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Making it (net)work: a social network analysis of “fertility” in Twitter before and during the COVID-19 pandemic

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Objective: To characterize activity, text sentiment, and online community characteristics regarding “fertility” on Twitter before and during the COVID-19 pandemic using social network analysis.
Design: Cross-sectional analysis.
Setting: Publicly available Twitter data.
Patient(s): Not applicable.
Intervention(s): Not applicable.
Main Outcome Measure(s): Number of users (vertices); edges (connections, defined as unique and total); self-loops (tweet without connection to another user); connected components (groups of users communicating back and forth frequently); maximum vertices in a connected component (largest group size); maximum and average geodesic distance (number of tweets to connect two users in the network); graph density; positive and negative sentiment tweets; and top 5 hashtags and top 5 word pairs.
Result(s): There were 1426 unique users and 401 groups in the pre-COVID-19 data compared to 1492 unique users and 453 groups in the during COVID-19 data. There was no difference in the number of total connections (96.8% [1381/1426] vs. 96.0% [1433/1492]) or self-loops (20.0% [286/1426] vs. 22.1% [329/1492]) before and during the COVID-19 pandemic. The percentage of unique connections per user decreased during COVID-19 (91.6% [1381/1508] pre-COVID-19 vs. 83.3% [1433/1720] during COVID-19). The average and maximum distance between users in the community increased during COVID-19 (maximum: 5 pre-COVID-19, 8 during COVID-19; average 1.95 pre-COVID-19, 2.43 during COVID-19). The percentage of positive sentiments per total number of tweets increased during COVID-19 (58.1% pre-COVID-19 [773/1331] vs. 64.3% [1198/1863] during COVID-19). The top 5 hashtags changed during COVID-19 to include COVID-19. The top word pairs changed from “family, hereditary; parents, children” to “fertility, treatment; healthcare, decisions.”
Conclusion(s): Despite the challenge to the fertility community amidst the COVID-19 pandemic, the overall Twitter sentiment regarding fertility was more positive during than before the pandemic. Top hashtags and word pairs changed to reflect the emergence of COVID-19 and the unique healthcare decision-making challenges faced. While the character, the number of users, and the total connections remained constant, the number of unique connections and the distance between users changed to reflect more self-broadcasting and less tight connections. (Fertil Steril Rep® 2021;2:472–8. ©2021 by American Society for Reproductive Medicine.)
Key Words: Social media, Twitter, COVID-19 pandemic, fertility

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Social media has altered the transmission of information, interpersonal communication, and cultural influence. Indeed, the availability, rapidity, and flow of information have been completely upended with the advent of smartphones and social media. Those with a smartphone can use a simple search function to find opinions, statements, and individuals to get information from or talk to regarding any inquiry, from restaurant recommendations to breaking political news. These cultural and technological phenomena have uniquely impacted healthcare and the dissemination of information from physician to patient. A large majority, up to 80%, of Americans have searched the internet for health-related information and, more alarmingly, up to 40% doubt a professional opinion when it conflicts with web-based findings, even if from a nonphysician-based source (1, 2).

Much of the literature regarding social media and medicine have evaluated users' demographics, what

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contributes to online influence, and if social media outreach leads to health behavior change (3–5). Relatively little is known about how users in a particular community interact and whether this structure changes over time, particularly when major events affect that community. The COVID-19 pandemic presented a unique and unprecedented challenge to the fertility community. While the country witnessed profound economic and social changes, so did fertility patients and physicians. Specifically, on March 30, 2020, the American Society of Reproductive Medicine recommended suspending any new treatment cycles and embryo transfers given the public health emergency and the uncertainty around COVID-19's effect on pregnancy (6).

Given the unprecedented impact of COVID-19 on the delivery of fertility care as well as the concurrent increase in people at home with perhaps both, more time for social media, and a need for a supportive community; we hypothesized the COVID-19 pandemic might have changed the social media landscape regarding infertility, fertility, and treatment. Social network analysis (SNA) is the process by which one can analyze and visualize social structures, meaning users in an online community and how they interact (7). SNA allows for analysis of the behavior of individuals, patterns of relationships, the interaction between these two, and sentiment analysis (7). Therefore, our objective for this study was to characterize activity, text sentiment, and online community characteristics regarding "fertility" on Twitter before and during the COVID-19 pandemic using SNA.

MATERIALS AND METHODS

Design

We performed a cross-sectional, SNA of public-facing Twitter accounts. SNA was performed using NodeXL, a network analysis and visualization software package for Microsoft Excel that accesses publicly available social media data and imports the data into Microsoft Excel for analysis. We chose to analyze two distinct periods: "pre-COVID" or just before the emergence of the pandemic (pre-COVID-19) in the United States, which was chosen to be from February 20, 2020, to February 27, 2020, and "during COVID-19" or when the fertility community was perhaps most impacted which was chosen to be from April 29, 2020, to May 6, 2020. Twitter was chosen as the platform of interest because of its consistent use in transmitting news and events (8). Moreover, several popular platforms such as Instagram and Facebook cannot be analyzed by NodeXL because of restrictions on accessing data from those platforms at present, and of the accessible platforms, Twitter was chosen as the most representative of the active social media community (9). Many search terms were considered, including but not limited to fertility, infertility, ART, IVF, etc. However, we chose the term "fertility" because we felt it would best capture tweets about "fertility treatment," which we felt would be most reflective of the impact of COVID-19 on treatment cessation. The time period from April 29, 2020, to May 6, 2020, was chosen to be relevant to treatment interruptions caused by the pandemic outbreak. The NYU Langone Health self-certification form from the Institutional Review Board was used to determine that this study's research question and design did not qualify as human subjects research. As such, Institutional Review Board approval was not required.

TABLE 1

NodeXL Variables and Common Definitions.

NodeXL variable term	Definition
Vertices	Users
Edges	Connections
Self-loops	Tweet with no interaction with another user
Connected component	Groups of users communicating back and forth frequently
Maximum vertices in a connected component	Largest group size
Maximum geodesic distance	Lengthiest number of tweets to connect two users
Average geodesic distance	Average number of tweets to connect two users

Smith. Social media analysis of fertility, COVID. Fertil Steril Rep 2021.

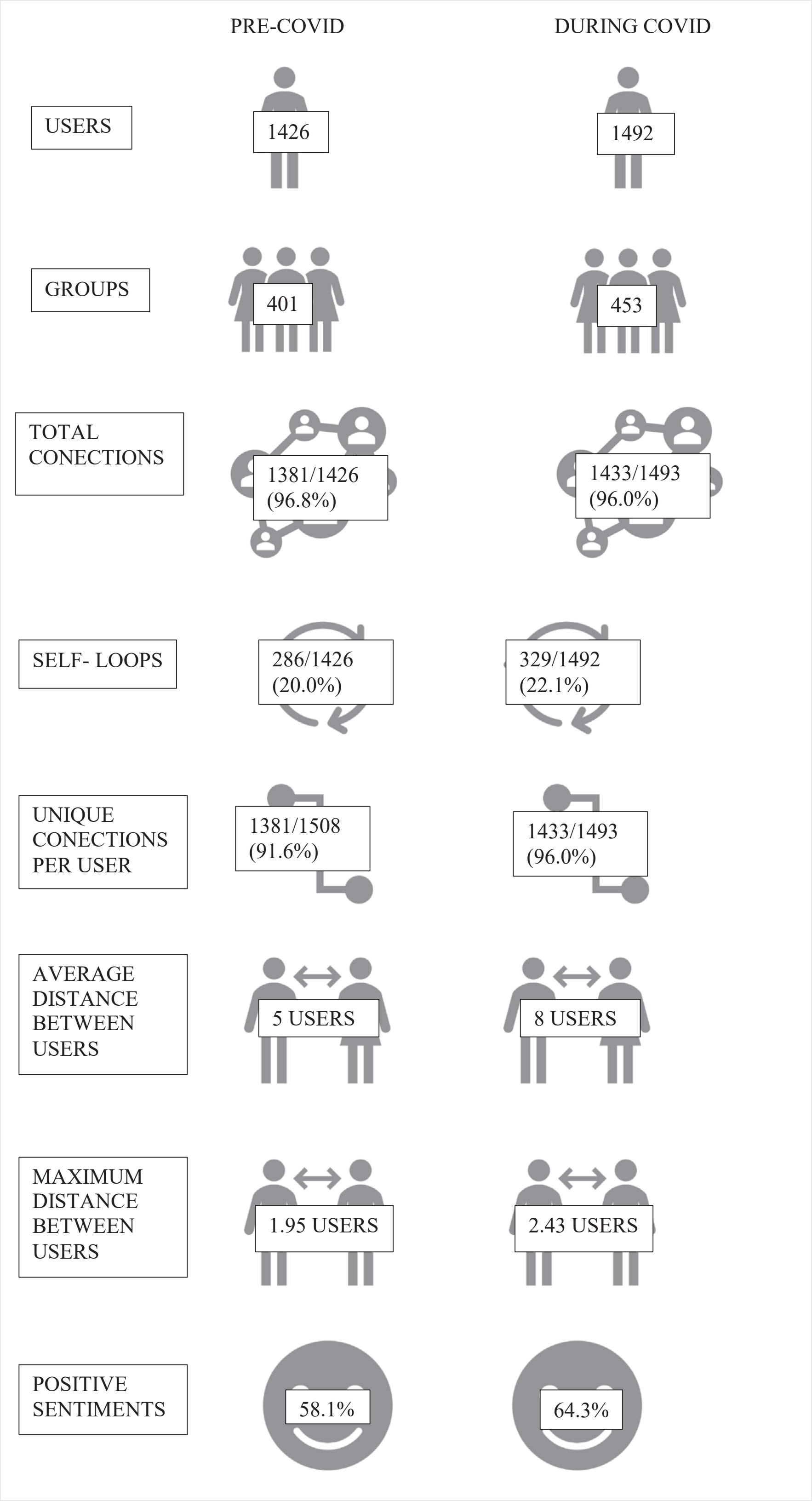
Variables and Data Collection

The search term "fertility" was used for the 2 weeks as outlined above. Within each period, user demographics were collected. Of note, NodeXL defines these demographic indices in variables or terms that differ from lay language. The NodeXL variables are listed as follows (Table 1), with the more common term or definition in parentheses. These variables included: total number of vertices (users); total edges between vertices (total connections); unique edges between vertices (unique connections); self-loops (tweet without a connection to another user); connected component (groups of users communicating back and forth frequently); maximum vertices in a connected component (largest group size); and maximum and average geodesic distance (number of tweets to connect two users in the network). Tweet content was analyzed by looking at the number of tweets with a positive vs. negative sentiment and the top five hashtags and word pairs used. NodeXL comes with embedded language processing within the software to categorize tweets as positive or negative based on the words in the English language that are associated with positivity or negativity. Finally, we used NodeXL to create a visual representation of the "fertility" social network during each period. These social network graphs allow us to analyze and convey the overall network structure derived from granular information given by the various outputs of NodeXL.

Analysis

Raw numbers of vertices, edges, maximum and average geodesic distance, and the total number of tweets were compared with z-comparisons where appropriate. The top five hashtags and top five word pairs were compared. Given that these results are qualitative, no statistical analysis was performed on these variables. The number of vertices and edges during each period was used to determine the

FIGURE 1



Fertility Twitter network characteristics pre-COVID-19 and during COVID-19.

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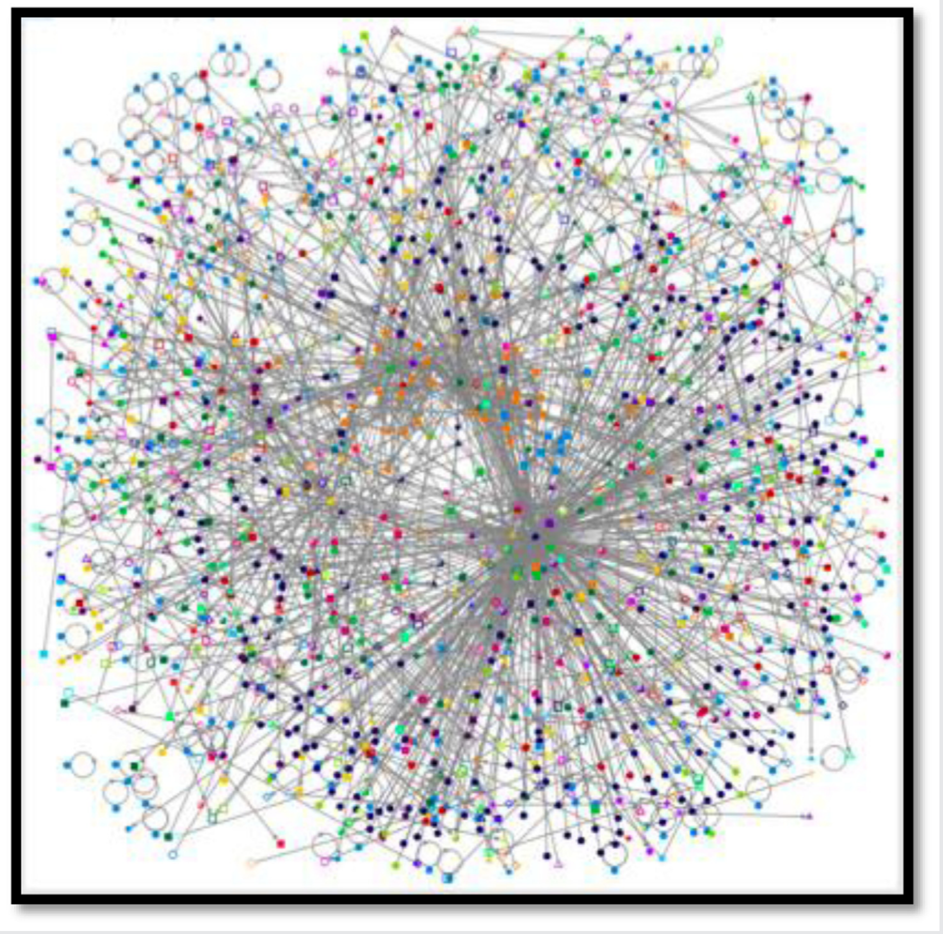
FIGURE 2



Fertility Twitter network shape, pre-COVID-19.

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percentage of unique connections per user, total connections per user, and self-loops per user. Similarly, the number of total tweets was used to generate a percentage of positive and negative tweets during each period. Of note, positive and negative tweets are distinct from the word pairs, meaning that the top word pairs are not synonymous with the sentiment. These were analyzed using a z-ratio for comparison of proportions, with $P<.05$ considered significant. Finally, the social network graphs were compared visually by two independent reviewers to categorize the shape of the social network graphs. The graphs generated from our collected data were compared with representative graphs shown on the NodeXL website and in the software's accompanying guidebook (10).

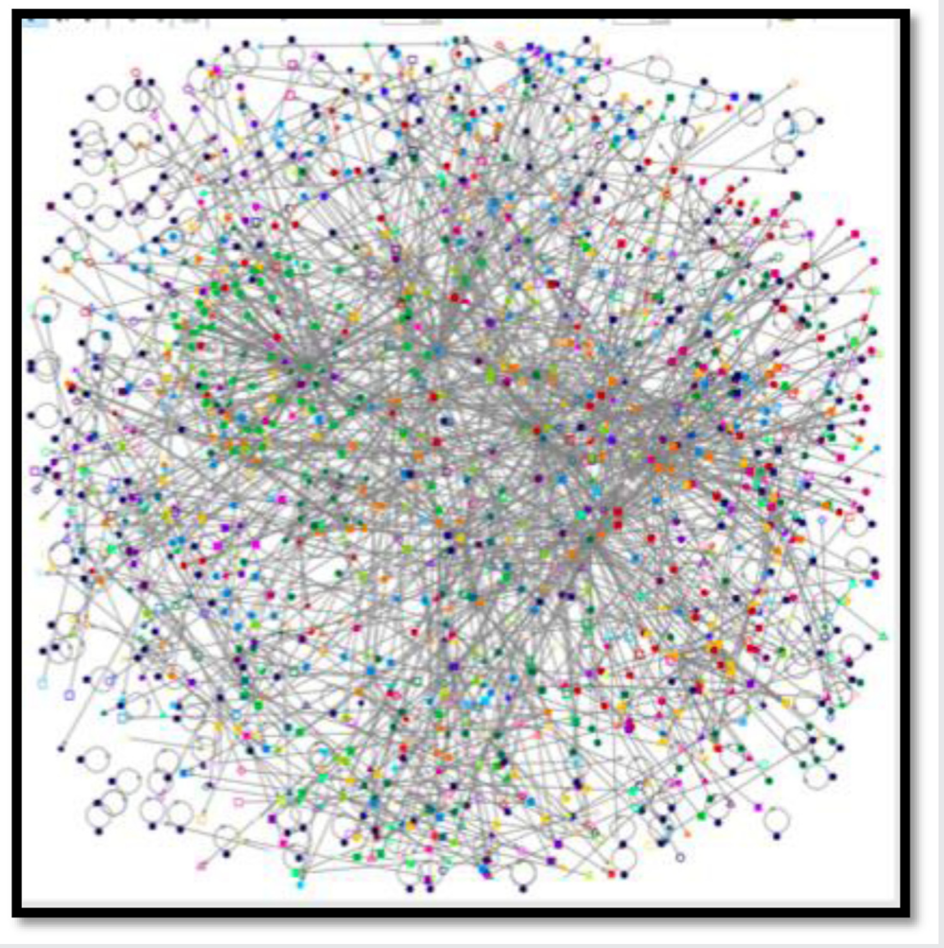
RESULTS

We identified 1426 unique users and 401 groups in the pre-COVID-19 period compared to 1492 unique users and 453 groups during COVID-19 (Fig. 1). We observed no difference in the number of total connections (96.8% vs. 96.0% [1433/1492], $P=.25$; or self-loops 20.0% [286/1426] vs. 22.1% [329/1492], $P=.19$) before and during the COVID-19 pandemic. However, the percentage of unique connections per user decreased during COVID-19 (91.6% [1381/1508] pre-COVID-19 vs. 83.3% [1433/1720] during COVID-19, $P<.0002$). Moreover, the average and maximum distance between users in the community increased during COVID-19 (maximum: 5, pre-COVID-19, 8, during COVID-19; average: 1.95, pre-COVID-19, 2.43, during COVID-19). When looking at tweet sentiment, the percentage of positive sentiments per total number of tweets increased during COVID-19 (58.1% pre-COVID-19 [773/1331] vs. 64.3% [1198/1863] during COVID-19, $P<.0004$).

The overall character of the Twitter fertility social network remained constant at both time points with a broadcast "spoke and out wheel" shape seen before and during COVID-19 (Fig. 2 and 3) and confirmed unanimously by the two reviewers.

The top five hashtags changed during COVID-19 to include COVID-19 (Supplemental Table 1, available online). The top word pairs changed from "family, hereditary" and

FIGURE 3



Fertility Twitter network shape, during COVID-19.

Smith. Social media analysis of fertility, COVID. Fertil Steril Rep 2021.

"parents, children" pre-COVID-19 to "fertility, treatment" and "healthcare, decisions" during COVID-19.

DISCUSSION

To our knowledge, this is the first study to use SNA to investigate the fertility community on Twitter. Moreover, this is one of the first studies to assess the impact of the COVID-19 pandemic on the online discourse surrounding fertility. The overall shape of the Twitter "fertility" network did not change with the emergence of the pandemic; we found network structure to remain as a "spoke and out wheel." This network structure represents a "broadcast" type of network in which relatively few sources supply a vast majority of the information, with other accounts repeating these same messages, such as a "retweet" (11). This broadcast notion was substantiated by our finding of less unique connections, meaning self-broadcasting, during the COVID-19 pandemic between Twitter users in the community. For fertility physicians and organizations alike, this is a critical piece of information. Those with accurate information, like physicians or professional organizations, should aim to make themselves the hubs in their community, so their message is amplified, rather than those that may not broadcast factual or evidence-based information. However, while the shape of the network did not change, the overall content did. Ironically, we found the overall sentiment on Twitter regarding "fertility" was more positive during the COVID-19 pandemic than before the onset of the pandemic, perhaps reflecting the appreciation for the support and communication fertility physicians provided during this time. The top hashtags and word pairs changed during the pandemic to reflect the emergence of COVID-19 and the unique health care decisions many were facing. Thus, while interruptions in treatment were certainly upsetting to physicians and patients alike, overall, it seems the severity and tragedy of the COVID-19 pandemic were apparent and reflected in online discourse in the fertility community.

Since the advent of social media, there has been an interest in using the medium for public health to disseminate information, research purposes, and practice promotion and marketing. Indeed, a 2016 publication by Hadi and Fleshler (12) described the successful implementation of a Social Media Monitoring Team within the New York City Department of Health and Mental Hygiene. The effort helped the department better understand the success and failure of public messaging, dispel rumors and misinformation, and monitor, geographically, where new incidents or outbreaks may be taking place, specifically related to the Ebola and Legionnaire's disease epidemics. Others have investigated adherence to and experience with breast cancer screening, finding that non-healthcare Twitter uses often tweet about confusion with screening guidelines, yet those who do undergo screening encourage other women to do the same (13, 14).

Several publications have assessed overall online discourse regarding the COVID-19 pandemic. Lwin et al. (15) assessed Twitter trends of four main emotions—fear, anger, sadness, and joy—and the narratives behind those emotions at the outset of the pandemic. Fear over personal protective equipment and COVID-19 testing shortages then transitioned to anger around stay-at-home notices. Sadness and joy were understandably linked to losing friends and family or expressing good fortune over good health. Pascual-Ferrá et al. (16) found that the overall network of conversations surrounding COVID-19 is highly decentralized, fragmented, and loosely connected, which can undermine the messages that public health officials are trying to disseminate. However, others have found that a more targeted look at online discourse regarding COVID-19 and a specific recommendation, such as mask-wearing, finds more interaction between users and less broadcasting (17). Our study adds to the emerging literature regarding social media use in medicine and the online dialogue regarding the COVID-19 pandemic. Moreover, like the study looking at tweets on masks, our addresses a specific topic related to COVID-19 and fertility. While the community tweeting about masks favored a "community cluster," meaning several small groups talking back and forth, the fertility community itself was largely a broadcast network. Why and how certain topics take different social structures online should become a focus for those who aim to spread evidence-based information.

Our study has several important implications. The first is that the "fertility" online community is largely a broadcast network. While it was not the aim of the present study, our prior work has shown that the most influential voices online in the fertility community are often not physicians or professional societies (18). Therefore, because a few voices dominate the shape of the fertility network, those professionals in our community active on social media should look to become "influential" so the most accurate messages are being spread. Second, despite many patients' huge interruptions in treatment, the overall online sentiment toward fertility was more favorable during the pandemic than before. Thus, despite canceled cycles and delayed dreams of building a family, an online backlash toward fertility physicians and practices did not ensue.

The main strength of our study is that this is the first study to harness SNA to assess the Twitter fertility community. Moreover, to our knowledge, this is the first study to investigate online sentiment regarding fertility during the emergence of the COVID-19 pandemic. However, our study does have several limitations. First, NodeXL cannot be used with all social media platforms, including Facebook and Instagram. Second, we only searched for "fertility" with this study. Different platforms and/or different search terms may have led to different results. NodeXL does not break down accounts by "account type," meaning whether the account is a doctor, patient, or medical society. Thus, it is not possible to delineate where most tweets are stemming from and if this impacts sentiment data. Finally, our analysis looked at the period just before and after the emergence of the pandemic. Given the ongoing and ever-changing nature of the COVID-19 pandemic and the rollout of the COVID-19 vaccines, it is possible that online social network structure, characteristics, and sentiment has changed since our study was performed.

CONCLUSION

Our SNA of the Twitter fertility community before and during the COVID-19 pandemic revealed that while the user concentration and network shape did not change, the online sentiment, top hashtags, top word pairs, and overall amount of self-broadcasting did change. Despite interruptions in treatment, Twitter sentiments regarding fertility were more positive during the pandemic, and the difficult decisions faced by patients were reflected in the top word pairs. As social media use by patients and providers alike continues to evolve, understanding how major events shape online conversations is critical. Moreover, as this pandemic continues, understanding the social media landscape will allow physicians to arm themselves with the relevant online narratives that patients may be encountering before presenting to the virtual or brick-and-mortar office. Continued research and strategic implementation of social media by physicians and professional societies should focus on becoming the broadcast centers of the online fertility network to ensure the correct information is being amplified.

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