Examination of Change in Perception Toward Virtual Medical Education After COVID-19 Pandemic in the U.S. Using Twitter Data

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Abstract

COVID-19 introduced a large percentage of the world's students and teachers to virtual learning. The purpose of this study was to examine the changes in perception toward virtual medical education during the pandemic in the U.S. Twitter data (tweets) associated with the virtual educational experience in the medical fields was obtained. Three analysis methods (topic modeling, sentiment analysis, and longitudinal cluster analysis) were adopted for the study. Across the selected topics, we found differences in conversations in virtual medical education fields. The topical patterns by frequency, polarity, and subjectivity identified the needs of those involved in virtual medical education and the areas that need to be overcome to improve virtual learning. More findings and implications are further discussed.

Keywords: virtual medical education, twitter, pandemic, COVID-19

Introduction

The COVID-19 pandemic has been changing our world significantly. In this situation, many fields mostly get a negative impact, but some do not. Virtual education can be the second case. Under the severe restriction of contacting others to prevent the spreading of the disease, virtual education grabs a chance to be utilized in most educational organizations. Even people who did not favor virtual learning and did not have experience of it face the situation where there is no choice but to receive virtual learning. In this situation, they might be able to find positive aspects of it. On the contrary, the probability of finding virtual education's problems that have not been detected also increases by the increment of the frequency of virtual learning. Remote work and virtual education are likely to continue, albeit less intensely than at the pandemic's peak. As the pandemic has brought the future to the present with communication, professional development, and technology in medical education, virtual learning may have influenced a shift in people's perception of medical education during the pandemic. This leads to examining the changes in perception of virtual medical education to identify a need to improve the quality of virtual medical education.

Literature Review

The pandemic has had profound impacts on medical education globally. One of the fields that has the greatest resistance toward virtual learning is medical education. Many medical schools have adapted to virtual classes by altering their real-time clinical exposure to online modes (Rose, 2020; Ferrel & Ryan, 2020). Some schools echoed concerns over clinical experience and assessment during these times because practice-based learning is the backbone of medical education. Inevitably, most medical students' clinical placements stopped, and learning in classrooms and laboratories was cancelled, leaving students to continue their studies remotely (Ahmed, Allaf, & Elghazaly, 2020; Ferrel & Ryan, 2020; Sahi, P. K., Mishra, D., & Singh, T., 2020). Medical professionals also have cancelled their training to cope with pressures from cases of COVID-19, which is considered fundamental in their education, training, and progression (Gill, Whitehead, & Wondimagegn, 2020; Rajab, Gazal, & Alkattan, 2020; Sandars & Patel, 2020).

The emergence of social media platforms can be traced back to 1996, but truly emerged in their modern form in the early 2000s (Singh, 2019). With platforms such as LinkedIn, Facebook, Twitter, Instagram, YouTube, and more, the number of worldwide users has jumped from almost a billion in 2010 to 2.62 billion in 2018 (McFadden, 2018; Singh, 2019). Social media platforms allow users to share knowledge simultaneously (Toprak v.d., 2009, pp.28-84). In this vain, social media opens up new possibilities to understand people's perception (Selwyn, 2007). Studies show that Twitter, which is one of the most commonly used worldwide social network tools, is used all around the world as the most chosen educational tool (Elavasky, Mislan, & Elavsky, 2011; Feliz, Ricoy, & Feliz, 2015; Junco, Heiberger, & Loken, 2010; Park, 2013; Rinoldo, Tapp, & Laverie, 2011; and Zainal & Deni, 2015). This research study was conducted to analyze the use of Twitter.

The worldwide COVID-19 pandemic crippled health systems and closed schools across the globe. This challenge makes educational organizations, educators, and instructional designers fall into problematic situations. As we move forwards, a COVID-19 generation of students and doctors need to continue their education and training. While pandemics have historically created challenges, identifying these challenges is the first step in converting them into opportunities.

Purpose of the Study

The pandemic has provided an opportunity to investigate whether learners or education providers in medical education have positive or negative perceptions, or whether there is a change in their perceptions for virtual learning. These investigations would allow us to identify their needs in virtual medical education, the reason why they do not favor virtual learning can be analyzed, and the way to break through the problems. This study, thus, aims to examine the changes in perception toward virtual medical education after COVID-19 pandemic in the U.S. using tweets. This study has the following research questions: (a) What are the topical patterns in tweets related to virtual medical education over the past five years?; and (b) What are the trajectories in the characteristics (i.e., frequency, polarity, and subjectivity) of the topical patterns on virtual medical education?

Analytical Framework

Given the nature of our research questions, the study adopted a quantitative research method to yield a comprehensive analysis. In this study, the change in perception toward virtual education of stakeholders in medical education organizations in the U.S. were examined by Twitter data (tweets). The topic modeling method is useful to find how many topics in the collected tweets dataset and what do the topics represent. Cross-validation is a type of model validation technique for assessing how the results of a statistical analysis generalize to an independent data set. Each topic can be allocated to individual tweets, and the change in the number of tweets in the topics for each year can be inspected to find the change in people's interest. Also, sentiment analysis is useful to find the changes in people's polarity and subjectivities in a period. The segment analysis allows to systematically identify, extract, quantify, and study affective states and subjective information. Lastly, longitudinal cluster analysis is useful to find groups that share trends among trajectories of the topics over a certain time.

Method

Data Collection

In order to extract tweets that represent the perception toward virtual medical education, predefined keywords that can be categorized in four primary ways (virtual: 10, medical: 30, education: 24, and region: US) and Twitter Premium API were used. Two software tools, Python 3.8 and Microsoft Visual Studio 2019, were used to execute this process iteratively for one year after the national emergency declaration for the COVID-19 pandemic (March 13th, 2020 - March 12nd 2021) and the period of four years precedent the declaration (March 13th, 2016 - March 12nd 2020). A total of 6,542 tweets over five years were collected.

Preprocessing

Before analysis, by following steps, the extracted dataset was cleaned to increase the clarity of the result. First, tweets that were too short thereby often meaningless (i.e., < 60 characters) and were therefore excluded. Second, using the NLTK library (Bird et al., 2009) in Python, stop words such as pronouns, prepositions, and postpositions were filtered out. Finally, 'term frequency-inverse document frequency (tf–idf) was used to select words that frequently occur but are not shared across all tweets.

Data Analysis

Three primary analysis methods, the Latent Dirichlet Allocation (LDA; Blei, Ng, & Jordan, 2003), sentiment analysis, and longitudinal cluster analysis, were employed to examine the changes in perception of stakeholders of medical fields toward virtual education after the COVID-19 pandemic situation.

Latent Dirichlet allocation (LDA; Blei et al., 2003), so-called topic modeling, one of the unsupervised machine learning techniques, was employed to identify topics in a set of documents (e.g., tweets). The topic models (Grün & Hornik, 2011) package in R (R Core Team, 2020) and RStudio 1.3.1056 (RStudio Team, 2020) was utilized for LDA. As the initial stage of LDA, the optimal number of topics were determined (Zhao et al., 2015) using the ldatuning package (Nikita & Chaney, 2020). Figure 1 shows three different metrics of Griffiths (2004), Cao and Juan (2009), and Arun (2010). They all suggested 20—30 topics as optimally emerging in the tweets—i.e., with 20 - 30 topics, the Griffith value was maximized (approaching 1), and the Cao and Juan and Arun values were stabilized.

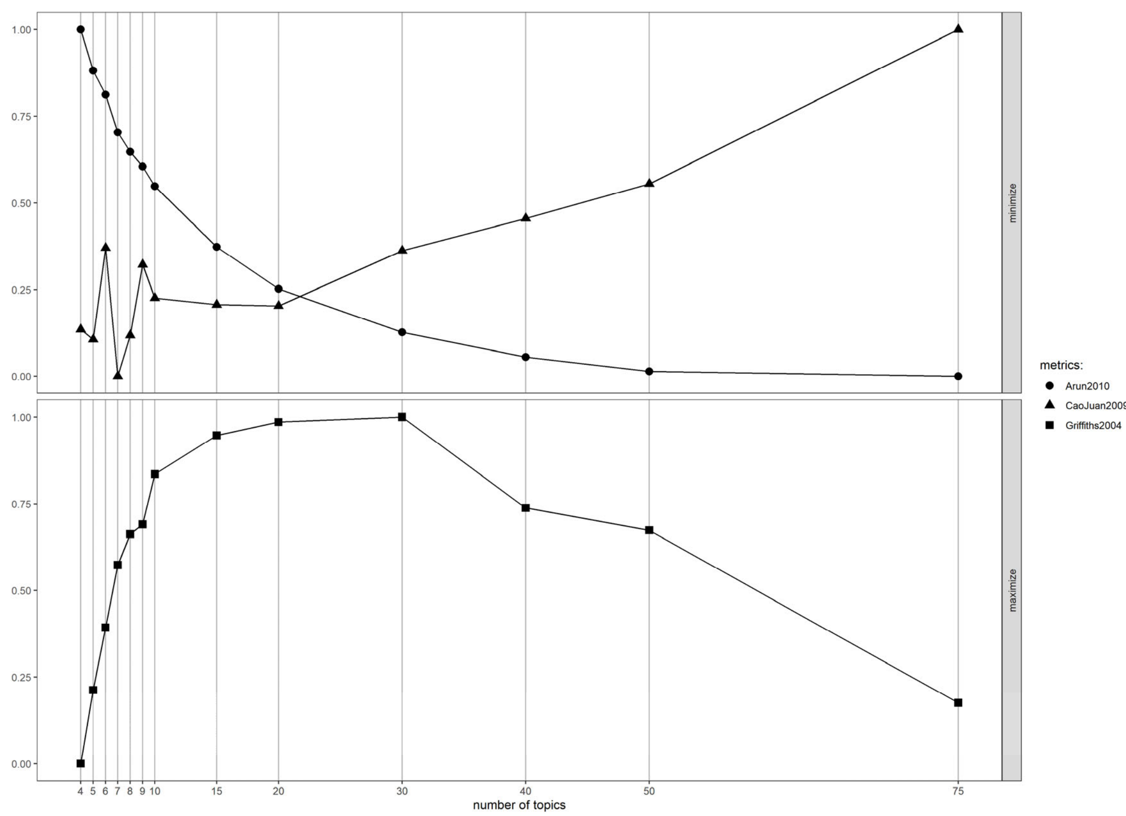

Figure 1. The optimal number of topics identified by different metrics

Sentiment analysis was conducted for finding the authors' emotional states using the TextBlob library in Python. Specifically, the tweets having a subjectivity value (range from 0 to 1) greater than or equals to .50 were classified as subjective otherwise categorized as objective. The polarity and subjectivity were estimated for each tweet. Polarity has ranged from –1 to +1, and the tweets were classified by the polarity value— negative (polarity ≤ –0.30), neutral (–0.30 < polarity < 0.30), and positive (polarity ≥ 0.30).

The longitudinal cluster analysis, an unsupervised machine learning technique, could find groups that share trends (such as increasing, decreasing, steady) among trajectories of the topics over a certain time without human intervention. When there are too many objects to be compared, it is more effective and easier for interpreting that grouping objects to a smaller number of groups according to characteristics (trends) and compare the groups rather than directly comparing each object; therefore, in this study, longitudinal cluster analysis was hired to find clusters of the topics that share unique joint-trajectories across the 5-years. The changes in three factors 1) frequency of the topics, 2) averages of polarities, and 3) average of subjectivities over the 5-year period were used to group topics, using kml (Genolini et al., 2013) package.

Findings

LDA found 30 topics from the extracted tweets, but only 24 were clearly interpretable and relevant to the study of those topics; therefore, the remaining 6 topics and their words were excluded from the analysis. The 24 selected topics were labeled as remote learning (topic 1), support (topic 2), virtual program (topic 3), family support (topic 4), nursing program (topic 5), social distance and safe (topic 6), Benefits (topic 7), anatomy class (topic 8), mental health (topic 9), negative feeling (topic 10), professional development (topic 11), clinical study (topic 12), course assignment (topic 13), registration (topic 14), virtual meeting (topic 15), virtual medical lab (topic 16), quality of education (topic 17), stakeholders (topic 18), gratefulness of online learning (topic 19), working from home(topic 20), nursing classes (topic 21), hybrid modality (topic 22), virtual commencement (topic 23), medical training/certification (topic 24).

From the sentimental and longitudinal cluster analyses, four clusters are identified with 19 selected topics using their trajectories for the 5 years. The longitudinal clustering algorithm found three, four, and two unique trajectories of topics from the frequencies of the topic, polarities, and subjectivities across the 5-years, respectively (see Figure 2, 3, & 4).

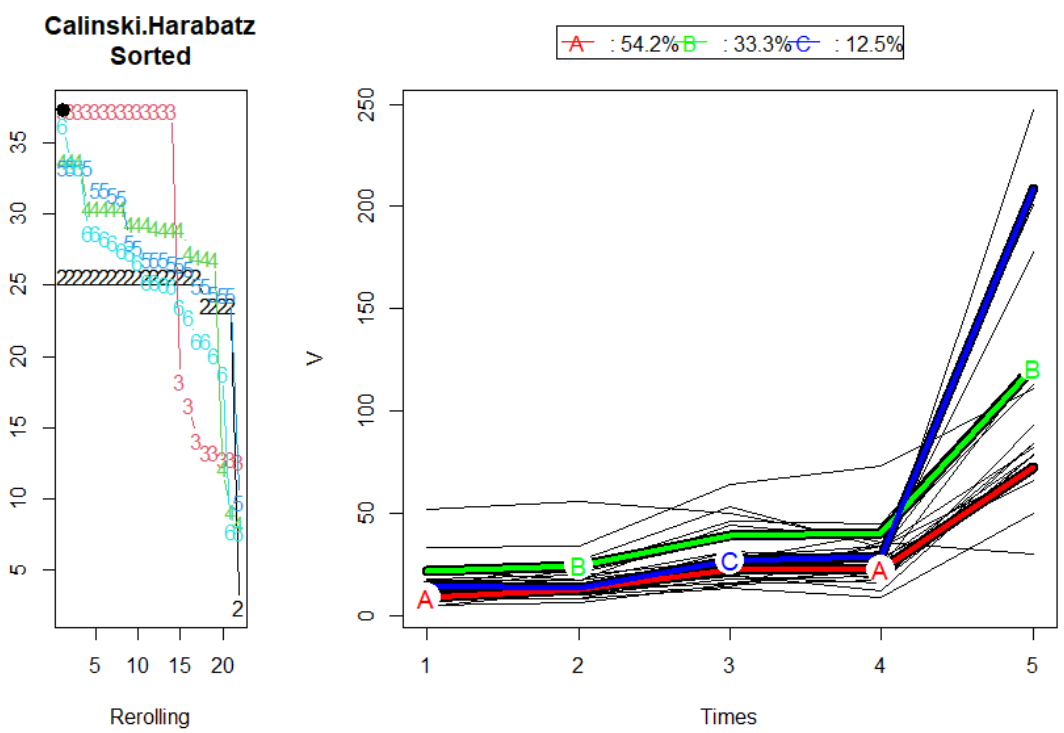

Figure 2. Graphs for results of longitudinal cluster analysis by frequency

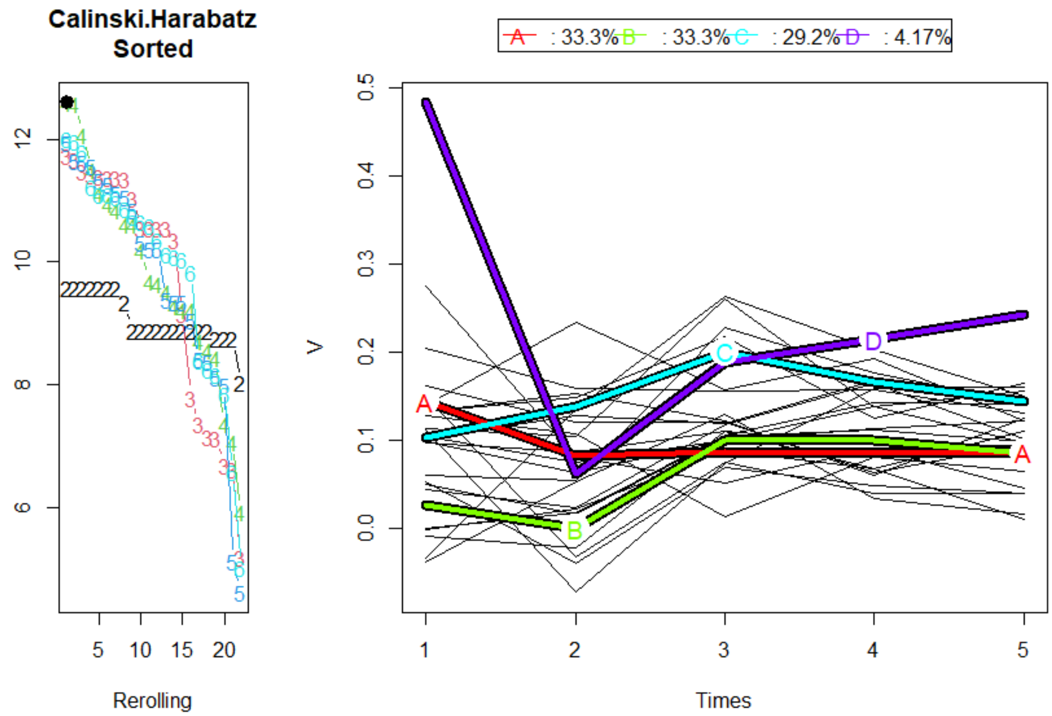

Figure 3. Graphs for results of longitudinal cluster analysis by polarity

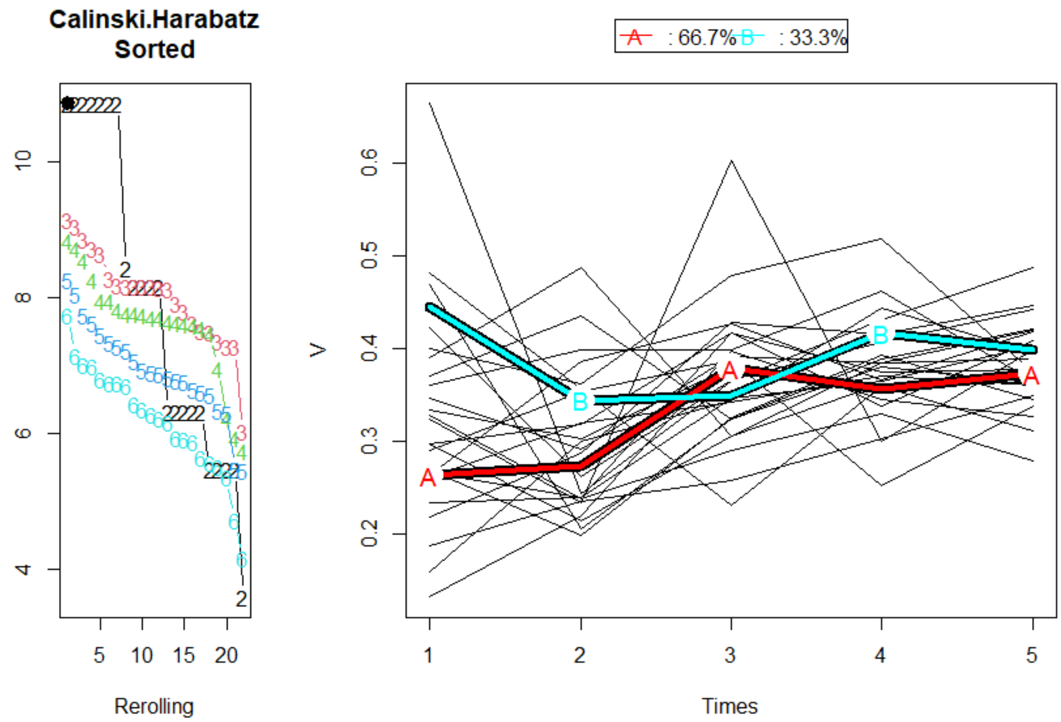

Figure 4. Graphs for results of longitudinal cluster analysis by subjectivity

In frequency, cluster A (54.2%) showed the tendency of increasing frequency after the pandemic but compared to other clusters, the slope was gradual. As the graph shows, cluster B (33.3%) reported medium steeper increasing trend after the pandemic. The most dramatic trend—an exponential increase after the pandemic—was displayed in cluster C (12.5%).

In polarity, the algorithm found four clusters. Cluser A (33.3%) shows mostly steady polarity around 0.1 after dropping in 2017, which means the topics belong to cluster A had been written in a neutral mood in the period. Cluster B (33.3%) and C (29,2%) displayed slight decrease tendencies after 2020, so it can be said that there were a few more negative tweets on the topics after the pandemic. However, cluster C has noticeably more positive tweets compared to cluster B during the whole period. Cluster D showed a very unique pattern that it was rapidly dropping in 2017, after then has been increasing regardless of the pandemic. Thus, it might be guessed that something probably happened in 2017 that influenced in the negative direction to cluster D which has only one topic, gratefulness about online learning (topic 19). However, after 2017, the mood has been moving toward a positive direction.

In subjectivity, only two clusters were suggested. As through the pandemic, cluster A (66.7%) showed a slight increase pattern that means people wrote more subjective tweets, and cluster B (33.3%) illustrated the opposite result (more objective viewpoint). All identified clusters by three factors and their topics are shown in Table 1. The cluster names were arbitrary assigned by the algorithm. For instance, Cluster A found by frequency is different from cluster A identified by polarity.

Table 2. *Identified clusters and their topics by frequency, polarity, and subjectivity.*

Cluster	By frequency (Topic #)	By polarity (Topic #)	By subjectivity (Topic #)
A	professional development (11) clinical study (12) course assignment (13) registration (14) virtual meeting (15) virtual medical lab (16) quality of online course (17) stakeholders (18) gratefulness about online learning (19) working from home (20) hybrid modality (22) virtual commencement (23) medical training/certification (24)	remote learning (1) benefits (7) anatomy class (8) clinical study (12) virtual medical lab (16) quality of online course (17) working from home (20) medical training/certification (24)	remote learning (1) support (2) virtual program (3) nursing programs (5) benefits (7) anatomy class (8) mental health crisis service and support (9) professional development (11) clinical study (12) course assignment (13) registration (14) virtual meeting (15) virtual medical lab (16) working from home (20) virtual commencement (23) medical training/certification (24)
B	support (2) virtual program (3) family support (4) nursing program (5) benefits (7) anatomy class (8)	virtual program (3) social distance and safe (6) mental health crisis service and support (9) negative feeling (10) course assignment (13) stakeholders (18)	family support (4) social distance and safe (6) negative feeling (10) quality of online course (17) stakeholders (18) gratefulness about online learning (19)

	negative feeling (10) nursing classes (21)	nursing classes (21) hybrid modality (22)	nursing classes (21) hybrid modality (22)
C	remote learning (1) social distancing and safe (6) mental health crisis service and support (9)	support (2) family support (4) nursing programs (5) Professional development (11) registration (14) virtual meeting (15) virtual commencement (23)	-
D	-	gratefulness about online learning (19)	-

Discussion and Implications

The study examined the changes in perception of medical fields toward virtual education on tweets for the last five years including the COVID-19 pandemic period. Across 24 selected topics, major themes were identified in conversations in virtual medical education fields. First, medical education schools were unprepared and ill-equipped to handle the overwhelming obstacles and immediate needs (e.g., new planning, support, accessibility, mental health crisis, registration). Second, COVID-19 has accelerated reshaping of medical education (e.g., leadership, safe learning environment, clinical study, group activities, virtual lab, quality of online course, hybrid). Third, virtual medical education was not only challenging for the last 12 months but they also look to the future possibilities (e.g., benefits, professional development, experiential learning).

The results from the sentimental and longitudinal cluster analyses identified clusters and their topics by frequency, polarity, and subjectivity. The trajectories information over the past five years helps explain a need in virtual medical education and the reason whether they favor virtual learning or not. Virtual education has grown rapidly since the pandemic. Medical education has also seen a rapid increase over the past year. As formal medical education had to move to remote format for social distancing, mental health crisis also increased (Cluster C). In order to reduce these side effects, many supports have also been increasing (Cluster B).

The polarity of the tweets over the period shows that there were more positive statements, especially since the pandemic of gratefulness for virtual education has seen the highest rise in positivity on average. Conversely, there was a slight decline in other clusters (Clusters A, B, & C, indicating many difficulties and challenges for virtual medical education.

Lastly, the subjectivity. Subjective statements about virtual medical education generally represent personal opinions, feelings, or judgments, while objective ones represent factual information. Both clusters identified were found to be subjective due to the nature of expressions on social media. In the past, there was a large difference between Cluster A and B, but recently the gap has been gradually narrowing. Social safety, negative emotions, and family support have been expressed a more subjective expression on their tweets. On the other hand, as for the general views of virtual medical education, the effort was reflected by increasing objectivity during the period (Cluster A).

Virtual education continues, although less intense than at the peak of the pandemic. We hope that this study contributes to broadening our understanding of virtual medical education. By understanding their needs for virtual medical education, we expect to be connected in a concrete way to how to solve problems in virtual medical education.

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