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Data Science in Action

Traditional and GenAI Text Analysis of COVID-19 Pandemic Trends in Hospital Community Benefits IRS Documentation

Emily Hadley[1,*], Laura Marcial[1], Wes Quattrone[1], and Georgiy Bobashev[1]
[1]*RTI International, Durham, NC, U.S.A*

Abstract

The coronavirus disease 2019 (COVID-19) pandemic presented unique challenges to the U.S. healthcare system, particularly for nonprofit U.S. hospitals that are obligated to provide community benefits in exchange for federal tax exemptions. We sought to examine how hospitals initiated, modified, or disbanded community benefits programming in response to the COVID-19 pandemic. We used the free-response text in Part IV of Internal Revenue Service (IRS) Form 990 Schedule H (F990H) to assess health equity and disparities. We combined traditional key term frequency and Hierarchical Density-Based Spatial Clustering of Applications with Noise (HDBSCAN) clustering approaches with a novel Generative Pre-trained Transformer (GPT) 3.5 summarization approach. Our research reveals shifts in community benefits programming. We observed an increase in COVID-related terms starting in the 2019 tax year, indicating a pivot in community focus and efforts toward pandemic-related activities such as telehealth services and COVID-19 testing and prevention. The clustering analysis identified themes related to COVID-19 and community benefits. Generative Artificial Intelligence (GenAI) summarization with GPT3.5 contextualized these changes, revealing examples of healthcare system adaptations and program cancellations. However, GPT3.5 also encountered some accuracy and validation challenges. This multifaceted text analysis underscores the adaptability of hospitals in maintaining community health support during crises and suggests the potential of advanced AI tools in evaluating large-scale qualitative data for policy and public health research.

Keywords *generative artificial intelligence; hospital administration; natural language processing; text mining*

1 Introduction

The COVID-19 pandemic dramatically reshaped the U.S. healthcare landscape, particularly in 2020 and 2021 when hospitals faced unprecedented challenges in managing the surge of patients, supporting frontline workers, and addressing public health needs. During this period, U.S. nonprofit hospitals were still obligated to engage in community benefit spending in exchange for exemption from federal taxes. Because of lack of attention and delays in data reporting, little information is currently available on whether and how hospitals adapted community benefits programming as a result of the COVID-19 pandemic (Zare et al., 2021).

The IRS applies the community benefit standard as a criterion to assess whether a hospital is actively engaged in the charitable purpose of promoting health (Service, 2023b). Community benefit spending was originally focused on charity care and financial assistance, but the concept

*Corresponding author. Email: ehadley@rti.org.

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was subsequently expanded to include activities that promote the overall health of a community (House, 2023). Nonprofit hospitals are required to conduct a Community Health Needs Assessment (CHNA) every 3 years and adopt an implementation strategy that meets the needs identified in the CHNA to maintain their nonprofit status. Hospitals have conducted a wide range of activities such as substance abuse prevention programs, school-based interventions to reduce childhood obesity, and lead risk assessments (Hadley et al., 2023). During the COVID-19 pandemic, anecdotes suggested that hospitals pivoted community benefits efforts to include providing telehealth services, meals and necessities to patients in their homes, COVID-19 testing, and personal protective equipment (Atkeson and Rosenthal, 2020; Hearle, 2020).

Hospitals submit public proof of community benefit spending compliance annually with IRS Form 990, which includes multiple voluntary free-response (unstructured) text sections in Schedule H. Previous research includes a novel text analysis of F990H data with attention to how hospitals address health equities and disparities with community benefits programming (Hadley et al., 2023). Our current work described in this article revealed the detail available in the free-response text, which can provide substantially more nuance than empirical analysis alone (Young et al., 2013; Rubin et al., 2013). The analysis to assess health equity and disparities observed mentions of COVID-19 in the text data, and the authors determined that a follow-up analysis was appropriate and relevant.

We also considered the current analysis to be an opportunity to explore an innovative GenAI approach. Traditional text analysis methods like key term frequency and clustering are useful for appreciating what terms and language are used in a text data source but may not be sufficient for understanding context or meaning. In this article, we explore the use of search with generative GPT to reveal contextual elements of the impact of COVID-19 on hospital community benefits.

We present a text analysis of IRS documentation related to hospital community benefits and investigate whether hospitals initiated, modified, or discontinued community benefits programming in response to the COVID-19 pandemic. Our research is the first known work to use the F990H free-response text on a national scale in an attempt to understand this challenge. We seek to understand broad patterns and trends rather than analyze specific hospitals. We utilize and compare traditional key term frequency and clustering approaches and a novel generative AI method to provide a variety of perspectives that stakeholders can use to grasp the impact of COVID-19 on hospital community benefits. Interested parties can use the results of this work to better understand how the COVID-19 pandemic shaped community benefits and suggest ideas for future research. Social science researchers can review a comparison of text analysis approaches with real-world text data and consider opportunities. Policymakers and decision-makers can appreciate how novel text analysis approaches can be used for robust interpretation of F990H documentation and to inform policy action or improved community benefits documentation.

2 Methods

Our work described in this article builds off prior research using text analysis for assessing health equity and disparities in F990H text responses (Hadley et al., 2023) by focusing explicitly on the impact of the COVID pandemic. We implemented three separate and different text analysis approaches: key term frequency analysis, clustering analysis, and GenAI analysis. Each approach offers a different perspective on the data. Figure 1 summarizes the methodological workflow. We compare and contrast the findings and limitations of each.

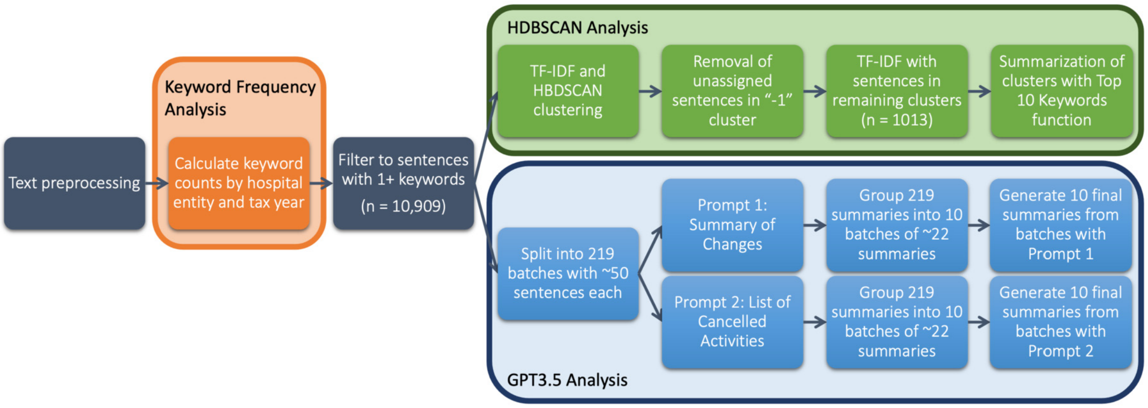

Figure 1: Summary of steps in methodological approaches including key term frequency, clustering, and GenAI analysis.

2.1 Data

The data used in this analysis are free-response text submitted in Part VI of the F990H by hospital reporting entities between 2010 and 2021. Free-response text is required and provided by approximately 99% of U.S. nonprofit hospitals. Hospitals that do not operate as nonprofits such as for-profit and government hospitals do not submit the F990H. A hospital reporting entity is defined as having a unique Employer Identification Number and may be the reporter for multiple hospital facilities. Figure 2 shows the number of hospital reporting entities per year. Data were only available for approximately 50% of hospital reporting entities in 2021 because of delays or tax extension requests. IRS tax data reports also often lags by 1 to 2 years. The overall number of hospital reporting entities decreased from 2010 to 2020, likely reflecting national trends in hospital consolidation and closure (Williams et al., 2020; Saghafian et al., 2022).

The text source is F990H Part VI. This tax section includes questions requiring description of the CHNA, financial assistance policy, and activities related to promotion of community health (Service, 2023a). Text responses are typically full sentences and paragraphs. There are no formatting standards for the text responses, so response structure and length varies. Colloquial terminology and misspellings are infrequent. Across all hospitals and tax years, the corpus contains approximately 2.7 million sentences.

We collected and maintained data through the Community Benefit Insight project (Ortiz et al., 2022). and completed analysis in Python and Jupyter Notebook using pandas, numpy, nltk, sklearn, HDBSCAN, and openai. During the text preprocessing step shown in Figure 1, we converted all text to lowercase and stripped of common punctuation such as parentheses, commas, and dashes.

2.2 Key Term Analysis

As shown in Figure 1, we first completed a key term frequency analysis to assess the occurrence of specific terms or phrases. This approach searches the entire free-response submission for occurrences of an exact term or phrase (Azam and Yao, 2012). Key term analysis is useful for highlighting prominent or recurrent themes or concepts.

We used principles of computational grounded theory, a methodological framework for combining qualitative coding and computational techniques for large datasets, to derive a list of

COVID-related terms, regularly seek expert feedback, and validate our results (Nelson, 2020). We first convened a team of four subject matter experts at RTI International with expertise in COVID and community benefits research. These experts had previously contributed to either client-funded projects or research related to these topics. This team was tasked with selecting terms or phrases to capture trends related to COVID that were likely to appear in community benefits documentation. Over several meetings, these subject matter experts selected six of the final terms: "COVID," "pandemic," "telehealth," "mask," "vaccine," and "personal protective equipment." These were not intended to be representative of all possible COVID-related terms but instead were deemed of likely interest to grassroots community benefits partners.

Initial exploratory analysis confirmed that these terms were present in the data. The initial analysis also resulted in term refinement in alignment with computational grounded theory. We added the term "coronavirus" because some hospitals used that term instead of "COVID". We shortened term "vaccine" to "vaccin" to identify variations in phrasing such as "vaccine" or vaccination". We considered the abbreviation "PPE" along with "personal protective equipment". We specifically added the term "COVID test" to better distinguish COVID testing from COVID efforts broadly. The subject matter experts reviewed and validated these changes.

The nine final terms and phrases were:

- "COVID"
- "coronavirus"
- "pandemic"
- "telehealth"
- "mask"
- "vaccin*"
- "personal protective equipment"
- "PPE"
- "COVID test" (will overlap with "COVID")

We assessed whether each term or phrase was used at least once by a hospital in each year of data collection. We searched all terms in lower case. In the Results section, we examine changes in the usage of these nine phrases or terms, especially around the COVID-19 pandemic.

As shown in Figure 1, the corpus was then filtered to the 10,909 sentences with at least one key term or phrase for the clustering and GPT3.5 analyses. The average number of words per sentence was 67 and the median was 36. Average words per sentence was skewed by sentences that contain lists. The most common term among the nine evaluated was "COVID," which occurred 4,967 times.

2.3 HDBSCAN Analysis

Clustering analysis is a method of computationally grouping units that are similar to each other and can be used to better understand the context in which frequent terms were used. Figure 1 summarizes the steps in the clustering process. We selected the HDBSCAN clustering algorithm because it does not require prespecification of number of clusters, permits clusters of varying shapes and densities, and can support a hierarchical structure (HDBSCAN, 2023). HDBSCAN is also well known and utilized in natural language processing tasks. We performed the following steps in the HBSCAN analysis:

1. Select corpus: The corpus was the 10,909 sentences with at least one term or phrase from the key term frequency analysis in Section 2.2.
2. Prepare text data: We vectorized the corpus with the sklearn implementation of term fre-

quency-inverse document frequency (TF-IDF) vectorization and removal of English stopwords (scikit learn, 2023).

3. Apply clustering algorithm: We used the HDBSCAN clustering algorithm with a minimum cluster size of 20 and a minimum sample of 5 (HDBSCAN, 2023). We also evaluated a second parameter set cluster size 20 and a minimum sample size 5 but this resulted in a larger noise cluster (Cluster -1).
4. Removal of unassigned sentences: The HDBSCAN clustering classified 9,896 sentences in the noise cluster. These were not considered further in the HDBSCAN clustering.
5. Second vectorization: We performed a second round of TF-IDF vectorization on the remaining 1013 sentences assigned to a cluster to facilitate automated keyword selection.
6. Automated cluster keyword selection: We described each cluster with 10 keywords using the automated HDBSCAN "top keyword" function. This is a practical approach for rapidly describing HDBSCAN clusters.

We evaluated the final clusters and compared the top HDBSCAN cluster keywords with the findings from the frequency analysis.

2.4 GenAI Analysis

Research methods with GenAI are still in development. One area where GenAI appears to perform well is summarizing information from longer amounts of text (Alomari et al., 2022). We explore how GPT3.5 can be used to get summary information tailored to a specific prompt as an alternative to more traditional clustering methods. As highlighted in Figure 1, we split the filtered corpus of 10,909 sentences with at least one COVID-related term into 219 batches of approximately 50 sentences. We organized the batches according to their index in the original dataset, ensuring that sentences from the same hospital were typically grouped together. Variations in batch size seemed to have minimal effect on the summaries. Similar to the clustering analysis, we did not aim to make summaries by hospital or year but instead aimed to explore the extent to which GenAI could be used to identify broad patterns and trends.

We asked the GPT3.5 to summarize the sentences in each batch using one of two prompts:

- Prompt 1: "Based on these sentences, make a list of changes during the COVID-19 pandemic"
- Prompt 2: "Based on these sentences, make a list of the sentences that describe an activity that was cancelled, if any"

This resulted in 219 summaries. This still represented a substantial amount of text and far exceeded the number of clusters in Section 2.3, so we performed a second round of GPT3.5 summarization on these summaries to get results more similar to the clustering output. As stated in Figure 1, we performed this second round of GPT3.5 summarization on 10 new batches of approximately 22 original summaries. We batched summaries in order of index.

We then manually assessed the 10 overall summaries for similarities and patterns for each prompt. For Prompt 1, the minimum length of each summary was 95 words and the maximum length was 2256 words. For Prompt 2, the minimum length of each summary was 46 words and the maximum length was 2614 words.

We performed this work with the GPT3.5 API. We selected batch sizes because of context window limits at the time of analysis.

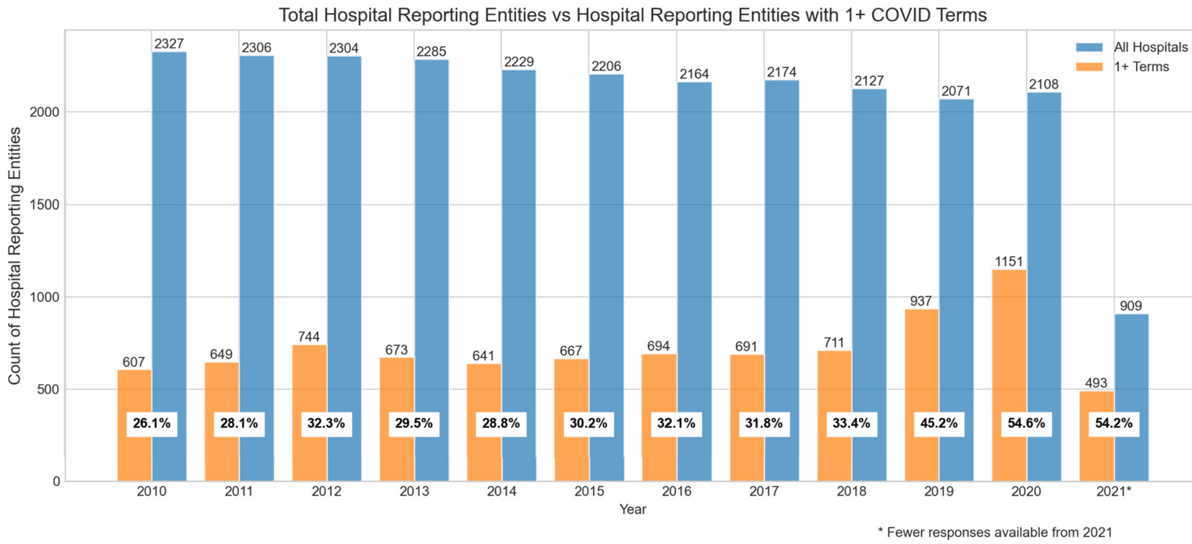

Figure 2: Count of hospital reporting entities with one or more uses of a COVID-related term or phrase by year. Percentages indicate proportion of total hospital reporting entities using one or more COVID-related terms or phrases per year.

3 Results

3.1 Key Term Frequency Results

Figure 2 shows the number of hospitals with one or more uses of a key term or phrase by year compared to the overall number of hospitals submitting F990H documentation. This figure highlights that more hospitals used at least one COVID-related term starting in 2019. Although complete data for 2021 were not yet available at the time of analysis, the high proportion of responding hospitals with one or more COVID-related terms in 2021 suggests that this trend may continue for at least 2021.

Note that 2019 tax documents were submitted in 2020 and although hospitals likely should not have commented on COVID during the 2019 tax year, a number still did likely as a result of tax document submission occurring after the COVID pandemic began. More granular key term frequency analysis results by year are illustrated in 3. These findings highlight that many COVID-related terms increased in usage starting with the 2019 F990H. "Pandemic," "telehealth," "mask," and "vaccin" were all terms that were used prior to the start of the COVID-19 pandemic and greatly increased in usage in 2019 onward. "Personal protective equipment (PPE)," "COVID," and" "coronavirus" were mostly novel terms with usage starting in 2019.

3.2 Clustering Results

The HDBSCAN algorithm categorized 1013 of 10,909 sentences (9.3%) with 1 or more COVID-related terms into seven clusters. In HDBSCAN, all data points are assigned to one cluster or designated as noise. The ordering of cluster number labels has no meaning. Clusters 0, 1, and 2 had fewer than 100 sentences while clusters 3 and 5 had more than 200 sentences. The HDBSCAN results suggested that clusters are mostly distinct and lack substantial hierarchical substructure.

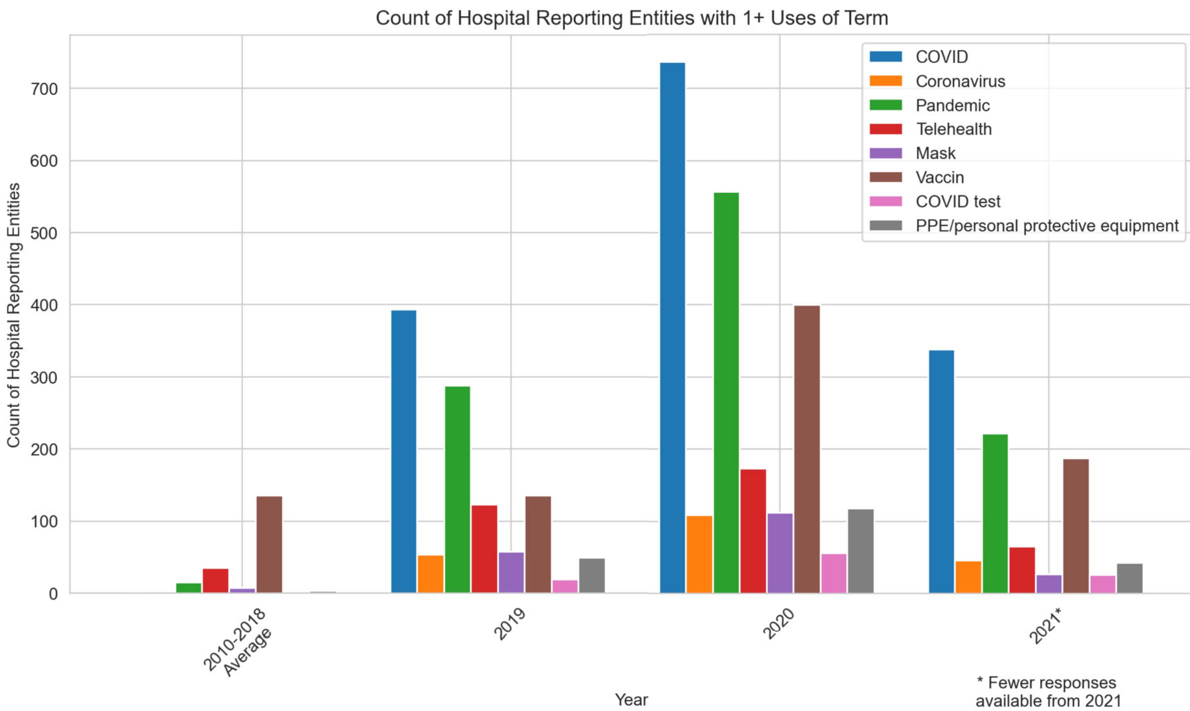

Figure 3: Count of hospital reporting entities with one or more uses of a COVID-related term by term and year.

Table 1 summarizes the top 10 key term for each cluster. These key terms are intended to give a sense of the cluster theme, although some are more tractable than others. Cluster 3, a larger cluster, appears to be related to the pandemic and vaccinations specifically. Cluster 5, the other largest cluster, appears to center on community benefits related to healthcare finances, like charity care and bad debt. Cluster 4 appears to be related to CHNAs while Cluster 6 seems to consider communication items like translators and reading. The smaller clusters (0, 1, 2) were more challenging to interpret.

3.3 Generative AI Analysis Results

The resulting summaries from Prompt 1, "Based on these sentences, make a list of changes during the COVID-19 pandemic," were all in list format and varied in length from 20 items to 225 items. In the longer lists, many items were duplicated or unrelated. We reviewed these lists manually and selected relevant and accurate items. A detailed list is provided in Appendix A. Key findings include the following:

- Changes at hospital and healthcare systems included implementing COVID safety protocols, renting additional beds, establishing fever clinics, and creating negative pressure rooms, and prohibiting visitors.
- Community program changes included new collaborations with community partners for COVID-19 outreach, increased support for food pantries and distribution, holiday toy drives, and drive-through drug takeback events.
- Telehealth and virtual changes included a large increase in virtual and telehealth services, integration of language interpreters with telehealth platforms, increased use of online symptom trackers, and virtual formats for festivals, patient education, and support groups.

Table 1: HDBSCAN results by cluster with top 10 cluster keywords and apparent theme (if any).

Cluster	N Sentences	Top 10 Cluster Keywords	Theme (if any)
−1	9896		
0	61	social, systems, member, largest, country, delivery, catholic, community, health, trinity	
1	67	upper, assistance, financial, ummc, revised, chesapeake, areas, patient, patients, available	
2	66	improvement, director, partnership, st, dept, joseph, health, chip, county, chippewa	
3	229	adults, houston, vaccines, administered, 2020, vaccinations, held, pandemic, 19, covid	COVID Vaccinations
4	120	2019, implementation, strategy, health, assessment, list, needs, community, appendix, chna	Community Health Needs Assessment
5	367	cost, assistance, line, charity, patient, bad, care, debt, expense, financial	Health Finances
6	103	individuals, medical, reading, registration, non, speaking, clerks, translators, read, incapable	Communication

- COVID-19 testing, masks, and vaccination changes included development and implementation of testing and vaccination programs for patients, staff, and the broader community; distribution of in-kind PPE donations, masks, hand sanitizer, and soap; and car-side immunization and testing services.
- Efforts to address health disparities included establishment of a health equity advisory council, collaboration with community organizations, and introduction of mobile vaccination programs for high-risk and vulnerable residents.
- Changes to mental health resources included expansion of mental health services, hosting of virtual mental health seminars, and collaboration with local organizations.
- Financial aid changes included expansion of charity care programs, promotion of financial assistance resources, and changes to collection tactics.
- Research changes included new research on Long COVID, treatments for COVID-19, and the impact of COVID-19 on hospitals.
- Changes related to hospital finances included changes in medical advancements for emergency medical technicians and ambulances; increased costs for supplies, cleaning, and waste disposal; and support for financial assistance from the Coronavirus Aid, Relief, and Economic Security Act but also a note that government reimbursements were insufficient to cover costs, which were then reported as a community benefit.

The results of the second prompt, “Based on these sentences, make a list of the sentences the describe an activity that was cancelled, if any,” highlight varying batch quality and validation challenges. Some of the batches listed verbatim sentences while others were generated sentences. Three of the 10 summary batch responses included more than 60 sentences in the response and a number of these sentences were not related to the prompt. This questionable accuracy suggests that these results are not an accurate summary of all sentences related to cancellations. But GPT3.5 did pick up on sentences that did not explicitly use the word "cancel" and still referred to some degree of cancellation, such as "Due to COVID-19, in-person programming was suspended in March 2020," and "The diabetes support group did not meet in 2021 due to COVID-19".

We focused on using these results to understand general trends in cancellations. While manually reviewing the output, we found that most extracted sentences belonged to five main categories:

- Job-Related Activities: Sentences that discussed job training, education, or similar that was cancelled or postponed.
- Specific Events: A specific one-time or potentially annual event that was cancelled or postponed.
- Recurring Programs: A recurring program offered by the hospital that was cancelled or postponed.
- Facilities: A cancellation or change in hospital facility offerings.
- Health Services: Health-related procedures and referrals.

These categories provide a broad overview of cancellation patterns; more detailed examples are listed in Table 2. These items reveal the breadth of and variety in cancellations and postponements as a result of the COVID-19 pandemic.

4 Discussion

All three text analysis approaches – key term frequency, clustering, and GenAI with GPT3.5 - demonstrated changes in hospital community benefits during the COVID-19 pandemic. However, each approach provides a different perspective and insights.

The key term frequency analysis is particularly useful for appreciating change across time. Figure 2 shows that more hospitals started using terms related to the COVID pandemic in F990H documentation in 2019. Figure 3 shows that use of pandemic-related terms prior to 2019 was mostly for "vaccin". Further assessment revealed that this term is frequently used in the context of community benefits programming related to flu vaccination. Starting in 2019, "COVID" was frequently used and "pandemic," "telehealth," and "vaccin" all surged in use. Prior to 2019, "pandemic" was used to describe other health events and "telehealth" was used to describe hospital efforts to incorporate telehealth into their practices. The terms "coronavirus," "personal protective equipment," and "mask" were used frequently starting in 2019.

Key term frequency analysis can be used for comparison. For example, "COVID" is used much more often than "coronavirus," potentially reflecting the accessibility and familiarity of the shortened term even in tax documentation where more formal language is often used. Overall, the results from the key term frequency analysis suggest that hospitals increasingly incorporated vaccination, PPE, and telehealth into community benefits programming as a result of the COVID-19 pandemic.

However, a major limitation of key term frequency analysis is not being able to discern the context for use. In Figure 3, "COVID test" is a small fraction of the use of "COVID," suggesting that "COVID" is more often used in other contexts in community benefits tax documentation. Although key term frequency analysis allows us to discern that there was some change in language usage in community benefits IRS documentation because of the COVID pandemic, it does not permit substantial understanding of the context of these changes in practice.

Table 2: Summary of items listed in the output for Prompt 2, "Based on these sentences, make a list of the sentences that describe an activity that was cancelled, if any".

Cancelled Activities Prompt	
Job-Related Activities	Job shadow programs Medical resident programs Hospital tours Student internships and mentoring Healthcare scholarships
Specific Events	Marathons and runs Health fairs and health literacy events Fundraisers Mission trips Summer camps Holiday events
Recurring Programs	Community walking and chair yoga programs Drug takeback events Community gardening programs CPR and first aid classes Support groups for many topics, including grief, diabetes, and cancer School-based programming such as kids safety Mental health training for law enforcement Childbirth and mother and baby classes Smoking cessation programs Healthy cooking classes
Facilities	Free meeting room space for nonprofits cancelled. Warming center closed Access to the fitness center was limited
Health services	Community-based clinical services that do not generate a bill (ex. biometrics screenings, colorectal cancer screenings, mammograms) Elective procedures Referals to SMILES network of volunteer dentists

Clustering with HDBSCAN is a traditional text analysis method that is useful for understanding similar groupings of sentences that emerge from the data. One cluster highlights terms that appear to be related to the pandemic and COVID vaccination in adults. This was also one of the larger clusters among the sentences that were able to be clustered, suggesting that it occurs more frequently. Other clusters appeared to highlight topics known to be important to community benefits programming, namely CHNAs and financial assistance. However, HDBSCAN was unable to categorize most sentences (90.7%). This suggests that it is challenging to separate the sentences in this text into distinct and hierarchical clusters. HDBSCAN performs best with clear clusters and is known to assign a large proportion of data points to the noise category (Cluster -1) when the data lacks sufficient structure or has overlapping themes. Although this unsupervised approach to clustering is useful for illuminating topics not previously identified through key term frequency analysis, it is still limited for understanding contextual usage and specific details.

Summarizing with GPT3.5 was useful for uncovering an underlying shift in community benefits spending resulting from the COVID-19 pandemic. Hospitals described modifications to hospital facilities such as retrofitting rooms and implementing sanitation measures. They also described substantial vaccination and testing efforts for patients, staff, and the community. Hospitals also distributed PPE, collaborated with community organizations, led information campaigns, and shifted numerous activities onto virtual and telehealth platforms. Hospitals expanded financial assistance programs, showed increased attention to mental health and behavioral support, and directly contributed to food pantry and distribution activities. Although these efforts have been well documented, we have not found evidence that they have previously been linked to community benefits. We share these as a novel finding of the underlying shift in the use of community benefits funds during the COVID-19 pandemic to be more focused on pandemic needs.

In contrast to the increase in COVID-19-related community benefits programming, the second GPT3.5 prompt uncovered many examples of pre-pandemic community benefits programs that were cancelled or postponed during the COVID-19 pandemic. These included health and education activities, annual events, and public safety programs. The cancellation of mission trips, support groups for illness or mental health, and school-based programming may have disproportionately impacted vulnerable populations that relied on these services. The loss of job-related programming may have substantially impacted the training and careers for individuals interested in healthcare. The loss of events like fun runs, summer camps, and fundraisers may have affected community engagement. We do not know whether these programs have been restored.

The GenAI summaries suggest that during the COVID-19 pandemic, many hospitals substantially changed the focus of community benefits programming from locally driven community engagement to pandemic-related needs. This is likely appropriate given the circumstances, but it also may have had substantial unknown adverse effects. Future research could explore the impact of the loss of these programs.

Although the GenAI summaries provided helpful insights, they were also inconsistent in length and format and were not useful for quantifying the number of hospitals involved in COVID-related changes. Validation concerns also remain as we observed examples of relevant sentences being missed and irrelevant items being included. We consider this an experimental effort for highlighting examples of changes and cancellations related to community benefits during the COVID-19 pandemic but do not recommend broad generalizations. Future work may investigate approaches to address GenAI validation concerns.

A limitation of the work described in this article is that there is no standard level of detail, formatting, or structure for F990H community benefits documentation. Some hospitals voluntarily include more detail than others, which may have impacted this analysis in terms of both underreporting and overreporting. The absence of COVID-related terms from a F990H response does not mean a hospital ignored COVID in community benefits programming. We do not encourage generalizations from these findings about the number of hospitals that did or did not address COVID with community benefits programming. Pandemic-era tax data will continue to be collected for 2021, 2022, and onward, and we recommend an updated analysis to validate these findings.

5 Conclusions

All three text analysis approaches used in this article suggest that community benefits programming was modified during the COVID-19 pandemic. The key term analysis aligned with a growing awareness of the pandemic starting with F990H documentation submitted in 2019. Clustering analysis identified limited themes connected to COVID and community benefit spending. The GenAI summaries provided specific examples of changes in community benefits programming, namely increased attention to pandemic needs and cancellations of preexisting community engagement programs. This cohesive analysis considering all three approaches highlights how hospitals initiated, adapted, and cancelled community benefits initiatives because of the COVID-19 pandemic. Future work continuing to investigate the long-term impact of COVID on community benefits programming and extend the GenAI approach evaluated in this work is needed.

Supplementary Material

The zipped supplementary material file includes code and output for this analysis.

A Appendix 1

Table 3: Selected sample of output for Prompt 1, “Based on these sentences, make a list of changes during the COVID-19 pandemic”.

Prompt 1: List of Changes During the COVID-19 Pandemic	
Hospital and healthcare system measures	Development of clinical and operational guidance for COVID-19 prevention. Treatment of admitted patients with COVID-19 using authorized treatments such as convalescent plasma treatment. Surge in COVID-19 patients during certain quarters. Changes in hospital operations and staffing to accommodate COVID-19 patients. Changes in visitor policies and restrictions in healthcare facilities. Social distancing measures in physical activities and events. Retrofitting hospital rooms to become negative pressure rooms. Renting additional hospital beds. Establishment of emergency operations center Establishment of fever clinics for COVID-19 screening. Requirement for all students to be vaccinated for COVID for job shadowing in early 2022.
Community Programs	Collaboration with community partners and coalitions for COVID-19 response. Community health improvement initiatives and programs to address COVID-19 impacts.

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Table 3 – Continued from previous page

Prompt 1: List of Changes During the COVID-19 Pandemic	
	Increased community health education and outreach about COVID-10. Collaboration with local health systems and governments to ensure sufficient resources for the pandemic. Increase in charitable organizations shipping food supplies overseas. Food pantry assistance and expansion of food distribution due to increased demand during COVID-19. Coordination of food delivery services to homebound individuals. Promotion of health information related to COVID-19 in local newspapers. Extension of memberships and offering free memberships to encourage active lifestyle during closure. Challenges in collecting survey responses and engaging with the community due to the pandemic. Holiday toy distribution and community support efforts during the pandemic. Implementation of COVID-19 hotline. Implementation of drive-through drug take back events
Telehealth and Virtual	Interpretation services conducted in person, over the phone, and via video during the pandemic. Integration of interpreters into telehealth platforms for language services. Increase in virtual and telehealth services. Shift to digital lessons and remote learning during the pandemic. Festivals launched virtually with social media campaigns and educational videos. Transition to virtual/telehealth formats for patient education and support groups. Increased use of online symptom trackers.
COVID-19 Testing, Masks, and Vaccination	Development of COVID-19 testing and vaccination programs for staff and patients. Distribution of COVID-19 vaccines at community vaccination events. Hosting of free pediatric COVID-19 vaccine clinics. Offering free cloth masks to the community during the pandemic. In-kind donations of PPE for surrounding communities during the pandemic. Volunteer efforts to sew and distribute masks in the community. Distribution of masks, hand sanitizers, and soap to support hygiene practices. Provision of plastic face shields for staff.

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Table 3 – Continued from previous page

Prompt 1: List of Changes During the COVID-19 Pandemic	
	Conducting COVID-19 testing and vaccination clinics. Implementation of variant polymerase chain reaction testing for COVID-19. Shift to car-side immunization services. Increased testing for COVID-19 among employees.
Address Disparities	Establishment of COVID-19 health equity advisory council. Collaboration with community organizations to address social determinants of health exacerbated by COVID-19. Implementation of vaccine equity strategies and development of community hubs. Focus on communities particularly impacted by COVID-19, including communities of color, immigrants, individuals with disabilities, lesbian, gay, bisexual, and transgender individuals, older adults, and people experiencing homelessness. Launch of mobile vaccination programs to reach high-risk and vulnerable residents. Efforts to provide testing and vaccinations to vulnerable populations during the pandemic. Support for seniors and at-risk populations.
Mental Health	Increased focus on mental/behavioral health support and awareness. Collaboration with local organizations to address rising rates of suicide and mental health issues. Hosting virtual mental health seminars to address quarantine stressors. Expansion of mental health services and support.
Financial Aid	Financial assistance and charity care programs expanded. Promotion of educational resources and assistance for patients without insurance. Changes in collection tactics for outstanding balances in medical facilities. Implementation of sliding fee schedules for financial assistance patients. Uncollectible accounts were written off as bad debt expenses in audited financial statements. Financial assistance for homeless patients.
Research	Research on long-term sequelae of COVID-19. Research efforts at medical centers focused on various disciplines, including COVID-19. Conducting clinical trials for COVID-19 treatments

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Prompt 1: List of Changes During the COVID-19 Pandemic	
	Research on the impact of COVID-19 on hospital operations and patient care.
Hospital Finances	Suspension of traditional annual budget processes in favor of quarterly planning.
	Financial assistance provided to healthcare providers under the CARES Act.
	Increased funding for healthcare providers to cover expenses and lost revenues attributable to coronavirus.
	Changes in medical advancements for ambulance EMTs, paramedics, fire and rescue teams.
	Increasing medical waste disposal services and cleaning/disinfection costs.
	Increased staffing shortages and inflated costs of temporary labor and supplies.
	Government reimbursements were insufficient to cover costs, considered a community benefit.

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