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Vaccine hesitancy, parental concerns, and COVID-19 in a digital leisure context: Implications for out-of-school time

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ABSTRACT
Due to the increasing prevalence of parental vaccine hesitancy or refusal, it is important to understand parental motives for vaccine hesitancy. This study examines social media conversations and commentaries regarding concerns about parenting, vaccine hesitancy, and the COVID-19 pandemic within an in-person leisure and recreation context: out-of-school time (OST) programs. A generative, probabilistic Bayesian machine learning model was used to analyze 31,925 tweets and group them into seven categories: *Government*, *Feelings*, *School*, *Public Health*, *Christmas*, *Risk and Safety*, and *Families*. As a result, recommendations for research and practice are discussed in connection to both OST programs and digital leisure, including a diverse range of vaccine hesitancy motivations related to children and parents, communication management strategies for OST professionals, and the impact of the politization of leisure in a digital leisure context.

KEYWORDS
Digital leisure; machine-learning; vaccine hesitancy; out-of-school time

The COVID-19 pandemic highlighted social media's role in public health communication, and how rapidly misinformation can spread online (Himelein-Wachowiak et al., 2021). As the COVID-19 vaccines emerged in the fall of 2020, there appeared a seemingly vast network of misinformation including false cures: "*Florida Family Indicted for Selling Toxic Bleach as Fake 'Miracle' Cure for Covid-19 and Other Serious Diseases, and for Violating Court Orders*" (U.S. Food and Drug Administration, 2021), incorrect information regarding vaccine side effects: "*Chicago doctors battle COVID vaccine misinformation: No, the shot won't make you infertile, and other myths*" (Chase, 2021), and conspiracy theories: "*Why it's not possible for the Covid vaccines to contain a magnetic tracking chip that connects to 5 G*" (Tarasov, 2021). Social media is an increasingly common setting for studies of digital leisure (Lehman, 2021; Mayoh, 2019; Silk et al., 2016) which is defined as the unstructured time spent in digital environments, online, or using digital technologies (Silk et al., 2016). This increase in research in digital spaces reflects leisure sciences' interdisciplinary relation to public health (Liu et al., 2022; Young et al., 2021) and youth development (Quarmby et al., 2019). However, examination of vaccine hesitancy and parental concerns in a digital leisure context (i.e., social media), within the shifting nature of a global pandemic and in connection to the related

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leisure and recreation context of out-of-school time (OST) is less evident within the current research space.

While the social media environment may look different than traditional leisure contexts, digital leisure offers insight and connection into in-person leisure environments (Ho & Cho, 2021). Through an application of uses and gratifications theory (i.e., a subfield of media effects studies), Ho and Cho (2021) examined the role of social media in the leisure behavior of new mothers, not only as a leisure activity in and of itself as a source of entertainment, but also as a source of connection to in-person leisure activities. Digital leisure serves a dual purpose in both entertainment and connection–useful not only for new mothers' navigating their new roles, but for any individual experiencing leisure constraints, including but not limited to the ramifications of a global pandemic on leisure (Du et al., 2021). In addition to the constraints on in-person leisure activities, the COVID-19 pandemic also fostered growing parental discontent surrounding vaccines, as research regarding vaccine hesitancy continues to evolve (Kricorian et al., 2021; Lockyer et al., 2021). Moreover, conversations on social media platforms may be amplifying concerns about vaccines and vaccine hesitancy (Capurro et al., 2018; Kata, 2012; Sharevski et al., 2020).

The motives and attitudes toward vaccines are relevant to the OST industry, specifically in the context of a global pandemic (Ambrose et al., 2019; Garst et al., 2021). While some OST programs were able to operate initially in 2020 (Blaisdell et al., 2020), many programs were compelled to shut down (Szablewski et al., 2020); due in part to ambiguous or non-existent guidance at federal, state, and organizational levels. As OST organizations prepared for another summer of programming amidst the pandemic in 2021, the development and approval of COVID-19 vaccines offered a lifeline to programmers and the communities they served (Rodrigues & Plotkin, 2020). However, increasing rates of vaccine hesitancy acted as a potential threat to a return to a pre-pandemic state (e.g., a return to in-person programs), in addition to communication struggles regarding parental concerns about COVID-19. Given the lack of in-person data collection opportunities during the pandemic, and that online spaces contribute to a significant portion of anti-vaccine (i.e., anti-vaxx) and vaccine-hesitant discourse (Jenkins & Moreno, 2020; Puri et al., 2020), the present study examines social media conversations and commentaries regarding concerns about parenting, vaccine hesitancy, and the COVID-19 pandemic within one in-person leisure and recreation context: OST programs.

Literature review

Vaccine hesitancy and refusal are complex issues identified within public health literature and by healthcare professionals (Larson et al., 2014). Parents who exhibit hesitancy toward vaccinations for their children may reject one or two vaccines, or seek to delay immunization.(Estep & Greenberg, 2020; Wightman et al., 2011). Origins (e.g., causes, determinants) of vaccine hesitancy are numerous across the literature, with primary factors including social or cultural differences, contextual issues, and medical or pharmaceutical specific issues (Dubé et al., 2013). Some research suggests up to 40% of medical providers would dismiss families who refuse routine vaccinations (Flanagan-Klygis et al., 2005) which may only increase parental anxiety and mistrust associated with vaccines (Leask et al., 2014). Emerging research has illustrated that vaccine hesitancy may harm the operations of OST programming (Garst et al., 2021).

Broad evidence supports the benefits of OST experiences for youth, including social-emotional skill development (Warner et al., 2021), nature connectedness and spirituality (Heintzman, 2009), career readiness and socioemotional development (Gagnon & Sandoval, 2020), and sociopolitical development of youth (Brown et al., 2018). From an economic perspective OST programs contribute significantly to both regional and national economies, with the direct impact of the summer camp industry in the Northeastern United States totaling over $3.2 billion (ACA New England & ACA New York and New Jersey, 2017), with over 7.7 million children involved in after-school activities nationally (Afterschool Alliance, 2020). As out-of-school-time (OST) experiences for youth diversify beyond traditional sleepaway summer camps to incorporate youth sports, after-school programs, and health-related interventions, OST program providers face evolving challenges as was demonstrated by the COVID-19 pandemic.

Parental vaccine hesitancy in the context of out-of-school time programs

Because OST providers are responsible for the safety, health, and well-being of youth under their care and supervision, OST providers are required to follow numerous health, safety and risk management policies and procedures (American Camp Association, 2020; Association for Camp Nursing, 2017). Maintaining accurate and updated documentation is an important dimension of such health and safety protocols, and this documentation generally includes information about health history, required medications, special medical needs, and immunization. Efforts to bolster immunization requirements within the context of OST programs has intensified to strengthen youth harm reduction strategies (Ambrose et al., 2019; Francis & Francis, 2020; Garst et al., 2021). However, increases in the spread of infectious diseases at the community level has been an ongoing challenge faced by OST providers seeking to keep their program sites free of communicable diseases. Indeed, infectious diseases considered to be eradicated in the United States as a result of childhood vaccinations (i.e., measles, polio, pertussis), were already on the rise prior to the COVID-19 pandemic due (in part) to increasing rates of parental vaccinee hesitancy (Phadke et al., 2016; Wightman et al., 2011). Vaccine hesitancy or refusal, for example hesitating to or refusing to have one's child vaccinated as directed by public health agencies, has become a critical issue as the COVID-19 pandemic evolved and as vaccines emerged to stop the spread (Oliver et al., 2021). Parental vaccine hesitancy is rooted in parental anxiety about their child's health (Garst et al., 2021). Given the evidence of challenges OST providers face in communicating effectively with parents prior to COVID-19 (Garst et al., 2020), the COVID-19 pandemic likely exacerbated existing parental anxiety and the communication struggles between parents and OST providers.

Vaccine hesitancy and/or refusal is referred to as a "cultural epidemic" (McIntosh et al., 2016, p. 248) with regard to children's healthcare, as parents are heavily influenced by sociocultural factors outside of the healthcare setting, including historic discrimination (Quinn et al., 2019), mistrust or worry toward healthcare systems or government agencies (Wiley et al., 2020), and individualism (Estep & Greenberg, 2020).

These factors represent a perceived assumption of risk mitigation guided by parental choice and control rather than a doctor's orders and/or guidance (Sadaf et al., 2013). This presumption of parental expertise exemplifies the other previously mentioned factors, as parents are choosing what is best for their child based on their own research (e.g., individualism), experiences (e.g., discrimination), and fears (e.g., mistrust or worry) rather than adhering to established vaccine schedules recommended by public health authorities. Put simply, some parents are more willing to assume risks related to not vaccinating their child based on their own expertise, rather than that of their healthcare providers. Personal belief exemptions from routine vaccinations (e.g., non-medical exemptions) exacerbate the influence of vaccine-hesitancy on public health (Quinn et al., 2019). Within this shift toward individualism in parental medical decision making, one environment that is frequently associated with increasing vaccine hesitancy is the context of social media.

Social media in the context of parental vaccine hesitancy

Parents and caregivers with questions or concerns about vaccines often seek information online and face outrage (e.g., belittling or berating) from pro-vaccine voices, thus shutting down a communication channel to safely educate themselves about vaccination and immunization (Capurro et al., 2018). For example, a common vector of vaccine disinformation is Andrew Wakefield's widely discredited study (Horton, 2004) which falsely linked the Measles, Mumps, and Rubella (i.e., MMR) vaccine to increasing rates of autism (McKeever et al., 2016; Yuan et al., 2019). The growth of vaccine-hesitant communities, both in-person (Attwell & Smith, 2017) and online (Jenkins & Moreno, 2020; Puri et al., 2020), has also spurred negative reactions from pro-vaccine voices (Capurro et al., 2018). For instance, a measles outbreak traced to Disneyland in California led to 125 confirmed cases in 2015; 45% of these cases were among unvaccinated children (Zipprich et al., 2015). Subsequent media coverage in both the United States and Canada vilified those infected and involved, as deliberately remaining unvaccinated was described as intellectual, moral, societal, and ethical parental failure (Capurro et al., 2018; Yuan et al., 2019).

As noted earlier, social media is a key catalyst and/or setting for the growing levels of vaccine-hesitancy, as parents and caregivers look to online resources to investigate their concerns regarding their child's health-care needs, and frequently find settings rife with misinformation (Park et al., 2016; Schmidt et al., 2018). These social media spaces function as communities (Jenkins & Moreno, 2020) and are especially important in the face of contention or vilification of vaccine hesitancy from more mainstream media sources, as many vaccine-hesitant or vaccine-refusing parents attest to the pressure or isolation they feel from more mainstream (e.g., pro-vaccine) culture (Attwell et al., 2018). Digital leisure offers a framework in which to contextualize this vaccine hesitancy issue further, specifically for leisure and recreation researchers and professionals, where emerging techniques such as web-scraping and machine learning, can help capture, analyze, and communicate the complex, challenging, and large datasets associated with these vaccine hesitant communities.

Study purpose

The present study examines conversations and commentaries occurring on the social media site Twitter regarding parental concerns, vaccine hesitancy, and COVID-19 in connection to a related in-person leisure and recreation context: OST programs serving youth. The subsequent analysis of web-scraped data through a machine-learning technique is paired with recommendations for the leisure and recreation fields regarding the use of social media data and machine-learning as an emergent research context, in combination with recommendations for OST professionals in regard to strategies for parent communication during a pandemic.

Method

Machine-learning is an intersection between computational science, statistics, and communication, defined as an automation of learning process algorithms (Mitchell, 1997). Put simply, machine-learning allows computers to learn and be taught, and then to generate predictions based on prior and incoming data (Landers et al., 2016; Lantz, 2019). Prior and incoming data refers to the testing and training datasets discussed at a later point in the following sections, used to validate a machine learning model. For example, a search engine's autocomplete feature can be eerily correct or humorously off the mark, but both instances are examples of machine learning as the search engine uses prior search history and current search trends to generate autocomplete results (Goldberg et al., 2021). Machine learning enables a research team to complete previously insurmountable tasks. A human may be able to reasonably analyze the content of 200 tweets, but 200,000 would likely be untenable. Several types of machine learning models exist, all of which require some input (i.e., data) to then calculate an output (Burger, 2018). This study focuses on classification models designed for text data, specifically Latent Dirichlet Allocation (LDA; Blei et al., 2003).

Data collection

Data were collected using the Twitter Application Programming Interface (API) between December 14, 2020 and December 21, 2020 (see Figure 1). Consisting of 126,068 tweets, the data were obtained through the use of the rtweet package v0.4.0 (Kearney, 2019) in R v.1.3.1056 (R Core Team, 2021). Collection through the API was filtered in two ways: (1) date, as only tweets sent within the previous seven days are available to the API and (2) keywords with Boolean operators. The keywords utilized within this study were child OR parent OR kid, AND vaccine OR covid OR corona, notated in R script as child OR parent OR kid (vaccine OR covid OR corona). As the study focused on children and parents in a digital leisure space within the context of vaccines and the COVID-19 pandemic, it was important to have both sets of Boolean operators, to ensure that tweets collected included both topic areas (Allem et al., 2018; Dahal et al., 2019). As data collection occurred on social media, keywords were chosen based on their subjective usage within the Twitter platform and reflected a more colloquial tone.

The Twitter API streams a random sample of 1% of all public tweets from the last seven days at the time of data collection (Dahal et al., 2019). The research team

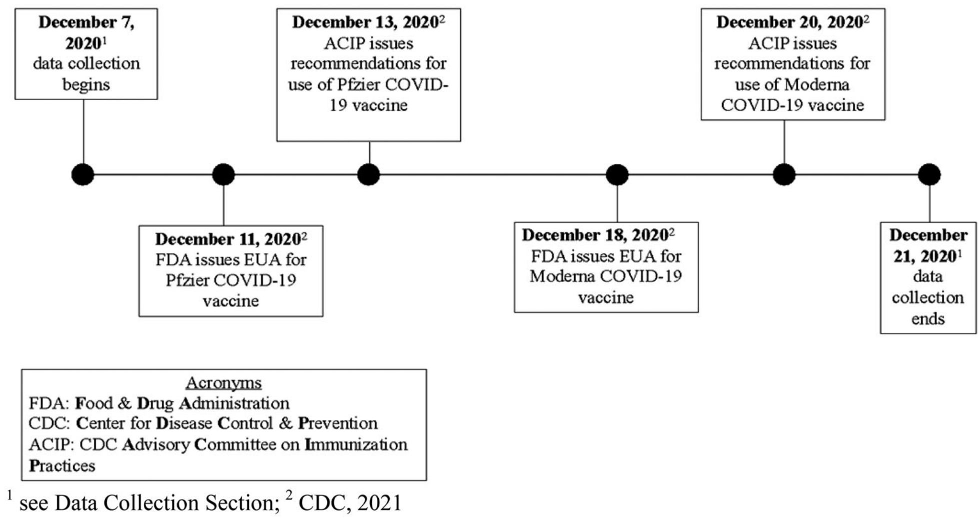

Figure 1. Data collection and immunization authorization timeline.

members were impacted by rate limits in the API, which restricted "pulls" (e.g., collected tweets from the web-scrape itself) to 18,000 tweets per 15-minute window (Kearney, 2019). Therefore, the tweets available for data collection and subsequent analysis were not only limited by keywords and Boolean operators, but also by the Twitter API process (i.e., rate limit restrictions).

Data cleaning

Prior to the analyses, the data were cleaned and preprocessed in RStudio to facilitate both usability and study replication, following the recommendations of Jacobi et al. (2016) and Maier et al. (2018) (see also Figure 2). Specifically, data cleaning involved removing retweets (i.e., non-unique tweets, similar to a copy and paste or email forward), as well as ensuring the remaining tweets were interpretable to human researchers rather than software. Additionally, ASCII (computer encoded symbols), URLs or external links, and line breaks were also removed at the cleaning stage. Due to the size of the initial dataset ($N = 126{,}068$ tweets), data cleaning was done using RStudio on a super computing cluster, to facilitate more efficient computation (Palmetto Cluster, 2021).

Data pre-processing

After the data were imported from the Twitter API, it was converted to a data frame, with the full text of all tweets intact. After data cleaning, data pre-processing (see Figure 2) prepared the dataset for analysis by converting the cleaned file into the different R data-storage objects. This data pre-processing and object conversion is fundamental to topic modeling (i.e., the method for classifying collections of documents or text; see also Silge & Robinson, 2020), as converting from a data frame, to a corpus, to a document-feature matrix, to a document-term matrix facilitates further analysis using both the

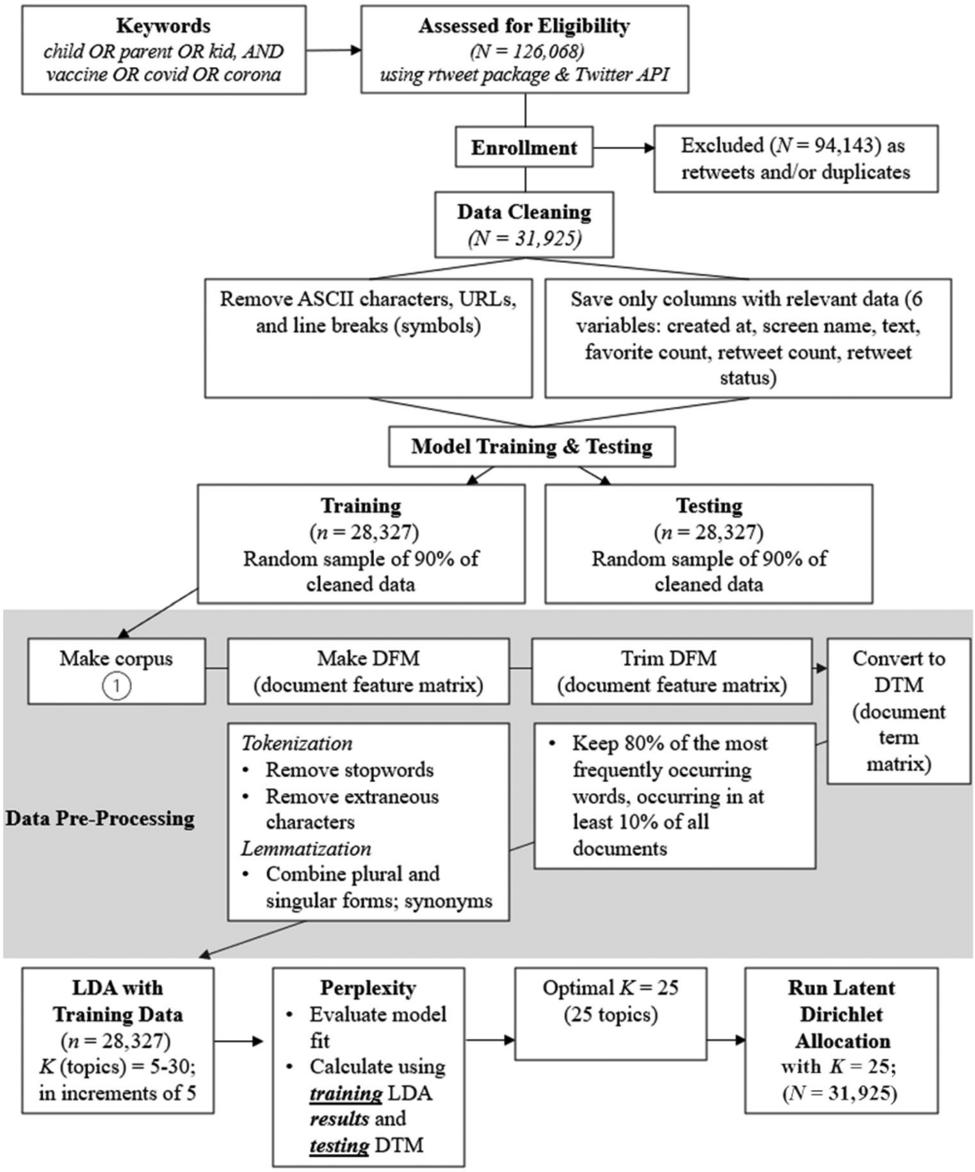

Figure 2. Study method (data flow).

quanteda (v.2.1.2; Benoit et al., 2018) and topicmodels (v.0.2.12) packages in R, as well as subsequent visualization using the LDAvis package (v.0.3.2; Sievert & Shirley, 2014).

Analyses

Latent Dirichlet Allocation

Latent Dirichlet Allocation (LDA) is a generative, probabilistic Bayesian model which identifies topics across a collection of data (Blei et al., 2003; Ostrowski, 2015). In the context of LDA, "generative" refers to the input-output nature of the model where there is generation of content or output after the model is run. Similarly, "probabilistic" refers to the structure of the algorithm employed by an LDA model; which is best explained using the "bag of words" analogy (Blei, 2012; Ostrowski, 2015; Rodriguez & Storer, 2020; Silge & Robinson, 2020). A bag of words assumption on a basic level assumes that the position of the words in a sentence are equal, and therefore can be analyzed as random versus in a sentence structured order.

Model training and testing

At a broad level, machine-learning and more specifically, LDA, are Bayesian approaches: a process of training and testing models (i.e., updating based on priors–-prior probability distributions) in order to reach conclusions that most accurately reflect the data (Blei et al., 2003). Logistically, this analytic approach (i.e., to develop priors) requires splitting the dataset into a training sample and testing sample. In the present study, the dataset of 31,925 tweets was split into the training sample ($n = 28{,}733$) and the testing sample ($n = 3{,}193$). The two sample groups were randomly assigned to reduce potential biases and misinterpretation. Training the model (e.g., the LDA) on a sample of 90% percent of the data (Maier et al., 2018) facilitated interpretation on a large portion of the data. Furthermore, using the LDA model performed on training data (e.g., 90% sample) with data that were reserved for model testing (e.g., testing data; 10% of overall cleaned sample) allowed us to evaluate model perplexity. Comparable to an R^2 in linear regression (Jacobi et al., 2016) perplexity is a measure of goodness of model fit (e.g., the ratio of unexplained/explained variance). Higher R^2 levels (i.e., closer to one), typically indicate a stronger association between the dependent variable and predictor variable(s). Conversely, higher levels of perplexity indicate more error, therefore a lower value of perplexity is preferable.

Model perplexity

Perplexity was calculated using the perplexity function in the topicmodels package (v. 0.2-12; Grün & Hornik, 2011). Specifically, six models at $K = 5$, $K = 10$, $K = 15$, $K = 20$, $K = 25$, and $K = 30$ (K = model parameter that defines number of topics) were evaluated utilizing an approach recommended by Jacobi et al. (2016) and Maier et al. (2018): a randomly selected 10% of the overall data set using the test data ($n = 3{,}193$) that had been randomly assigned and reserved for comparison (see Figure 3). In utilizing the testing data to calculate the perplexity of the six fitted models, we were able to evaluate how well the proposed model was able to generate predictions relative to unexplained variance (i.e., goodness of fit) (Maier et al., 2018). The model with the lowest perplexity score utilized twenty-five topics (see Figure 3). As such, the twenty-five-topic model was selected for analysis and interpretation using the full dataset ($N = 31{,}925$) (Blei et al., 2003).

Model interpretation

Model interpretation was the phase where the researchers and theoretical grounding informed the analytic choices and interpretation of model results. Topics can be named and further categorized based on the research teams' interpretation of the top terms

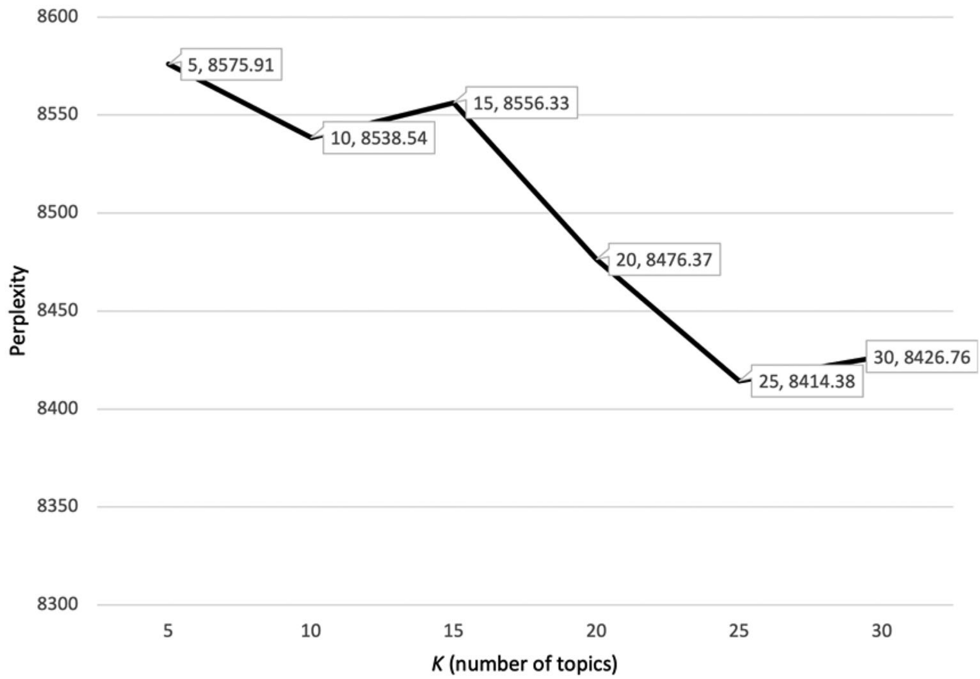

Figure 3. Perplexity graph to evaluate model fit.

occurring in each topic, based on the topic probability distribution per word ratio (Blei et al., 2003; Jacobi et al., 2016). However, this frequency-based approach can increase difficulty in interpretation, as key terms can appear across multiple topics (Sievert & Shirley, 2014). As such a blended approach was utilized which combined word-count frequencies with a relevance metric (discussed below), as well as researcher-led investigation back into the data (i.e., full text of tweets) to identify the words in context. After selecting and running a model with twenty-five topics as described in the perplexity analysis, words which were most relevant (discussed below) were used to characterize each topic. To aid in practical application and translation, 25 topics were grouped into seven categories based on their content and connection to the overall study purpose. Topics and subsequent categories were named by an expert review panel in partnership with the authors.

Relevance

The relevance metric reordered the top terms for each topic based on overall corpus frequency (Maier et al., 2018; Sievert & Shirley, 2014). Relevance was set using λ as a weighting parameter set between 0 and 1, and optimized at 0.6 (Sievert & Shirley, 2014). When λ is set to 1, the top words reflect the pure probability, while when $\lambda = 0$, the top words are the most specific words to that topic (e.g., occurring less frequently in the rest of the corpus) (Maier et al., 2018; Sievert & Shirley, 2014). The use of the visualization package LDAvis (v.0.3.2) aided in interpretation, not only in the use of the relevance metric to identify top words more specific to each topic, but also in visualizing the distribution of top terms across the entire corpus (the visualization for the top 30 terms in the $K = 25$ model are available at: https://bit.ly/vaccineLDAvis).

Results

Twenty-five latent topics were identified from the LDA ($K = 25$) model and were sorted into seven categories: *Government*, *Feelings*, *School*, *Public health*, *Christmas*, *Risk and Safety*, and *Families* for additional interpretability (see Table 1).

Most relevant terms

The LDA model with $K = 25$ resulted in twenty-five topics. For practical interpretability, topics were grouped together taking the most relevant terms into account (see Table 1). The visualization was crucial in grouping topics together, as the interconnectedness of the topics was apparent and traceable. Mathematical coherence (e.g., $K = 25$ as the most mathematically sound option for the ideal number of topics) often does not parallel the need for practical interpretability (Maier et al., 2018), therefore grouping topics together by categories facilitates interpretation not only for research, but for the creation of recommendations for practitioners. In exploring the visualizations of each topic in this category (Sievert & Shirley, 2014), and looking at representative tweets, recommendations were developed to address the issues raised from the topics. Recommendations for practice (e.g., evaluation of conversations and commentary occurring on Twitter about parents, vaccines, and COVID-19) and recommendations for research (e.g., evaluation of LDA as a technique for leisure research) are explored in the discussion section.

Table 1. Topics with most relevant terms.

Category	Topics	Most relevant words
Government	1: COVID-19 assistance	Care, relief, families, workers, food
	2: Trump	Trump, realdonaldtrump, white, man, god
	3: Support seeking	Support, hope, rise, share, economy
	7: Economic impact	Deal, closed, big, time, small
	8: Jobs	Work, due, job, time, single
	13: Poverty	Government, public, poverty, years, lives
Feelings	4: Mixed emotions	Good, day, feel, bad, make
	19: Positive	Great, play, making, real, left
	20: Adverse communication	Put, lot, things, talking, poor
	23: Upset	Fuck, sick, give, gonna, won
School	6: Teachers & students	Teacher, student, learning, person, part
	24: Masks	Year, mask, wear, masks, primary
	9: Abuse worries	Die, abuse, rate, community, number
Public health	5: Symptoms	Positive, tested, case, symptoms, staff
	12: Pregnancy	Woman, baby, age, pregnant, pfzier
	17: Vaccine history	Polio, anti, remember, doctor, disease
	15: Patient medical care	Live, medical, line, heart, patients
	18: Health issues	Health, life, issues, early, immune
Christmas	14: Christmas cheer	Home, Christmas, safe, stay, love
	25: Christmas restrictions	Worry, santa, are, worried, restrictions
Risk & safety	11: Safety concerns	Safety, important, learn, call, visit
	16: Risk of spread	Risk, young, spread, stop, virus
	21: Long-term & global effects	Long, world, social, effects, term
Family	10: Fathers & sons	Back, dad, son, lost, friend
	22: Mothers	Family, mom, flu, court, test

School

The *School* category (see Table 2) included three of the latent topics identified in the LDA ($K = 25$), characterized initially by the top relevant words in Table 1. Terms associated with this category ranged from “teacher” and “student” to “abuse” and “masks,” and reflected concerns related to those most involved in education (e.g., teachers and students) and the concerns associated with education during a pandemic, specifically mask usage and lack of child neglect and abuse prevention due to the lack of in-person education.

Public health

The *Public health* category (see Table 3) included five of the latent topics identified in the LDA, characterized initially by the top relevant words in Table 1. Terms associated with this category ranged from “pregnancy” and “women” to “polio” and “doctor,” reflective of the diverse range of concerns from parents regarding the COVID-19 pandemic.

Risk and safety

The *Risk and safety* category (see Table 4) included three of the latent topics identified in the LDA, characterized initially by the top relevant words in Table 1. Terms associated with this category ranged from “safety” and “risk” to “worry” and “virus.” This category reiterated concerns in both the *Schools* and the *Families* categories, from language reflecting vaccine-hesitancy (Estep & Greenberg, 2020) as well as associated risks in returning to in-person education (ElSaheli-Elhage, 2020). This category is an excellent example of the connectivity between topics in an LDA model, as terms are not mutually exclusive to individual topics.

Table 2. School category representative tweets.

Zero kids in OR and WA have died of covid. Death by suicide is 120x more likely to happen to a kid than death by seasonal influenzas. Zero educators in WA have died of covid. Average age of teacher is 40. No one will die! #openourschools
Why would the parents of my mother’s student - who felt sick last week - wait FOUR DAYS to tell her (and the school) the kid tested POSITIVE for Covid. It feels like the scene in every zombie movie when the bitten person goes “I’m fine, I’m totally not bitten” #StayHomeSaveLives

Table 3. Public health category representative tweets.

COVID-19: Pregnant women allowed partner at birth under new coronavirus rules. This is how sheep like we have become. “Allowed”? Fuck off! You’d need to fight me to stop me being at the birth of my child!
Do you realize that it usually takes a bit of time for babies to show symptoms of autism after being born? Stop acting like a vaccine causes autism. Go talk to people who lived through smallpox or polio. All of these diseases are vaccinated for a reason. Protect your child.

Table 4. Risk and safety category representative tweets.

Nothing like sacrificing your precious child to a vaccine with NO safety data for pregnant, breastfeeding mothers or for rapidly growing children. Sure hope he’s not harmed
I’m a single parent dad and I would rather b at home with my kids [than] put them at risk in school which every week u [hear] a new case of Covid. Only parents that seem 2 want to put the kids in school are the 1s that don’t want to stop working or don’t want 2 b stuck at home [with] them.

Families

The *Families* category (see Table 5) included two of the latent topics identified in the LDA, characterized initially by the top relevant words in Table 1. Terms associated with this category ranged from “family” and “mom” to “son” and “court.” This category reflected concerns raised in other studies of the effects of the COVID-19 pandemic on families; exacerbating issues associated with single parent homes and the difficulties in work-life balance (Fisher et al., 2020).

Government

The *Government* category (see Table 6) included six of the latent topics identified in the LDA characterized initially by the top relevant words in Table 1. Terms associated with this category ranged from “realdonaldtrump” (i.e., former U.S. president Donald Trump’s personal Twitter username) to concerns related to economic relief and job security.

Feelings

The *Feelings* category (see Table 7) included four of the latent topics identified in the LDA characterized initially by the top relevant words in Table 1. Terms associated with this category ranged from “good” and “great,” to “fuck” and “bad,” indicative of the range of emotions associated with the cleaned dataset of tweets related to the COVID-19 pandemic, children, and parents.

Christmas

The *Christmas* category (see Table 8) included two of the latent topics identified in the LDA, characterized initially by the top relevant words in Table 1. Terms associated with

Table 5. Families category representative tweets.

My abuser owes nearly $16k to my children. Stopped paying 1.5 yrs ago … but state retirement he receives still sends his money, but has refused to cooperate with the child support office & court order & take CS out of his retirement. Covid canceled our court date in March.
Yeah cause Justin time-travelled back to August and renegotiated the vaccine deals because Erin criticized him on Twitter three days ago. Did your mom drop you on your head as a kid?

Table 6. Government category representative tweets.

It isnt the dems who want YOU to be free an in charge of your own life no that is Trump. IT WASNT THE DEMS WHO SIGNED AN E.O. TO STOP CHILD TRAFFIKING IT WAS TRUMP. It wasnt the dems who wanted to give you a check for covid cuz they held it up but Trump wanted to. Its not the *(tweet ends)*
@FLOTUS husband pulled food, housing subsidies. Let COVID run rampant, costing millions their jobs & lets McConnell delay any relief. GOP is the reason there are so many needy children. Just go away.

Table 7. Feelings category representative tweets.

I’m not taking no vaccine and neither is my child. **Fuck**[a] these pharmaceutical companies.
My kid had tumor surgery postponed 6+ months — it’s unlikely to be cancer and we’re **good**, but others haven’t been that lucky.
Happened all around the world to millions. The people who decided to deny care due to Covid restrictions are genocidal sociopaths.

[a]The term “fuck” was not modified for presentation in text in order to preserve the tweet in it’s original form.

Table 8. Christmas category representative tweets.

In case you're wondering how the end of term is going, I'm in bits listening to the kids speaking to **Santa** with [username] on R5. Their questions for **Santa**: When will coronavirus end, and can you give an extra present to children who lost a parent to Covid?
Please God get us to Friday so I can get my kid out of school. The covid anxiety is too much. We were supposed to be going on a massive two week sunny vacation this Christmas. Now just looking forward to staying in and getting to know our new games and puzzles.

this category ranged from "Christmas" and "santa" to "worry" and "restrictions." The appearance of two latent topics related to Christmas is not surprising when you consider the time of data collection (see Figure 1). This category speaks the most to the concerns of children, evident in a tweet that contained the relevant keywords from the topics in this category; the user spoke about the end of the term (e.g., academic semester) and the concerns of children related to holiday celebrations during the COVID-19 pandemic.

Discussion

As a study focused on the examination of vaccine hesitancy, parental concerns, and COVID-19 in a digital leisure context in connection with OST programs, findings are discussed here in relation to OST programs and professionals. Some Twitter users spoke of their concerns about overall health and wellness, from both a maternal health and pediatric perspective (*Public health* category; Table 3). Vaccine safety and parenting concerns, specifically thoughts regarding vaccine safety for children, as well as the risks associated with in-person education (explored in depth in the *School* category in Table 2) were evident across topics, yet concentrated in the *Risk and safety* category (Table 4). Concerns related to governmental aid and tension were also shared (*Governmen*t category, Table 6). Concerns in general related to COVID-19 and vaccines were further exemplified in the *Feelings* category (Table 7). The influence of the period during which data were collected was also evident, as users expressed concerns related to holiday celebrations, from Santa Claus' visits during a pandemic to lamentation regarding the loss of previous traditions (*Christmas* category; Table 8). Other concerns related to the difficulties COVID-19 caused families were also apparent (*Families* category; Table 5).

Recommendations for practice

As instant communication has become more normative, OST administrators have reported increasing struggles to maintain a balance between customer service through social media and offering programming for youth (Kingery et al., 2012). It is with these lenses that the interpretation of the *School, Public Health, Risk and safety,* and *Parent* and *Families* categories were structured around communication recommendations for OST professionals running programs during and following the COVID-19 pandemic.

Drawing on OST programs' relation to education, the *School* category reflected the varied responses collected as part of this study. Some stakeholders focused on the lack of training educators received in the transition to online education (ElSaheli-Elhage, 2020), while others were concerned about students' minimal access to social services and the associated consequences (Lancker & Parolin, 2020). Mental health and suicide rates were also a continued concern (Reger et al., 2020), as healthcare workers worried about the convergence of conditions all typically associated with higher suicide rates (e.g., growth of unemployment, political turmoil, health crises). Some OST program participants may have been fully in-person all school year, while some were fully online. Within this environment of increasing mental, emotional, and social health (MESH) concerns, OST professionals should consider mental health resources to better support the needs of youth and staff (see Alliance for Camp Health, 2022).

From a risk mitigation perspective, explored in the *Risk and safety* category, OST professionals should consider: What is your program's immunization policy management strategy? Who is checking forms, or attestations? Or do you have a policy to begin with? Policies are not the same as procedures, and the logistics of public health at OST programs can be very complicated. Policy management is key to public health and safety in OST programs. OST professionals should plan on how they are going to communicate their new COVID policies and procedures to parents, and then develop responses for their staff to use when talking with parents, using the Twitter responses collected as part of this study as examples of potential feelings and frustrations.

As noted previously, the COVID-19 pandemic exacerbated existing health disparities, felt not only by those contracting COVID-19 but by others suffering from clinic closures and difficulties of telehealth, including pregnant women (Bruno et al., 2021). Support during labor and delivery (e.g., partner in the room) is associated with better perinatal outcomes (Bruno et al., 2021), and lack of support due to COVID-19 procedures (e.g., partner not allowed in the delivery room) was not well-received by the public. The initial COVID-19 vaccine trials did not include pregnant women, and this lack of evidence fueled concerns that the vaccines were not safe for this population (Farrell et al., 2020). With specific regard to families, spouses planning on divorcing were unable to do so, leaving their families in a holding pattern (Lebow, 2020). Even when court proceedings were able to be held in an online format, the resources required to do so were often lacking and further disrupted the process (Baldwin et al., 2020). Humor was also present, in keeping with studies associating humor as a coping mechanism during COVID-19 (Bischetti et al., 2021), as people sought stimulation from online spaces for their daily interactions (Barnes et al., 2021).

Recommendations for research

As recreation and leisure scientists exploring a novel method through a digital leisure lens, further contextualized by vaccine hesitancy, the *Government, Feelings,* and *Christmas* categories did not aid in an examination of conversations and commentary occurring on Twitter about parents, vaccines, and COVID-19. However, these categories did present issues relevant to the study from a methods perspective. From a governmental perspective, how do recreation and leisure scientists integrate the politicization of leisure into their study design? More work is needed to understand the role of politics and governmental agencies' role in digital leisure spaces, and how that may change the nature of the online space.

The *Feelings* and *Christmas* categories exemplified how Twitter data are complex, both in its raw form as incomplete sentences with grammatical errors and misspelling, as well as the use of slang and other characteristics specific to social media (e.g., the @ symbol noting a reply to another user, or # followed by words which may or may not relate to the tweet's overall message). While this messiness did result in several stages of data cleaning and data pre-processing (Figure 2), it also indicates the authenticity of the data. Opinions, jokes, complaints, and debates regarding parents, children, vaccines, and COVID-19 all indicate how multidimensional these issues are.

For example, during the model training phase (see Figure 2) several words continued to show up within the top 30 most relevant terms for a topic, but were seemingly nonsense (e.g., "goibibo" and "ik4ea9l4kr"). Instead of taking a more conservative approach and removing the terms from the cleaned dataset, we were able to use both R and the original data saved as a spreadsheet, to trace where these terms came from. All tweets within the dataset were publicly available through the Twitter API and using the full tweet containing "goibibo" and "ik4ea9l4kr," we were able to make sense of what appeared to be a misspelling. Goibibo is an Indian airline and hotel reservation website, and "ik4ea9l4kr" corresponds to a specific reservation identification code. Customers used Twitter to communicate with the travel company after COVID-19 canceled their travel plans. To aid in model interpretation, "ik4ea9l4kr" was removed but "goibibo" was kept and was one of the top 30 terms for Topic 9 (see LDAvis visualization: https://bit.ly/vaccineLDAvis).

Research at the frontier: Limitations, challenges, and future directions

Social media data can present serious data analysis challenges (Stieglitz et al., 2018). Even with keywords, our model output included a range of text data, from curse words to Christmas wishes. This is why model interpretation is the beginning, not the conclusion to LDA (Blei et al., 2003), particularly for social scientists. In many studies utilizing LDA for data analysis, the model interpretation includes perplexity evaluation and top-terms, concluding in a discussion regarding whether or not the model was able to identify interpretable topics (see Allem et al., 2018; Dahal et al., 2019; Jacobi et al., 2016; Maier et al., 2018). While this perplexity is not terribly surprising given the exploratory nature of LDA, it does leave social scientists somewhat unfulfilled. Prior to data collection, we investigated the topic areas surrounding the selected keywords: parenting styles, vaccine-hesitancy, and COVID-19, following a similar process used in traditional experimental design. These a priori analyses did inform our interpretation of the LDA, but more work is needed regarding LDA interpretation, and the implications of such interpretation, within the social sciences (Sievert & Shirely, 2014).

Interpretation can prove difficult after running an LDA model even after calculating perplexity and establishing an optimal value for K (see Figure 3). While an optimal value for the number of topics (K) was established for this study, the calculation of perplexity still involved decision-making by the researchers, to run training models with a range of K values to use for the perplexity evaluation. In addition to parameter estimation challenges, data cleaning and pre-processing resulted in several interesting situations, in which the researchers were the mechanism used to decide what to keep or what to remove.

Future directions for this research topic span methodological and content-specific contexts, as continuation of this project could involve replication of leisure studies with social media data and/or machine learning methodologies, or further exploring the relation between in-person and digital leisure spaces as it relates to recreation and OST programs.

Conclusion

Addressing 21st century issues requires 21st century skills. The pandemic brought many leisure and recreation behaviors and programs to a halt, and a vaccine provides significant relief to many that a return to normalcy might be close. However, the consequences of vaccine hesitancy persist as a critical factor in the continuation of the COVID-19 pandemic, limiting the operation of many OST programs. Vaccine hesitancy and parental concerns span a variety of issues demonstrated through this study's use of digital leisure focused data collection, from governmental failures to familial strife and educational turmoil. The recommendations for OST professionals highlighted in this study provide real comments and critiques on a range of issues related to vaccine hesitancy and parental concerns, in the hope that program providers can use these recommendations to inform future post-COVID-19 program operation. In addition, the recommendations for research offer leisure and recreation scholars, consistent with the advice of Wood et al. (2019), ways to advance digital leisure research by collaborating with our computer science colleagues.

Emergent issues may span multiple disciplines, lived experiences, and environments, and a machine-learning approach helps to continue providing research that serves our communities best in a changing landscape. Transdisciplinary research, or research that combines knowledge from multiple sources, sectors, and experiences (Wada et al., 2021) embodies both the successes and shortcomings of this study. A machine-learning approach affects not only data analysis but study design and development, as researchers utilize testing and training data to better infer results indicative of the problem in its entirety. Machine-learning offers social scientists a critical capacity to explore concerns and commentaries occurring in digital leisure spaces, from social media, web-based platforms, large Internet-based datasets, and more. As with any worthwhile research study, we are left with more questions than answers, and we look forward to exploring these questions further through a machine-learning approach to transdisciplinary leisure research.

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Ethics statement

At the time of data collection, the Clemson University's Institutional Review Board did not require review of publicly accessible data. All data were anonymized prior to analysis, and the analyses conducted did not focus on user-level information.

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