Decision Analytics Journal 6 (2023) 100187

Contents lists available at ScienceDirect

Decision Analytics Journal

journal homepage: www.elsevier.com/locate/dajour

The role of artificial intelligence and predictive analytics in social audio and broader behavioral research

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ARTICLE INFO

Keywords:
Artificial intelligence
Behavioral research
Public health
Social audio
Social media
Predictive analytics

ABSTRACT

Social media data are increasingly being studied for their potential use in addressing and mitigating public health issues. Data from text and image-based social media have been used for observational and intervention studies, and have been collected from a variety of social media platforms. Artificial intelligence techniques have been used to analyze social media data for surveillance and prediction of public health concerns, including near real-time case identification of emerging infectious disease and mental health cases. A new and emerging type of social media, social audio, uses voice to engage users in conversation. This paper explores the potential use of artificial intelligence to analyze data from social audio for prediction and broader behavioral health research. Advantages of social audio over traditional social media and challenges in implementation are also discussed.

Social media technologies have been used by researchers for study-related activities such as recruitment, surveillance, intervention, and data collection [1–4]. For example, image-based social media platforms that allow users to post and comments on photos (e.g., Instagram, Flickr, Pinterest, Tumblr) have been used in observational and intervention studies to examine mental health and substance use, chronic diseases, infectious diseases, injury prevention, and sexual and reproductive health [5,6]. In one study, Instagram picture features (e.g., brightness, hue) were able to predict participants' personality characteristics [7]. Likewise, social media applications that are primarily text-based, such as Twitter, have been used for surveillance, event detection, disease tracking and forecasting, and pharmacovigilance [8]. Prediction studies, which often use artificial intelligence (AI), have used Twitter for detecting COVID-19 cases using online search engines [9] and for predicting syphilis cases [10], HIV cases [11,12], and excessive alcohol use at the county level [13].

Recently, a new form of social media, called social audio, has gained popularity. In contrast to image- or text-based social media, social audio allows users to share their content through voice [14]. Social audio is similar to a phone conversation that allows a large number of people with a similar interest in a topic to join a phone call. Social audio can be a standalone feature of a social media technology, or can be incorporated into a social media that uses traditional image- and text-based social media too. Given the emergence of social audio, this paper seeks to explore the potential use of social audio and AI in public health research and the considerations that warrant examination in implementation.

1. Artificial intelligence in social media research

Applications of artificial intelligence (AI) in social media research encompass a variety of methods across several health disciplines and various platforms [15,16]. For instance, investigators have used deep learning methods to predict the mental health status of Reddit users and found that, for disorders with a large number of users discussing it, artificial intelligence worked well, but for disorders with a smaller number of users, traditional approaches (logistic regression) were better for prediction [17]. Machine learning was used to identify and categorize tweets into 3 categories: no opioid misuse, pain-related misuse, and recreation-related misuse. Trained classifiers were able to identify subtle differences in tweets to distinguish between pain-related and recreation-related motivation for misuse [18]. Another example of AI analysis of social media was the use of natural language processing and deep learning techniques on Facebook posts and Twitter tweets to predict COVID-19 vaccine-related sentiment [19,20] and discussion topics. In addition, investigators layered the analysis using geospatial mappings to ascertain the locations of positive, negative, and neutral posts [21].

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https://doi.org/10.1016/j.dajour.2023.100187
Received 19 June 2022; Received in revised form 30 November 2022; Accepted 7 February 2023
Available online 10 February 2023

2. Social media

Digital tools such as social media continue to evolve and thrive in our society. There are different types of social media that coexist and often overlap in features, such as social networks (e.g., Facebook, Twitter, LinkedIn), consumer review networks (e.g., Yelp, TripAdvisor), media sharing networks (e.g., Instagram, Snapchat, YouTube), blogging and publishing networks (e.g., Medium, Tumblr), discussion forums (e.g., Reddit, Quora), and sharing economy networks (e.g., AirBnb, Rover), among others [22]; although some of these companies are owned by one parent company (e.g., Meta), making them distinct but with overlapping end business goals, each of these technologies was initially designed to have its own unique purpose in helping people to communicate online. For marketers and public health researchers to properly use these tools to engage the public, it is important that they have an understanding of the differences between social media types and their respective strengths and weaknesses.

For example, social audio has new and specific implications for use in AI and public health research. This audio-focused social network started to grow in popularity to connect users through voice at a time when the COVID-19 pandemic left many feeling isolated [14] and fatigued from Zoom meetings [23]. More than thirty-four social audio applications have been developed and launched since 2020, following the success of Clubhouse, a leading social audio platform [24]. Users can typically engage in social audio through two formats: synchronous and asynchronous. Synchronous platforms such as Clubhouse, Chalk, and Space are live chat rooms where users can enter a "room" on the site/app anytime during the session. Asynchronous social audio such as Cappuccino and Swell have short snippets of audio recordings that are published and can be listened to at the user's convenience. Social audio is similar to podcasts in that both allow for information dissemination, however, podcasts are typically pre-recorded and limited to a small number of people (e.g., one or a small group of people speaking on a topic; one person interviewing another), while synchronous social audio are live chat rooms where a large and potentially unlimited number of people can join a real-time chat room to share their thoughts on a topic. For example, while a podcast might be compared to listening to a lecture or symposium of speakers, social audio would differ by allowing anyone from the audience to request to "join on stage" to add their opinion.

Additionally, most asynchronous platforms publish short audio clips in bursts instead of longer sessions like podcasts [25]. Social audio differ from videoconferencing technologies, such as Facetime, in that videoconferencing is typically done among (a small number of) people who know each other and/or are invited, while social audio occurs in "rooms" where a potentially unlimited number of people who do not know each other can meet to share thoughts and ideas on any topic, including daily news, political views, investing ideas, social activities, health education, and/or romantic connections (see Fig. 1).

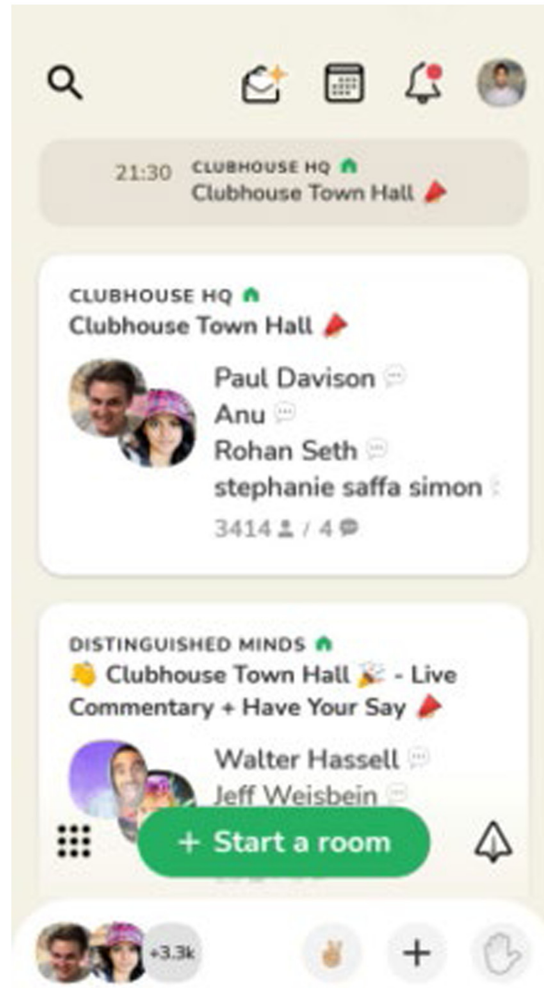

Fig. 1. Clubhouse audio. Image from https://en.wikipedia.org/wiki/Clubhouse_(app).

2.1. Social audio and public health studies

The authenticity afforded by social audio to focus on audio lends to its unique utility in research. It potentially provides users a more intimate experience when hearing a voice instead of reading text or watching a video. Social audio may also be a richer data source compared to some popular platforms like Twitter which has character restrictions on posts. Although algorithms are capable of identifying sentiment [26] on tweets, character limitations create a challenge to adequately express intended thought [27]. Additionally, intonation of voice can affect context, which text cannot easily relay. Social audio might not suffer from these limitations of other forms of social media data.

Similar to other social media formats, social audio data can potentially be used in epidemiology and prediction studies using AI. Transcription of audio data is already a very common qualitative research method, such as for transcribing interviews with patients [28–30]. Collection of audio data also has many benefits compared to collection of written (non-verbal/audio) data. For example, in one study, participants were given the opportunity to use written and audio diaries. In general, participants preferred the audio diary because it was perceived as less onerous and challenging compared to the written diary [31]. Audio data might therefore allow researchers to collect a dataset that is more topically-rich compared to other forms of social media data. These rich audio data from social audio might be transcribed to text and cleaned for analysis. As social audio can provide a large amount of "big data", AI using natural language processing might help to assist with data analysis. AI analysis of audio data is already being studied for application in settings such as recording studios [32] and might also be applied in areas related to this paper. Asynchronous audio clips are short and might be easier to transcribe for analysis than synchronous data. Synchronous platforms usually have topic-focused live chats which can be helpful when examining a specific topic instead of filtering thousands of posts based on keywords. Furthermore, synchronous platforms are somewhat similar to focus groups with multiple speakers engaged in conversations and can provide data from multiple people. Verbal conversations, whether synchronous or asynchronous, may provide more insight about opinions, attitudes, and knowledge than one or two tweets/posts. There are a number of potential applications based on analysis of social audio data. For example, similar to studies using Twitter and other text-based social media to predict HIV, substance use, mental health, and COVID-19 outcomes [20,33,34], social audio data might be converted to text and have the same prediction model methods applied.

3. Challenges to implementation

However, there are many challenges to implementing the use of AI with social audio in the real-world. Investigators should consider available technology that will convert audio to text, the type of software or application to use, and whether they are free or paid services. Additional software considerations include the capacity of the software to distinguish between speaker voices, as well as recognize and parse different accents. For example, compared to social media text (e.g., Twitter) data, audio data might include more filler words that are present within natural speech (e.g., umm, uhhh). While AI might be used to help to filter out these filler words, the models and algorithms will need to be tested and refined to ensure they are not changing or misrepresenting the intent of the speech. Therefore, it will be important to have human involvement for fidelity checks throughout the process of using and training AI in using social audio data.

Ethical issues should also be studied on this topic to improve safety for participants and improve potential likelihood of implementation of research methods [35] into policy and practice. In particular, researchers should study the potential privacy and confidentiality issues associated with research using social audio data, as has been done with other forms of social media data [28,35,36]. With respect to platforms, investigators should be familiar with terms of use and privacy. For example, Clubhouse has a rule that prohibits recording or transcribing of live chats [37] and Twitter only keeps data for 30 days [38]. Despite chats and recordings available for public listening, some content creators or moderators may be open to have their discussion consumed for entertainment purpose only and not necessarily for research purposes, especially if they are interested in monetizing their content. Currently, as social audio is a new type of social media, saturation of use is still low compared to traditional social media platforms, and the number of users overall are still far lower than traditional text/video social media platforms. Investigators also need to know the target population well to determine which platform and format will be best to use to answer their specific research questions and which will work with their algorithms and analysis plan. Another consideration is private rooms on synchronous platforms will not be accessible to the public and researchers who do not have permission to join the chat rooms, therefore, researchers may miss out on data.

The novelty of social audio and its potential use in public health beyond disseminating information necessitate more research. Investigators should look into the topics discussed in conversations, live or recorded, and how these verbal conversations are different from traditional text-based social media platforms to determine whether and how social audio might be a better source of data than traditional social media to answer their research questions. Studies on attitudes and willingness of social audio users regarding use of their voice and data for research purposes would also shed light into public perception on privacy and confidentiality. Moreover, studies on the ethics of using publicly available voice data instead of text data, from the standpoint of the public and ethics committees, may be informative on research conduct.

4. Conclusion

Social media platforms continue to be an expansive source of data for public health researchers with innumerable functionality. The immense amount of data obtained from social media compel the use of artificial intelligence for surveillance, observation, and predictive studies. Social audio presents benefits above those of traditional text and video-based social media for authentic dialogue and engagement that may result in richer data for investigators. Further study would behoove public health researchers in exploring these platforms for future use.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Sean Young reports no personal related financial support. Funding for this study was provided by the National Institute of Allergy and Infectious Diseases (NIAID), National Center for Complementary and Integrative Health (NCCIH), and National Institute on Drug Abuse (NIDA). Renee Garett reports a relationship with ElevateU – a NIH-funded research organization studying digital health that includes: board membership, employment, equity or stocks, and funding grants.

Data availability

No data was used for the research described in the article.

Acknowledgements

The authors wish to thank Arjuna Ugarte for assistance in previous versions of this manuscript.

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