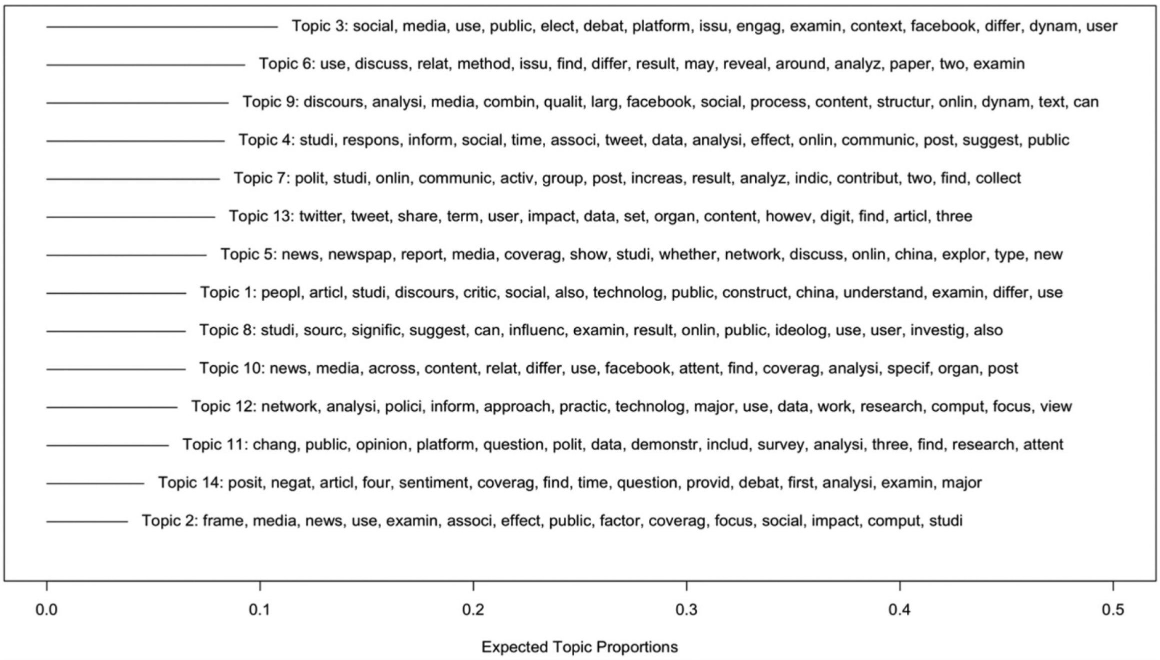

Figure 1. A Visualization of Topic Modeling Output. *Notes*. Figure 1 shows an example of the output from a structural topic model (K=14). The model input is the abstract of the empirical studies using topic modeling in communication.

Theory building and testing

Normative argument 1: proper conceptualization

A fundamental expectation in theory building and testing is that a topic modeling study needs theory-based conceptualizations in the research context. In other words, researchers have theories to explain the reasons for using topic modeling to analyze texts. We should first clarify the meaning of "theory" in computational social science (CSS) studies. A part of theory-driven research involves generating hypotheses based on a formal theory (particularly the meso-level theory, such as agenda setting) and using data to test the hypotheses. In CSS studies, a theory can denote specific patterns of previous findings or a theoretical framework that can explain what affects how digital trace data are created, distributed, and consumed (Patty & Penn, 2014). Similarly, Margolin (2019) considers a "theory" in CSS studies as causal claims (A may cause B, or why/how A may cause B). Waldherr et al. (2021) suggest that CSS researchers connect their research to macro-level theories, such as the theory of mediatization (Krotz, 2007) and the theories of the public sphere (Habermas, 1991). Macro-level theories can provide normative frameworks and concepts that may better explain the complexities, interdependence, and multi-level dynamics that are common for communication phenomena in the digital world (Schroeder, 2018; Waldherr et al., 2021).

Topic modeling studies often show limited connections to theories while mainly describing the frequencies and nature of certain contents. Admittedly, topic modeling was created for information retrieval but not necessarily for testing or building social science theories (Ying et al., 2021). Topic modeling produces data-driven outcomes and assumes that the prior knowledge of a given text is limited. However, this does not mean that the application of topic modeling is limited only to largely descriptive studies. Before employing topic modeling, researchers can contextualize a specific communication phenomenon within a theoretical framework. After running topic modeling, researchers can use specific theoretical lenses to interpret their findings. By incorporating theoretical contexts into a topic modeling study, researchers can examine potential predictors and outcomes of topics in digital media.

A proper conceptualization of communication phenomena of interest could be an important start for theory building and testing (Slater & Gleason, 2012). To set a research context in theories, researchers can conceptualize the problem of interest, explain critical concepts, and generate theory-guided research questions. Digital-trace behavioral data provide opportunities for communication scholars to identify new concepts or refine an existing concept. Communication scholars can also conceptualize a data-generating process in a theoretical framework instead of treating it as a concrete case study. For example, studies examining the formation of public opinion on social media may tie the online exchange of opinions to “networked public spheres” (Waldherr et al., 2021, p. 164). Likewise, Studies analyzing social media engagement metrics and their effects on election results may broadly consider social media engagement metrics as a type of “politically oriented collective behavior” (Margolin, 2019, p. 12). Considering the importance of conceptualization in theory building and testing, we first ask:

RQ1: To what extent have the previous topic modeling studies incorporated a theory-based concept-(s) in the literature review?

Normative argument 2: test hypotheses or generate new hypotheses

Social scientists often tend to move beyond exploration and make inferences about the causes or outcomes of text data (Roberts et al., 2016). As a critical part of theory building and theory testing, another expectation is that researchers can use topic modeling deductively to test hypotheses based on prior literature findings (theories). A deductive study starts with known propositions for hypothesis testing based on a theory that explains a communication phenomenon. To utilize topic modeling to test hypotheses, researchers can propose the presence of specific topics in a given text or compare their prominences across the texts from different sources, regions, or time periods. For instance, researchers can use structural topic modeling (STM) (Roberts et al., 2016) to test how topic probabilities covariate with variables from the text metadata (e.g., publishing time, authors, sources). Researchers can also propose the potential causes or effects of topics. Topic modeling can process a large quantity of data. This strength is helpful in testing hypotheses by analyzing a massive volume and diversity of digital data.

Alternatively, researchers can use topic modeling inductively to generate new hypotheses based on the interpretations of topics. Topic modeling is a powerful tool for inductive studies, but “inductive” differs from “descriptive.” An inductive study begins with an explorative theory-guided analysis and concludes with propositions for generating new hypotheses. Describing the nature of texts is only a part of an inductive study. The inductive approach is typical for qualitative text analysis studies. For example, topic modeling is a critical part of the computational grounded theory approach (Nelson, 2020). Researchers first use topic modeling to identify patterns in an inductive analysis, interpret the patterns based on the prior literature, and then generate or refine new hypotheses. In this context, an inductive or exploratory analysis using topic modeling should ground in theories and contribute to the current literature.

Testing or proposing new hypotheses in a study may indicate that the study is theory-based, either testing an existing theory or building a new one (Slater & Gleason, 2012). To examine the extent to which topic modeling studies have linked their findings to theory testing and building, we put forward the following research questions:

RQ2: To what extent have studies integrated topic modeling results to test hypotheses?

RQ3: What communication theories or concepts have the reviewed studies tested using topic modeling results?

RQ4: To what extent have communication studies only used topic modeling to describe the content of texts? To what extent do those studies generate new hypotheses for future research?

Normative argument 3: pick the most appropriate method

The third expectation is that topic modeling is not always the best method to extract every concept of interest and researchers need to pick the most appropriate text analysis method. Admittedly, as another aspect of theory building, topic modeling provides innovative and scalable ways to extract meaningful theoretical concepts from text data. For example, in political science studies, researchers utilize the method to measure existing concepts, such as frames (DiMaggio et al., 2013) and political agendas (Grimmer & Stewart, 2013). In a systematic review of management studies, Hannigan et al. (2019) found that management research also used topic modeling to explore new constructs and advance conceptualization. However, topics are simply clusters of words generated by algorithms. The estimation of topics relies on the assumptions of a topic modeling algorithm. For example, critical assumptions about LDA and many of its extensions include that (1) words that are semantically similar tend to cluster together in a topic; (2) the orders of words in a document can be neglected to understand the major content in a document (the "bag-of-words" assumption); (3) each document is a representation of a set of topics and each topic is a representation of a set of words from the text data (Blei, 2012; Blei et al., 2003). A topic model produces inaccurate results when used in violation of assumptions. Thus, researchers need to consider other more sophisticated methods (e.g., supervised machine learning, deep learning, embedding techniques) or rely on manual content analysis (Baden et al., 2022; Nelson et al., 2018) for more accurate results.

Topic modeling may not generate the most accurate results in three conditions. First, topic modeling cannot accurately identify implicit concepts in texts (Grimmer et al., 2022). The bag-of-words assumption and the proportions of word co-occurrence constrain the performance of many topic models. Therefore, if the presentation of a concept depends on the syntactic relationship between words, orders of words, or linguistic features that only occasionally cluster together in texts, topic modeling may not be the best choice for identifying the concept. For example, Nelson et al. (2018) employed topic modeling to identify news reports that covered economic inequality. They found that topic modeling could not detect news that mentioned economic inequality as a minor theme and news that covered implicit inequality (e.g., discussion about low-income workers vs. good-fortune executives). In comparison, supervised machine learning methods produced better results. Manual content analysis based on a sufficient sample is perhaps more reliable than topic modeling to identify implicit concepts from texts (Baden et al., 2022). More recent innovations combining transformer models also address the limitations of the bag-of-words assumption. Particularly, topic models combining Bidirectional Encoder Representations from Transformers (BERT) (Devlin et al., 2019) or Sentence BERT (Reimers & Gurevych, 2019), such as BERTopic (Grootendorst, 2022) consider the context of words in a document using document-embedding techniques.

Second, topic models assume that semantic words co-occur together and form a topic, but this assumption does not hold for multilingual texts (Maier et al., 2022). To estimate topics more accurately, researchers need to rely on multilingual probabilistic topic modeling, such as bilingual LDA (Vulić et al., 2015), or rely on machine translation, multilingual dictionary, or conduct different text processing procedures using language-specific stop words and lemmatization (Lind et al., 2021; Maier et al., 2022). Researchers also developed language-specific models considering the unique linguistic patterns of different languages. For example, (Q. Zhao et al., 2011) developed the character-word topic model to analyze Chinese.

Lastly, topic models (e.g., LDA, STM) assume that a document is a representation of multiple topics. This assumption affects the accuracy of analyzing short texts (e.g., tweets), particularly for texts shorter than 50 words (Vayansky & Kumar, 2020). For example, applying an LDA to analyze short texts will pose a data sparsity problem, as the frequency of words in an individual text makes it difficult