Department	Shooter	Killed
KW 9	Back	Democratic	Black	Killed	Victim
KW10	Good	Campaign	Charged	Told	Borderline
	Topic 11	**Topic 12**	**Topic 13**	**Topic 14**	**Topic 15**
KW 1	Medium	Violence	Student	Family	State
KW 2	Pittsburgh	Law	High	Child	Court
KW 3	Synagogue	Health	Florida	Home	Law
KW 4	Video	Year	Parkland	Son	Amendment
KW 5	Email	Mental	Douglas	Told	Wilson
KW 6	News	Death	Stoneman	Friend	Judge
KW 7	Photo	Mass	Cruz	Life	Federal
KW 8	Tweet	State	March	Year	Case
KW 9	Facebook	Firearm	Marjory	Day	Firearm
KW10	Twitter	Percent	Teacher	Time	Government

and gun control, (8) police officers and race/ethnicity, (9) police officers, (10) mass shooting cases, 1(1) gun violence and race/ethnicity, (12) gun violence and mental health, (13) school shootings and demonstrations, (14) family and children, and (15) the Second Amendment and gun regulations. Notably, when we increase the number of topics to 15, redundancy occurs—for example, many topics are related to gun control—and certain "topics" (e.g., Topic 6) are not semantically meaningful. This indicates that we may have reached, or are close to reaching, the saturation point; further increasing the number of topics would be less likely to generate any new topical information.

After the users try a series of numbers and qualitatively explore the corresponding topic matrices in datasets of different languages, they will be able to develop a preliminary idea of the multilingual data. This concludes the first step of the framing analysis.

Step 2: Decide Frames Inductively and Deductively

In this second step, researchers are recommended to consult the LDA topic modeling results from Step 1 (inductive) and previous literature about media framing of the issue under investigation (deductive), and then decide a list of frames to be analyzed.

For a comparative news frame analysis, researchers should consider multilingual LDA outputs and review literature for generic, issue-specific, and domestic media frames that apply to all societies under analysis.

For our case study, based on the LDA modeling results of the news coverage of gun violence in both English and German and the literature review of the media framing of this topic, we decided on the following list of frames: (1) Gun/2nd amendment rights; (2) Gun control/regulation; (3) Politics; (4) Mental health; (5) School or public space safety; (6) Race/ethnicity; (7) Public opinion; (8) Society/culture; and (9) Economic consequences.

On this list, some frames are *issue-specific frames* that are unique to the media coverage of gun violence such as "gun/2nd Amendment rights" and "mental health;" others are *generic frames* such as "economic consequences" that apply to all kinds of issues. It is also important to note that although the LDA topic modeling results do not explicitly reference "society/culture," we still include it because it is a media frame discussed in the previous literature about gun violence media coverage (Birkland and Lawrence 2009; Callaghan and Schnell 2001). We may end up finding that this frame appears very rarely in our data. This would still be an important finding. After all, media framing is not just about inclusion and emphasis, but also exclusion.

Step 3: Label Frames with Content Analysis

After deciding the list of frames, the user should then draw a sample of the data and apply quantitative content analysis to manually label frames. This annotated sample will be used as the ground truth to train an ML model in Step 4.

In our case study, we selected a random sample of 1,300 English and 350[7] German news headlines respectively, and recruited two native speakers for each language to annotate the frames of the headlines. We chose to focus on news headlines because they are often seen first and can determine the perception of the following text (Tankard 2001). Of course, users can consider other units of analysis (e.g., news body paragraphs, tweets, etc.). Following the quantitative content analysis procedure (Krippendorff 2004), we created a codebook to explain each frame (see the Appendix) and held multiple training sessions for the coders to understand how to identify up to two dominant frames of the news headlines. To test intercoder reliability, the two coders for English were instructed to code a sample of 200 English news headlines, and the two German-speaking coders coded all 350 news headlines independently and their results were compared. They ultimately reached an acceptable level of intercoder reliability for each of the two frames: English: 0.90, 0.82; German: 0.89, 0.69, all in Krippendorff's α.[8] The coders then completed the annotation of all the remaining English news headlines.

Step 4: Build a Frame Classification Model with Deep Learning

The goal of Step four is to use the documents labeled in Step three to build supervised ML models that can predict frames in unlabeled documents. Our analytical framework incorporates the state-of-the-art language model BERT, which stands for

Bidirectional Encoder Representations from Transformers (Davlin et al. 2018). More specifically, to analyze text in multiple languages, we use a recent extension of BERT: XLM-Roberta (Conneau et al. 2019). BERT and its extension XLM-Roberta are based on deep learning, which is an advanced form of ML. The algorithm mimics the network of neurons in a brain, which processes a large amount of input data and operates them through multiple layers. At each layer, the network can learn increasingly complex features of the data and can be used to make predictions. Deep learning is a very powerful tool and has been demonstrated to outperform traditional ML in many contexts (e.g., Hatcher and Yu 2018).

BERT is one of the most successful models in natural language processing (Devlin et al. 2018). Trained on a large text corpus (i.e., Wikipedia pages and books), the model produces embeddings (i.e., vectors of numbers) to represent the meaning of sentences, taking into consideration the relationships between words and the communication context. This approach has proved superior to many other text classification models that process each word separately using the bag-of-words model (Davlin and Chang 2018). In other words, the BERT model can be used to detect abstract, complex frames (e.g., *conflict*, *human interest*) based on the context of the description rather than relying on a list of separate words and terms. XLM-Roberta is further trained on a large corpus of multilingual data: 2.5TB of filtered web data in 100 languages. The vector representations of text in any of these 100 languages can then be used to generate insight into any text in the given language.

Building a deep learning model from scratch is hard because it requires extensive training data. A more common approach in computer science is to "borrow" insight from a *pretrained* deep learning model and use it to perform similar tasks on another dataset. This is called *transfer learning*. XLM-Roberta—a pretrained deep learning model—can be fine-tuned by adding specific prediction schemes to continue supervised ML on a variety of tasks. In other words, the machine first obtains some knowledge from XLM-Roberta about how to create meaningful vector representations of text in multiple languages, and then it learns from the provided human annotations how to perform a particular task (e.g., frame classification). In short, for multilingual frame prediction, combining the knowledge from XLM-Roberta and the user-provided ground truth frame labels will yield state-of-the-art prediction performance. With the capability of transferring knowledge from a pretrained model to the current task, one can build a model with a high level of accuracy even using a small sample of ground truth labels.

Using the OFAI, once the user uploads a labeled dataset, the labeled documents will be input into XLM-Roberta and fine-tuned by adding a new layer of prediction scheme (i.e., frames) on neural network classification. To assess the ML model performance, a typical way is to divide the labeled documents into a training set and a testing set. The model will be trained by learning the labeled documents in the training set. Then the trained model will be used to predict the labels (e.g., frames) of documents in the testing set so that the predicted labels can be compared with the ground truth labels. To reduce the bias of selecting training and testing data, *K*-fold cross-validation is an effective method to validate the model performance on multiple folds of the data. The OFAI implements 5-fold cross-validation. Specifically, the user-labeled data will be randomly split into five folds. For each fold, we take the documents in this fold

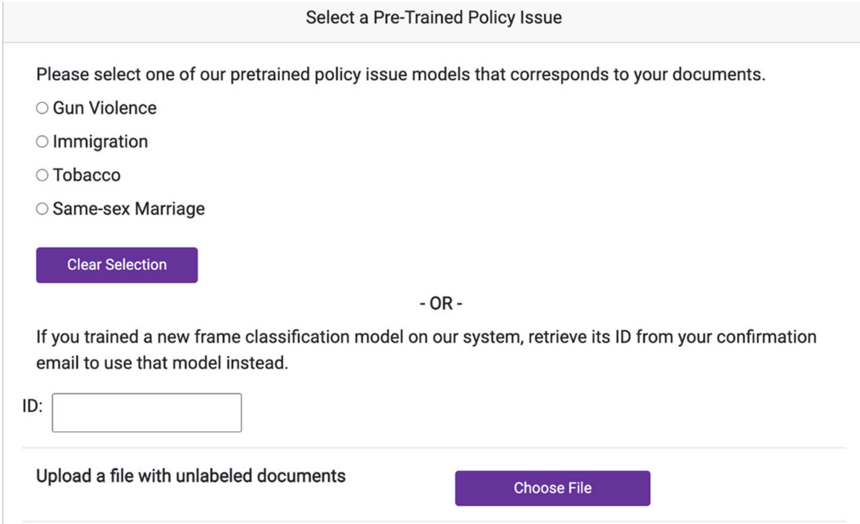

Figure 3. Screenshot of part of the Web page for frame prediction.

as the testing set and the documents in the remaining four folds as a training set. A model is trained on the training set and evaluated on the testing set. For each of the five models, the evaluation scores will be reported and summarized.

The OFAI provides three evaluation scores—precision, recall, and F-score (e.g., Stryker et al. 2006)—to assess the performance of the trained models. *Precision* is the ratio of true positives to the total predicted positive observations. For example, when predicting a given frame "mental health," the precision score measures how many of the news headlines predicted as "mental health" were indeed coded as "mental health" by human coders. *Recall* is the ratio of true positives to all observations in the actual case. In our example, it measures how many of the headlines coded as "mental health" by human coders were identified by the model. *F-score* is the weighted average of precision and recall. If there is more than one frame under consideration (i.e., multiclass prediction), the average precision, recall, and F-score will be reported. Using 5-fold cross-validation, five sets of precision, recall, and F-score will be reported. We recommend that the user should aim for an average of 80% in terms of both precision and recall. If the model performance is less than satisfactory, there are several improvement strategies available, including adding more annotated documents and combining label categories.

As for our gun violence study, we used the above-discussed approach to train a fine-tuned deep learning model. Based on 5-fold cross-validation, the model to predict frames in the English news headlines reached 0.83 precision and 0.83 recall. The German model reached 0.73 precision and 0.81 recall.[9] The precision of the German model is not ideal, but impressive given the small size of the annotated sample.

Step 5: Predict Frames with Deep Learning

Once the user is satisfied with the average model performance from Step 4, a new model will be trained based on all labeled documents. Researchers can then upload

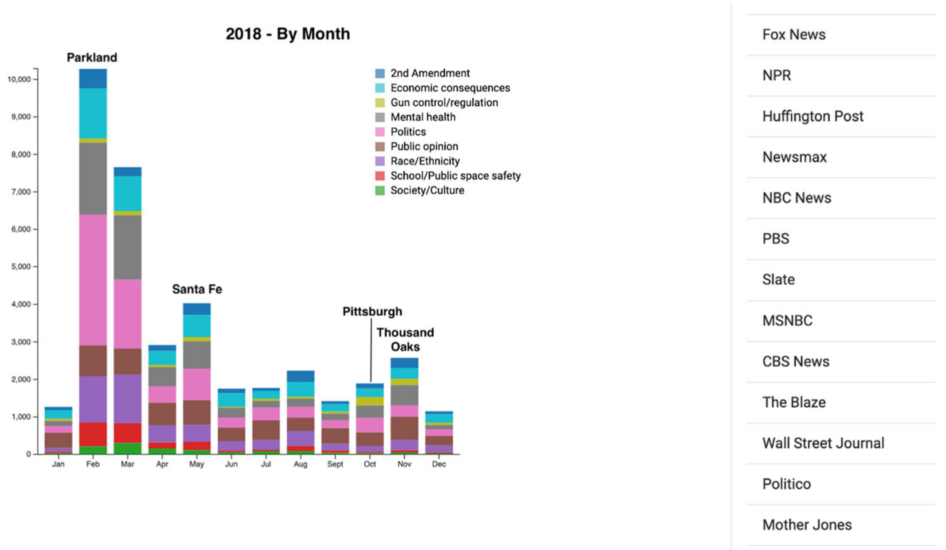

Figure 4. Screenshot of part of the Web page for the gun violence study demo. *Note.* The right sidebar provides the list of news organizations included in the analysis. (The screenshot shows part of the list.).

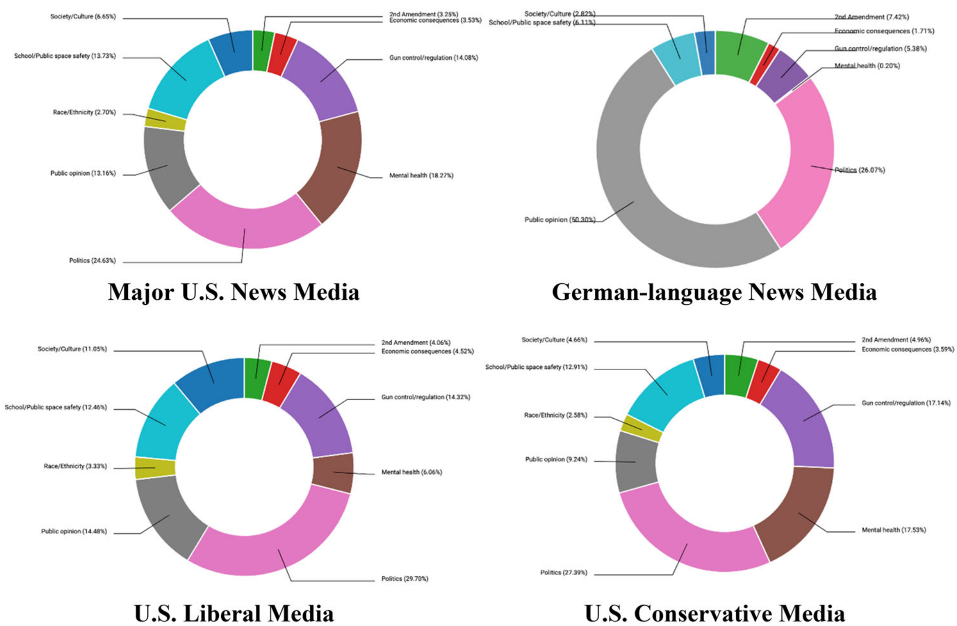

Figure 5. A comparison of the U.S. and German news coverage.

an unlabeled dataset, and the trained model will be used to predict the frames of the documents in the dataset (see Figure 3). The OFAI also provides four English pre-trained models on the topics of gun violence, immigration, tobacco, and same-sex marriage. If users happen to work on a news dataset corresponding to one of these topics, they can directly use our models to predict news frames. Of course, the users should understand that if their data are considerably different from the data used to train the model (e.g., published in different time periods), the accuracy of prediction may not be ideal.

Using the two gun violence models—English and German—trained in Step 4, we predicted the frames of the remaining English and German news headlines about the U.S. gun violence issue in 2018. Figures 4 and 5 visualize the results. For the U.S., it is clear that the volume of coverage increased after each mass shooting (see Figure 4). Overall, the issue was largely politicized in the media discourse across all datasets (see Figure 5). Comparing conservative- and liberal-leaning media in the U.S., the former emphasized the mental health frame more than the latter. It is also interesting to observe that the German-language news media paid considerable attention to the public opinion of this foreign issue. With the results of news frames like the ones demonstrated here, users can run additional statistics to compare news framing strategies across different societies or different types of news media within a certain society.

Conclusion

In this article, we reviewed the status quo of computational framing analysis and discussed the importance of combining inductive and deductive reasoning to examine news frames in cross-cultural contexts. We then proposed a five-step computational framing analysis framework to analyze multilingual news data. Additionally, we introduced and demonstrated the open-sourced OFAI tool with which users can perform the proposed framing analysis.

Our work advances computational communication research in general and framing research in particular theoretically, methodologically, and practically. Given the abundance of descriptive analyses, we advocate for theory-driven computational research and provide a comprehensive approach that integrates media framing theory and a series of computational methods into a solid analytical framework. Within the framework, we introduce the state-of-the-art BERT model, which facilitates the detection of complex news frames in multiple languages by considering the context of the text rather than relying on a bag of words. The deep learning model is expected to achieve strong frame prediction performance while requiring a comparatively small sample of manual annotations. Also remarkable is our effort to make advanced computational analysis open and available to researchers without a programming background. This to some degree bridges the digital divides in the communication research discipline and beyond.

Notes

1. In essence, the OFAI provides a tool for researchers with little to no programming experience to run text-based computational analysis. As will be detailed in the article, the system has features that allow researchers to classify text into categories in both unsupervised and supervised ways. The “categories” can be frames or other constructs such as topics and sentiment. That is, while our proposed analytical framework focuses on frames based on a specific theoretical perspective, researchers may use our system to identify

frames defined in a different way, or other constructs. In addition, though we propose a 5-step text analysis, users do not have to follow and can just use one of the features (e.g., LDA topic modeling, deep learning) for their analytical purposes.

2. A similar approach in framing analysis is to manually code framing elements and then apply a cluster analysis to reduce framing elements into clusters, which are treated as frames (Matthes 2009).
3. It is important to note that work has been done to validate topics generated by topic models. See the R package oolong for an example (Chan and Sältzer 2020).
4. See more studies (Eshima, Imai, and Sasaki 2020; Fogel-Dror, Shenhav, and Sheafer 2021; Watanabe and Zhou 2020) for how to combine different approaches (e.g., lexical-based analysis, unsupervised ML, supervised ML) to conduct theory-driven analysis of large corpora.
5. Our search retrieves all relevant news coverage in German from 339 news websites, which include German language news websites in countries other than Germany. The top 10 news websites in terms of the number of articles in our sample are: stern.de, msn.com, langenthalertagblatt.ch, welt.de, spiegel.de, n-tv.de, thunertagblatt.ch, and berneroberlaender.ch. We mainly use the German news data for tool demonstration purposes. Future research should consider analyzing news frames in different countries separately.
6. The LDA topic modeling algorithm may generate "topics" that do not contain meaningful, coherent concepts and therefore researchers may choose to remove the "topic" from the further analysis (Maier et al. 2018).
7. The "ground truth" sample for the German data is relatively small. We use the small sample mainly for the purpose of tool demonstration. Researchers are recommended to provide a larger annotated sample for a real study.
8. In this study, the coders were instructed to annotate up to two frames for each news headline. For the purpose of creating a machine learning model for this demonstration discussed in the next section, we only used the first frame. That is, the model is trained on nine classes.
9. The average model performance is reported and the performance to predict each of the nine frames varies. More information is available upon request.

Disclosure Statement

No potential conflict of interest was reported by the authors.

Funding

This study is supported in part by the U.S. NSF grant 1838193.

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References

Akyürek, A. F., L. Guo, R. Elanwar, P. Ishwar, M. Betke, and D. T. Wijaya. 2020. "Multi-Label and Multilingual News Framing Analysis." In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*.

Bakir, V., and A. McStay. 2018. "Fake News and the Economy of Emotions: Problems, Causes, Solutions." *Digital Journalism* 6 (2): 154–175.

Benoit, K. 2020. "Text as Data: An Overview." In *The SAGE Handbook of Research Methods in Political Science and International Relations*, edited by L. Curini and R. Franzese, 461–497. London: Sage.

Birkland, T. A., and R. G. Lawrence. 2009. "Media Framing and Policy Change after Columbine." *American Behavioral Scientist* 52 (10): 1405–1425.

Blei, D. M., A. Y. Ng, and M. I. Jordan. 2003. "Latent Dirichlet Allocation." *Journal of Machine Learning Research* 3: 993–1022.

Boukes, M., B. van de Velde, T. Araujo, and R. Vliegenthart. 2020. "What's the Tone? Easy Doesn't Do It: Analyzing Performance and Agreement between off-the-Shelf Sentiment Analysis Tools." *Communication Methods and Measures* 14 (2): 83–104.

Boumans, J. W., and D. Trilling. 2016. "Taking Stock of the Toolkit: An Overview of Relevant Automated Content Analysis Approaches and Techniques for Digital Journalism Scholars." *Digital Journalism* 4 (1): 8–23.

Boyd, Danah, and K. Crawford. 2012. "Critical Questions for Big Data: Provocations for a Cultural, Technological, and Scholarly Phenomenon." *Information, Communication & Society* 15 (5): 662–679.

Burscher, B., D. Odijk, R. Vliegenthart, M. De Rijke, and Claes H. de Vreese. 2014. "Teaching the Computer to Code Frames in News: Comparing Two Supervised Machine Learning Approaches to Frame Analysis." *Communication Methods and Measures* 8 (3): 190–206.

Cacciatore, M. A., D. A. Scheufele, S. Iyengar. 2016. "The End of Framing as We Know It … and the Future of Media Effects." *Mass Communication and Society* 19 (1): 7–23.

Callaghan, K., and F. Schnell. 2001. "Assessing the Democratic Debate: How the News Media Frame Elite Policy Discourse." *Political Communication* 18 (2): 183–213.

Chan, C., and M. Sältzer. 2020. "Oolong: An R Package for Validating Automated Content Analysis Tools." *Journal of Open Source Software* 5 (55): 2461.

Chan, C., J. Zeng, H. Wessler, M. Jungblut, K. Welbers, J. W. Bajjalieh, W. van Atteveldt, and S. L. Althaus. 2020. "Reproducible Extraction of Cross-Lingual Topics (Rectr)." *Communication Methods and Measures* 14 (4): 285–305.

Colleoni, E., A. Rozza, and A. Arvidsson. 2014. "Echo Chamber or Public Sphere? Predicting Political Orientation and Measuring Political Homophily in Twitter Using Big Data." *Journal of Communication* 64 (2): 317–332..

Collingwood, L., and J. Wilkerson. 2012. "Tradeoffs in Accuracy and Efficiency in Supervised Learning Methods." *Journal of Information Technology & Politics* 9 (3): 298–318..

Conneau, A., K. Khandelwa, N. Goyal, V. Chaudhary, G. Wenzek, F. Guzmán, E. Grave, M. Ott, L. Zettlemoyer, and V. Stoyanov. 2019. "Unsupervised Cross-Lingual Representation Learning at Scale." *arXiv Preprint arXiv:1911.02116*.

Davlin, J., and M.-W. Chang. 2018. Open Sourcing BERT: State-of-the-Art Pre-training for Natural Language Processing. *Google AI Blog*. November 2. https://ai.googleblog.com/2018/11/open-sourcing-bert-state-of-art-pre.html.

Davlin, J., M.-W. Chang, K. Lee, and K. Toutanova. 2018. "Bert: Pre-Training of Deep Bidirectional Transformers for Language Understanding." *arXiv Preprint arXiv:1810.04805*.

De Grove, F., K. Boghe, and L. De Marez. 2020. "(What) Can Journalism Studies Learn from Supervised Machine Learning?" *Journalism Studies* 21 (7): 912–927.

Devlin, J., M.-W. Chang, K. Lee, and K. Toutanova. 2018. "Bert: Pre-Training of Deep Bidirectional Transformers for Language Understanding." arXiv preprint arXiv:1810.04805.

De Vreese, Claes H., J. Peter, and H. A. Semetko. 2001. "Framing Politics at the Launch of the Euro: A Cross-National Comparative Study of Frames in the News." *Political Communication* 18: 107–122.

Dörr, K. N., and K. Hollnbuchner. 2017. "Ethical Challenges of Algorithmic Journalism." *Digital Journalism* 5 (4): 404–419.

Eshima, S., K. Imai, and T. Sasaki. 2020. "Keyword Assisted Topic Models." *ArXiv Preprint ArXiv: 2004.05964*.

Esser, F., and P. D. Angelo. 2006. “Framing the Press and Publicity Process in U.S., British, and German General Election Campaigns: A Comparative Study of Metacoverage.” *Harvard International Journal of Press/Politics* 11 (3): 44–66.

Flaounas, Ilias, Omar Ali, Thomas Lansdall-Welfare, Tijl De Bie, Nick Mosdell, Justin Lewis, and Nello Cristianini. 2013. “Research Methods in the Age of Digital Journalism: Massive-Scale Automated Analysis of News-Content—Topics, Style and Gender.” *Digital Journalism* 1 (1): 102–116.

Fogel-Dror, Y., S. R. Shenhav, and T. Sheafer. 2021. “A Weakly Supervised and Deep Learning Method for an Additive Topic Analysis of Large Corpora.” *Computational Communication Research* 3 (1): 29–59.

Grimmer, J., and B. M. Stewart. 2013. “Text as Data: The Promise and Pitfalls of Automatic Content Analysis Methods for Political Texts.” *Political Analysis* 21 (3): 267–297..

Günther, E., and T. Quandt. 2016. “Word Counts and Topic Models: Automated Text Analysis Methods for Digital Journalism Research.” *Digital Journalism* 4 (1): 75–88.

Guo, L. 2018. “Ignorance or Uncertainty: How the ‘Black Box’ Dilemma in Big Data Research May ‘Misinform’ Political Communication.” In *Digital Discussions: How Big Data Informs Political Communication*, edited by N. J. Stroud and S. McGregor, 50–67. New York: Routledge.

Guo, L., A. Holton, and S. H. Jeong. 2012. “Transnational Comparative Framing: A Model for an Emerging Framing Approach.” *International Journal of Communication* 6: 1918–1941.

Guo, L., C. Vargo, Z. Pan, W. Ding, and P. Ishwar. 2016. “Big Social Data Analytics in Journalism and Mass Communication: Comparing Dictionary-Based Text Analysis and Unsupervised Topic Modeling.” *Journalism & Mass Communication Quarterly* 93 (2): 332–359..

Hatcher, W. G., and W. Yu. 2018. “A Survey of Deep Learning: Platforms, Applications and Emerging Research Trends.” *IEEE Access* 6: 24411–24432.

Hecking, T., and L. Leydesdorff. 2019. “Can Topic Models Be Used in Research Evaluations? Reproducibility, Validity, and Reliability When Compared with Semantic Maps.” *Research Evaluation* 28 (3): 263–272.

Heidenreich, T., F. Lind, J.-M. Eberl, and H. G. Boomgaarden. 2019. “Media Framing Dynamics of the ‘European Refugee Crisis’: A Comparative Topic Modeling Approach.” *Journal of Refugee Studies* 32 (Special_Issue_1): i172–i182.

Hilbert, M., G. Barnett, J. Blumenstock, N. Contractor, J. Diesner, S. Frey, S. Gonzalez-Bailon, et al. 2019. “Computational Communication Science: A Methodological Catalyzer for a Maturing Discipline.” *International Journal of Communication* 13: 3912–3934.

Jacobi, C., W. van Atteveldt, and K. Welbers. 2016. “Quantitative Analysis of Large Amounts of Journalistic Texts Using Topic Modeling.” *Digital Journalism* 4 (1): 89–106.

Krippendorff, K. 2004. *Content Analysis: An Introduction to Its Methodology*. Thousand Oaks (CA): Sage.

Kwon, K. H., and S.-I. Moon. 2009. “The Bad Guy is One of us: Framing Comparison between the US and Korean Newspapers and Blogs about the Virginia Tech Shooting.” *Asian Journal of Communication* 19 (3): 270–288.

Lind, F., J.-M. Eberl, T. Heidenreich, and H. G. Boomgaarden. 2019. “When the Journey is as Important as the Goal: A Roadmap to Multilingual Dictionary Construction.” *International Journal of Communication* 13: 4000–4020.

Maier, D., A. Waldherr, P. Miltner, G. Wiedemann, A. Niekler, A. Keinert, B. Pfetsch, et al. 2018. “Applying LDA Topic Modeling in Communication Research: Toward a Valid and Reliable Methodology.” *Communication Methods and Measures* 12 (2–3): 93–118.

Matthes, J. 2009. “What’s in a Frame? A Content Analysis of Media Framing Studies in the World’s Leading Communication Journals, 1990–2005.” *Journalism & Mass Communication Quarterly* 86 (2): 349–367.

Matthes, J., and M. Kohring. 2008. “The Content Analysis of Media Frames: Toward Improving Reliability and Validity.” *Journal of Communication* 58 (2): 258–279.

Neumann, R., and S. Fahmy. 2012. “Analyzing the Spell of War: A War/Peace Framing Analysis of the 2009 Visual Coverage of the Sri Lankan Civil War in Western Newswires.” *Mass Communication and Society* 15 (2): 169–200.

Neuman, R. W., M. R. Just, and A. N. Crigler. 1992. *Common Knowledge: News and the Construction of Political Meaning*. Chicago (IL): University of Chicago Press.
Nicholls, T., and P. Culpepper. 2021. "Computational Identification of Media Frames: Strengths, Weaknesses, and Opportunities." *Political Communication* 38 (1–2): 159–181.
Nisbet, M. C. 2010. "Knowledge into Action: Framing the Debates over Climate Change and Poverty." In *Doing News Framing Analysis: Empirical and Theoretical Perspectives*, edited by P. D'Angelo and J. A. Kuypers, 110–134. New York: Rutledge.
Opperhuizen, Alette Eva., Kim Schouten, and Erik Hans Klijn. 2019. "Framing a Conflict! How Media Report on Earthquake Risks Caused by Gas Drilling: A Longitudinal Analysis Using Machine Learning Techniques of Media Reporting on Gas Drilling from 1990 to 2015." *Journalism Studies* 20 (5): 714–734.
Reber, U. 2019. "Overcoming Language Barriers: Assessing the Potential of Machine Translation and Topic Modeling for the Comparative Analysis of Multilingual Text Corpora." *Communication Methods and Measures* 13 (2): 102–125.
Reese, S. 2007. "The Framing Project: A Bridging Model for Media Research Revisited." *Journal of Communication* 57 (1): 148–154.
Reese, S. D. 2001. "Prologue: Framing Public Life: A Bridging Model for Media Research." In *Framing Public Life: Perspectives on Media and Our Understanding of the Social World*, edited by S. D. Reese, O. H. Gandy, and A. E. Grant, 7–31. Mahwah (NJ): Lawrence Erlbaum Associates.
Reese, S. D., O. H. Gandy, and A. E. Grant. 2001. *Framing Public Life: Perspectives on Media and Our Understanding of the Social World*. Mahwah (NJ): Lawrence Erlbaum Associates.
Semetko, H. A., and P. M. Valkenburg. 2000. "Framing European Politics: A Content Analysis of Press and Television News." *Journal of Communication* 50 (2): 93–109.
Strubell, E., A. Ganesh, and A. McCallum. 2019. "Energy and Policy Considerations for Deep Learning in NLP." *arXiv Preprint arXiv:1906.02243*.
Stryker, J. E., R. J. Wray, R. C. Hornik, and I. Yanovitzky. 2006. "Validation of Database Search Terms for Content Analysis: The Case of Cancer News Coverage." *Journalism & Mass Communication Quarterly* 83 (2): 413–430.
Tankard, J. W. 2001. "The Empirical Approach to the Study of Media Framing." In *Framing Public Life: Perspectives on Media and Our Understanding of the Social World*, edited by S. D. Reese, O. H. Gandy, and A. E. Grant, 95–105. Mahwah (NJ): Lawrence Erlbaum Associates.
van Atteveldt, W., and T. Peng. 2018. "When Communication Meets Computation: Opportunities, Challenges, and Pitfalls in Computational Communication Science." *Communication Methods and Measures* 12 (2–3): 81–92.
van Atteveldt, W., K. Welbers, C. Jacobi, and R. Vliegenthart. 2014. "*LDA Models Topics*.... *But What Are "Topics*." Big Data in the Social Sciences Workshop.
Vliegenthart, R. 2012. "Framing in Mass Communication Research – An Overview and Assessment." *Sociology Compass* 6 (12): 937–948.
Vliegenthart, R., and L. Van Zoonen. 2011. "Power to the Frame: Bringing Sociology Back to Frame Analysis." *European Journal of Communication* 26 (2): 101–115.
Walter, D., and Y. Ophir. 2019. "News Frame Analysis: An Inductive Mixed-Method Computational Approach." *Communication Methods and Measures* 13 (4): 248–266.
Watanabe, K., and Y. Zhou. 2020. "Theory-Driven Analysis of Large Corpora: Semisupervised Topic Classification of the UN Speeches." *Social Science Computer Review*: 089443932090702.
Wilkinson, D., and M. Thelwall. 2012. "Trending Twitter Topics in English: An International Comparison." *Journal of the American Society for Information Science and Technology* 63 (8): 1631–1646.

Appendix: News Framing of Gun Violence Codebook

Q: What is the main theme of this news story?

Note: Code up to two dominant themes. Consider the following headline as an example: "The Second Amendment rights of more than four million Americans are at risk thanks to Republicans in Congress." This headline should be coded as both (1) Gun rights, and (3) Politics.

Variable	Definition	Example
Gun rights	The story is related to the Constitution, the second amendment, and protection of individual liberty and gun ownership as a right, including: • Meaning of the 2nd amendment • The irrefutability of one's right to own guns • Gun ownership as critical to democracy and protecting oneself	"Membership, interest in gun rights groups soar in the weeks after the Florida high school shooting" "Rapper 'Killer Mike', NRA host Colion Noir: No guns would turn people into slaves"
Gun control	The story is about issues related to regulating guns through legislation and other institutional measures. • Enforcing and/or expanding background checks • Limiting sale of guns and/or related dangerous equipment (e.g., AR15s, semi-automatic rifles, bump stocks, large-capacity ammo) • Increasing age limits on gun purchases • Implementing licensing and gun safety training programs	"GOP lawmaker calls for age restriction on AR-15s" "No bump stocks turned in to Denver police after ban"
Politics	The story is mainly about the political issues around guns and shootings, including: • Political campaigns and upcoming elections (e.g., using guns as a wedge issue or motivating force to get people to the polls) • Fighting between the Democratic and Republican parties, or politicians • Political money contributions from gun lobbies (e.g., NRA) • One political party or one politician's stance on gun violence. Therefore, as long as the news headline mentions a politician's name, it often indicates the theme of politics. • Often times, the politicians' names or the party names should be mentioned.	"How Illinois governor candidates would address gun violence" "Trump warns Dems will 'take away your Second Amendment'" "Lindsey Graham: Both parties will suffer if Congress doesn't act on new gun bill"
Mental health	The story is about issues related to individuals' mental illnesses or emotional well-being, or the mental health system as a whole, including: • Predicting and preventing mental health breakdowns • Treating mental illness • Creating measures to ensure mentally ill people do not have access to guns • Descriptions of individuals' behavioral / personality traits that indicate instability, impulsivity, anger, etc.	"Gun debate hits home for families dealing with myths about violence, mental illness" "Renewed Debate Over Gun Access, Mental Health" "Las Vegas gunman lost money, became unstable before shooting"
Public/school safety	Issues related to institutional and school safety, including: • Awareness and monitoring of "troubled" individuals by law enforcement (e.g., local police, FBI) • Safety measures in schools to prevent or mitigate shootings (e.g., police/safety officers in the school, armed teachers, metal detectors, clear backpacks) • Note that a headline simply mentioning "school shooting" does not necessarily mean it uses this safety measure frame.	"Preschoolers among students required to carry clear backpacks in Texas school district" "Scott wants armed police at Stoneman Douglas after disturbing incidents at Parkland school" "Sales of bulletproof school supplies spike after Florida shooting"

(*continued*)

Appendix. Continued.

Variable	Definition	Example
Race/ethnicity	The story is about gun issues related to certain ethnic group(s), including: • Angry, isolated white men as primary perpetrators of domestic gun violence • Immigrants from Mexico bringing in guns from across the border • Muslim "terrorists" • Gun violence in African American communities	"Illegal immigrant acquitted of Kate Steinle's murder faces judge on gun charges" "The disparities in how black and white men die in gun violence, state by state"
Public opinion	The study is about the public's, including a certain community's reactions to gun-related issues, including: • Public opinion polls related to guns • Protests • Mourning victims of gun violence • The public's emotional responses	"Baltimore students walk out of class to protest gun violence"
Social/cultural issues	Societal-wide factors that are related to gun violence, including: • Violence in media (e.g., TV/movies and video games) • Social pressures that may incite someone to violence (e.g., cliques/bullying and isolation) • Breakdown in family structures, so there is a lack of familial support and stability • Breakdown in community structures (e.g., religious organizations, other civic-oriented groups), so there is a lack of community support and stability	"There's Not A Single Ounce Of Evidence To Link Mass Shootings To Video Games"
Economic consequences	The story is about financial losses or gains, or the costs involved in gun-related issues, including: • The actual sales of firearms • The financial consequences of gun regulation (e.g., lost tax revenue, or gun manufacturing companies moving to a different state) • The financial state of gun-related lobbying groups (e.g., the NRA) • Federal budget for gun-related programs	"The NRA Is In Deep, Deep Financial Trouble"

Whichever theme that comes first in the headline should be entered as Theme1. Enter "99" if there is no theme identified.

1) Gun/2nd Amendment rights
2) Gun control/regulation
3) Politics
4) Mental health
5) School or public space safety
6) Race/ethnicity
7) Public opinion
8) Society/culture
9) Economic consequences
99) None of the above