Transforming Government: People, Process and Policy

Using ChatGPT to enhance public participation: an analysis of public comments to reschedule marijuana

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Abstract

Purpose – In May of 2024, the U.S. Drug Enforcement Agency (DEA) proposed to reschedule marijuana from Schedule I to Schedule III of the Controlled Substances Act (CSA). As part of the rescheduling process, public comments were solicited online during a three-month period. At the end of the public comment period, 42,903 comments were submitted. The collection and analysis of a large volume of public comments is a challenge for policymakers, especially when the timeline for policymaking is finite. The purpose of this study is to respond to emerging scholarship that has identified the need for transformative changes to make planning and policymaking processes more collaborative and effective using advanced tools.

Design/methodology/approach – This study proposes a methodology for using ChatGPT to perform sentiment analysis and topic modeling on public comment data as a tool to enhance the citizen participation process. This analysis examines the sentiments in public comments submitted to the DEA about marijuana rescheduling and highlights professional and institutional tendencies voiced in them.

Findings – This study compared sentiments expressed in unique comments (43.6%) to duplicate comments written by institutional interests and posted by their constituents (46.3%) and found that duplicate comments were less likely to agree with rescheduling marijuana and more likely to advocate for descheduling marijuana from the CSA entirely.

Practical implications – The use of ChatGPT to analyze public comment data has general applicability across the rulemaking process and allows policymakers to systematically analyze the opinions of the constituency. This analysis provides policymakers with evidence to support efforts to build artificial intelligence (AI) capacity and put data protection systems in place to maintain the trust of participants in public deliberations.

Originality/value – This study introduces methods to apply AI tools such as ChatGPT in citizen participation. These methods can increase the capacity of government agencies to analyze volumes of data that come from the public participation process.

Keywords Artificial intelligence, Sentiment analysis, Public participation, ChatGPT, Agency rulemaking process, Online public comments

Paper type Research paper

1. Introduction

In May of 2024, the U.S. Drug Enforcement Agency (DEA) proposed to reschedule marijuana from Schedule I to Schedule III of the Controlled Substances Act (CSA). If

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adopted, this would move marijuana from the most restrictive category in the DEA drug schedule reserves for highly addictive drugs with no medical use, like heroin to a category of drugs with low potential for addiction and some therapeutic value, such as Tylenol with codeine. After rescheduling, marijuana would continue to be regulated by the DEA, but marijuana related infractions would be less severe and opportunities to use marijuana in medical research would be expanded.

During the rescheduling process, a 90-day online public comment period was held from May 2024 to July 2024, resulting in the submission of 42,903 comments. While the extensive feedback highlights significant public interest and engagement, the sheer volume of user-generated data, with its varied quality, structure, formats and reliability, presents a substantial challenge for policymakers. Analyzing and incorporating such a large amount of input is particularly difficult, especially given the finite timeline for policymaking (Balla *et al.*, 2022; Wang and Yin, 2023). One of the core questions examined in this article is how to apply artificial intelligence (AI) tools, such as ChatGPT, to efficiently analyze large volumes of public comments and inform the policy process in a timely manner. The substantial number of public comments submitted in response to the DEA's proposed rescheduling of marijuana provided us with an opportunity to test the capacity of AI tools in analyzing citizen input in the policy process.

Emerging scholarship (Ingrams, 2020; Johnson, 2023) underscores the need for transformative changes to make planning and policymaking processes more collaborative and effective using advanced tools. This article adds to the literature by proposing a methodology for using ChatGPT to perform sentiment analysis and topic modeling on public comment data as a tool to enhance the citizen participation process and inform policy development. Our study examines the sentiments in public comments submitted to the DEA about marijuana rescheduling. We compare sentiments expressed in unique comments (43.6%) to duplicate comments (46.3%). This contrast is noteworthy because the former group of comments consists of unique comments submitted by individuals, while the latter group consists of *verbatim* text submitted by groups of individuals. The presence of duplicate comments reflects a more organized effort by institutional interests that provide their constituents with prewritten text to submit as public comments, thereby amplifying their group's perspective (Balla *et al.*, 2022). This analysis found that duplicate comments were less likely to agree with rescheduling marijuana and more likely to advocate for descheduling marijuana from the CSA entirely. This distinction is discussed in more detail in subsequent sections of this article.

Applying AI tools, our findings distinguish between the sentiments expressed by unique individuals engaging in the citizen participation process and those of more organized groups. The findings are important for refining methods to apply AI tools such as ChatGPT in citizen participation. Developing these methods is a core element of addressing the challenge that public agencies face in managing the large volumes of data collected during public engagement processes. Although our analysis focuses on marijuana rescheduling, it has a direct application to a range of policy questions.

2. Literature review

2.1 Public participation in policy making

Scholars have examined the impact of public participation on the policy process since Arnstein (1969) published her seminal article describing a ladder of citizen participation. In that work, she concluded that participatory processes often fall short of providing citizens with meaningful access to the policy process. Subsequent works built on Arnstein's have come to similar conclusions (Silverman, 2005; Shipley and Utz, 2012; Silverman *et al.*, 2020). In response to this dilemma, the concept of deliberative democracy was introduced

and calls for the development of tools to augment citizen participation in the design and framing of public policies through discussion and dialogue with policymakers were made (Bessette, 1997; Forester, 1999). Nonetheless, efforts to expand the scope of citizen participation and institutionalize participatory democracy have fallen short. Fung (2015) argues that expanding citizen participation was compounded by three obstacles: a lack of systematic leadership in government to champion institutional change, a lack of public consensus on the role of public participation in democratic institutions and limits on the scope and impact of reforms. These critiques have carried over to new applications of deliberative democracy tools using social media and e-participation tools (Chambers, 2023; Karlsson and Adenskog, 2024).

Incorporating deliberative democracy tools in decision-making processes related to policy options, services and infrastructure investments is often fraught with added challenges due to competing economic interests, varying political perspectives and diverse cultural values. The traditional "predict and plan" paradigm is inadequate for addressing these complexities. Many studies have called for a shift toward decision support tools and implementation mechanisms enabled by advanced technology to engage community participation, promoting anticipation and adaptation (Brail, 2008; Klosterman, 2012; Batty, 2014; Yin and Shiode, 2014; Ingrams, 2023; Oloonabadi and Baran, 2023).

Some of the more promising innovations in public participation emerged in decision support systems and e-governance. These systems can act as platforms for public involvement in decision-making and facilitate communication between the public and government officials about alternative policies and their impacts (Klosterman, 2012; Yin and Hastings, 2007; Yin and Shiode, 2014). Although e-governance is a broad field, at its core, it involves expanding the public participation process using remote access and various forms of electronic communication tools. Despite the expansion of e-governance tools, scholars have continued to raise doubts about their impact. In a recent evaluation of e-governance tools, Brown and Eckold (2020) concluded that the degree of access to the participation process varied by constituencies. They found that public comment tools had a bias toward proponents of policies being considered, while other tools, such as community surveys and public participation GIS, provided a broader spectrum of community interests to be identified.

Despite their limitations, e-governance tools have become a core component of the rule-making process for federal and state agencies. Carlitz and Gunn (2002) discussed the mainstreaming of e-governance in the federal rulemaking process. As a standard practice, federal agencies announce public rules and policies under consideration in the *Federal Register* and through other government notices. These announcements include information about how to submit comments electronically to agencies and those comments are made available in real time.

2.2 Analyzing public comments using artificial intelligence-based methods

While the adoption of e-governance tools in the rulemaking process has become integral to all federal agencies' public participation processes and a key national policymaking venue, concerns have arisen about processing the vast amount of data for timely decision-making and ensuring its representativeness. The surge in public comments has overwhelmed many agencies, with feedback varying greatly in quality, relevance and format, similar to other types of user-generated urban big data (Wang and Yin, 2023). Beever and Taylor (2022) point out that public comment tools are not designed to verify the identity of individuals who make submissions. In part, this is to provide participants with anonymity. However, the open

nature of electronic platforms for submitting public comments increases the chances for manipulation.

One of the more prevalent types of manipulation of the contemporary public comment process is the phenomenon of mass comment campaigns. Balla *et al.* (2022) defined this phenomenon as occurring when identical or duplicate comments sponsored by organizations are submitted by their supporters to federal agencies. In response to this phenomenon, there has been growing interest among researchers in developing analytic techniques to identify duplicate comments and measure their impact on policy outcomes (Ingrams, 2020; Johnson, 2023; Handan-Nader, 2023; Vasilakopoulos *et al.*, 2024).

Another body of literature focuses on leveraging AI-based tools, such as Natural Language Processing and OpenAI tools, to streamline the analysis process. These tools categorize and summarize large volumes of comments or social media chats about sentiments expressed and topics discussed, helping to understand public concerns (Jelodar *et al.*, 2019; Hollander *et al.*, 2023; Yin *et al.*, 2024; Fu *et al.*, 2024; Yin *et al.*, 2026).

OpenAI models such as ChatGPT 4.o demonstrate strong performance across Valence, Arousal and Dominance dimensions, providing meaningful emotion representations for analyzing human emotions (Broekens *et al.*, 2023). This is an improvement on sentiment analysis that identifies positive, negative and neutral tones, offering a more nuanced interpretation of specific feelings such as anger, fear, happiness or anticipation. Comparative analyses across multiple data sets establish its effectiveness as a universal sentiment analyzer, often surpassing prevailing lexicon-based approaches, including those based on machine learning or deep learning (Wang *et al.*, 2023; Yin *et al.*, 2024). For instance, Belal *et al.* (2023) found that ChatGPT achieves a remarkable 20% increase in accuracy for sentiment analysis on the tweet data set. Additionally, research highlights ChatGPT's potential in decision-making by analyzing sentiment and topics, offering valuable insights for management, public health and other purposes (Suriani *et al.*, 2023; Yin *et al.*, 2024; Fu *et al.*, 2024). The next sections document how AI tools were used to enhance the analysis of public comment data and close some methodological gaps.

3. Methods

This analysis builds on traditional content analysis methods described by Krippendorff (2013), applying automated content analysis techniques while following methodological approaches for validating results suggested by Grimmer and Stewart (2013). The analysis is also informed by recent work utilizing the GPT-4o-mini API from OpenAI (hereafter referred to as ChatGPT) to perform sentiment analysis and topic modeling on public comment data, enhancing the citizen participation process (Yin *et al.*, 2024; Yin *et al.*, 2026). We collected data from the Federal eRulemaking Portal. In May of 2024, the U.S. Drug Enforcement Agency (DEA) published its notice to reschedule marijuana from Schedule I to Schedule III of the CSA in the Federal Register (Schedules of Controlled Substances, Rescheduling of Marijuana, 2024). This announcement opened a 90-day public comment period on the Federal eRulemaking Portal. The public comment period closed on July 22, 2024. After the public comment period closed, 42,903 comments (excluding seven blank ones) were submitted to the Federal eRulemaking Portal, and they were downloaded from the portal for analysis.

3.1 Descriptive analysis – duplicate comments vs unique comments

To distinguish between duplicate and unique comments, we used the Python package pandas. We first identified comments that appeared multiple times, flagging them as duplicates. Among these, we classified comments submitted more than five times as group submissions,

indicating coordinated or advocacy-driven efforts. Additionally, we merged comments that differed only by minor formatting variations – such as extra spaces or punctuation marks – to avoid counting them as separate entries.

We then summarized the characteristics of unique comments and duplicate comments using quantitative methods. The last column of Table 1 summarizes the characteristics of the full data set. For the entire data set, the average comment length in characters (2,551.78) translated into approximately 452 words and the standard deviation (1,768.03) suggested that comments ranged from 139 to 765 words [1].

Table 1 summarizes a comparison of unique and duplicate comments. Table 1 shows that there were contrasts in the length of unique comments compared to duplicate comments. For unique comments, the average length in characters (1,448.69) translated into approximately 257 words, and the standard deviation (1,438.04) suggested that comments ranged from 2 to 510 words [1]. For duplicate comments, the average length in characters (3,404.55) translated into approximately 603 words and the standard deviation (1,508.34) suggested that comments ranged from 336 to 870 words [2].

A more detailed examination of the duplicate comments revealed that there was a total of 381 duplicate comments that appeared two or more times in the data set, and 51 comments appeared five or more times. The 51 comments that appeared at least five times in the data set were manually reviewed to remove duplicates. Each comment was checked to ensure that, aside from minor word omissions, the content was essentially identical and expressed the same opinion. This resulted in a final count of 17 duplicate comments that represent the institutional actors' opinions. The remaining duplicate comments represent the smaller groups and other efforts amplify shared opinions about marijuana rescheduling.

Identifying unique and duplicate comments allowed us to optimize computational and financial resources when using the ChatGPT API. Among 24,206 duplicate comments, we discovered they corresponded to only 17 distinct comment texts. Consequently, the subsequent ChatGPT analysis focused solely on these 17 unique entries.

3.2 Sentiment analysis and topic modeling

Sentiment analysis and topic modeling were applied to the full data set and the two subgroups of data based on their categorization as unique and duplicate comments using ChatGPT. We conducted the sentiment analysis in two layers: opinions on rescheduling and emotions expressed regarding these opinions, which involved multiple iterations of ChatGPT-based analysis, followed by researcher discussions to validate and refine the approach before the final runs. A random sample of about 1% of comments was manually reviewed by researchers to assess opinions, emotions and topics. These manual assessments were then compared with ChatGPT's classifications to validate the model's accuracy and refine the categories.

The first step of analysis focused on the opinions expressed in the comments. To achieve this, comments were grouped according to their stance on rescheduling marijuana. ChatGPT

Table 1. Descriptive statistics comparing unique and duplicate comments on rescheduling marijuana

Metric	Unique comments	Duplicate comments	Total
Total number of comments	18,697	24,206	42,903
Mean comment length in characters	1,448.69	3,404.55	2,551.78
Comment length in characters – S.D.	1,438.04	1,508.34	1,768.03

Source(s): www.regulations.gov/docket/DEA-2024-0059/comments

was instructed to classify the comments into three categories based on the opinion expressed: (1) disagree with rescheduling marijuana, (2) agree with rescheduling marijuana or (3) favor descheduling marijuana entirely. To improve accuracy, the prompts included definitions for each opinion so ChatGPT could apply the classifications more consistently.

In the second step, ChatGPT performed emotion analysis to identify the range of emotions expressed in the comments. Drawing on Nandwani and Verma's (2021) framework, we defined four emotion categories: optimism, disgust, anticipation and anger, based on characteristics observed in the comments. We then instructed ChatGPT to conduct a multi-class sentiment analysis using these four categories, which were clearly specified in the prompt. Finally, we used ChatGPT for topic modeling, focusing on five themes identified through test runs and researcher discussions: personal experience, professional experience, advocacy for some type of change, concerns related to policy, law and regulation and calls for social justice. These topics were explicitly included in the prompt.

4. Findings

The results of the analysis of public comments submitted in response to the DEA's proposed rescheduling of marijuana from Schedule I to Schedule III of the CSA are summarized in this section using Sankey diagrams (Gesmann and de Castillo, 2011). These are flow diagrams used to visualize the magnitude of impact that variables have on subsequent measures in a model, which enable the visual analysis of multidimensional data (Lupton and Allwood, 2017). In this analysis, the Sankey diagrams effectively capture opinion-emotion-topic relationships and illustrate how emotions and topics are distributed across opinion categories.

The Sankey diagrams in our study show the connection of the primary measurement of the opinions expressed about rescheduling marijuana, on the secondary measurement of the sentiment and emotion expressed about rescheduling marijuana, and then how this flowed to the predominant topic of the comment that was submitted. The width of the arrows in the Sankey diagrams is proportionate to the magnitude of impact that the primary measurement had on subsequent measurements.

4.1 Summary of all comments

Figure 1 presents the Sankey diagram for all comments submitted in response to the DEA's proposed rescheduling of marijuana from Schedule I to Schedule III of the CSA. This diagram reflected the overall opinion-emotion-topic relationships across all comments submitted.

Several things are noteworthy about the opinions expressed across all comments. First, there was a clear preference for descheduling marijuana entirely and removing it as a controlled substance regulated by the CSA. This opinion is linked to subsequent steps for emotions and topics in the analysis in the diagram. Comments that emphasized descheduling marijuana primarily contained sentiment that either expressed anticipation or anger about the DEA proposal, and this is associated with an emphasis on topics that focused on advocacy for a different approach than what the DEA was proposing. In these comments, advocacy was for the DEA to move away from rescheduling in favor of removing marijuana from the list of controlled substances entirely.

Second, the group of comments that expressed opinions agreeing with the idea of rescheduling marijuana represented the second largest. Comments that agreed with rescheduling marijuana primarily contained sentiment that expressed anticipation about the DEA proposal, and this led to an emphasis on topics that focused on advocating for what the DEA was proposing.

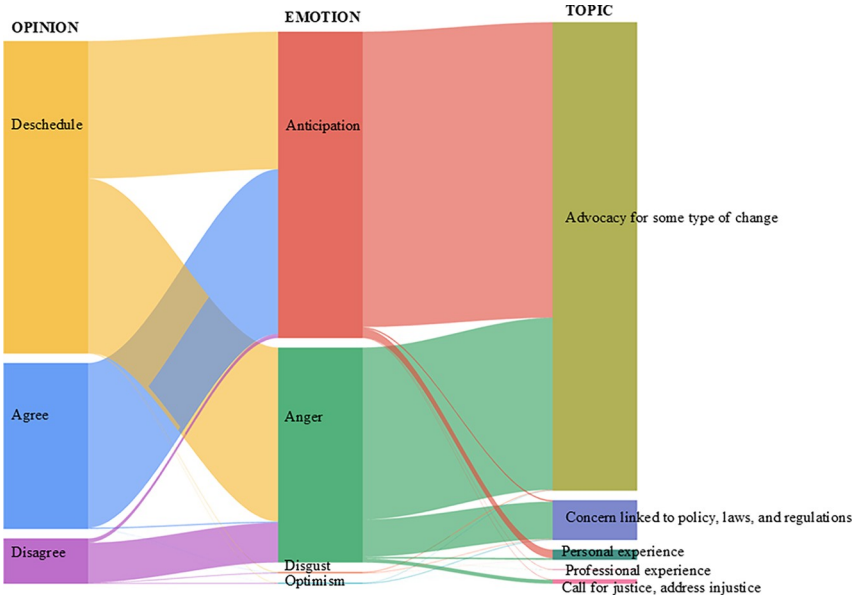

Figure 1. Sankey diagram for all comments (N = 42,903)

Finally, the group of comments that expressed opinions disagreeing with rescheduling marijuana represented the minority. Comments that disagreed with rescheduling marijuana primarily contained sentiment expressed anger about the DEA proposal, and this led to an emphasis on topics that focused on concerns about changes to policies, laws and regulations.

4.2 Summary of unique comments

Figure 2 presents the Sankey diagram for unique comments submitted in response to the DEA's proposed rescheduling of marijuana from Schedule I to Schedule III of the CSA. This diagram reflected the opinion–emotion–topic relationships in comments that were submitted by unique individuals and that were not duplicated by others.

Several things are noteworthy about the opinions expressed across the unique comments. First, there was a slight preference for descheduling marijuana entirely and removing it as a controlled substance regulated by the CSA. This distinction sets the unique comments apart from the opinions expressed in Figure 1 from all other comments. The connection of this opinion to subsequent steps in the analysis is represented in the diagram. For this subgrouping, comments that emphasized descheduling marijuana primarily contained sentiment that either expressed anticipation or anger about the DEA proposal, and this led to an emphasis on topics that focused on advocacy for a different approach than what the DEA was proposing. In these comments, advocacy was for the DEA to move away from rescheduling in favor of removing marijuana from the list of controlled substances entirely.

Second, the group of comments that expressed opinions agreeing with rescheduling marijuana represented was slightly smaller than the group advocating for descheduling. This is a distinct pattern in the unique comments. Comments that agreed with rescheduling

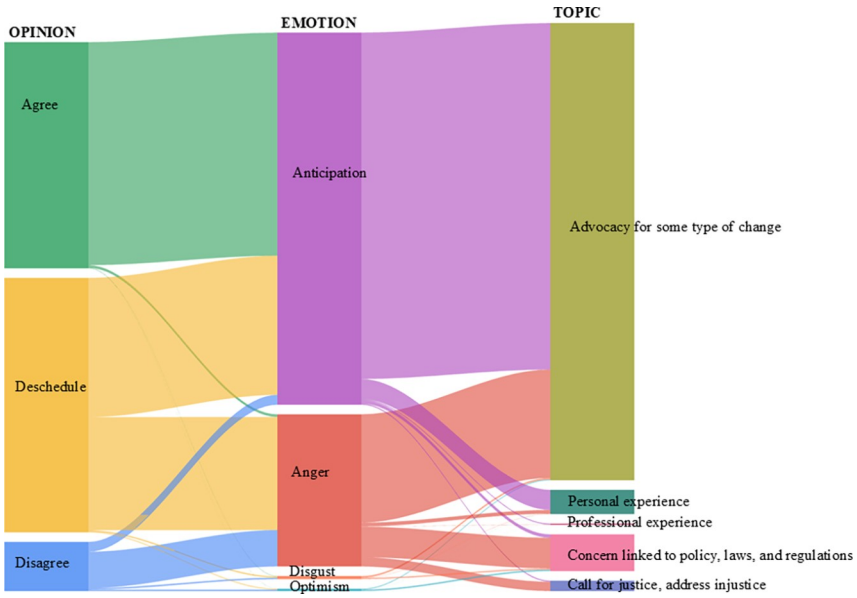

Figure 2. Sankey diagram for unique comments (N = 18,697)

marijuana primarily contained sentiment that expressed anticipation about the DEA proposal, and this led to an emphasis on topics that focused on advocating for what the DEA was proposing.

Finally, the group of comments that expressed opinions disagreeing with rescheduling marijuana represented the minority of the unique comments. Comments that disagreed with rescheduling marijuana primarily contained sentiments expressing anger and disgust about the DEA proposal, and this led to an emphasis on topics that focused on concerns about changes to policies, laws and regulations.

As summarized in Table 1, unique comments were somewhat shorter than duplicate comments. The content of the comments ranged from support and opposition to rescheduling to a preference for descheduling, as summarized in Figure 2. Many of the unique comments were more impromptu and spontaneous in character than the duplicate comments discussed in the next section. For example, some comments were relatively short but measured like this one in support of rescheduling, which stated, "Please Reschedule Marijuana to a Schedule III drug, spend your resources on hard drugs like fentanyl!" Other comments attributed political motives to past decisions about making marijuana a Schedule I drug under the CSA during the Nixon administration and the continuation of this policy during the Reagan administration. Some of these comments referred to racial disparities that grew out of these policies. For instance, one comment tapped into this sentiment, stating that, "the Fascist, Racist, rulers of Amerika have imprisoned thousands of Sisters and Brothers!" Other comments argued that the proposed rescheduling of marijuana was part of a "political stunt" by the Biden administration, which would keep marijuana on the CSA's list of scheduled drugs and avoid political fallout for pursuing full descheduling and decriminalizing. One comment captured this perspective speculating that, "Maybe if Joe Biden fends off Trump's plans to steal the

Presidency, the Democrats will drum up support in four years and we can hope for more progress then […], this is getting silly at this point, JUST LEGALIZE IT." Another characteristic of some unique comments was that they contained expletives. For example, one comment that advocated for descheduling marijuana ended by saying, "Fuck off already, you all are a bunch of suit dummies that do not know shit about shit!" In contrast to the more impromptu nature of the unique comments, duplicate comments were relatively focused and structured by institutional actors that supplied text to their constituents to submit as part of mass comment campaigns.

4.3 Summary of duplicate comments

Figure 3 presents the Sankey diagram for duplicate comments submitted in response to the DEA's proposed rescheduling of marijuana from Schedule I to Schedule III of the CSA. This diagram reflected the opinion–emotion–topic relationships in *verbatim* comments that were submitted by multiple individuals.

Several things are noteworthy about the opinions expressed across the duplicate comments. First, there was a strong preference for descheduling marijuana entirely and removing it as a controlled substance regulated by the CSA. This is distinct from the opinions expressed in the unique comments. The connection of this opinion to subsequent steps in the analysis is represented in the diagram. For this subgrouping, comments that emphasized descheduling marijuana primarily contained sentiment that either expressed anticipation or anger about the DEA proposal, and this led to an emphasis on topics that focused on advocacy for a different approach than what the DEA was proposing. In these comments, advocacy was for the DEA to move away from rescheduling in favor of removing marijuana from the list of controlled substances entirely.

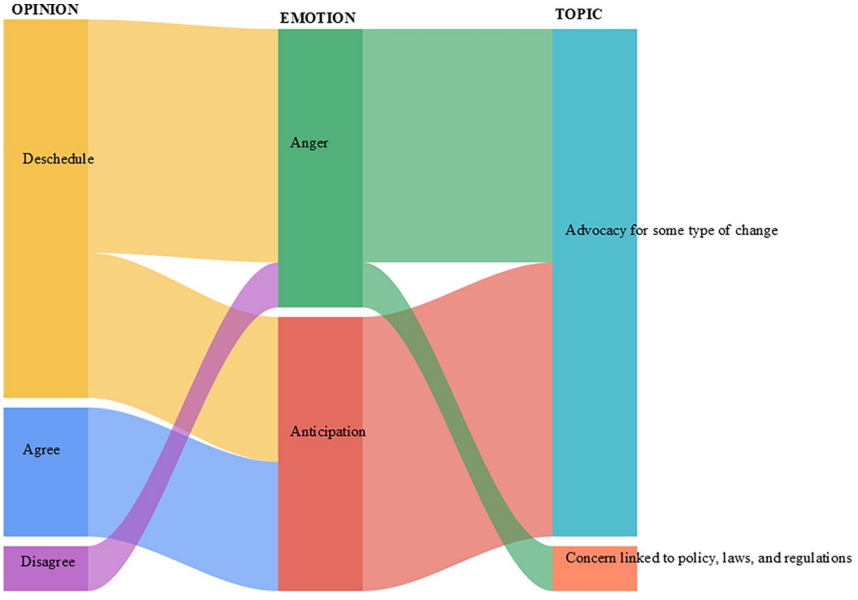

Figure 3. Sankey diagram for duplicate comments (N = 24,206)

Second, the group of comments that expressed opinions agreeing with rescheduling marijuana represented was smaller than the group advocating for descheduling. Comments that agreed with rescheduling marijuana primarily contained sentiment that expressed anticipation about the DEA proposal, and this led to an emphasis on topics that focused on advocating for what the DEA was proposing.

Finally, the group of comments that expressed opinions disagreeing with rescheduling marijuana represented the minority of the duplicate comments. Comments that disagreed with rescheduling marijuana primarily contained sentiment expressing anger about the DEA proposal, and this led to an emphasis on topics that focused on concerns about changes to policies, laws and regulations.

As summarized in Table 1, duplicate comments were somewhat longer than unique comments. The content of the comments ranged from support and opposition to rescheduling to a preference for descheduling as summarized in Figure 3. The duplicate comments were focused on a specific position about the proposal to reschedule marijuana and were written in a deliberate manner. As noted in the discussion of Figure 3, the duplicate comments predominantly advocated for descheduling marijuana. These comments tapped into some of the same sentiment as the unique comments advocating for descheduling, but they were more cogent. For example, one of the duplicate comments summarized the argument for descheduling in this manner:

> Rescheduling marijuana to Schedule III is not enough. Marijuana must be removed from the CSA and should be federally regulated for both medical and adult use. Rescheduling will not end federal marijuana criminalization. Rescheduling will not end federal marijuana arrests, even for possession and use. Rescheduling will not release anyone in prison for marijuana. Rescheduling will not expunge previous marijuana arrests. Rescheduling will not end deportations, immigration consequences, or tourist visa restrictions stemming from marijuana activity. Rescheduling will not restore access to government benefits that people have lost due to marijuana activity. Rescheduling will not bring state marijuana programs into compliance with federal law. Rescheduling will not guarantee fair working conditions for individuals working in the marijuana industry. Rescheduling will not facilitate patients′ access to medical marijuana.

Other duplicate comments in favor of descheduling made similar points while placing specific emphasis on how classifying marijuana as a controlled substance under the CSA perpetuated racial discrimination. For example, one duplicate comment stated:

> The criminalization of cannabis as a legacy of the War on Drugs was a policy decision rooted in racism. In the decades since, its enforcement has been disproportionately targeted at Black people and other people of color. It′s time to abandon this draconian approach. I support descheduling cannabis from the CSA as a step toward righting the wrongs of its criminalization.

The duplicate comments advocating for descheduling marijuana had a similar tone and sentiment as unique comments, but they were more focused. Arguments for descheduling crystalized around racial inequality emanating from treating marijuana as a controlled substance and concerns that rescheduling would not be sufficient to remedy these policy outcomes.

The second largest group of duplicate comments advocated for adopting the proposal to reschedule marijuana as a Schedule III drug. These comments mirrored the sentiment for this position found in the unique comments, but in a more evidence-based and focused manner. The emphasis of comments in support of rescheduling was on medical benefits. The duplicate comments cited empirical research and endorsements from professional associations in this manner:

> Humanity has been aware of cannabis′ medical benefits for thousands of years. Since 1970, U.S. Federal Law has ignored this reality, ignoring the lived experience of people with cancer and AIDS who found relief from wasting and nausea, those suffering from chronic pain and many others. The American Nurses Association has supported allowing medical cannabis since 1996. Numerous health organizations have joined the ANA, including the American Academy of HIV Medicine, the American Public Health Association, the Leukemia and Lymphoma Society, the National Multiple Sclerosis Society, the U.S. Pain Foundation and the Epilepsy Foundation. A 2022 survey authored by Centers for Disease Control and Prevention researchers found that 69% of practicing physicians believe cannabis has medical value.

Duplicate comments in favor of rescheduling cited the existing body of medical studies and argued that it was currently misclassified as a Schedule I drug. One duplicate comment pointed out that:

> Cannabis has currently accepted medical use[s] and has a far lower potential for abuse than Schedule II drugs, including fentanyl, oxycodone and morphine. It also has a lower abuse potential and a lower level of physical or psychological dependence than alcohol, which is not scheduled.

In general, advocacy for rescheduling marijuana focused on medical benefits and argued that, in terms of toxicity and addiction, marijuana fell somewhere between hard drugs and legal substances such as alcohol and nicotine.

Although in the minority, there were some duplicate comments that opposed rescheduling marijuana. Like unique comments that opposed rescheduling, duplicate comments offered rebuttals to claims that marijuana was less toxic and addictive than other controlled substances. However, they grounded these arguments in empirical research, citing studies from the National Institutes of Health (NIH), Mayo Clinic, Cleveland Clinic and the World Health Organization. One duplicate comment cited analysis that showed marijuana was more potent today than decades ago and available in more forms for consumption, including gummies, drinks and other edibles. These comments argued that the "increased THC amounts plus the ease of consuming it has led to an uptick in cannabis use disorders."

In addition to making arguments to thwart advocacy for rescheduling based on medical benefits, opponents to rescheduling also argued that young people were at particular risk of harm. For example, one duplicate comment said, "a study in the *Journal of Pediatrics* found that instances of children under the age of six accidentally ingesting marijuana have jumped 1,375% from 2017 to 2021, climbing from 200 per year to more than 3,000 per year." Other duplicated comments opposed to rescheduling cited reports that marijuana users were more likely to need emergency care and hospitalization in the contemporary period.

Finally, duplicate comments opposed to rescheduling identified public safety, public health and other concerns that were specific to law enforcement. One duplicate comment argued that "studies have consistently shown that marijuana use impairs perception, coordination, and judgment, significantly increasing the risk of accidents and fatalities on roadways." This comment argues that legalized marijuana has experienced increases in marijuana-related traffic accidents and deaths.

5. Discussion

This analysis compared opinions, related emotions and topics expressed in unique comments (43.6%) to duplicate comments (46.3%) and found that duplicate comments were less likely to agree with rescheduling marijuana and more likely to advocate for descheduling

marijuana. The findings are important for refining methods to apply AI tools such as ChatGPT in citizen participation.

Given the inherent biases and limitations of AI tools such as large language models such as ChatGPT, human oversight – through prompt refinement and output review – remains essential (Grimmer and Stewart, 2013; Yin *et al.*, 2026). To address concerns raised by Grimmer and Stewart (2013), we used a randomly selected subset of the data for human evaluation, ensuring that model outputs aligned with expected interpretations and analytical goals. Additionally, we incorporated domain knowledge, including emotion categories informed by Nandwani and Verma's (2021) work, to define relevant comment classifications and enhance both interpretability and analytical rigor.

These comments revealed that mass comment campaigns such as those described by Balla *et al.* (2022) were prevalent in the public comment data related to the DEA's proposal to reschedule marijuana. This analysis provides a workflow that identifies duplicate comments and understands their differences and similarities to unique comments. This response to calls for the development of such tools (Ingrams, 2020; Johnson, 2023; Handan-Nader, 2023; Vasilakopoulos *et al.*, 2024) represents an advancement in using data from public comments to inform the policy process. Using ChatGPT, this analysis identified differences between unique and duplicate public comments. Unique comments were more impromptu and spontaneous in nature; duplicate comments were more focused and evidence-based. Although both types of public comments tended to favor either rescheduling marijuana or descheduling it entirely, there was more emphasis on descheduling in the duplicate comments. Across both types of public comments, opposition to rescheduling was an extreme minority opinion.

There was also consistency between unique and duplicate comments about the rationale for taking different positions. Comments in favor of descheduling marijuana and removing it from the list of controlled substances are based that position largely on concerns about inequities growing out of the criminalization of marijuana. Comments in favor of rescheduling marijuana focused on medical benefits that would accrue from making marijuana more widely available to researchers, health care providers and patients. In contrast, comments opposed to rescheduling cited public safety, public health and other concerns about law enforcement implications.

The use of ChatGPT to analyze public comment data is a powerful tool for policymakers. It has general applicability across the rulemaking process and allows policymakers to systematically analyze the opinions of the constituency. It also allows policymakers to detect the presence and scope of mass comment campaigns on public deliberations. The application of AI tools to the analysis of public comment data is somewhat unique, since this data is in the public domain. Unlike other data held by public agencies, this type of data has fewer data protection challenges. Still, policymakers need to put data protection systems in place to maintain the trust of participants in public deliberations (Sharma *et al.*, 2025).

Moreover, ethical concerns remain about how AI is used in analysis, particularly in relation to potential manipulation of AI-generated classification. Yang and Roberts (2023) discuss this issue in the context of the authoritarian data problem, where policymakers deliberately manipulate data to produce desired outcomes while coopting democratic processes. Even in the absence of this level of purposive manipulation, concerns remain about the lack of ability individuals have to question classification systems used in analysis or challenge AI-driven decisions (Birahim, 2025; Brown, 2025). To address this, agencies need to be more proactive about the development of internal guidelines to ensure fair interpretations of data and public input in how classification systems are applied in analysis.

6. Conclusions

This analysis has introduced a mode for using ChatGPT and other AI tools to analyze public comments and inform the public policy process. The analysis distinguished between unique public comments and duplicate comments that were part of mass comment campaigns. Understanding the nuances between these types of comments is important to weigh the influence of institutionally driven efforts to influence the citizen participation process.

Further research is needed to address two issues. First, the public participation process needs to be designed in a more intentional manner to carve out spaces for individual and group engagement in the public participation process. AI tools offer one method for separating these two sources of information and analyzing them comparatively. In this analysis, AI tools allowed unique comments and duplicate comments to be examined separately. The ability to identify and differentiate between individuals and institutional interests in the public participation process allows policymakers to carve out space in other aspects of the public participation process so that both perspectives are represented. For example, changes in the scope and format of public hearings may be made to ensure that all interests have access to steps in the policy-making process that follow online public comment periods.

Still, policymakers need to consider how to incorporate results from AI analysis more systematically and ethically when making decisions. Decisions about how to weigh sentiment from individuals and institutional interests are central to having a process that is democratic and transparent. Although AI analysis can inform these decisions, decision-makers and agencies need to create internal guidelines and a structure for public participation that is fair and inclusive to the polity.

This article contributes to the application of AI tools to the analysis of public participation. Further research is needed on the capacity of government agencies to analyze volumes of data that come from the public participation process. In this study, there were 42,903 comments submitted. Analyzing that volume of comments in a reasonable timeframe is a challenge for public agencies. This study suggests that models need to be developed for the analysis of data collected in the public participation process that are accessible to government agencies. Policymakers need to advocate for the development of this and allocate resources to public agencies to build capacity to apply AI tools to the public deliberation process.

Notes

[1.] These estimates are based on midpoint for word ranges generated using https://charactercounter.com/characters-to-words

[2.] These estimates are based on midpoint for word ranges generated using https://charactercounter.com/characters-to-words

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