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Original Research

Artificial Intelligence and Stigma in Addiction Research: Insights From the HEALing Communities Study Coalition Meetings

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Abstract

Objectives:

This paper describes how artificial intelligence (AI) was used to analyze meeting minutes from community coalitions participating in the HEALing Communities Study. We examined how often coalitions discussed stigma when selecting evidence-based practices (EBPs), variations in stigma-related discussions across coalitions, how these discussions addressed race, ethnicity, and racial inequity, and whether the frequency of stigma discussions was associated with the proportion of minoritized populations in each community.

Methods:

We used Natural Language Processing, Machine Learning, and Large Language Models, employing ChatGPT Enterprise to code data, ensuring data security and privacy compliance with the General Data Protection Regulation and HIPAA.

Results:

Community coalitions varied in the extent to which they discussed stigma during meetings focused on EBPs to reduce overdose deaths. Stigma was mentioned more frequently in the context of medication for opioid use disorder compared with other EBPs. As the percentage of racial/ethnic minority populations increased in a county, so did the strength of the association between discussions of EBPs and stigma. Counties with a greater proportion of racial/ethnic minority populations were more likely to integrate discussions of EBPs with stigma-related issues. Specifically, discussions about stigma were ~57% more likely to occur when racial or ethnic disparities were mentioned, compared with when they were not (odds ratio=1.57; 95% CI: 1.22, 2.03).

Conclusions:

The paper highlights the potential for integrating AI-human collaboration into community-engaged research, particularly in leveraging qualitative data such as meeting minutes. It shows how AI can be used in real-time to enhance community-based research.

Stigma is a complex social process characterized by labeling, stereotyping, discrimination, and exclusion based on a perceived attribute, such as having an opioid use disorder (OUD) or using medications for opioid use disorder (MOUD).[1,2] Stigma results in negative behaviors from health care providers and in community narratives surrounding treatment,[3,4] and as a result significantly affects access to evidence-based practices (EBPs).[2,5–7]

Stigma-reduction campaigns, such as those implemented for HIV prevention and smoking cessation, have shown promise in reducing stigma and improving access and linkage to EBPs in these areas.[8–10] However, examples of stigma-reduction campaigns for substance use disorders and overdose prevention are limited.[2,5–7,11,12] The HEALing Communities Study (HCS) was a multisite, community-level, cluster-randomized controlled trial designed to evaluate the effectiveness of the Communities That HEAL (CTH) intervention in reducing opioid-related overdose deaths in highly affected communities.[13] A total of 67 communities in Kentucky, Massachusetts, New York, and Ohio were randomly assigned to either wave 1 implementation (34 communities) or wave 2 implementation (33 communities), with stratification by state. The study was approved by Advarra, an independent research review organization, which served as the single institutional review board.

The CTH used community coalitions to help select and implement EBPs such as overdose education and naloxone distribution (OEND), MOUD, and safer opioid prescribing. In addition, coalitions worked with community-based organizations and agencies to implement stigma-reduction communication campaigns.[14,15] Communication campaigns were selected and tailored by coalition members to reduce stigma toward people who use drugs, people receiving MOUD, and their families.[6] Although each county's coalition set its own agenda and varied in campaign design and intensity, all received support through the CTH intervention.[6]

The HCS coalitions comprised community partners from public health, social services, criminal justice, health care, addiction services, and people with lived experience with OUD. In New York State, 16 communities deployed a total of 213 EBPs and locally tailored communications campaigns.[6] To document coalition actions, meeting minutes were collected in 13 of the 16 counties, with each meeting lasting between 2 and 4 hours. Activities included creating shared charters, learning about EBPs, reviewing local data, and developing community action plans.[16] The process involved analyzing epidemiological data, scoring EBP strategies for effectiveness, and identifying implementation partners. The minutes, gathered either in written form or as audio recordings, offer valuable insights into coalition deliberations, including challenges faced, strategies selected, and successes and progress made over time.[16]

During HCS implementation, artificial intelligence (AI) tools were not readily available; however, after the HCS was completed, we used AI analytical methods including Natural Language Processing (NLP), Machine Learning (ML), and Large Language Models (LLM) to examine the following research questions: (1) How often did the coalitions discuss stigma when selecting EBPs? (2) Were there differences in how often stigma was discussed across the coalitions? (3) Was the discussion of stigma framed within the context of race, ethnicity, and racial inequity? (4) Was the frequency of stigma discussions associated with the percentage of minoritized populations in each of the communities?

METHODS

Data: HCS Coalition Meetings

During coalition meetings, researchers informed members that recordings and minutes would be used for research in compliance with approved IRB protocols. Meeting minutes were collected from both wave 1 (2020–2023) and wave 2 (2023–2024) communities during their active intervention phase. Of the 250 coalition meetings that occurred during this time, 127 were audio-recorded and transcribed for analysis. Three counties used written summaries instead of recordings, and some meetings in the remaining counties were unrecorded due to technical difficulties or scheduling conflicts. In some cases, coalitions chose to delete audio recordings after meeting summaries were created. Since recording coalition meetings was optional, the NLP analysis includes all 127 available transcripts suitable for systematic analysis.

Confidentiality and Data Security

We used Columbia University's ChatGPT Enterprise to code data, ensuring data security and privacy compliance with the General Data Protection Regulation (GDPR) and HIPAA. Data were housed on secure Columbia University IT servers for efficient processing; topic segmentation was employed to manage summaries within LLM token limits (Supplemental Materials S1, S2, Supplemental Digital Content 1, https://links.lww.com/JAM/A665). From the 127 minutes, we extracted a total of 67,969 sentences for analysis.

Our Human AI Collaboration (HAIC) workflow included 6 steps. In Figure 1, we show a side-by-side comparison of the human-only versus human-AI collaboration for the steps in the workflow.

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FIGURE 1:
Diagram comparison of the workflow for the Human versus AI/ML approach. Red represents the human approach, blue represents the AI approach, and purple represents the AI with human-in-the-loop approach.

Step 1—Data Collection

Raw data was standardized into text transcripts. Video recordings of Zoom meetings were converted to audio files and then transcribed to text using the Insanely Fast Whisper (IFW) model,[17] a local, fast version of OpenAI's Whisper[18] with 95%–98.5% accuracy.[19] Due to varying audio quality, we reviewed the transcriptions using ChatGPT to identify and correct repeated sentences or nonsensical fragments.

Step 2—Data Processing

We selected sentences as the unit of analysis. Text was automatically segmented into sentences, SpaCy's pretrained Named Entity Recognition (NER) pipeline was used to deidentify personal names and organizations,[20] and nonletter characters were removed to ensure clean, consistent input for topic modeling. Cleaned sentences were stored in a data frame, along with metadata such as county, date, filename, wave (ie, wave 1 or wave 2 counties per the study design), word count, and sentence length. Researchers reviewed the output and verified the completeness of the data set and deidentification.

Step 3—Topic Modeling Using BERTopic

We selected BERTopic[21] for its ability to leverage contextual word embeddings, which provides more coherent and semantically meaningful topics, particularly in data sets with nuanced language. BERTopic modeling has the advantage over traditional techniques such as LDA (Latent Dirichlet Allocation)[22] of identifying and excluding outlier sentences that do not fit into any specific topic. The BERTopic modeling pipeline was used to identify and assign topic distributions and representations to each sentence. This process involved 4 steps: (1) document embedding, (2) dimensionality reduction,[23] (3) clustering,[24] and (4) topic Representation (Supplemental material Figure S3, Supplemental Digital Content 1, https://links.lww.com/JAM/A665). The output initially identified 859 potential topics, represented as sets of keywords, each with associated probabilities (Supplemental Material Figure S4.1, Supplemental Digital Content 1, https://links.lww.com/JAM/A665).

Step 4—RRR (Reduce, Represent, and Refine) Topic Fine-Tuning Using a Human-in-the-Loop Approach

We considered both LDA and BERTopic for topic modeling. Working with 859 topics was not practical, especially when some topics, like topic 148 (keywords: sign, log, login, password) were irrelevant to the study's focus (Supplemental Material Figure S4.1, Supplemental Digital Content 1, https://links.lww.com/JAM/A665). In this step, the BERTopic pipeline was fine-tuned with human inputs to reduce and cluster topics into broader groups. This involved merging related topics to create meaningful clusters based on researchers' feedback. We used seed words in the BERTopic model to focus on concepts central to the study. In BERTopic's class-based TF-IDF matrix, seed terms receive higher weights, making related documents more likely to cluster and appear in final topics. This helps the model to surface themes aligned with implementation science priorities rather than just frequent terms. For stigma-related discussions, seed words included "stigma" and other domain-specific terms such as "at-risk," "populations," "race," "MOUD," "medication," "methadone," "harm reduction," "EBP," "equity," and others. This ensured that critical themes—like stigma and treatment access—remained central, rather than being drowned out by more frequent but less relevant vocabulary.

Seed words selected based on a codebook designed by HCS researchers for qualitative interview analysis were used to initialize the topic modeling with more weights on important keywords. This process reduced the number of topics to 71, leading to a more manageable exploration that was aligned with the study's objectives (Supplemental Material Figure S4.2, Supplemental Digital Content 1, https://links.lww.com/JAM/A665). Two HCS investigators further reduced topics by selecting only those relevant to the study and reassigning irrelevant topics as outliers (topic 1), reducing the total to 36 topics. Topic keywords were used to generate descriptive sentences with ChatGPT. Two HCS investigators reviewed the outputs to ensure relevance. Broad topics, such as "demographic distribution by age, gender, race, and ethnicity," were refined into subtopics using the BERTopic pipeline, keeping relevant content and marking others as outliers. The final 36 topics, excluding outliers, were used for analysis (Supplemental material Table S5, Supplemental Digital Content 1, https://links.lww.com/JAM/A665).

Step 5—Analysis of Topics to Examine the Research Questions to Test

Each sentence's metadata (eg, study wave, county name, document date, word count) was combined with outputs from topic modeling to generate a data frame with relevant information for each sentence. Topics were then manually categorized into different EBP types (ie, OEND, MOUD, safer prescribing, and non-EBP) by an expert with content knowledge. We categorized sentences related to stigma and race by defining a context window of ±5 sentences around it and then used the ChatGPT application programming interface (API) to determine whether or not each sentence was related (yes/no).

We used χ^2 tests to evaluate the association between EBP topics and sentences related to stigma across various subgroups (eg, year, wave, county). For the county-level analysis, the association between a sentence's stigma relevance and its EBP relevance (discussion of EBP vs. non-EBP) was first evaluated within each county to generate *P* values. Odds ratios were calculated based on 2×2 contingency tables to measure effect size. Within the subset of sentences identified as EBP-relevant, we evaluated the association between discussion of stigma and racial/ethnic disparities and EBP types within each county. In this second analysis, *P* values were derived from 3×2 contingency tables based on EBP type versus stigma-related (Supplemental Material S10.1, Supplemental Digital Content 1, https://links.lww.com/JAM/A665), accompanied by Cramér's V values to measure effect size. For both approaches, while performing a χ^2 test of independence, we used Monte Carlo simulations to evaluate the significance of the observed association. We generated 10,000 simulated data sets that reflected the expected distribution of the data under the null hypothesis and compared the observed test statistic to the distribution of test statistics from these simulations.

We evaluated whether the percentage of the racial/ethnic minority population within a county was associated with the degree to which discussions of EBP implementations and stigma co-occurred. The Percentage of Minorities (PoM) for each county was computed using demographic data from the US Census Bureau. A Pearson correlation was calculated between the odds ratios and the PoM in each county. To determine the association between stigma and racial/ethnic disparities, we used a χ^2 test of independence with Yates' continuity correction to adjust for potentially small sample sizes in our contingency table (Supplemental Material S10.2, Supplemental Digital Content 1, https://links.lww.com/JAM/A665).

A variable called "Discussion Counts" was used to quantify the number of topics discussed between stigma and race in each sentence (0=none of the topics were discussed; 1=at least one topic was discussed; 2=both topics were discussed). We used a Kruskal-Wallis test to compare the distribution of topic discussions between counties (Supplemental Material S10.3, Supplemental Digital Content 1, https://links.lww.com/JAM/A665). We used the Dunn test of nonparametric pairwise multiple comparisons of independent groups to test pairwise comparisons of counties (Supplemental Material S6, Supplemental Digital Content 1, https://links.lww.com/JAM/A665).

Step 6—Summarize the Context of Stigma Across Counties

Given a county and a topic of interest, all relevant context sentences were extracted and summarized through the ChatGPT API. The summarizations allowed comparison of different patterns, trends, and outliers in community discussions.

A list of sentences was created for each county where at least one of the selected topics (stigma and race/ethnicity disparities) was mentioned in the context window of the sentence. We used the following prompt: "I will provide two Python lists containing sentences related to addressing stigma and race, ethnicity, and disparities. The first list {first county list}, and the second list is {second county list}. Analyze the two lists and provide a detailed summary highlighting the similarities and differences between the two counties. Focus on key themes, recurring language, and unique aspects of how each county approaches these topics." This approach provided insights for each county (Supplemental Material S-11, Supplemental Digital Content 1, https://links.lww.com/JAM/A665).

For stigma alone, EBPs alone, and their points of intersection, we also extracted the relevant sentence sets and asked the LLM to generate concise summaries. Examples of these sentences, together with the resulting topic-model outputs and LLM summaries, are provided in Supplemental Materials S-7, S-8, and S-9, Supplemental Digital Content 1, https://links.lww.com/JAM/A665.

RESULTS

Frequency of Discussions of Stigma in Relation to EBP's

We identified stigma-related sentences both directly (topic 36) and contextually (±5-sentence window), counting each sentence only once to prevent overestimation. To account for differences in meeting volume, we calculated county-level proportions, normalizing by total sentence count within each county. Figure 2 shows the percentage of contextually stigma-related sentences by county, capturing broader conversations rather than isolated mentions. Counties A, H, and K had the highest percentage of contextually stigma-related sentences; counties G, J, L, and M had about half as many discussions on the topic.

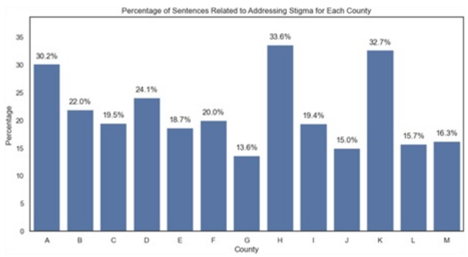

FIGURE 2:
Percentage of sentences related to the discussions of stigma for each county.

Figure 3 shows the percentage of stigma-related sentences within each EBP type by county, as well as the corresponding *P* value and Cramér V measures. County H had a higher percentage of discussions that involved stigma for sentences related to MOUD, compared with OEND and safer prescribing. County K had the highest percentage of discussions of stigma in sentences about safer prescribing. County C had a relatively low percentage of stigma discussions related to MOUD, while County G had a lower overall percentage across all 3 EBPs. County E showed a significant association between EBP type and stigma-related sentences, as indicated by *P* value (P=0.001) and a relatively strong Cramér V (V=0.23). This combination of statistical significance and effect size suggests a notable relationship in County E, where the proportion of stigma-related sentences varied meaningfully across the 3 types of EBP. Such a result may reflect differences in how stigma is addressed or perceived within specific EBPs (MOUD, OEND, and safer prescribing) in this coalition. Finally, County G showed both a nonsignificant *P* value (P=0.54) and a small Cramér V (V=0.07) between EBP type and stigma-related sentences. In County G, the proportions of stigma-related sentences remained low across all 3 EBP types.

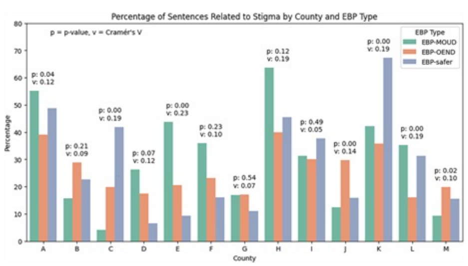

FIGURE 3:
Proportions of stigma-related sentences among EBP types, by county. *P* values and Cramér V values from the χ^2 tests of independence between EBP types and stigma-related sentences are annotated above the bars for each county.

Summary of Themes

As described in the supplemental materials, Supplemental Digital Content 1, https://links.lww.com/JAM/A665, the coalition discussions focused on the types of stigma faced by people who use substances and identified strategies to reduce stigma. Stigma was highlighted as a significant barrier to accessing and maintaining MOUD, especially for people from racial/ethnic minority groups. Common misconceptions included the belief that MOUD is replacing one drug for another and/or that true recovery is not possible while using MOUD. One county discussed how stigma in pharmacies impacted the distribution of medication and proper disposal practices.

Coalitions proposed several strategies to reduce stigma. These strategies included community-specific marketing campaigns focused on MOUD, sharing personal stories to humanize and normalize MOUD, and reducing stigma within health care settings and among first responders. It was stressed that these campaigns should involve community partners and people with lived experience to better address overdose risks (Supplemental Material S7, S8, Supplemental Digital Content 1, https://links.lww.com/JAM/A665).

Associations Between the Size of Racially Minoritized Communities and Discussion of Stigma and EBPs

A number of counties (A, B, D, H, I, J, K, and L) showed a significant association between EBPs and stigma (Table 1). Counties like J demonstrated a relatively strong relationship, indicating that EBP interventions in these counties were more than twice as likely to be associated with stigma compared with non-EBPs. This highlights the critical role of stigma in discussions of EBPs for many coalitions. Further investigation examined whether the PoM within a community influenced these associations, focusing on counties with both significant *P* values and higher odds ratios.

TABLE 1 - *P* Values and Odds Ratios for the Association between Sentences Related to Stigma and EBP-non-EBP Interventions, Analyzed Across Counties

County	*P*	Odds Ratio	Percentage of Minorities
A	0.00	1.84	13.70
B	0.01	1.35	7.62
C	0.51	1.09	10.82
D	0.00	0.65	5.36
E	0.44	1.13	6.10
F	0.12	1.25	12.41
G	0.27	1.21	2.96
H	0.01	1.66	29.53
I	0.00	2.02	33.16
J	0.00	2.21	19.74
K	0.00	1.41	33.62
L	0.00	1.59	25.02
M	0.40	1.09	17.58

Figure 4 shows a positive linear relationship between the PoM within a county and the odds ratios (Table 1). As the percentage of racial/ethnic minority populations increased, so did the strength of the association between discussions of EBPs and stigma (Supplemental Material S-5, Supplemental Digital Content 1, https://links.lww.com/JAM/A665).

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FIGURE 4:
Scatter plot showing the relationship between the percentage of the racial/ethnic minority population and the odds ratio for the association between sentences related to stigma and EBP versus non-EBP interventions, analyzed across counties.

Topics of Stigma, Race/Ethnicity, and Disparities Discussed by Coalitions

We found a significant association between the number of sentences related to stigma and sentences on race/ethnicity (P=0.001). Specifically, discussions about stigma were ~57% more likely to occur when racial or ethnic disparities were mentioned, compared with when they were not (odds ratio=1.57; 95% CI: 1.22, 2.03). While discussions about stigma and race/ethnicity were statistically associated, the strength of this association was modest (Table 1).

Discussion of Stigma and Race, Ethnicity, and Inequities Across Counties

We used a Kruskal-Wallis test to examine whether the distribution of discussion counts varied across counties. The test yielded a highly significant P value (P=0.001), indicating notable differences in the distribution of discussions on stigma, race/ethnicity, and inequities across counties. However, the calculated effect size (η=0.03) suggests a modest impact.

DISCUSSION

We found variability across communities in the frequency of discussions about stigma when selecting and deploying EBPs, as well as in the planning of stigma communication campaigns. Stigma was most often discussed in the context of MOUD use and delivery, compared with OEND or safer prescribing practices. This may stem from longstanding misperceptions about how the medications work, for instance, the misperception that MOUD is simply substituting one drug for another.[25] This pattern underscores the broader cultural challenges surrounding MOUD acceptance and highlights the need for targeted efforts to improve MOUD access, uptake, and effectiveness.[26] One county demonstrated a notably higher frequency of stigma discussions related to safer prescribing practices. Research shows that stigma disproportionately affects pain management, with health care providers often treating people with substance use disorders differently, even when they have the same medical conditions.[27] Health care providers may exhibit biased attitudes toward individuals with substance use histories, leading to underestimation of pain and reluctance to prescribe opioid medications.[28,29]

Although discussion of stigma was more likely to occur in counties with larger minoritized populations, stigma presents a barrier in all communities. In step 6 of our methods, we used an LLM to summarize how counties with statistically significant differences discussed stigma, race/ethnicity, and disparities in coalition meetings. For instance, County A often linked stigma to barriers in accessing MOUD within health care settings, particularly when addressing issues related to race, ethnicity, and systemic discrimination. In contrast, County H focused on stigma reduction through community-based campaigns. This variation highlights the role of local context in the framing of stigma. After generating LLM-based summaries for counties with statistically significant differences, we conducted a comparative thematic synthesis. A qualitative matrix was used to compare how each county framed stigma-related discussions, highlighting recurring patterns or unique local emphases. This approach enabled a narrative cross-case analysis that drew attention to contextual nuances across counties. The findings highlight the need to prioritize stigma reduction efforts in all communities, including those with smaller minoritized populations. Addressing this pervasive issue is essential to ensuring equitable and effective implementation of EBPs.

This paper is the first to use AI-assisted methods such as NLP, ML, and LLM to analyze coalition meeting minutes in community-engaged research. We examined how stigma was discussed in the context of deploying EBPs such as MOUD, OEND, safer prescribing, and stigma-reducing communication campaigns. A unique feature of this paper is its use of AI to analyze coalition meeting minutes—a resource often underutilized due to the amount of time required for manual coding. By embedding AI in the early stages of implementation, community-engaged researchers can expedite the data analyses, integrate diverse data streams, and deliver actionable findings to the community in real time. Future initiatives can use AI tools during study implementation, moving beyond the postimplementation analysis described in this paper.

Limitations

The data set was comprised of the minutes of 127 meetings representing data from 13 New York communities participating in the HCS. Three counties were excluded due to missing meeting minutes; while they did not differ systematically by race/ethnicity, their exclusion could still bias findings. Missing data may reflect either avoidance of sensitive topics or greater openness, introducing potential bias in interpreting patterns by race and stigma. The study also faced some limitations in analyzing stigma-related discussions during EBP selection. For instance, counties with larger racial and ethnic minority populations were more likely to engage in stigma discussions, suggesting diversity may shape implementation priorities, though this influence was not directly examined. Unequal numbers of coalition meeting recordings across counties may have led to under-representation or over-representation of stigma discussions, affecting comparability. We did not conduct a longitudinal trend analysis of stigma discussions over time or in relation to campaign rollout, but this is an important future direction for understanding whether discussions increased as stigma-reduction efforts advanced. Finally, contextual factors like the COVID-19 pandemic and remote meetings may have influenced how stigma was discussed. The waitlist design of HCS meant some coalitions began implementation earlier, potentially shaping the nature and timing of their discussions.

CONCLUSIONS

This paper shows how AI can be used to analyze community coalition meeting minutes, focusing on how stigma was discussed and integrated into the discussion of EBP deployment. The methods and findings in this paper highlight the potential of AI-human collaboration in community-engaged research. Our findings suggest that AI may be useful for real-time quality improvement in community-engaged research.

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