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From patterns to meaning: a mixed-methods framework that integrates computational and qualitative text analysis

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Abstract
Applications of automated text analysis techniques have gained significant attention in recent years. Automated text analysis methods are transforming research by offering valuable tools for robust textual analysis and data-driven theory-building. These methods' impacts on the rigor of qualitative text analysis remain under-researched. We use an advanced automated text analysis method, structural topic model (STM), to assess whether or not a mixed-methods approach that combines automated with qualitative text analysis improves analytical rigor by focusing on four widely recognized criteria: credibility, transferability, dependability, and confirmability. Based on these criteria, our study shows how the combination of automated text analysis and qualitative text analysis can enhance analytical rigor. Ultimately, our research argues that automated techniques are powerful tools in a mixed-methods framework, effectively complementing qualitative-interpretive analysis without replacing the insights and understanding provided by human researchers. We conclude by discussing the implications for future studies employing this mixed-methods approach.

Keywords Mixed methods · Automated text analysis · Qualitative content analysis · Topic modeling · Research rigor · Computational social science

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1 Introduction

In recent years, applications of automated text analysis techniques in the social sciences and the computer science research have increased substantially (Jelodar et al. 2019). These methods, based on machine learning (ML) algorithms such as Natural Language Processing (NLP), have gained popularity for their abilities to efficiently analyze large volumes of text and to uncover hidden patterns (Abram et al. 2020; Pandey and Pandey 2017; Roberts et al. 2019; Rüdiger et al. 2022; Guenduez and Walker 2025; Wilkerson and Casas 2017). Notably, the number of publications on widely-used automated text analysis methods – such as Latent Dirichlet Allocation (LDA), Structural Topic Model (STM), or sentiment analysis – has surged when searching for these terms in titles, abstracts, author keywords, and Keywords Plus on Web of Science. Our search yielded approximately 6350 publications on LDA and an impressive 23,700 publications on sentiment analysis. With the advent of advanced large language models (LLMs) such as ChatGPT and Google Gemini, there is also increasing discussion about the extent to which these new tools can be used in qualitative text analysis (Markowitz 2024).

Researchers are acknowledging the potentials of automated text analysis to overcome some limitations inherent in qualitative text analysis (Engstrom et al. 2022). Automated text analyses allow for the rapid processing and analysis of extensive text volumes, significantly reducing the required time, compared to manual analysis (Banks et al. 2018). Time constraints and the limited amount of text feasible for manual analysis are no longer barriers (Abram et al. 2020). The reliance on human coders in conventional qualitative text analysis introduces potential limitations owing to subjectivity and the risks of confirmation biases (Nelson 2020; Renz et al. 2018). NLP methods and algorithms designed to enable computers to understand, interpret, and generate human language provide a systematic and standardized approach to text processing (Isoaho et al. 2021). While efficient, automated text analysis often fails to capture the nuancedness and context-dependency of complex sociological discourses (Németh et al. 2020). In contrast, qualitative text analysis, with its reliance on human interpretation and expertise, enables in-depth understanding, but is also inherently resource- and time-intensive (Nelson 2020).

Ensuring qualitative research findings' rigor has been a key concern for researchers (Thomas and Magilvy 2011), and efforts to enhance this have spurred the development of explicit criteria and guidelines for qualitative inquiry. Guba and Lincoln's (1985) seminal quality criteria – *credibility* (i.e., internal validity), *transferability* (i.e., the degree to which qualitative research results can be generalized or transferred to other contexts or settings), *dependability* (i.e., the degree to which another researcher studying the same case and using the same approach would come to the same conclusions), and *confirmability* (i.e., the degree to which researchers' own biases affect their conclusions) – have emerged as standards for evaluating qualitative research (Nowell et al. 2017a, b; Trochim 2001; Shenton 2004; Elo et al. 2014). However, qualitative text analysis struggles to meet these criteria owing to the inherent limitations of human coders, limited resources, and the process's time-intensiveness (Crowston et al. 2012).

With this in mind, we ask: *How do automated text analysis techniques contribute to the analytical rigor of text analysis?*

We present how such an integrated approach contributes to the rigor of text analysis, evaluating this against four criteria – credibility, transferability, reliability, and confirmabil-

ity – using an illustrative mixed-methods case study that focuses on artificial intelligence (AI) policies. Our study builds on previous research (Isoaho et al. 2021; Nelson 2020) and shows that automated text analysis can complement qualitative text analysis and can thereby increase its rigor.

The remainder of this study is structured as follows. Section 2 provides an overview over rigor in qualitative text analysis, highlighting the challenges and criteria associated with ensuring qualitative findings' validity. In Sect. 3, we explore the integration of automated text analysis techniques with qualitative text analysis and introduce a five-phase framework. In Sect. 4, we present the exemplar study that focuses on AI policies, showing how the combination of automatic text analysis and qualitative text analysis affects analytical rigor. Section 5 offers a comprehensive discussion of the findings, outlining our study's contributions to mixed-methods research, its limitations, and avenues for further research.

2 Rigor in qualitative text analysis

2.1 Qualitative research

Qualitative research stems from the idea that meaning is not fixed but emerges through interpretation. It does not seek to identify absolute truths, but relies on different interpretations and understandings (Denzin and Lincoln 2011). A central idea in this tradition is that researchers have active roles in shaping how meaning is produced, a perspective often referred to as *interpretive agency* (Guba and Lincoln 1994). Researchers bring their own background, experiences, and theoretical lenses to an analysis, which influence how interpretations develop. This awareness of a researcher's perspective and its roles in shaping the process is commonly described as *reflexivity* (Finlay 2002). The process of developing interpretation in this context is often described as *meaning-making*, an open and iterative engagement with data that remains sensitive to ambiguity and context (Creswell and Poth 2016

2.2 Qualitative text analysis

Qualitative text analysis is the most prominent form of qualitative analysis and rests on the idea of treating text as data (Grimmer and Stewart 2013). In the context of qualitative text analysis, any form of text can be analyzed (e.g., interviews, scientific/grey literature, social media posts, news articles, survey responses, political scripts and speeches, and observations) (Chen et al. 2020; DiMaggio et al. 2013; Ebadi et al. 2021; Gilardi et al. 2021 ; Sachdeva et al. 2017; Tvinnereim et al. 2017; Wilkerson and Casas 2017). The textual data are then coded with the goal of extracting information specifically linked to the research question. Qualitative text analysis involves the identification and labeling of patterns, themes, or concepts in the texts to facilitate analysis and interpretation (Kuckartz 2019). It is done either deductively or inductively, or as a combination of both (i.e., abductively), depending on whether pre-defined codes are systematically applied to the text and/or the codes emerge organically from the text (Grimmer and Stewart 2013).

Scholars use diverse coding techniques (e.g., semantic, process, or latent coding) to identify, categorize, and interpret textual data (Saldaña 2014). The qualitative text analysis pro-

cess is generally time- and resource-intensive (Nelson 2020; Elo et al. 2014). Researchers use various strategies to reduce workloads (such as the random sampling of text data) to maintain the manual effort at a manageable level (Elo et al. 2014). Further, the process of extracting information from text data via manual analysis is susceptible to errors owing to the subjectivity of analyzing textual materials and the inherent potentials for biases (e.g., selection biases or confirmation biases) (Nelson 2020). Therefore, measures such as intercoder reliability are employed to detect and minimize possible biases on the part of the individual coders (Krippendorff 2004). Intercoder reliability, for instance, can be used to assess the extent of agreement or consistency between two or more coders (also known as raters or annotators) who independently classify, rate, or code a dataset (O'Connor and Joffe 2020).

2.3 Key factors to assess rigor in qualitative text analysis

Since the 1980s, there has been ongoing discussion on how to assess rigor in qualitative text analysis. An array of terms have emerged from this, including reliability, plausibility, generalizability, dependability, credibility, trustworthiness, goodness, transferability, and validity (Creswell and Miller 2000; Gioia et al. 2013; Golafshani 2003; Grodal et al. 2021; Lincoln and Guba 1985; Merriam 1998; Tracy 2010; Whittemore et al. 2001). Various strategies have been proposed to enhance rigor in qualitative text analysis, including triangulation, member-checking, or prolonged engagement (Denzin 1978; Koch 2006; Morse 2015; Morse et al. 2002; Nowell et al. 2017; Ospina et al. 2018; Shenton 2004).

We adopt the criteria put forth by Lincoln and Guba (1985) – credibility, transferability, reliability, and confirmability – to investigate the impacts of combining automated text analysis with qualitative text analysis on analytical rigor. These criteria are widely recognized as benchmarks for text analysis (Nowell et al. 2017a, b; Trochim 2001; Shenton 2004; Elo et al. 2014). We will now describe these criteria and will examine strategies to improve rigor in qualitative text analysis.

2.4 Credibility

Credibility, the internal validity of qualitative research findings, focuses on the extent to which findings align with reality and are considered credible or believable (Shenton 2004; Tobin and Begley 2004; Trochim 2001). However, achieving credibility is challenging owing to inherent limitations in qualitative research. Data reduction techniques such as random sampling and logical argumentation (e.g., selecting only articles published on a specific day) are used to manage the amount of data, resulting in approximations of reality (Nelson 2020). Collecting and analyzing all the available data on a topic is often not feasible. Lincoln and Guba (1985) propose strategies to enhance the credibility of qualitative research findings, such as prolonged engagement, persistent observation, triangulation, peer debriefing, negative case analysis, and member checks.

2.5 Transferability

Transferability refers to the degree to which qualitative research results can be generalized or transferred to other contexts or settings (Nowell et al. 2017). Although comparable with external validity, the findings of qualitative research only concern case-to-case transfers

(Tobin and Begley 2004). Qualitative research is inherently specific to a particular context, environment, and persons, making it hard to directly apply the findings to other situations or groups. To demonstrate transferability, a researcher is responsible for providing rich descriptions of a case and its context for the reader to assess whether the findings can be transferred to other situations in which similar empirical phenomena are represented (Lincoln and Guba 1985).

2.6 Dependability

Dependability ensures that a study's conclusions are based on a stable and systematic research process that is logical and transparent, rather than being influenced by inconsistent or arbitrary decisions (Trochim 2001). The focus is on ensuring that the research methods and procedures are well documented and repeatable, so that others can replicate the study under similar conditions. Challenges include tracking and clearly communicating the decisions taken during data collection and analysis. Strategies proposed by Lincoln and Guba (1985) include maintaining an audit trail, reporting a research design and its implementations, and employing reflective evaluation of the inquiry process to ensure consistency and reliability (Shenton 2004).

2.7 Confirmability

Confirmability emphasizes the neutrality and objectivity of research findings, ensuring that they are shaped by the data rather than a researcher's personal biases or interpretations (Trochim 2001). This criterion addresses the extent to which the results can be independently verified by others. A key challenge is minimizing the influences of investigator biases, where a researcher's own perspectives may skew the findings. Strategies to enhance confirmability include providing a detailed audit trail to demonstrate how theoretical, methodological, and analytical choices were grounded in the data, as well as maintaining reflexivity to acknowledge and mitigate potential biases (Koch 2006). While dependability focuses on the research process, confirmability relates to a study's results.

We will now discuss automated text analysis techniques and their integration with qualitative manual text analysis. This sets the stage for our exemplary study, showcasing how automated text analysis can enhance rigor in qualitative text analyses.

3 Automated text analysis techniques

Automated text analysis utilizes NLP techniques to analyze and extract insights from textual data. NLP provides computational methods, models, and tools that enable the automation of text analysis (Crowston et al. 2012). NLP is a collection of computational techniques for automatic analysis and representation of human languages (Chowdhary 2020). It encompasses a wide range of sub-techniques, including entity recognition, sentiment analysis, topic modeling, text clustering, and word embeddings. These techniques have been extensively studied and are well documented in the literature (Banks et al. 2018).

Researchers employ NLP to influence, guide, or refine the analysis process to different degrees, depending on their research goals and requirements. Fully automated and unsu-

pervised clustering methods in NLP – such as LDA or STM – are commonly employed to estimate the topics as well as to uncover hidden structures and patterns in unstructured text data using probabilistic models (Blei and Lafferty 2009; Blei 2012; Grimmer and Stewart 2013; Isoaho et al. 2021). These methods require researchers to determine the number of topics for their study and to interpret their meanings (Lucas et al. 2015; Roberts et al. 2019; Wesslen 2018), and they are commonly used for exploratory research to inductively discover concepts (DiMaggio et al. 2013; Macanovic 2022; Wilkerson and Casas 2017), but also to make causal inferences using texts (Egami et al. 2022).

Topic modeling methodology encompasses a range of methods that seek to reveal underlying themes and thematic structures in a substantial collection of text-based documents – also known as a corpus – through the use of mathematical algorithms (Blei and Lafferty 2009; Blei 2012; Valdez et al. 2018).

The supervised methods train algorithms to code theoretical concepts of interest, particularly when the concepts are complex, theory-informed, and co-occur with other concepts that are hard to infer from individual words (Macanovic 2022). Supervised text analysis serves as a labor-saving tool by replicating the coding process performed by human coders for larger volumes of text (Wilkerson and Casas 2017).

The latest NLP techniques, such as ChatGPT and Google Gemini, are making automated text analysis more accessible to researchers. For instance, Gilardi, Alizadeh and Kubli (2023) show that ChatGPT can outperform crowdworkers in several research tasks at a fraction of the cost. However, currently, their usability for text analysis in a scientific context is still hindered by a lack of methodological transparency and insufficient consistency in the results, leading to low replicability and higher potentials for biases than with more traditional automated text analysis techniques (Markowitz 2024). Despite these hurdles, the shift towards more user-friendly NLP tools is already empowering researchers from diverse backgrounds, enabling the broader adoption of automated text analysis in research without the need for expertise in complex coding languages (de Kok 2023; Markowitz 2024).

We use STM, a well-established technique in automated text analysis, to illustrate how combining automated text analysis with qualitative text analysis can improve rigor. STM utilizes a probabilistic Bayesian framework to uncover latent themes in large text corpora, such as news articles, social media posts, and scientific papers (Blei and Lafferty 2009; Blei 2012; Grimmer and Stewart 2013; Isoaho et al. 2021). Building on the foundation of LDA, a similar probabilistic topic model, STM offers enhanced capabilities; it not only identifies latent themes within text data, but also incorporates and analyzes document-level metadata as covariates. This enables researchers to explore how identified themes are influenced by or correlate with these variables (Roberts et al. 2019). This makes STM an ideal tool for automated text analysis, especially in studies that require in-depth analysis of the thematic structures of complex and large document collections with associated metadata (Roberts et al. 2019).

3.1 Combining automated text analysis with qualitative text analysis

Researchers emphasize the benefits of integrating automated text analysis with qualitative text analysis to triangulate findings and gain a deeper understanding of texts and topics (Isoaho et al. 2021). The literature offers frameworks and guidelines for integrating qualitative and quantitative approaches (Greene et al. 1989; Venkatesh et al. 2013), and studies

indicate various potential benefits. Integrating both methodologies can help mitigate the drawbacks associated with qualitative text analysis and automated text analysis. Automated text analysis not only reduces subjectivity in text analysis and the corresponding workload (Lindstedt 2019; Nelson et al. 2021), but also enhances the efficiency and systematic nature of the analysis by helping researchers to process and extract meaningful information from extensive volumes of text as well as to generate insights that would be hard or impossible to obtain through manual analysis (Abram et al. 2020; Crowston et al. 2012; Jacobs and Tschötschel 2019).

However, researchers have also identified several limitations of integrating automated text analysis. While subjectivity and researchers' biases can be reduced through automated text analysis, several research phases must still be conducted manually (e.g., the selection of the textual data, interpretation, and more); therefore, researchers' subjectivity and potentials for biases remain (Nelson 2020). Further, automated text analysis can also internalize human biases inherent in their design or training data (Bender et al. 2021; Macanovic 2022). In contrast, qualitative text analysis facilitates the in-depth examination of outputs, allowing for interpretation and engagement with the data through various theoretical lenses so as to provide nuanced understanding (Isoaho et al. 2021).

4 Exemplar study: a step-wise approach

We present an exemplar study to illustrate how combining automated text analysis with qualitative text analysis contributes to the rigor of text analysis. To assess this, we build on the four criteria set out in Sect. 2 – credibility, transferability, reliability, and confirmability – which serve as a framework to guide our study.

Following Nowell et al. (2017a, b), we use examples from our study on the strategic frames in AI policy documents (Guenduez et al. 2025). We use an automated text analysis technique to analyze the content of 27 policy documents on AI. Specifically, we use STM, an established automated text analysis technique based on a Bayesian probabilistic framework (Roberts et al. 2019). STM incorporates ML techniques to automatically identify topics or themes within the text data. These techniques involve algorithms that learn patterns and structures in the text data, allowing STM to uncover latent themes without the need for manual intervention (Guenduez and Mettler 2023). We follow a step-wise approach to show how the use of STM can enhance rigor in text analysis.

Studies that use automated text analysis typically involve a five-step process encompassing both qualitative and automated text analysis components (Andreotta et al. 2019; Banks et al. 2018; Chen et al. 2020; Maier et al. 2018; Roberts et al. 2019): (1) data collection, (2) text preprocessing, (3) computational analysis, (4) interpretation, and (5) reporting. We build on these phases.

Following Nowell et al. (2017a, b), in each analysis step, we document the following:

- The common actions that researchers take when using automated text analysis methods.
- Our own experiences gained from the exemplary STM application.
- The resulting implications for qualitative text analysis.

The analysis steps of our example study are presented in Fig. 1; we will discuss these in some detail.

4.1 Phase 1: data collection

The basis for automated text analysis is texts in any form, such as PDFs, Word documents, or Twitter tweets. This methodology offers two major advantages compared to a purely qualitative text analysis. First, the analysis is not limited by the amount of textual data to be processed. This means that researchers can include an almost unlimited number of text files in the analysis, allowing them to explore large numbers of tweets (Sachdeva et al. 2017), published studies (Chen et al. 2020; Ebadi et al. 2021), newspaper articles (DiMaggio et al. 2013; Gilardi et al. 2021 ,), survey responses (Tvinnereim et al. 2017), or scripts of political speeches (Wilkerson and Casas 2017). Second, document-level metadata (e.g., the publication year, the publisher, and the country of publication) can also be collected as variables for later analysis (Roberts et al. 2019).

4.2 Our experiences in the exemplar study

We were interested in understanding the strategic priorities and intentions of governments for AI development, as expressed in policy documents (Guenduez and Mettler 2023). Specifically, we searched for all AI policies listed on the website of the OECD Artificial Intelligence Policy Observatory (OECD 2022) that were written or co-authored by a government authority, published on an official government website, available in English, and classified as a policy, a roadmap, or an action plan focusing specifically on the technology of AI. In total, 31 documents published between 2017 and 2023 were retrieved from 27 countries. These documents comprise a text corpus of around 438,796 words, which is equivalent to >1,000 A4 pages of 400 words each. This data size is well suited for automatic analysis (Lucas et al. 2015; Roberts et al. 2019). Manually analyzing this substantial volume of information would would be time-consuming, labor-intensive, and error-prone. Automated text analysis can help to overcome these challenges (Guenduez and Mettler 2023).

4.3 Implications for rigor in qualitative text analysis

Our experiences here underscore the significance of automated text analysis, which offers the advantage of analyzing an entire corpus of available and relevant text data, eliminating the need for sampling or restricting the text corpus. Researchers' flexibility in selecting the

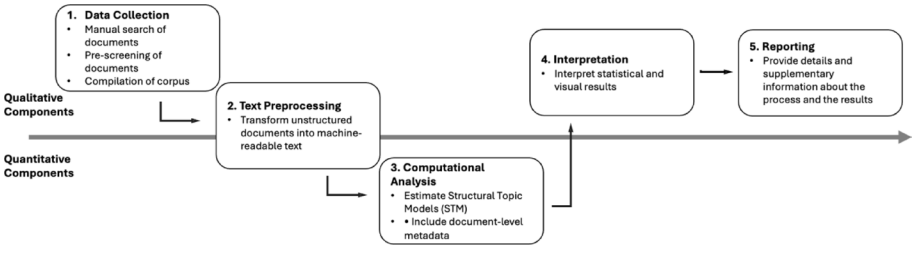

Fig. 1 Phases of analysis of automated text analysis and their implications for rigor in qualitative text analysis

amount and type of textual data for analysis also enables the investigation of research questions that were previously unfeasible owing to the large volume of data. Including larger text documents in a study can improve the findings' transferability, as the textual corpus can account for a greater variety of textual data (Haupt et al. 2023). This can also enhance a study's credibility by providing a more robust and diverse understanding of the research topic.

4.4 Phase 2: text preparation

After collecting data, researchers must undertake data preparation steps to make the data suitable for automated text analysis. This involves removing irrelevant information such as special characters, punctuation, and numbers. It also requires the removal of stop words, i.e., eliminating commonly-occurring words that contribute little meaningful information to the analysis, such as prepositions and conjunctions. Further, researchers determine the appropriate unit of analysis (Wilkerson and Casas 2017), such as full documents (e.g., Li et al. 2023), smaller paragraphs (e.g., Gilardi et al. (2021), tweets (e.g., Fresneda et al. 2021), or responses to free-text questions in questionnaires (e.g., Wright et al. 2022). Selecting the appropriate unit of analysis is a crucial step in preparing data for automated text analysis and is guided by the research goals and the nature of the data being analyzed. For instance, analyzing full documents provides a holistic understanding, while focusing on smaller paragraphs or tweets allows for more fine-grained analysis.

4.5 Our experiences in the exemplar study

For the STM analysis, we followed the standard procedure of Roberts et al. (2019) for preparing textual data with the R package stm. This involves transforming unstructured documents such as PDFs or words into machine-readable text (Lucas et al. 2015). After ingesting the data into R, the next steps of text processing include reducing the words to their basic form, i.e., stemming (for instance: *technology* and *technological* become *technolog*), flowed by removing punctuation, special characters, boilerplate text, and lowercasing (Fig. 2). Next, so-called stop words are removed, as they may distort the topics with their high occurrence frequency (Lucas et al. 2015); stm provides predefined stop word lists such as 'the,' 'by,' or 'in.'

Based on the initial STM analysis results, we iteratively refined our list of stop words by removing additional words such as 'policy,' 'AI,' and 'artificial intelligence' that occur much more frequently than others and provide no discriminative power in topic modeling. The unit of analysis includes text chunks of 250 words. With this approach, the number of data points was satisfying, and the different document lengths were considered. However, we could not process all nontextual information such as pictures or images, because the automatic text analysis only considers textual data.

4.6 Implications for rigor in qualitative text analysis

Compared to conventional content analysis, where text is not pre-processed, a researcher plays a significant role in the results obtained from automated text analysis. A researcher's influence has two key aspects: the definition of the unit of analysis and the choice of stop

```
##############################################################################
# PROJECT: AI STRATEGY PROJECT                                               #
# SCRIPT : STM Basics                                                        #
##############################################################################
# Prep environment, load packages and data
rm(list=ls())                                          # Clean Memory
setwd("C:/Users/(USER)/desktop/Projects/AIStudie")     # Set working Directory
library(stm)                                           # Load Library
library(ggplot2)                                       # Load Library
library(rbind)                                         # Load Library
set.seed(190)                                          # Set Seed
data  <- read.csv("AggregatedDataset.csv")             # Read Aggregated Dataset

##############################################################################
# Pre-Processing
##############################################################################
## Removal of Addditional Stop Words
processed <- textProcessor(data$Text, metadata = data, customstopwords = c( "america", "american", "artificial intelligence", "artificialintelligence", "australia", "artificial-intelligence", "belgian", "belgium",
"canada", "china", "czech republic", ))))
## STM Dataset prep (remove low frequency words)
out   <- prepDocuments(processed$documents, processed$vocab, processed$meta, lower.thresh = 5)
docs  <- out$documents
vocab <- out$vocab
meta <-out$meta
## Set Numbers of Topics to 3 (after analysis using: searchK(out$documents, out$vocab, K = c(3:100), prevalence =~  s(date), data = meta, set.seed(190)))
N<-3

##############################################################################
# STM Regression
##############################################################################
poliblogPrevFit <- stm(documents = out$documents, vocab = out$vocab, K = N,
                       prevalence =~ Nr_Words + econ_pillar + rd_pillar + s(Year),
                       max.em.its = 150, data = out$meta,
                       init.type = "Spectral")
## Topic Labels with top 20 most frequent Words
label_Topics_20 <- labelTopics(poliblogPrevFit, n = 20)
## Save Regression summary for each topic
RegSummary<-paste("K_",N,"_STM_Regression_Summary_RC.txt",sep="")
sink(RegSummary)
for (i in 1:N){  print(summary(prep, topics=i))}
sink()
closeAllConnections()

##############################################################################
# Estimate Effects for each topic
##############################################################################
prep <- estimateEffect(1:N ~ Nr_Words + econ_pillar + rd_pillar + s(Year),
                       poliblogPrevFit, meta = out$meta, uncertainty = "Global")

## Plot Time Effects
```

Fig. 2 stm R code script for text pre-processing

words to be removed. Determined by the researcher, the unit of analysis sets the level at which the text data will be analyzed, such as entire documents, paragraphs, or smaller units. This decision affects the identified topics' granularity, depth, and interconnectedness.

The selection of stop words is a decision that can affect analysis outcomes. Excessive removal of stop words carries the risk of constricting the scope of analysis scope, thereby introducing subjective biases and failing to capture the full textual meaning. To mitigate these potentials for biases, we utilize a pre-defined list of stop words. Thus, attention to both the unit of analysis and stop word selection is essential for ensuring findings' credibility, dependability, and transferability.

A study's credibility also depends on the data's quality and the analysis methods' robustness. Our example study clearly showed that the exclusion of nontextual elements from automated text analysis can lead to information loss, because visual data such as figures and images can convey important information that complements and enriches the textual data, while their exclusion can undermine the results' credibility.

Researchers can use several strategies to enhance the rigor of automated text analysis. One such strategy is peer debriefing (Lincoln and Guba 1985), where other experts review and provide feedback on the decisions taken during data preprocessing. This external input helps to validate and improve a researcher's choices, increasing a study's credibility. Further, documenting all the details of the text processing in a separate supplementary information document, as exemplified by Gilardi et al. (2021) as well as Guenduez and Mettler (2023), can serve as an audit trail. This documentation provides transparency and allows an analysis to be reviewed and replicated. It enhances a study's credibility and confirmability by providing a comprehensive record of the pre-processing steps and facilitating the assessment of a study's dependability.

4.7 Phase 3: topic modeling

In this analysis step, researchers use topic modeling algorithms such as LDA or STM to estimate topic models that unveil the hidden structure in the textual data (Blei 2012). These algorithms identify latent topics by analyzing patterns in word uses across documents. STM

builds on LDA by incorporating document-level metadata, allowing researchers to examine how topic prevalence and content vary with covariates (Roberts et al. 2014). The resulting outputs support the evaluation and selection of topic models through metrics such as semantic coherence, which assesses generated topics' internal consistency, meaningfulness, and interpretability (Roberts et al. 2014). Additional outputs such as the top words for each topic, representative paragraphs, and topic correlation statistics further aid interpretation and model selection (Roberts et al. 2019).

The choice of the number of topics and the covariates depends on a study's epistemological interest and goals. If the aim is to uncover the main topics in the data, a model with fewer topics may yield better results, while a larger number of topics is more suitable for revealing a more detailed structure (Blei and Lafferty 2009). Using topic modeling metrics, researchers can evaluate different topic models, and can iteratively assess their quality and interpretability to select the most suitable topic model that aligns with their research goals and provides meaningful insights into the data (Grimmer and Stewart 2013).

4.8 Our experiences in the exemplar study

We used STM because it allows us to incorporate document-level metadata into the modeling process, making it particularly well suited for analyzing policy texts where variations across documents are theoretically meaningful (Roberts et al. 2019). We used the semantic coherence analysis provided by STM to guide our selection of the topic number. Figure 3 showcases the semantic coherence analysis' results. The topic coherence metric measures how semantically related the words in a topic are, i.e., whether they make sense from a human perspective. The figure shows that semantic coherence decreases as the number of topics increases, because the differences between topics become more fine-grained. This decline indicates that, as granularity increases, it becomes hard to differentiate between topics.

STM provides a range of valuable outputs. This includes top words with the highest probability of occurrence (i.e. high probability words) and FREX words that are both frequent and highly exclusive to a topic (Fig. 3) (Bischof and Airoldi 2012). STM also provides

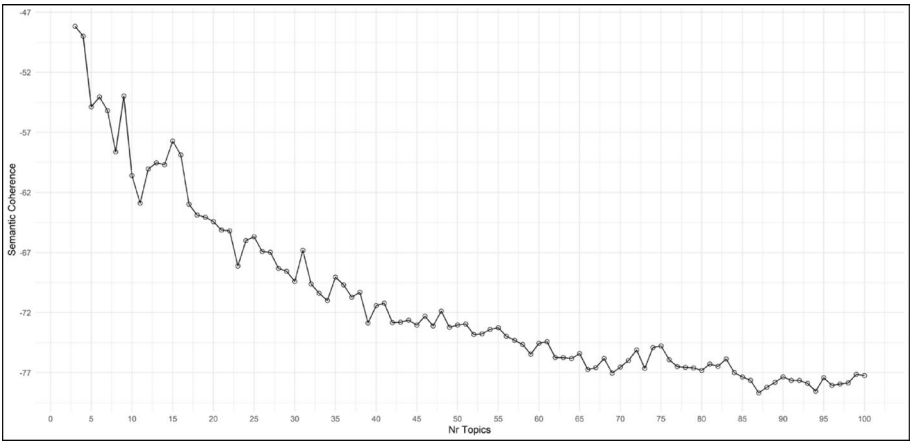

Fig. 3 The semantic coherence of the selection of the number of topics

Fig. 4 The word cloud analyses for the three-topic model

Topic 1:

AI performs functions *alongside* a person: AI systems perform peripheral tasks that support a human decision-maker. For instance, AI can assist persons with working memory, short-term or long-term memory retrieval, and prediction tasks. AI performs functions when a person encounters high cognitive overload: AI systems perform complex monitoring functions (such as ground proximity warning systems in aircraft), decision-making, and automated medical diagnoses when persons need assistance. AI performs functions *in lieu of* a person: AI systems perform tasks for which humans have very limited capabilities, such as for complex mathematical operations, control guidance for dynamic systems in contested operational environments, aspects of control for automated systems in harmful or toxic environments, and in situations where a system should respond very rapidly (e.g., in nuclear reactor control rooms).

Fig. 5 Representative paragraph of topic 1 based on the three-topic model

word cloud analysis, as depicted in Fig. 4, with a larger font indicating a higher occurrence likelihood. Further, STM provides representative text samples for each topic extracted from a text corpus. As illustrated in Fig. 5, this paragraph exemplifies the content and themes associated with a topic, allowing for a more comprehensive understanding (Table 1).

Table 1 The 20 top words for the three-topic model

Topic	Highest probability	FREX words
1	data, system, use, can, develop, technolog, human, learn, servic, process, need, exampl, intellig, inform, make, new, also, algorithm, applic, solut	patient, traffic, imag, predict, detect, person, intellig, robot, sensor, languag, vehicl, agricultur, algorithm, medic, control, transport, car, decis, smart, perform
2	research, will, technolog, develop, innov, educ, compani, industri, busi, programm, new, skill, sector, also, digit, invest, train, fund, work, need	student, attract, school, job, skill, talent, cours, educ, univers, startup, start-up, billion, smes, teach, programm, compani, capit, career, graduat, growth
3	develop, govern, will, public, technolog, use, strategi, data, ethic, nation, secur, research, sector, innov, feder, promot, societi, intern, includ, polici	ethic, feder, strateg, trustworthi, framework, standard, shall, strategi, regulatori, coordin, commiss, rdi, legal, govern, polici, guidelin, ministri, societi, agenc, principl

4.9 Implications for rigor in qualitative text analysis

Applying automated text analysis for generating topics has significant implications for the findings' credibility, transferability, dependability, and confirmability. The scalability and speed of topic modeling contribute to the categorizations' comprehensiveness, enabling researchers to uncover patterns and connections that may have been overlooked in manual qualitative analysis and improving the findings' transferability (Crowston et al. 2012).

Further, the research findings' confirmability is impacted by the decision-making process in topic modeling, particularly when determining the number of topics in the model. Topic modeling such as STM enables systematic comparison of multiple models with varying numbers of topics, empowering researchers to select the most coherent and meaningful topic model for their specific research goals. This systematic comparison enhances the findings' credibility and provides a more reliable basis for interpretation (Nikolenko et al. 2016). Also, automated text analysis reduces a researcher's influence on topic generation, shifting the dependability from the researcher to the algorithm. In contrast, manual analysis of textual data is influenced by a number of factors, such as the number of coders, their analysis skills, the data volume, and the analysis stage.

Further, incorporating supplementary metrics, such as topic proportion or time trends through including covariates, enhances an analysis' credibility (Gilardi et al. 2021). By considering these metrics, researchers can obtain a more comprehensive and informative assessment of the topic model, providing deeper insights into the distributions and evolution of topics over time (Roberts et al. 2016).

4.10 Phase 4: interpretation

In the interpretative phase of topic modeling, a theoretical perspective becomes crucial for understanding and making sense of the identified topics (Isoaho et al. 2021; Macanovic 2022). By examining topic modeling's output, researchers can establish meaningful connections between the identified topics and relevant concepts, theories, and the literature

in the study field. This theoretical lens serves as a guide for interpreting topics from various angles, such as frames (DiMaggio et al. 2013; Gilardi et al. 2021), narratives (Guenduez and Mettler 2023; Mettler et al. 2024), or discourses (Törnberg and Törnberg 2016), depending on their research question or study goals.

Interpreting the topics from a theoretical perspective not only facilitates a deeper understanding of the topics; it also helps researchers to avoid potential misinterpretation of the topic modeling results. Further, it allows researchers to contextualize and interpret the topics in their research area and in existing theories. By combining the findings from topic modeling with relevant theoretical frameworks, prior knowledge of the literature, and their own expertise, researchers can achieve rigorous and comprehensive interpretation.

4.11 Our experiences in the exemplar study

We sought to extract policy frames from AI policies, critically evaluating the topic modeling results through the lens of the policy frames perspective and comparing it to existing theoretical frameworks and established knowledge of policy frames in the field (Aukes et al. 2020; Steensland 2008; Ulnicane et al. 2021). We conducted an exploratory inductive analysis of the topic modeling results, considering keywords, word clouds, and line-by-line reading of the representative paragraphs from the AI policies associated with each topic (Isoaho et al. 2021). To determine the appropriate number of topics, we evaluated the STM models with 3, 6, 9, and 15 topics based on the following criteria outlined by Chen et al. (2020):

- Top representative words, paragraphs, and word clouds form a meaningful topic.
- There is no overlap between topics in a topic model.

Using these criteria, two researchers independently analyzed the various STM outputs with 3–15 topics, i.e., the highest-probability and FREX words as well as the representative paragraphs from the AI policies. Following previous research (Gilardi et al. 2021), we conducted a policy frame analysis (Entman 1993), applying four key elements: problem definition, attribution of cause, moral evaluation, and treatment recommendation (Matthes and Kohring 2008). We adopted a structured, theory-informed coding approach (source). Prior to interpreting the STM output, two coders in the research team familiarized themselves with the conceptual foundations of policy frame analysis, drawing on existing frame typologies and the relevant theoretical literature (Aukes et al. 2020; Gilardi et al. 2021; Ulnicane et al. 2021). Analyzing the frames in AI policy documents enabled us to explore how governments address public controversies surrounding AI (Ulnicane et al. 2021) and to articulate their strategic intentions and policy priorities (Aukes et al. 2020).

The coders independently reviewed the STM models with 3, 6, 9, and 15 topics by examining the top words, word clouds, and 10 representative paragraphs associated with each topic. We held several consensus-building sessions to compare the individual interpretations and reach agreement. When disagreements arose, we consulted additional representative paragraphs from the policy documents to discuss interpretations. This iterative process, which involves repeated cycles of text analysis and discussion, led us to select the three-topic model as the most suitable one, because it provides a high-level overview over the AI policy frames. We labeled the three topics and compiled brief descriptions for each topic. The final analysis with topic labels and descriptions was then reviewed by three additional

researchers not previously involved in the interpretation process to verify its interpretability and coherence.

We identified three basic policy frames: exploiting the potentials of AI (Frame 1), the need for capacity-building around AI (Frame 2), and developing human-centered AI (Frame 3). Table 2 provides an excerpt of the analysis results, the topic labels, and brief descriptions.

By using STM, researchers can estimate the prevalence of a selected solution in the entire text corpus. Figure 6 illustrates the topic prevalence, indicating the prominences and saliences of the three frames in all AI policies.

One advantage of STM over other topic modeling approaches is its ability to incorporate document-level metadata as covariates, enabling the detection of relationships between covariates and the text corpus' content (Roberts et al. 2014, 2016, 2019). We selected the country issuing the AI policy and the publication year as covariates to examine the topic prevalence in each policy document and over time.

We interpreted the covariate analysis results illustrated in Figs. 7 and 8. Figure 7 presents the prevalences of the three frameworks across AI policy documents from different countries, offering insights into the similarities and differences between them. By interpreting these frames' distributions, we can gain valuable insights into the diverse emphases and priorities that each country has placed on AI policy.

Figure 8 illustrates the temporal development of the three frames. Their interpretation sheds light on the dynamics of frame importance over time in AI policies. This analysis

Table 2 Overview over the 3-, 6-, 9-, and 15-topic models

The 15-subtopic STM solution	The 9-subtopic STM solution	The 6-subtopic STM solution	The 3-subtopic STM solution
Topic 1: Building an AI database This subtopic focuses on the personal, company, and governmental data required as a basis for AI technologies. In this context, the public access, availability, sharing, exploitation, and storage of data and data minimization, consent, and control over personal data are highlighted.	**Topic 1: Governing access to and the uses of sensitive data** This subtopic emphasizes the regulation and governance of the access to and the sharing of personal and governmental data. It emphasizes the need to protect privacy rights and sensitive data, and to prevent discrimination and biases.	**Topic 1: Governing access to and uses of sensitive data** This subtopic emphasizes the regulation and governance of the access to and the sharing of personal and governmental data. It emphasizes the need to protect privacy rights and sensitive data, and to prevent discrimination and biases.	**Topic 1: Exploiting the potentials of AI** This frame encompasses the importance and potentials of AI as a new technology. Fostering AI applications in the public and private sectors and advancing in the global AI race are key aspects in this frame.
Topic 2: Fostering private sector adoption and development of AI solutions The need to develop and adopt AI solutions in the private sector, overcome challenges, and remove barriers are stressed in this subtopic. The opportunities offered by AI applications for the domestic marketplace are also highlighted.	**Topic 2: The need to accelerate the development of AI for a country's national economic competitiveness** This subtopic focuses on national competitiveness in the global AI race and emphasizes the need to promote domestic capacity-building around AI. It emphasizes the importance of using AI and its potentials to increase the domestic economy and research competitiveness.	**Topic 2: Developing a national AI ecosystem for adopting AI** This subtopic acknowledges the potentials for AI uses in various sectors and the challenges faced. It includes the need to gather research, knowledge, and skills to build a national AI ecosystem in which AI is adopted and advances society as well as the economy.	**Topic 2: Need for capacity-building around AI** This frame focuses on capacity-building around AI. Research, development, and education in AI are needed to increase the number of researchers, graduates, and professionals in the field, and the transfer of know-how and skills to industry is crucial to harnessing its potentials.
Topic 3: Defining a national strategic R&D agenda for AI This subtopic emphasizes the evaluation and advancement of national AI R&D efforts and the workforce, as well as the need to set strategic priorities.	**Topic 3: Developing ethical and secure AI** This subtopic indicates the importance of developing ethical reference frameworks and designing AI systems that align with ethical, legal, and social principles.	**Topic 3: Governing the ethical and security risks of AI** The implications of AI for society and work demand governance of the ethical and security risks, issues that are emphasized in this subtopic. It encourages the setting of strategic priorities, the formulating of guidelines and standards, and the coordinating of the stakeholders, so as to achieve trustworthy AI and mitigate risks.	**Topic 3: AI Governance** This frame emphasizes that social norms and human values that form the basis of the development and uses of AI technologies. It discusses the ethical and legal frameworks needed to regulate AI technologies.
Topics 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14 **Topic 15: Developing ethical and legal frameworks for AI** This subtopic focuses on developing ethical and legal frameworks and standards for AI so as to prevent discrimination and biases. Governing risks and possible implications for society and privacy owing to the uses of AI are also discussed.	*Topics 4, 5, 6, 7, 8* **Topic 9: Promoting education and AI-related skills** This subtopic stresses the need to promote education and AI-related skills at all stages, from primary school to university. It emphasizes the importance of AI and digital literacy, regardless of whether young adults pursue further studies in AI-related fields. This subtopic also includes the need to increase the offerings of university courses, PhD positions, and professorships in AI-related fields.	*Topics 4, 5* **Topic 6: The need for research int AI technologies** This subtopic stresses the need for research into improving and further developing AI technologies, such as AI system performance, human-AI interactions, language processing, and deep learning. Alignment of the development of AI and the needs of industries and governments are emphasized	

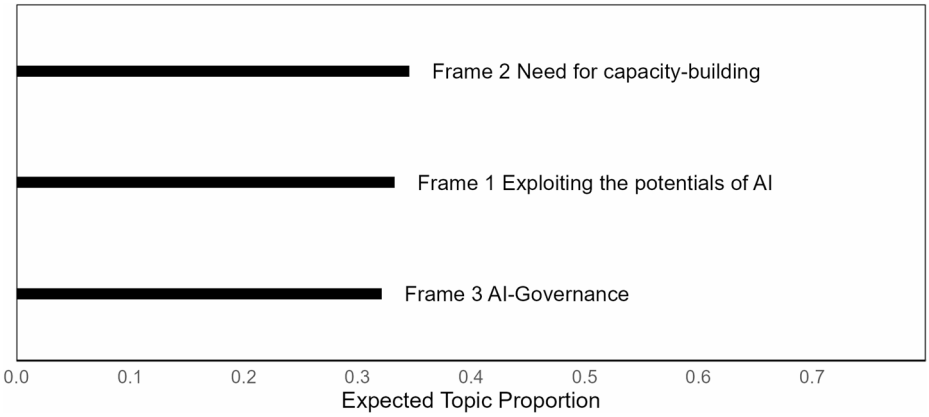

Fig. 6 The topic proportions

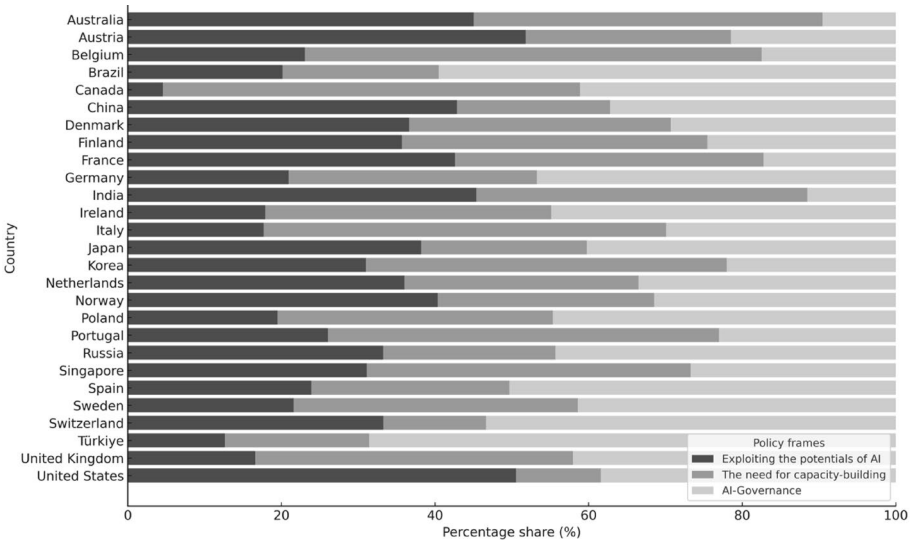

Fig. 7 The topic proportions by country

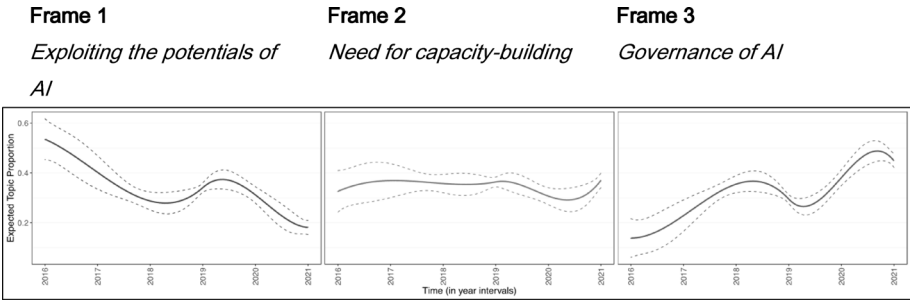

Fig. 8 The correlations between topics, times, and topic prevalences across the entire text corpus

unveils which frames experienced shifts in importance (i.e., increasing, decreasing, or remaining consistent). By examining these trends, valuable insights can be gained into the evolving emphases and priorities in the policy landscape.

4.12 Implications for rigor in qualitative research

Interpreting the topic modeling results offers several advantages over traditional content analysis. A major advantage of automated text analysis is that it allows researchers to refer to entire datasets or a substantial part of them. Also, the contextual data included as covariates support qualitative interpretation; these enable the discovery of patterns, relationships, and insights that go beyond individual cases or specific contexts, thereby improving the findings' transferability and credibility.

Further, statistical measures such as topic proportions, co-occurrence patterns, correlation maps, and temporal trends provide valuable insights and support the interpretation of the findings. Adhering to the defined topics and the associated statistical measures reduces the influences of subjective biases from a researcher, enhancing the research results' confirmability and credibility.

The quantitative component of the study complements the qualitative interpretation. Integrating the topic modeling results with a researcher's expertise, theoretical framework, and prior knowledge further increases interpretations' credibility and robustness.

4.13 Phase 5: reporting

When conducting a study based on topic modeling, researchers usually provide a detailed description of input data and results in their study in an appendix or a supporting information section so as to provide a comprehensive report of their study (Gilardi et al. 2021a, b; Guenduez and Mettler 2023). Information regarding input data (e.g., policy documents, newspaper articles, tweets, or an Excel sheet including all variables), as well as the topic modeling's outputs (e.g., the codes or scripts used, the topic descriptions and proportions, or the temporal trends) can be made publicly available. This information enables readers to better understand the individual analysis steps, results, and interpretations, as well as to replicate the analysis or modify it for their own research purposes.

4.14 Our experiences in the exemplar study

We include comprehensive supplementary material in our study, considering the limited word counts imposed by most journals; it contains detailed information about the input data, the R script used, all the STM outputs, and the procedure employed for deriving policy frames. Specifically, it includes a table that displays all the AI policies included in our study, with the publication years, the titles, and the publishing countries as input data. We further provide different topic models with varying numbers of topics and their interpretations (see Fig. 3). For the final topic model (three topics), we included the top words, the word clouds, and representative paragraphs for each of the three topics (see Figs. 4 and 5, and 6). This allows readers to understand the main themes and concepts captured by each topic. We also present the topic distribution in the entire dataset and in individual policies, providing insights into each topic's prevalence across different contexts (see Fig. 7). We also included

temporal trends and heatmaps that demonstrate how the topics evolved and fluctuated over time and across countries (see Figs. 7 and 8). For each visualization, we have provided an interpretation summary, highlighting the key findings and implications. These elements deepen readers' understanding of the topics and their significances in the study.

Further, to promote reproducibility, we have included the scripts used for conducting the topic modeling analyses, allowing interested readers to replicate the analysis or adapt it for their own research purposes. By compiling this supplementary material, we seek to ensure that all the relevant details and outputs relating to the topic modeling analysis are provided, while maintaining a concise and focused main study.

4.15 Implications for rigor in text analysis

Reporting the essential information of the topic modeling process – encompassing the input data, the data pre-processing steps, the choice of unit of analysis, the number of topics, and the approach for interpretation – can positively influence dependability, confirmability, and transferability. First, a comprehensive record improves confirmability by clearly documenting the decision-making process, such as explicit details regarding the criteria for selecting texts, determining the number of topics, interpreting and labeling topics, and the evaluation of the model's performance. Second, confirmability is improved because the documentation provides an auditable trail that enables other researchers to independently verify the findings and replicate the analysis. Reporting the source code, the software packages used, and the data processing scripts facilitates the assessment of the results' dependability. Third, by volunteering this extensive information on the study, its context, and the researchers' decision-making process, readers are empowered to assess the results' transferability to other cases and contexts.

5 Discussion and conclusion

The combination of automated text analysis with qualitative text analysis is a promising mixed-methods approach and a growing trend among researchers (Engstrom et al. 2022; Sripathi 2024). With the increasing availability of advanced computational tools and techniques, such as ChatGPT or Google Gemini, analyzing large volumes of textual data has become more accessible and easier to conduct. While these tools are often considered 'black boxes' owing to their lack of transparency and potential inherent biases (Markowitz 2024), more established (-semi) automated text mining techniques such as LDA, STM, or sentiment analysis offer more transparency and traceability, although they have limitations in certain contexts (Engstrom et al. 2022). Our aim was to answer this research question: *How does the inclusion of automated text analysis techniques contribute to the analytical rigor of text analysis?*

We have used a mixed-methods approach that combines automated text analysis and qualitative text analysis to evaluate how this mixed-methods approach enhances analytical rigor. This evaluation was anchored on four widely recognized criteria in qualitative research: credibility, dependability, transferability, and confirmability (Lincoln and Guba 1985; Trochim 2001; Shenton 2004; Elo et al. 2014). Based on this evaluation, the follow-

ing chapter derives key implications for enhancing analytical rigor in studies that combine automated and qualitative text analysis.

5.1 Implications for analytical rigor: lessons from the exemplar study

Guided by these four criteria, our results highlight the following implications for analytical rigor in mixed-methods studies that combine automated text analysis and qualitative text analysis:

Credibility of research findings refers to the degree to which they are considered believable and aligned with reality (Shenton 2004). When the amount of text to analyze is small (e.g., in interviews), manual analysis provides deep and rich insights. However, when the volume of text becomes large (e.g., thousands of tweets, newspaper articles), time and resource constraints force the reduction of the text volume through data reduction (e.g., sampling) (Elo et al. 2014). In this case, the application of automated text analysis allows researchers to flexibly select the type and amount of textual data. By analyzing a larger text corpus, the results become more comprehensive and representative and, therefore, more credible (Haupt et al. 2023).

Further, the systematic nature of automated text analysis and the incorporation of statistical measures – such as the publication year, the publisher, and the country of publication – as covariates help to uncover correlations and patterns that may have been overlooked in manual analysis. Such correlations can support, question, or enrich qualitative interpretation, enhancing the findings' credibility (Isoaho et al. 2021).

However, current automated text analysis techniques are specifically designed for textual data (Blei and Lafferty 2009). They are not directly applicable to nontextual data such as images, audio, or video, which may also contain valuable information. This leads to the omission of potentially important data, negatively impacting an analysis' credibility. Also, automated text analysis techniques may miss subtle nuances or cultural references, leading to potential misinterpretations or an incomplete understanding of a text's meaning, warranting a mixed-methods approach. Contextual and interpretative insights that humans understand from reading texts remain crucial for accurate analysis (Baumer et al. 2017). For instance, certain aspects of texts, such as emotions or reading between the lines, are subjective elements that require human judgment (Crowston et al. 2012).

After all, automated text analysis methods are not free from errors and may misclassify certain texts or struggle with ambiguous or nuanced language (Haupt et al. 2023). Further, the accuracy of the algorithm depends on the training data's quality. Like any data-driven approach, automated text analysis can be susceptible to biases or stereotypes, as they are designed by humans and learn patterns from human-generated data (Bender et al. 2021; Macanovic2022). To improve credibility, researchers can contextualize their results. For instance, in STM, researchers enhance their findings' credibility and comprehensibility by describing each identified topic with representative words or phrases from the data corpus and explaining its relevance to their studies' broader contexts (Grimmer and Stewart 2013).

Our findings indicate that using automated text analysis techniques enhances credibility by analyzing larger text volumes and including contextual variables; however, this credibility is potentially undermined by data omissions and algorithmic biases. To mitigate the potential decrease in credibility, researchers should use a mixed-methods approach, blending automated text analysis with qualitative text analysis. This involves integrating man-

ual checks and human interpretation at critical phases of the analysis so as to identify and correct for biases, omissions, or misinterpretations introduced by automated text analysis (DiMaggio et al. 2013; Grimmer and Stewart 2013).

Transferability: refers to the extent to which qualitative research results can be generalized or transferred to other contexts (Trochim 2001). In qualitative text analysis, researchers enhance transferability by providing detailed descriptions of a case and its context, allowing readers to assess the applicability of the results to other situations (Thomas and Magilvy 2011). Our analysis illustrates that transferability can be enhanced by the inclusion of automated text analysis. Utilizing a larger text corpus as well as incorporating statistical measures and correlations can potentially enhance the generalizability of findings from automated text analysis, enabling the discovery of patterns and relationships that extend beyond selective cases or individual contexts (Haupt et al. 2023). Transferability is increased if the presentation of results allows readers to explore alternative interpretations (Elo et al. 2014). By making their research scripts accessible, researchers enable other scholars to apply these to their own datasets. For instance, when using STM or LDA, the R script exemplified in our Fig. 2 could be shared alongside the publication as additional material. This practice not only validates the original research, but also enriches the field by allowing for the exploration of new settings, populations, or variables that were not considered by the original study (Lincoln and Guba 1985). It also facilitates interdisciplinary collaboration, where models or frameworks from one field may offer new insights into or solutions to problems in another field.

Dependability: refers to the extent to which a study's conclusions are grounded in the data rather than shaped by researcher biases (Lincoln and Guba 1985). Automated text analysis can enhance dependability by providing a systematic, consistent method for identifying patterns, reducing subjective influences. However, biases can still enter at various stages, such as text selection, preparation, and the removal of stop words, as well as through decisions taken during analysis. To support dependability, researchers can clearly document methodological choices, including model parameters and topic labeling decisions (Elo et al. 2014). Since automated results still require human interpretation, incorporating traditional methods such as intercoder reliability testing can further minimize biases and can strengthen the rigor of text analysis (Krippendorff 2004).

Confirmability: is defined as the extent to which a study's outcomes can be corroborated by other researchers, thereby validating its findings (Trochim 2001). Relying on the output of automated text analysis firstly restricts a researcher's discretion and reduces dependence on individual decision-making, ensuring that the findings are grounded in the data. To ensure confirmability, researchers must also document their manual research process and must provide an auditable trail that allows other researchers to independently verify the findings and reproduce the analysis (Elo et al. 2014). This contributes to an analysis' rigor and a study's confirmability. When applying an automated text analysis technique, researchers should ensure that the chosen method provides transparency and discloses the utilized algorithms and the analysis steps. While popular text analysis tools such as ChatGPT or Google Gemini are widely accessible, they can hinder confirmability depending on how they are used (de Kok 2023). In our analyses, we have demonstrated the application of STM, which allows researchers to share their R code files online as supplementary material alongside their papers. This transparency enhances confirmability by allowing others to

replicate the analysis; it also facilitates secondary analysis, enabling other researchers to use both the dataset and the script for their own investigations.

In sum, our results highlight that, while automated text analysis provides several key advantages compared to traditional qualitative text analysis, a rigorous analysis can be achieved through a thoroughly documented mixed-methods approach that combines automated text analysis with manual qualitative text analysis. These insights support previous studies that also highlight the importance of integrating automated text analysis with manual qualitative text analysis (Haupt et al. 2023; Mettler 2025; Sripathi et al. 2024).

5.2 Contributions to the mixed-methods research

Automated text analysis methods are transforming research by offering valuable tools for robust textual analysis and data-driven theory-building (Berente et al. 2019). Their abilities to uncover patterns in large text collections (Banks et al. 2018) enhance research speed, scalability, and data comprehension. Our study specifically contributes to mixed-methods research by demonstrating how combining automated and qualitative text analysis significantly elevates analytical rigor. We have used Lincoln and Guba's (1985) widely recognized criteria – credibility, transferability, dependability, and confirmability – to show this enhancement (Nowell et al. 2017a, b; Trochim 2001; Shenton 2004; Elo et al. 2014). This approach improves credibility and transferability by enabling more comprehensive identification of patterns across larger datasets (Haupt et al. 2023). Further, the structured application of automated methods with qualitative analysis boosts dependability by reducing subjective biases and strengthens confirmability by more firmly grounding conclusions in data (Grimmer and Stewart 2013). Our work provides comprehensive guidance on how researchers can effectively capitalize on these benefits in a mixed-methods design.

Besides these practical insights, our study takes an epistemological stance that views knowledge as emerging from the combination of computational and qualitative-interpretative approaches (Grimmer and Stewart 2013; Nelson 2020). We lever the strengths of both automated methods such as STM that reveal hidden structures in large texts and qualitative analysis, which provides interpretation and meaning (Creswell and Poth 2016). This combined approach offers a probabilistic framework that guides our initial interpretations. It reduces yet, crucially, does not eliminate, the need for human insights and reflection in the subsequent qualitative analysis. The integration of computational and qualitative text analysis is key to unlocking the full potentials of text analysis (Grimmer and Stewart 2013).

Our analysis shows that integrating automated text analysis techniques can enhance research findings' credibility. Analyzing larger text volumes by means of these techniques allows researchers to identify patterns or themes that may have been overlooked in smaller datasets, leading to more comprehensive and more representative results (Haupt et al. 2023). However, automated text analysis methods face several limitations regarding credibility and dependability (Németh et al. 2020; Macanovic 2022). These limitations may stem from various factors, including the input data's quality or the assumptions of the modeling algorithm (Haupt et al. 2023; Crowston et al. 2012). We underscore that researchers remain paramount for guiding the process and evaluating model outputs as well as for extracting meaningful insights and interpretations. As Schmidt (2012) adequately notes, "A poorly supervised machine learning algorithm is like a bad research assistant." Ultimately, our research argues that automated techniques are powerful tools in a mixed-methods framework, effectively

complementing qualitative-interpretive analysis without replacing the insights and understanding provided by human researchers.

5.3 Limitations and future research

This study has limitations. We have focused on a specific form of automated text analysis, STM; thus, our results may not directly apply to all cases. While STM offers valuable insights into text, structure, and content, numerous other text analysis methods are available, each with its own strengths and limitations. We encourage researchers to explore these alternative methods in greater depth, encompassing a broad spectrum of approaches such as sentiment analysis, LDA, and methods that incorporate multimodal elements, such as those that analyze text and images simultaneously. Also, there is a growing interest in newer tools such as ChatGPT and Gemini, which we excluded owing to their lack of methodological transparency (Markowitz 2024; de Kok 2023). Despite these constraints, our study provides a structured framework for assessing automated text analysis' potential contributions to analytical rigor. By systematically evaluating the interplays between automated text analysis and qualitative text analysis, we shed light on how these approaches can complement each other to enhance rigor in research. Our findings serve as a basis for further exploring how combining various automated text analysis tools with qualitative text analysis can enhance research endeavors' rigor.

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Declarations

Conflict of interest The Authors declare that there is no conflict of interest.

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