Analyzing Open Door Forum Transcripts to Identify Key Healthcare Topics Using Text Mining Techniques

Sharon Paruwani
American University
sp0458a@american.edu

Prince Enyiorji
American University
Pe7508a@american.edu

Tsungai Tsambatare
American University
tt0644a@american.edu

Abstract

The Centers for Medicare & Medicaid Services (CMS) hosts the Open Door Forum (ODF), which is a crucial forum for stakeholders, legislators, and healthcare professionals to engage on urgent healthcare-related issues. CMS interacts with participants on a variety of subjects, such as home healthcare, skilled nursing facilities, hospital services, rural health, and more. Transcripts and podcasts of these conversations offer insightful information about the difficulties and possibilities the healthcare system faces. Finding and comprehending the recurrent themes and issues raised in these forums is crucial for influencing well-informed decision-making, developing successful healthcare strategies, and eventually enhancing patient care outcomes as healthcare policies continue to change. The study aims to give policymakers actionable insights by utilizing techniques like topic modeling, sentiment analysis, and keyword frequency analysis to present a comprehensive picture of the dominant issues in these discussions about healthcare.

1. Introduction

The goal of this project is to identify the most frequently discussed healthcare issues in particular domains, such as home skilled nursing facility, hospitals, and rural health, by using text mining techniques to analyze the transcripts of the Open Door Forum which is hosted routinely by the Center for Medicare and Medicaid Services. Due to the sheer massive number of transcripts and podcasts, it is not possible to manually extract important insights. This study will efficiently analyze data to reveal underlying patterns and themes by utilizing advanced text mining techniques. These results will offer practical insights to healthcare providers, policymakers, and other stakeholders to effectively tackle the most pressing healthcare issues.

2. Literature Review

The conceptual framework is based on the idea that the language and topics in healthcare forums reflect key healthcare challenges and opportunities. Text mining techniques such as keyword frequency analysis, topic modeling, and sentiment analysis will be employed to identify patterns in these discussions. This framework assumes that frequent terms, repeated topics, and sentiment trends are indicators of key healthcare issues that require attention.

Numerous research works have investigated the use of big data analytics and text mining in the healthcare industry to better understand patient needs, increase the efficacy of policies, and improve decision-making procedures. Big data analytics can empower healthcare organizations by revealing patterns and insights from large datasets, as Wang, Kung, and Byrd (2018) demonstrated. Their work serves as an example of how analytics can be used to inform healthcare decisions and paves the way for the application of similar methods, like text mining, to the analysis of discussions in professional healthcare forums like the Open Door Forum.

In their 2006 study, Zeng and Tse examined the growth of consumer health vocabularies, highlighting the ways in which terminology related to health can improve communication between patients and providers. Their work lays the groundwork for understanding how text mining can be used in professional healthcare forums to identify important issues that could influence healthcare policies, even though it primarily focuses on consumer health language.

Furthermore, the topic modeling work of Blei and Lafferty (2007) shows how sophisticated text mining methods can be used to extract relevant topics from sizable text corpora. Their approaches provide insightful information about how comparable methodologies can be used to evaluate the massive volume of textual data from the Open Door Forum.

Notwithstanding these developments, the analysis of professional healthcare forums like the Open Door Forum has received little research attention. By using text mining techniques to analyze professional healthcare discussions, this research seeks to close this gap by identifying important themes and issues that can provide stakeholders, legislators, and healthcare providers with insightful information. The study has the potential to greatly impact healthcare strategies and enhance patient outcomes by expanding the body of knowledge on healthcare analytics into this field.

3. Research Questions

1. What are the most common healthcare topics discussed across different Open-Door Forum categories?
2. How do the themes vary across categories like rural health, hospital services, and skilled nursing long-term services?
3. What language and keywords are most associated with specific healthcare challenges (e.g., hospital care, rural health)?
4. How can policymakers and healthcare providers use these insights to address the key concerns discussed in the forums?

4. Methodology

The data mining process is methodically guided through its six steps in this study using the CRISP-DM framework:

Business Understanding: By examining CMS Open Door Forum (ODF) transcripts, the goal is to identify important healthcare issues and offer policymakers useful information.

Understanding the Data: We will examine the format and content of ODF transcripts, identifying trends and offering first perspectives on healthcare-related subjects.

Data Preparation: The data will be ready for analysis using preprocessing methods.

Modeling: Topics, sentiments, and other insights will be extracted using a variety of text mining algorithms.

Evaluation: To make sure the models' results are in line with the goals of the study, they will be evaluated extensively.

Deployment: Stakeholders will see and understand the insights.

5.1. Data Collection

We will use the transcripts and publicly available podcast recordings from the Centers for Medicare and Medicaid Services (CMS) Open Door Forum (ODF) series for this study (source: https://www.cms.gov/training-education/open-door-forums/about/odf-podcast-and-transcripts).

We have decided to title our dataset Healthcare Voices. The dataset comprises audio recordings from CMS's ODF sessions, which have been transcribed into text for analysis and the text files are what we will use for this study. Text transcripts of ODF sessions, organized as discussions between lawmakers, stakeholders, and healthcare experts, make up the dataset. These transcripts cover a broad spectrum of healthcare subjects, such as rural health, hospital services, and different facets of long-term care and support. Three crucial areas which we randomly selected will be the focus of our study specifically: skilled nursing facility (SNF)/ Long Term Care (LTC), hospital, and rural health.

The transcripts span from 2020 to 2024 and include around 56 meetings in the collection. Several pages of text spread among the 56 meeting transcripts are the estimated size. The full meeting transcripts from the audio recordings of the ODF discussions provide the collection's foundation. Every transcript adheres to a standard format, which comprises: Introduction and Opening Remarks: The moderators of CMS provide a brief overview of the session, thank the attendees, and provide any instructions or disclaimers that may be required

5.2. Data Preprocessing

Several preprocessing processes were used to clean up the unstructured material and convert it into a format that could be analyzed to get the transcripts ready for text mining analysis:

1. Tokenization: To divide the text into discrete words and phrases, we employed tokenization. Word frequency identification and contextual analysis were made possible by this phase.
2. Stop Word Removal: Commonly used phrases such as "and", "the," and "in" were eliminated to concentrate the study on more significant terms that offer deeper insight into healthcare conversations. We also created custom stop words which were aimed at removing words that commonly appeared throughout the dataset without the possibility of contributing any meaningful insights.

3. Lowercasing: To avoid case sensitivity problems during analysis, all text was changed to lowercase.
4. Lemmatization: When counting several forms of the same word together during frequency analysis, words were reduced to their base forms (e.g., "regulating” to “regulate”).
5. Construction of a Document-Feature Matrix (DFM): Following preprocessing, a Document-Feature Matrix (DFM) was created to measure how frequently each phrase appeared in the transcripts.

5.3. Modeling

Two types of analyses were conducted to address the research questions: inductive and deductive techniques.

1. Several techniques were used for inductive analysis (addressing research questions 1 and 2) to find themes and patterns in the data. To determine the most often used terms in the transcripts of ODF, term frequency (TF) of every phrase was computed. This is an exploratory technique which makes use of descriptive analysis. The Term Frequency-Inverse Document Frequency (TF-IDF) technique was employed to modify the term frequency by assigning greater weight to significant terms inside certain documents or categories and less weight to common phrases. This offers enhanced comprehension of distinct terminology and obstacles particular to various fields Topic Modelling, one of our advanced text mining techniques that relies on unsupervised machine learning. Latent themes were found using a Topic Modeling technique called Latent Dirichlet Allocation (LDA) in the whole corpus as well as in specific healthcare categories such hospitals, skilled nursing facilities, and rural health. Furthermore, common bigrams and trigrams were captured using Phrase Frequency Analysis (N-Grams), which offered additional insights into frequently occurring healthcare conversations.

We also made use of deductive approaches to try and confirm some preexisting notions that we had from a basic appreciation of what the dataset (addressing research questions 3 and 4). By classifying text using a bespoke healthcare lexicon based on recognized policy categories, categorization modeling, also known as dictionary-based analysis, enabled an organized investigation of certain subjects like service delivery and care quality. Lastly, sentiment analysis was employed to assess the emotional polarity and tone of the conversations. We were able to determine if talks were typically good, negative, or neutral by giving sentiment scores to each transcript. We hope to explore word co-occurrences using Hierarchical Cluster Analysis and identify theme clusters that reflect the important healthcare problems, such emergency services or workforce concerns.

The text mining techniques used in wrangling as well as analyzing our text data were from both R Studio and Python packages. For term frequency (TF), and Sentiment analysis, the R Studio tidytext, and VADER/text blob packages were used respectively. While for Term Frequency-Inverse Document Frequency (TF-IDF), Topic Modelling and N-gram analysis the python packages sci-kit learn, Gensim and NLTK were employed respectively.

6. Findings

Addressing Research Question 1

To answer the first question which pertained to the most common healthcare topics discussed across different Open-Door Forum categories, we performed keyword frequency analysis across the three main CMS categories that we had randomly selected namely: Rural Health, Hospital Services, and Skilled Nursing Long-Term Services. We determined the most common terms for each category by utilizing word frequency analysis and term frequency-inverse document frequency (TF-IDF) scores. We utilized both TF and TF-IDF because we wanted to derive a raw, unweighted view of the language used across categories which is offered by TF, while TF-IDF enhances comprehension by highlighting terms that are particular to or disproportionately significant.

From Term Frequency, we managed to establish that the most commonly occurring terms across all three categories were

- Regulation
- Will
- Intend
- Policy
- Document
- Link
- Refer
- Statute
- Payment

- Time

Figure 1: Top Terms in CMS Transcripts by Frequency

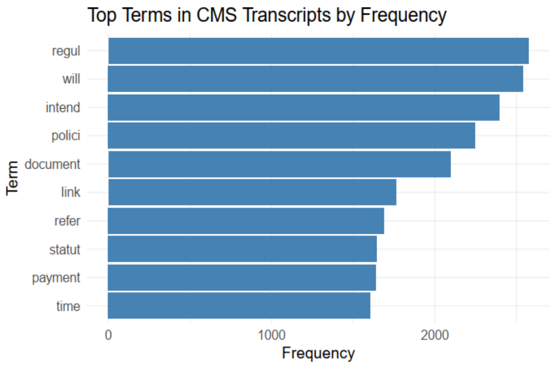
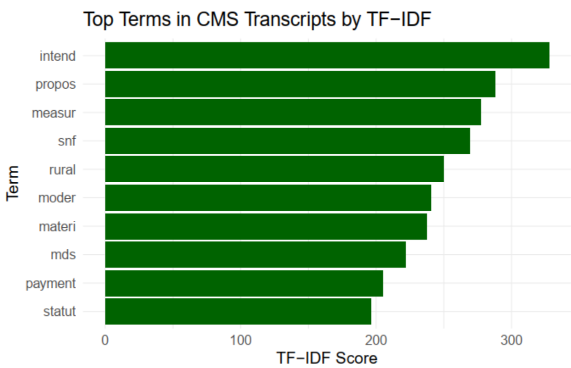


Figure 2: Top Terms in CMS Transcripts by TF-IDF



By considering the proportions and weighting of the words using inverse document frequency, we were able to establish a new set of most commonly occurring terms as highlighted in figure 2.

- Intend
- Propose
- Measure
- SNF
- Rural
- Modern
- Material
- MDS
- Payment
- Statute

We proceeded further by exploring the most frequently occurring words that commonly occur in meetings segregated by the three different categories to try and establish words that occasionally feature for each category.

Addressing Research Question 2

A dictionary-based classification approach was used to look at the theme variance among the three Open-Door Forum categories (Rural Health, Hospital, and Skilled Nursing Long-Term Services). This was instrumental in addressing the second question RQ2, which pertained to how themes vary across categories. This method made use of the Policy Agendas English dictionary, which has 28 general policy-related topics, including labor, agriculture, education, civil rights, healthcare, social welfare, and macroeconomics.

The following crucial steps were engaged in the process:
The corpus of forum transcripts was transformed into a Document Feature Matrix (DFM). A particular document type was represented by each row in the matrix, and a dictionary term was represented by each column.
Terms in the text were mapped to the predetermined categories using the dictionary that was applied to the DFM. Even when similar or related terms were employed in different situations, this procedure enabled us to group the text into pertinent themes.

The percentage of each dictionary category inside each forum was determined when the DFM was grouped by forum category (Long-Term Services, Rural Health, and Hospital Services). We were able to compare the prevalence of the most prevalent themes across forum categories as a result.

Four major components emerged as the most talked-about subjects after using the dictionary and figuring out the topic proportions for each category: healthcare, macroeconomics, labor, and education. Significant differences were found between the forum categories in the percentage for each theme:

Healthcare:
Since the focus of these forums is on addressing concerns linked to healthcare, it is not surprising that healthcare was the most talked-about topic across all boards. Discussions about healthcare were particularly prevalent in rural health forums, with a focus on the funding, quality, and access issues that are specific to rural regions.

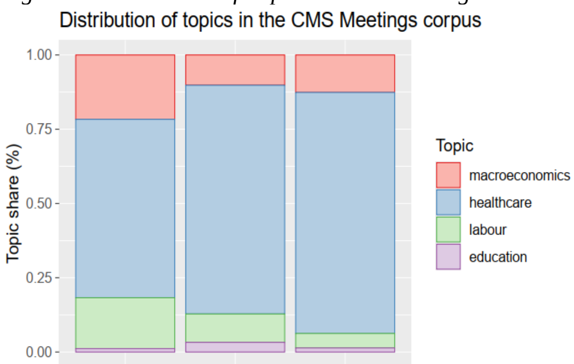
Macroeconomics:
The second most common topic of discussion was macroeconomics. Concerning financial limitations on service provision, and wider policy ramifications for the healthcare industry were all included in this category.

Labor:
A recurrent issue, particularly in forums devoted to Long-Term Services, was labor. This probably reflects issues like training, recruiting, retention, and shortages of healthcare workers in long-term care facilities.

Education:
Education was the least talked about of the four themes that were chosen, and it mostly came up in relation to provider training programs, public awareness campaigns, and the distribution of healthcare recommendations.

Figure 3 below shows a visual depiction of how the topics are distributed in the 3 categories.

Figure 3: Distribution of Topics in CMS meetings



Additionally, in answering the second question pertaining to theme variations, we also made use of topic modelling, particularly Latent Dirichlet Analysis. We made use of 5 topics $k=5$ after evaluating coherence scores for various topic numbers and balancing interpretability with meaningful distinctions between topics. Too few topics resulted in oversimplification of the findings, missing nuances in the data, while too many topics led to fragmentation, making it harder to generalize themes. Five topics provided an optimal granularity for identifying distinct themes across the dataset.

Figure 4
Five main themes emerged from the topic modeling analysis, each of which was represented by the terms that appeared most frequently. These subjects are recurrent issues that have been covered in many forum categories:

Topic 1: Payment Systems and Proposals
This topic, which is characterized by terms like "propose," "payment," and "rule," illustrates conversations around financial frameworks, payment methods, and healthcare policies.

Topic 2: Rural Difficulties and Healthcare Delivery
Words like "health," "rural," and "care" indicate a focus on providing healthcare, particularly in underserved and rural areas.

Topic 3: Policy Goals and Evaluations
Words like "intend," "policy," and "review" draw attention to conversations about strategic policy assessments and regulatory frameworks.

Topic 4: Statutory requirements and documentation
Using terms like "refer," "statute," and "document," this topic highlights legal and administrative compliance in the healthcare industry.

Topic 5: Informational Resources and Transcripts
Terms like "transcript," "link," and "material" imply an emphasis on communication tools and resource sharing.

Figure 4 below shows the distribution of the terms across each of the 5 topics.

Figure 4: Terms associated with each topic

	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
[1,]	"propos"	"health"	"regul"	"document"	"transcript"
[2,]	"payment"	"will"	"intend"	"statut"	"regul"
[3,]	"rule"	"transcript"	"polici"	"take"	"intend"
[4,]	"final"	"rural"	"will"	"will"	"document"
[5,]	"polici"	"regul"	"materi"	"just"	"refer"
[6,]	"year"	"refer"	"link"	"transcript"	"materi"
[7,]	"requir"	"intend"	"measur"	"facil"	"will"
[8,]	"health"	"materi"	"review"	"chang"	"polici"
[9,]	"rural"	"time"	"transcript"	"refer"	"link"
[10,]	"hospit"	"care"	"place"	"grant"	"statut"

There are notable variations in thematic concentration among the three forum types (Hospital, Rural Health, and SNFLTC) when the topic proportions are visualized:

Hospital Forums:
Topic 1 (Proposals and Payments) dominated the conversation, making up more than 60% of the total. This demonstrates a strong emphasis on finance concerns, reimbursement procedures, and regulatory reforms that are essential to hospital operations.
Topic 2 (Healthcare Delivery) and Topic 3 (Policy Reviews) are examples of secondary subjects.

Rural Health Forums:
Over 40% of the conversations were mostly centered on Topic 2 (Healthcare Delivery and Rural Challenges). This is in line with the difficulties in providing healthcare in rural areas, like accessibility and infrastructure.
Administrative problems are highlighted by the moderate representation of Topics 1 (Proposals) and 4 (Documentation).

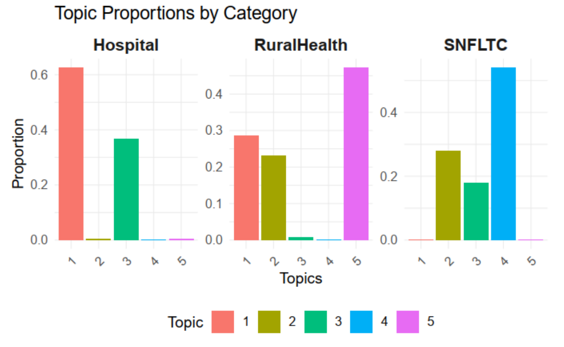
SNFLTC Forums: Long-Term Care & Skilled Nursing Facilities

Significantly impacted by Topics 3 (Policy Reviews) and 5 (Transcripts and Informational Resources),

which highlight the significance of information sharing and legal observance in long-term care.
Because long-term care operations rely heavily on compliance, Topic 4 (Documentation) is also very important.

Figure 5 below shows the proportions of each topic and how they relate to each of the three categories.

Figure 5: Topic Proportions by Category



The results show that different forum categories have both unique and overlapping theme focuses:

Unique Topics by Category:

Hospital forums place a strong emphasis on topics related to finances and reimbursement, which are essential to operational effectiveness.
Rural Health Forums provide a strong emphasis on delivery issues, with a particular emphasis on equity, access, and infrastructure.
The administrative complexity of long-term care is reflected in the SNFLTC Forums, which emphasize resource pooling, policy reviews, and documentation.
Typical Themes in All Categories:

All categories find resonance with topics such as Policy Reviews (Topic 3) and Healthcare Delivery (Topic 2), which reflect their general significance in healthcare forums.
Practical Advice for Stakeholders and Policymakers:

These topic variants can be used by policymakers to create focused initiatives. For instance:
Rural Health: To increase access to healthcare, enhance infrastructure and finance.

Hospitals: Take care of issues with reimbursement and policy changes.

SNFLTC: Enhance resource-sharing protocols and streamline compliance processes.

By using these insights, healthcare practitioners can better address important difficulties by coordinating their plans with category-specific priorities.

Addressing Research Question 3

To address the third research question, "*What language and keywords are most associated with specific healthcare challenges (e.g., hospital care, home health)?"*—sentiment analysis was conducted to examine the tone and emotional polarity of discussions in different categories. This provides insights into how positively, negatively, or neutrally specific healthcare challenges are addressed across forums.

To graphically represent the most common positive and negative keywords, a word cloud was created. It was easy to distinguish between critical and supporting language since negative words were shown in red and positive terms in blue.

The frequency of the top 10 sentiment words, both positive and negative, was displayed using horizontal bar charts. Deeper understanding of the words that dominated the sentiment landscape was made possible by these visualizations.

Keywords associated with negative attitudes:

- Emergency
- Critical
- Risk
- Impose
- Penalty

were commonly used in negative sentiments. These phrases brought to light urgent problems such systemic hazards in healthcare systems, time-sensitive problems, and regulatory difficulties. Words such as "problem," "delay," and "disorder" were indicative of poor patient outcomes and organizational inefficiency.

Keywords for a positive sentiment:
The following words were examples of positive language:

- Thank
- Delight
- Accurate
- Welcome
- Great

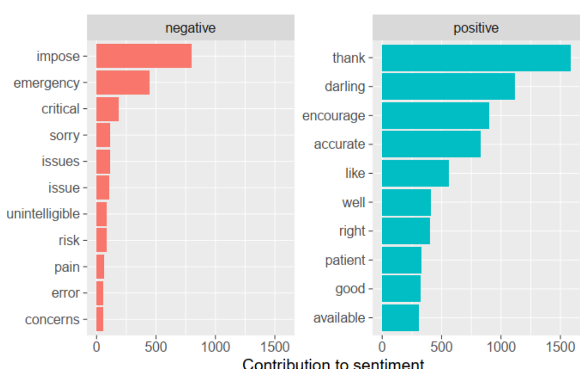
These remarks emphasized conversations on thankfulness, clear communication, and effective medical interventions. Satisfaction with patient care, administrative procedures, and compliance achievements were also expressed in positive sentiments.

Top Positive Words: With almost 1,700 instances, "thank" was the most often expressed positive word, emphasizing thankfulness and appreciation among stakeholders. Other high-frequency phrases that indicated optimism about progress, patient outcomes, and procedural clarity were "darling" (1,100), "encourage" (900), and "accurate" (800).

Top Negative Words: "impose" was the most often used negative word (around 800 occurrences), highlighting annoyance with regulatory impositions. Other noteworthy terms that highlighted the urgency and difficulties related to healthcare delivery and regulatory frameworks were "emergency" (450), "critical" (230), and "risk" (100). Words like "error," "concerns," and "issues" indicated discontent with procedures or results.

Figure 6: Sentiment analysis across all categories

Figure 7: Sentiment analysis across all categories



Addressing Research Question 4.

The sentiment analysis's results directly address the fourth study question by delivering insightful information about the main healthcare possibilities and challenges that were covered in the Open-Door Forums: How might the main issues raised in the forums be addressed by policymakers and healthcare professionals using these insights? Through sentiment analysis, we can pinpoint areas were stakeholders' express happiness or frustration, allowing us to take focused action to enhance healthcare systems.

Implications for Policymakers

Resolving Regulatory Dissatisfactions: Negative words like "impose" and "penalty" are frequently used, which suggests a high level of discontent with regulatory regimes. To lower administrative obstacles and guarantee adherence to quality standards, policymakers should concentrate on simplifying rules. Process simplification can raise stakeholders and healthcare provider satisfaction.

Enhancing Emergency Preparedness: The use of words like "emergency" and "critical" highlights worries about managing urgent medical requirements, particularly in hospitals and rural regions. To effectively handle high-risk situations, this emphasizes the necessity of more robust emergency preparedness strategies, improved resource allocation, and focused training.

Consequences for Medical Professionals

Making the Most Positive Comments Good words like "thank you," "accurate," and "welcome" imply that stakeholders respect clear communication and excellent treatment. Through upholding transparency, guaranteeing accuracy in the provision of care, and cultivating solid patient-provider connections, providers can use this feedback to increase confidence.

Overcoming Operational Difficulties: Negative terms like "delay," "error," and "risk" are indicative of operational flaws. To solve these issues and enhance the general patient experience, investments in technology, employee training, and workflow optimization are crucial.

Implications for Specific Healthcare Challenges

Hospital Treatment: The fact that "emergency" and "accurate" occur at the same time emphasizes how crucial prompt and accurate actions are in hospital settings. Hospitals should concentrate on bolstering their emergency care systems while upholding strict guidelines for therapeutic precision.

Home Health: Positive emotions like "encourage" and "delight" show that patients are happy with the individualized care they receive in home health settings. Nonetheless, the use of words like "problems" and "risk" points to the necessity of stronger non-hospital care support networks and improved quality assurance procedures.

Broader Impacts

Policymakers and healthcare professionals can create focused plans to address important issues, raise stakeholder satisfaction, and improve healthcare outcomes by utilizing the information gleaned from sentiment analysis. The healthcare system will adapt to the demands and expectations of its varied participants thanks to these findings, which provide a basis for evidence-based decision-making.

7. Discussions

Given the various challenges that hospitals, skilled nursing facilities, and rural healthcare encounter, it might seem at first that there is nothing in common with the healthcare conversations that take place in these settings. Nevertheless, several recurrent patterns show up when we look at the main ideas and vocabulary. These imply that although every healthcare environment faces different difficulties, they are all motivated by a few fundamental, underlying issues that transcend these divisions.

The emphasis on healthcare quality and access is among the most recurring topics in all categories. Frequently occurring terms pertaining to patient outcomes, care delivery, and operational difficulties indicated a shared interest in enhancing the efficiency and accessibility of healthcare services. This is especially important in a setting where providing healthcare requires navigating legal restrictions while maintaining patient satisfaction.

The worry over regulatory compliance is another common topic. Words like "penalty," "issues," and "compliance" draw attention to the administrative strains that healthcare practitioners, in whatever context, are subjected to. This consistency indicates that stakeholders are encountering comparable challenges in complying with the rules governing healthcare practice, irrespective of the category.

8. Limitations

These results highlight the significance of individualized methods to resource allocation and policymaking. Improving emergency response systems could help hospitals with important issues. While enhancing access and building out infrastructure are top concerns in rural health, skilled nursing institutions may benefit from concentrating on staffing solutions and quality control systems.

Through the prism of stakeholder involvement, this conversation offers a comprehensive knowledge of the healthcare landscape, supporting continued initiatives to address systemic and category-specific issues in healthcare delivery.

9. Future Research

Future research can leverage advanced techniques such as Bidirectional Encoder Representations from Transformers (BERT), Long Short-Term Memory (LSTM), and dynamic topic modeling to capture nuanced trends and shifts in healthcare discussions. Network analysis and named entity recognition (NER) could identify key relationships and entities, while emotion analysis and geospatial analysis would provide deeper insights into stakeholder sentiments and regional challenges.

Comparative studies across forums and linking discussions to policy outcomes could evaluate the real-world impact of healthcare forums. Tools like predictive analytics, interactive dashboards, and real-time text analysis would enhance the usability and immediacy of insights, driving informed policymaking and improved patient outcomes.

10. References

[1] Blei, David M, et al. “Latent Dirichlet Allocation.” Journal of Machine Learning Research, vol. 3, 1 Mar. 2003, pp. 993–1022, https://doi.org/10.5555/944919.944937.

{2] Henning Müller. “Medical (Visual) Information Retrieval.” Lecture Notes in Computer Science, 1 Jan. 2013, pp. 155–166, https://doi.org/10.1007/978-3-642-36415-0_10. Accessed 4 Dec. 2024.

[3] Jelodar, H., Wang, Y., & Yuan, C. (2019). Latent Dirichlet Allocation (LDA) and Topic Modeling: Applications in Health Informatics. Journal of Biomedical Informatics, 93, 103141. DOI: 10.1016/j.jbi.2019.103141

[4] Liu, Bing. Sentiment Analysis and Opinion Mining. Synthesis Lectures on Human Language Technologies, Cham, Springer International Publishing, 2012.

[6] Salton, Gerard, and Christopher Buckley. “Term-Weighting Approaches in Automatic Text Retrieval.” Information Processing & Management, vol. 24, no. 5, Jan. 1988, pp.

513–523, https://doi.org/10.1016/0306-4573(88)90021-0. Accessed 19 July 2019.

[7] Topaz, M., & Pruinelli, L. (2017). Big data and nursing: Implications for the future. Studies in Health Technology and Informatics, 232, 165–175. DOI: 10.3233/978-1-61499-738-2-165

[8] Wang, Yichuan, et al. "Big Data Analytics: Understanding Its Capabilities and Potential Benefits for Healthcare Organizations." Technological Forecasting and Social Change, vol. 126, no. 1, 2018, pp. 3–13, www.sciencedirect.com/science/article/pii/S0040162516000500.

[9] Zeng, Q. T., and T. Tse. "Exploring and Developing Consumer Health Vocabularies." Journal of the American Medical Informatics Association, vol. 13, no. 1, 1 Jan. 2006, pp. 24–29, https://doi.org/10.1197/jamia.m1761.