Alcohol Marketing on Twitter During the COVID-19 Pandemic: Theme Identification, Prevalence Comparison, and Sentiment Analysis

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ABSTRACT

Introduction: During the COVID-19 pandemic, increased social media use and targeted digital marketing by alcohol companies potentially heightened consumer exposure to alcohol advertising. This study aimed to identify themes used in tweets by alcohol brands early in the pandemic, determine if the prevalence of these themes differed across time, and characterize the sentiment used in the themes.

Method: We analyzed 5,872 tweets from 11 prominent alcohol companies on Twitter between January 2019 and July 2021. Themes were identified using a BERTopic modeling approach informed by the Themes and Topics system. We leveraged the GPT-4o Large Language Model for topic interpretation, alongside human evaluation for thematic validation. Theme prevalence was assessed by comparing tweets from pre- (January 2019 - January 2020), peri- (March 2020 - May 2020), and post-pandemic response periods (June 2020 - July 2021) using proportional z-tests. Sentiment analysis using Linguistic Inquiry and Word Count (LIWC) assessed cognitive, emotional, and excitative characteristics of thematic content, informed by the Differential Susceptibility to Media Effects Model (DSMM).

Results: Five primary themes emerged: Alcohol Delivery and Isolation Drinking, Restaurant Support, Social Media Promotions, Sports, and Gaming. Alcohol Delivery and Isolation Drinking, Restaurant Support, and Social Media Promotions themes had significantly higher prevalence during the peri-pandemic response period compared to pre- and post-pandemic response periods ($p<0.003$). Alcohol Delivery and Isolation Drinking, and Social Media Promotions had significantly higher prevalence during the post-pandemic response period compared to the pre-pandemic response period ($p<0.003$). The Sports and Gaming themes remained statistically stable across periods. Sentiment analysis revealed that Alcohol Delivery and Isolation Drinking,

Restaurant Support, and Social Media Promotions utilized stronger emotional and excitative appeals, while Sports and Gaming were more cognitively oriented and neutral.

Discussion: The findings suggest that alcohol companies adopted marketing content on social media that emphasized emotionally engaging and action-oriented messaging about ordering delivery alcohol, drinking while staying home, engaging with alcohol brands on social media, and supporting restaurants; and that some of this content remained in use at higher rates after the early pandemic period. Future research linking these themes with consumer behavior is needed. Understanding these dynamics is essential to developing effective policies and protective measures against exploitative marketing strategies during future crises.

INTRODUCTION

The alcohol industry has a history of adapting its marketing strategies during crisis events and major societal changes, such as wars, natural disasters, and economic downturns. For example, after World War II, returning soldiers brought back drinking habits shaped by their wartime experiences (Herrmann et al., 1996; Shephard, 2001; National World War II Museum, 2021). In response, alcohol companies used patriotic-themed advertisements in print and broadcast media to target this group (Samuel, 2001; Scott, 2009; Richards, 2022). During this time, the country also experienced increases in consumption of alcohol per capita (a trend that extended into the 1960's and accelerated in the 1970's) (Landberg, 2009). Such instances of strategic adaptation - numerous throughout history - raise concerns about the how the alcohol industry may use crisis events to sustain and expand its market.

Emerging evidence suggests that this pattern of adaptive alcohol marketing continued during the COVID-19 pandemic (Foundation for Alcohol Research & Education, 2020; Colbert et al., 2020; Gerritsen, et al., 2021; Huckle et al., 2021; Martino et al., 2021; Kennedy et al., 2022). Further, widespread stay-at-home orders confined the great majority of Americans to home, and pushed many aspects of daily life online, which led to a surge in social media usage during the early pandemic (Fernandez et al., 2020; Pandey et al., 2020; Al-Habaibeh et al., 2021; Meier et al., 2021; Pham et al., 2022, Cho et al., 2023; Kelly et al., 2023). The confluence of increased social media usage and targeted marketing by alcohol companies during the pandemic may have resulted in greater exposure to alcohol marketing. Further, alcohol-related mortality (e.g., death from acute alcohol poisoning) and morbidity (e.g., instances of liver-related hospitalizations) both increased during the early pandemic (Grossman et al., 2020; Koob et al., 2020; Foster et al., 2021; Moon et al., 2021; White et al., 2022). Given the well-established link between alcohol marketing exposure and increased alcohol use (Anderson et al., 2009; Smith et al., 2009; Jernigan et al., 2017; Curtis et al., 2018; Hendriks et al., 2021; Alhabash et al., 2022), this rise in marketing exposure may have contributed to higher levels of consumption, elevating the risk of negative health outcomes. This is especially concerning given that a large proportion of social media users are youth or young adults, populations that are both particularly vulnerable to marketing and, in some cases, under the legal drinking age (Arnett, 2014; Packer et al., 2022). Lastly, this marketing adaptation is important to

study because it demonstrates a recurring pattern of adaptation in response to crisis events; thus, there is opportunity for future action to mitigate harmful marketing adaptation during future crises.

Research examining alcohol marketing on social media during the COVID-19 pandemic has identified several emergent themes, including isolation drinking (e.g., intensified encouragement of home drinking), community support (e.g., virtual gatherings with alcohol present), promotion of hygiene (e.g., social distancing/washing hands/wearing masks while consuming alcohol), home or curbside delivery (e.g., using a web application or calling orders in), and promotion of corporate social responsibility (e.g., alcohol brands making sanitization products or calling for support of essential job workers) (Martino et al., 2021; Gerritsen et al., 2021). However, this research is not extensive, has a relatively small timeframe under investigation (i.e., only during the early lockdown phases of the pandemic without comparing to pre- or post- time periods), is limited in the number and types of advertisements, has only been conducted in a few countries around the world, and lacks sufficient information beyond broad themes/topics.

Given these limitations in the existing literature, there is a need to validate and expand upon previous findings using different datasets and methodologies. It is also crucial to test if these themes differed across time so that we can quantify the degree to which these themes were adapted specifically to COVID-related conditions. Further, previous research has largely focused on identifying themes without examining the linguistic structures and tones through which they were communicated. By incorporating sentiment analysis, we can investigate the tones in which these themes were conveyed - such as whether they were framed positively, negatively, or neutrally. This sentiment dimension is critical because linguistic structures such as emotional valence in marketing messages significantly influence consumer behavior (Vrtana, 2023; Zhao et al., 2025). Additionally, fitting these findings to a theoretical model can provide a more comprehensive understanding of how marketing may have reinforced or altered drinking behaviors during the pandemic. Reproducing and expanding upon this body of knowledge will not only strengthen existing evidence but also enhance our understanding of alcohol marketing strategies during times of crisis and their potential impacts.

Understanding the themes and sentiment contained within alcohol industry marketing content on social media during the COVID-19 pandemic and tracing the prevalence of these themes over time is crucial for public health. The alcohol industry's ability to rapidly adapt its messaging in response to the pandemic may have influenced drinking behaviors, shaped social norms around alcohol consumption, and exacerbated health risks. By examining these adaptations during a crisis event, the present study provides insight into the alcohol marketing playbook during such times which enables the development of mitigation strategies during future crises. Therefore, the purpose of the present study was two-fold. First, we validated previously documented themes used by the alcohol industry on social media during the COVID-19 pandemic and explored if additional themes were present. Using BERTopic (an advanced natural language model; Grootendorst, 2022), we analyzed marketing content on Twitter from alcohol companies targeting American consumers. We then analyzed if theme prevalence varied across three time periods: pre-pandemic (pre-; January 2019-

January 2020), early pandemic lockdown (peri-; March 2020-May 2020), and later pandemic phases (post-; June 2020-July 2021). Second, we explored the cognitive, emotional, and excitative composition of content related to these themes during the peri-pandemic phase (March-May 2020). This analysis utilized Linguistic Inquiry and Word Count (LIWC; Boyd et al., 2022), a text analysis tool that categorizes words into psychological and linguistic dimensions, alongside the Differential Susceptibility to Media Effects Model (DSMM; Valkenburg et al., 2013), which provides a framework for understanding how media messages influence individuals through various response states.

We hypothesized that themes related to isolation drinking, community support, hygiene promotion, delivery services, corporate social responsibility, and/or potentially other emerging themes would be more prevalent in alcohol brand tweets during the early phase of the COVID-19 pandemic (March-May 2020) compared to pre-pandemic and later pandemic periods. In utilizing LIWC and DSMM for sentiment analysis, this study is the first to explore the communications mechanisms underlying these themes, and thus this exploratory analysis has no specific hypothesis. Understanding the language used by the alcohol industry in social media marketing during the COVID-19 pandemic can inform public health policy and industry regulation, helping anticipate and mitigate similar marketing patterns during future crises.

METHOD

Twitter (now, X) emerged as a crucial communication platform during the COVID-19 pandemic, serving as a primary channel for information dissemination by government officials, health experts, and influential figures (Haman et al., 2020; Rufai et al., 2020). Beyond its role in pandemic communication, Twitter has established itself as a valuable resource for sociological research, offering real-time data from diverse users (Murthy, 2018). While Twitter's user demographic tends to skew toward younger, urban, and technologically engaged populations, this characteristic can be advantageous for specific research domains, particularly in analyzing digital communication patterns (Murthy, 2024). The platform's functionality as a digital public forum, combined with its active advertising environment makes it particularly suitable for research examining themes and sentiment among industry actors. Thus, the present study utilizes the platform Twitter for investigation.

Sample and Data Collection

The dataset comprised 5,872 tweets from 11 alcohol companies posted between January 2019 and July 2021, collected as part of the Prevention Research Lab at UT-Austin Twitter Marketing Study (PRL-TMS) (Table 1, Figure 1). PRL-TMS is a larger study of over 20,000 tweets from consumer product companies that aimed to document and describe marketing practices before, during, and after the onset of the COVID-19 pandemic; the data from the present study is a subset of alcohol companies. Alcohol companies were selected to include a variety of popular beverage types (i.e., beer, spirit, hard seltzer) with at least 10,000 followers. Data collection occurred between February

2021 and May 2022, with trained research assistants auditing verified Twitter profiles of selected alcohol companies. Research assistants systematically documented each tweet using a standardized data entry form. Weekly quality control reviews were conducted by a research coordinator, with regular team meetings including research assistants and the principal investigator. This study was reviewed by the UT-Austin institutional review board and determined to be non-human-subject research.

Company (n=11)	**Number of Tweets (n= 5,872)**	**Number of Followers (n=1,199,052) (single cross-section during study period)**
Bud Light	1,142	248,718
Truly Hard Seltzer	755	17,762
Malibu	695	46,824
Jägermeister	653	88,688
Samuel Adams Beer	594	81,707
Brooklyn Brewery	592	125,605
Jack Daniel's	535	198,896
Budweiser	409	220,140
Bacardi	233	99,687
Absolut Vodka	147	30,526
White Claw Hard Seltzer	117	40,499

Table 1. Summary of tweets included in Study 1

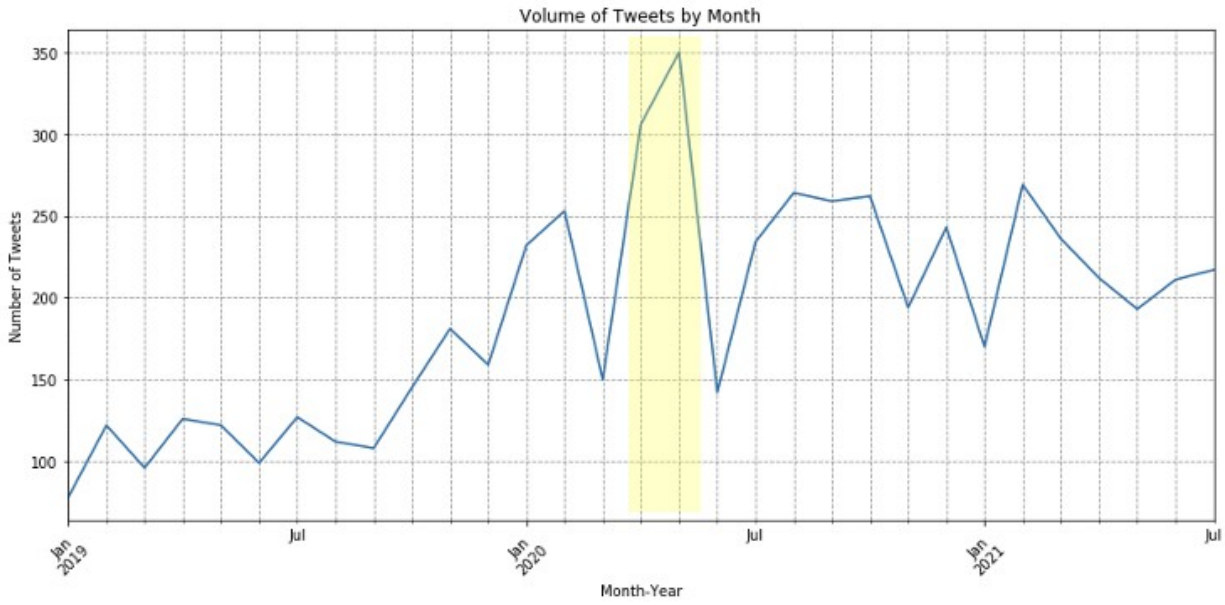


Figure 1. Month-over-month volume of tweets included in Study 1, COVID-19 Lockdown Period Highlighted (n= 5,872)

Analysis

The present study focused on coding the content of the alcohol company tweets using three primary analytic approaches: theme identification, prevalence comparison, and sentiment analysis.

Theme Identification

To identify themes, this study used the BERTopic algorithm (Grootendorst, 2022) for topic modeling, informed by the Themes and Topics framework (Gillies et al., 2022), wherein researchers apply human interpretation to identify themes from algorithm-derived topics. This framework is important because it helps ensure that the analysis is thoughtful and structured, rather than relying solely on automated results. It makes the findings easier to understand by organizing topics into broader themes that align with real-world concepts. It also adds depth by allowing researchers to consider the context and nuances of the data, reducing the risk of misinterpretation. BERTopic was chosen for its ability to create coherent topics and its flexibility in handling a varying number of topics (Grootendorst, 2022; Egger et al., 2022). The implementation was carried out using the BERTopic library in Python (version 3.9.12) (Python Software Foundation, 2022), and is available in Appendix 1.

The topic modeling process consisted of several key steps:

Tweet Preprocessing. Using Python (version 3.9.12) and the NLTK library (Bird et al., 2009), tweets underwent systematic preprocessing: removal of non-alphabetic characters, conversion to lowercase, tokenization using NLTK's *word_tokenize* function, and removal of standard and domain-specific stopwords (including brand terms and temporal references).

Embedding. The SentenceTransformer model "all-MiniLM-L6-v2" was used to convert the preprocessed tweets into dense vector representations. This model was selected for its balance of performance and computational efficiency (Wang et al., 2020).

Dimensionality Reduction. The high-dimensional embeddings were reduced to a lower-dimensional space using Uniform Manifold Approximation and Projection (UMAP) (McInnes et al., 2018). UMAP was configured with variable settings during hyperparameter fine tuning for the following: n_neighbors, n_components, min_dist, and metric, and uses the cosine metric.

Clustering. The reduced embeddings were clustered using the HDBSCAN algorithm (Campello et al., 2013). HDBSCAN was chosen for its ability to handle clusters of varying densities and its robustness to noise. The algorithm was configured with variable settings during hyperparameter fine tuning for min_cluster_size and uses the 'eom' (Excess of Mass) cluster selection method.

Topic Extraction. Topics were extracted from the clusters using a class-based TF-IDF approach (Ramos, 2003). This method helps identify the most representative words for each cluster while accounting for their relative importance across all clusters.

Topic Reduction. The initial topics were further refined through a topic reduction step, which aims to merge similar topics and remove less coherent ones (Grootendorst, 2022).

The BERTopic implementation was engineered to output several items for each iteration: a notation of hyperparameters that were used, a list of topics with representative words, and a coherence score. A hyperparameter optimization process was conducted using the BERTopic model to identify the optimal parameters for UMAP and HDBSCAN that yield the most coherent topics. The hyperparameter optimization process consisted of several key steps:

Parameter Space Definition. The parameter spaces for UMAP and HDBSCAN were defined with a range of values for each parameter (i.e., UPMAP = number of neighbors ranging from 5 to 35, number of components ranging from 3-10, minimum distance ranging from 0.01-0.5; HDBSCAN= min cluster size ranging from 5-35).

Iterations. A total of 50 iterations were performed. In each iteration, parameters were randomly sampled from the defined spaces for UMAP and HDBSCAN (Bergstra et al., 2012).

Topic Range Evaluation. For each hyperparameter set, models were evaluated with a range of maximum topic solutions from 2 to 25.

Model Evaluation. With 50 hyperparameter optimization iterations of 24 maximum topic solutions, a total of 1,200 models were evaluated. The coherence score for each model was calculated using the *c_v* coherence measure from Gensim's Coherence Model (Röder et al., 2015). This measure evaluates the degree of semantic similarity between high-scoring words in the topic.

Selection of Best Model. The parameter set and topic number that resulted in the highest coherence score was identified as the optimal configuration and selected as the final topic model. Using coherence score as the primary metric for model evaluation was chosen due to coherence score's correlation with human interpretability of topics (Newman et al., 2010) and use in similar research, including a recent study that used coherence score from BERTopic models to evaluate themes in tobacco marketing on social media (Lee et al., 2024).

The principal output from the BERTopic model is lists of topics defined by their representative words. These representative words must be evaluated for underlying semantic or contextual connections and synthesized into an understandable topic name. For example, a hypothetical representative word array of 'teacher, student, classroom, math, history, science' may be synthesized into the topic name 'education.' The synthesizing process was done using 5 thousand iterations of evaluation by the large language model (LLM) GPT-4o (OpenAI, 2024). Using LLMs to name topics is an emerging area of research, but preliminary research suggests that the approach is robust, and particularly good at naming topics without inherent bias that may result from a human with an a priori hypothesis naming the topics (Li et al., 2023). The process involved prompting the OpenAI API to name a topic based on the context of the topic words and looping through all identified topics with 5000 independent API pings for each. The LLM approach was democratic, meaning that in the case of multiple A.I. interpretations, the topic definition with the most "votes" out of 5000 iterations was selected. The implementation was carried out using the

OpenAI library in Python (version 3.9.12) (Python Software Foundation, 2022), and is available in Appendix 2.

Two researchers reviewed the BERTopic output, sample tweets that mapped onto each topic, and the LLM interpretation of the topics. These materials were viewed through the lens of the current literature regarding alcohol marketing on social media during the COVID-19 pandemic (e.g., Martino et al., 2021; Gerritsen et al., 2021). To transition from BERTopic-generated topics to qualitative thematic interpretations, the researchers first evaluated each topic by carefully examining representative tweets and comparing these against the machine-generated topic labels. This interpretive step involved assessing the coherence, meaning, and contextual relevance of topic terms provided by the LLM within the broader context of alcohol marketing literature. Researchers then considered whether the algorithmically-derived topic labels accurately captured the thematic essence of the sampled tweets or required refinement or adjustment.

Following this initial interpretation, the researchers collaboratively discussed the interpretations to establish preliminary thematic categories. This involved grouping topics based on conceptual similarity, shared underlying meanings, or relationships indicated by topic keywords and sample tweet content. For example, grouping the topics 'Virtual NFL Draft Party with Celebrity Hosts' and 'Home Sports Challenge Campaigns' into one 'Sports' theme. The grouping process allowed the researchers to identify overarching narratives, patterns, or messaging.

To validate the identified higher-order themes, the primary researcher performed additional checks, selecting representative tweets within each theme to ensure alignment between individual tweets, the LLM-generated labels, and the thematic interpretations derived by the researchers. The senior researcher reviewed and critiqued these thematic interpretations, providing a secondary check for interpretive validity. Differences in interpretation were reconciled through discussion, allowing the researchers to achieve consensus on clearly defined, higher-order themes that accurately reflected the underlying data.

Ultimately, this systematic and collaborative process of leveraging outputs from the BERTopic machine learning framework and integrating qualitative interpretation and validation aligned closely with methodological recommendations from the Theme and Topic system and established approaches in the existing literature (Gillies et al., 2022; Lee et al., 2024).

Prevalence Comparison

To evaluate the prevalence of themes across the pre- (January 2019 - January 2020), peri- (March 2020 - May 2020), and post-pandemic response (June 2020 - July 2021) periods, this study used GPT-4o (OpenAI, 2024) to classify all of the tweets during each of the specified periods into one of the identified themes, or "not belonging to any theme." Thus, every tweet received a classification. The process involved prompting the OpenAI API to classify text (i.e., a verbatim tweet) into a list of options (i.e., the identified themes + "not belonging to any theme"), and looping this procedure through an entire corpus of text (i.e., the dataset of tweets). LLMs are well suited for text

classification with recent review suggesting remarkable performance and versatility across many text classification tasks (Fields et al., 2024). Furthermore, during prompt engineering, researchers compared the LLM classifications to a sample of 250 human-labeled classifications to ensure >85% agreement. The implementation was carried out using the OpenAI library in Python (version 3.9.12) (Python Software Foundation, 2022), and is available in Appendix 3.

The proportions of tweets classified into each theme was calculated for each period (i.e., the number of tweets related to a theme divided by the total number of tweets in that period), and then periods were compared using proportional z-tests. Proportional z-tests were conducted comparing the pre-pandemic response period (January 2019 - January 2020) and the post-pandemic response period (June 2020 - July 2021) to the peri-pandemic response period (March 2020 - May 2020), using Stata 17 (StataCorp, 2021). Additionally, a proportional z-test was conducted comparing the pre-pandemic response period (January 2019 - January 2020) to the post-pandemic response period (June 2020 - July 2021). A Bonferroni correction was applied to the α value, adjusted proportionally to the number of identified themes multiplied by three, to account for the three tests conducted on each theme (Bland et al., 1995). The Bonferroni correction is justified because when conducting multiple statistical tests on a large dataset, the probability of observing at least one significant result by random chance alone increases dramatically with each additional test (known as the multiple comparisons problem), making it necessary to adjust the significance threshold to maintain the overall error rate at the desired level and prevent the proliferation of false positive findings that would otherwise occur when analyzing numerous variables simultaneously.

Sentiment Analysis

To describe the communication mechanisms used in these themes during the early lockdown phases of the pandemic as framed by the DSMM (Valkenburg et al., 2013), the entire collection of tweets for each theme was analyzed using LIWC (Chung et al., 2012; Boyd et al., 2022). LIWC functions as a linguistic magnifying glass, helping researchers understand the frequency of specific word types to gain insights into emotional states, social concerns, and thinking styles reflected in written content. The prominent cognitive, emotional, and excitative processes that LIWC yields were reported for each theme.

RESULTS

Sample Characteristics

Alcohol companies ranged in frequency of tweets from 117 to 1142 with an average of 534 tweets throughout the study period or approximately 17 tweets per month. Based on a single cross-sectional audit, the 11 companies had nearly 1.2 million Twitter followers around the early pandemic period (March/April 2020) (Table 1, Figure 1).

Topic Model Performance

Across 1,200 candidate models, the configuration with the following hyper parameters had the highest coherence score (0.768): iteration=25; UPMAP: number of neighbors=15, number of components=4, minimum distance=0.01; HDBSCAN= min cluster size=20; maximum topic solution=23 (Figure 2). This optimal configuration yielded seven topics.

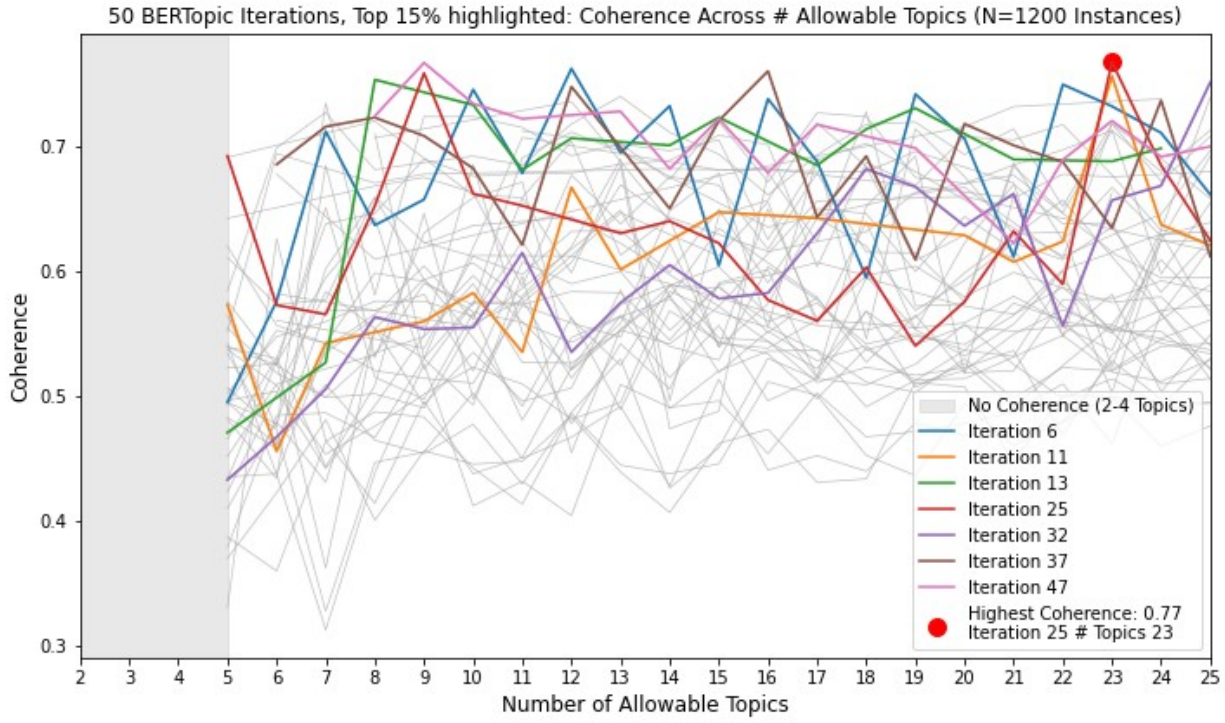


Figure 2. Topic Model performance

Theme Identification

The seven topics were synthesized using LLM and human interpretation into five themes: Alcohol Delivery and Isolation Drinking, Restaurant Support, Social Media Promotions, Sports, and Gaming (Table 2).

Prevalence Comparison

Given that five themes were identified, and three proportional tests were needed per theme, the alpha level was set at $\alpha=0.0033$ per the Bonferroni correction. The prevalence of Alcohol Delivery and Isolation Drinking tweets significantly increased from the pre- to peri-pandemic response period ($\Delta = 91.2\%$; $z=6.03$; $p<0.001$), significantly decreased from the peri- to post-pandemic response period ($\Delta = -31.6\%$; $z=-4.13$; $p<0.001$), but remained significantly higher comparing the post-pandemic to the pre-pandemic response period ($\Delta = 30.8\%$; $z=2.98$; $p=0.0029$). Similarly, Restaurant Support tweets significantly increased from the pre- to peri-pandemic response period ($\Delta = 189.5\%$; $z=4.89$; $p<0.001$), and significantly decreased from the peri- to post-pandemic

response period (Δ = -69.1%; z=-6.18; p<0.001). There was no significant difference between pre- and post-pandemic in Restaurant Support tweets (Δ = -30.8%; z=-0.50; p=0.62). Social Media Promotion tweets also significantly increased from the pre- to peri-pandemic response period (Δ = 150%; z=7.80; p<0.001), significantly decreased from the peri- to post-pandemic response period (Δ = -35.8%; z=-4.62; p<0.001), and the prevalence remained significantly higher in the post-pandemic period as compared to the pre-pandemic period (Δ = 60.6%; z=4.59; p<0.001). Sports and Gaming tweets did not differ across the any of the study periods (Sports pre- to peri-pandemic response period (Δ = 39%; z=2.59; p=0.01), peri- to post-pandemic response period (Δ = -21.9%; z=-2.17; p=0.03), and pre- to post-pandemic response period (Δ = 8.5%; z=0.083; p=0.41); Gaming pre- to peri- (Δ = 80.8%; z=1.80; p=0.07), peri- to post-(Δ = -20%; z=-0.79; p=0.43), and pre- to post- (Δ = -45.46%; z=1.40; p=0.16) (Table 3).

Theme	Constituent Topics (LLM Interpretation)	Representative Words	Example Tweets
Alcohol Delivery and Isolation Drinking	Pandemic Alcohol Delivery and Enjoyment	sunshine, drizly*, bit, day, order, happy, part, original, drink, get *delivery app company, acquired by Uber	Pro tip: Put your beer in a coffee mug and no one knows you're drinking on the video conference. Bring the beachside vibe *inside* with Malibu delivered to your door in 60 minutes or less Get $5 off your first order, courtesy of Drizly, with code 'Sunshine20'!
Restaurant Support	COVID-19 Restaurant Support and Donation Initiatives	restaurant, donate, support, worker, help, fund, restaurantstrong, strong, covid, donation	Yeah, we miss bars too. But we can still support restaurant and bar workers today. Order takeout and we'll buy your first round when they reopen. ATTENTION TWITTER: The people who serve us every day are depending on our support. Restaurants and bars, let us know that you're #OpenForTakeout, so we can spread the word.
Social Media Promotions	Virtual Bar Tours & Live Instagram Events	live, instagram, tune, tonight, ig, go, dive, tour, bar, edition	Going live now! doing a little thing with @budlight tonight on IG and facebook live. come hang 6pm pst / 9pm est #divebartour
	Pandemic Social Engagement & Promotions	whassup, say, tag, win, merch, friend, chance, need, collection, week	Win fresh Bud Whassup crewnecks for your happy hour crew! RETWEET + FOLLOW for the chance to outfit your crew.
Sports	Virtual NFL Draft Party with Celebrity Hosts	draft, boo, commish, nfl, youtube, drafterparty, robgronkowski, guest, host, camillekostek	TONIGHT!!!! @nfl @budlight
	Home Sports Challenge Campaigns	challenge, team, house, sport, league, submit, home, athlete, chance, video	Want to win a @trulyseltzer putting mat? Show us your #dailyninesetup. Photo, video, putting, chipping, whatever. Show us.
Gaming	Charity Gaming Events by Alcohol Brands	royale, twitch, tv, charity, money, tonight, dkm, therealgavinlux, snellzilla, final	Excited to announce the Bud Light Seltzer Charity Royale. 24 pro athletes compete in Call of Duty: Warzone to raise money for awesome local causes. Live right now on http://Twitch.tv/BudLight. Tune in!

Table 2. Theme Structure and Representative Content

Theme	Pre-Pandemic Response (%)	Peri-Pandemic Response (%)	Post-Pandemic Response (%)
Alcohol Delivery and Isolation Drinking	9.1*	17.4†	11.9*†
Restaurant Support	1.9*	5.5†	1.7*
Social Media Promotions	6.6*	16.5†	10.6*†
Sports	8.2	11.4	8.9
Gaming	1.1	2.0	1.6

* = Statistical difference from Period 2, $p < 0.0033$
† = Statistical difference from Period 1, $p < 0.0033$

Table 3. Theme Prevalence Across Periods

Sentiment Analysis

Linguistic markers derived from LIWC provided a descriptive analysis of five themes throughout the peri-pandemic response period in terms of their cognitive, emotional, and excitative characteristics. The entire output of applying LIWC to each theme corpus is available in Appendix 4, and a summary is reported in this section.

Alcohol Delivery and Isolation Drinking

Relative to the other themes, the Alcohol Delivery and Isolation Drinking theme exhibited high analytical thinking (85.63%; i.e., more logical, structured, evidence-based reasoning) with moderate clout (76.92%; i.e., more confidence, dominance, social authority) and relatively low authenticity (36.78%; i.e., a more guarded, strategic, or detached communication style.). The notably higher tone score (80.16%; i.e., emotional positivity) suggests predominantly positive emotional valence. The theme demonstrated relatively higher use of perceptual processes (9.64%; i.e., words related to seeing, hearing, feeling, and other sensory experiences) and spatial references (5.75%; i.e., words related to location, direction, distance, and spatial relationships), with minimal use of negative emotions (0.22%; i.e., words such as angry sad, hate) or conflict-related language (0%; i.e., words such as oppose, fight, win). The relatively higher presence of food-related terms (4.89%; i.e., words such as eat, drink) and physical references (5.84%; i.e., words related to the body or physical actions) suggests content possibly focused on sensory or experiential descriptions.

Restaurant Support

The Restaurant Support theme presented the highest clout score (94.38%) and high analytical thinking (89.68%), coupled with the highest tone score (98.49%) across all themes. It showed relatively lower authenticity (9.14%), suggesting formal or carefully constructed content. The text was characterized by relatively stronger social references (17.04%; i.e., words related to social interaction, relationships, communities) and higher affiliation markers (7.77%; i.e., words related to group membership, cooperation, unity), with higher lifestyle-related content (11.02%; i.e., words related to daily habits, routines, personal interests, ways of living). The complete absence of

negation words (0%; i.e., words related to contradiction, opposition, or refusal) and negative emotions (0%) reinforces its overwhelmingly positive orientation.

Social Media Promotions

The Social Media Promotions theme maintained relatively high analytical thinking (88.89%) and clout (93.8%), with moderate authenticity (32.37%). It showed relatively stronger perception-related content (12.04%) and motion references (2.73%; i.e., words related to movement, direction, and physical action), suggesting dynamic or descriptive content. The theme demonstrated relatively balanced use of temporal references (past: 0.50%, present: 2.70%, future: 1.49%) and maintained relatively higher positive emotional tone (88.52%) while keeping negative emotions minimal (0.20%).

Sports

The Sports theme showed the second-highest analytical thinking score (92.32%) with relatively higher clout (87.37%), but a relatively lower tone score (67.22%) compared to the previous themes. It maintained substantial perceptual processes (10.26%) and spatial references (6.28%), with increased use of numbers (5.85%) suggesting more technical or detailed content. The theme showed moderate social references (11.61%) and achievement-related content (2.31%; i.e., words related to success, goal-setting, progress, and performance), with balanced temporal orientation.

Gaming

The gaming theme exhibited the highest relative analytical thinking score (98.37%) but lower clout (71.90%) and tone (51.75%) compared to other themes. It showed the highest use of big words (26.99%; i.e., words six or more letters in length) and numbers (10.02%), suggesting technical or specialized content. The theme demonstrated relatively reduced function word usage (29.86%; i.e., words are essential for grammar, cohesion, and sentence flow) but increased technical references (3.48%; i.e., words related to STEM, precision, expertise) and perception-related content (11.04%), indicating possibly more complex or specialized subject matter.

Through the DSMM Lens

Building on the LIWC analysis through the lens of the DSMM, we can explore how these themes might employ certain cognitive, emotional, and excitative processes when consumed. From a cognitive processing perspective, the consistently high analytical scores (ranging from 85.63% to 98.37%) suggest content that elicits substantial cognitive engagement, with Gaming potentially eliciting the highest cognitive stimulation due to its elevated use of big words (29.86%) and technical language (3.48%). The emotional processing dimension showed an interesting gradient across themes, with Alcohol Delivery and Isolation Drinking, Restaurant Support, and Social Media Promotions displaying high positive emotional tone (ranging from 80.16%-98.49%) and minimal negative affect, suggesting content that might be more emotionally engaging and accessible. This emotional content notably decreased in The Sports and Gaming themes (67.22%

and 51.75% respectively), indicating a shift toward more neutral, technically-oriented content. Regarding excitative processes, the varying levels of perceptual references (particularly high in Social Media Promotions at 12.04%) and motion-related content (also peaking in Social Media Promotions at 2.73%) suggest different levels of arousal potential. Restaurant Support's high social and affiliation markers (17.04% and 7.77% respectively) might facilitate stronger state excitation through social engagement, while Gaming's elevated technical content and reduced social markers might demand more focused, less arousal-dependent processing.

DISCUSSION

The purpose of the present study was two-fold. First, to validate previously documented themes used by the alcohol industry on social media during the COVID-19 pandemic to market their products in a sample of alcohol companies targeted towards Americans, explore additional themes that may emerge, and asses the prevalence of these themes before (January 2019 - January 2020), during (March 2020 - May 2020), and after (June 2020 - July 2021) the early lockdown phases of the COVID-19 pandemic. Five themes were identified: Alcohol Delivery and Isolation Drinking, Restaurant Support, Social Media Promotions, Sports, and Gaming. Alcohol Delivery and Isolation Drinking, Restaurant Support, and Social Media Promotions were significantly more prevalent during the peri-pandemic response period (March 2020 - May 2020) compared to pre-and post-pandemic response periods, while Sports and Gaming were more stable.

The identification of five themes and their variation across time supports the study hypothesis. The findings align with existing research but also expands to new understandings potentially related to regional (i.e., U.S.) and platform (i.e., Twitter/X) differences. Specifically, this study reproduced Alcohol Delivery and Isolation Drinking, and Restaurant Support themes similar to previous research (Martino et al., 2021; Gerritsen et al., 2021). The significant increase in Alcohol Delivery and Isolation Drinking ($\Delta = 91.2\%$) during the peri-pandemic period demonstrates a clear shift in marketing focus. Although there was a subsequent decrease during the post-pandemic period ($\Delta = -31.6\%$), Alcohol Delivery and Isolation Drinking remained significantly higher post-pandemic compared to pre-pandemic ($\Delta = 30.8\%$). The consistency of these findings suggests that the alcohol industry focused marketing efforts on delivery services and at-home drinking activities during the early phases of the pandemic across regions and contexts, a period when alcohol-related morbidity and mortality also increased (Grossman et al., 2020; Koob et al., 2020; Foster et al., 2021; Moon et al., 2021; White et al., 2022). Exposure to these themes in marketing content may have contributed to spreading unhealthy ideas such as delivering alcohol to your home for consumption in isolation, though future research modeling the spread of these ideas between the industry and community is needed.

Similarly, Restaurant Support showed a substantial increase during the peri-pandemic period ($\Delta = 189.5\%$), highlighting the industry's use of corporate social responsibility (CSR) strategies previously documented within the alcohol industry (Martino et al., 2021; Babor et al., 2013; Mialon et al., 2018). While supporting struggling restaurants and bars during the pandemic was

essential and pro-social in helping mitigate substantial losses across the food and hospitality industries (Song et al., 2021), CSR also serves alcohol companies via reputation management and direct advancement of commercial interests simultaneously (Mialon et al., 2018). Importantly, despite the substantial initial increase, Restaurant Support messaging significantly decreased post-pandemic (69.1%), returning to below pre-pandemic levels (Δ = -30.8%). By positioning themselves as champions of restaurant recovery while simultaneously promoting home delivery and isolation drinking, alcohol companies created a dual narrative legitimizing their pandemic response through apparent social responsibility and expanding their direct-to-consumer channels, exemplifying CSR's function in deflecting regulatory scrutiny while advancing market objectives (Yoon et al., 2013).

This study identified the Social Media Promotion theme, which, although potentially similar to the Community Support theme identified in previous research (Martino et al., 2021), represents a distinct and unique theme. Tweets classified under this theme frequently mentioned events such as virtual happy hours and livestreamed gatherings, like Community Support themes in previous research. However, these tweets commonly contained explicit calls to action encouraging engagement with a brand's social media channels, thereby increasing exposure to marketing content and the likelihood of alcohol use. Social Media Promotions showed a notable surge (Δ = 150%) during the peri-pandemic period, aligning with broader trends of increased social media usage driven by people's pursuit of virtual connections amid physical isolation (Nabity-Grover et al., 2020). Despite a significant decrease post-pandemic (Δ = 35.8%), Social Media Promotion remained significantly elevated compared to pre-pandemic levels (Δ = 60.6%). The intersection of intensified alcohol marketing and heightened social media use is especially concerning given the established association between social media use and increased risks for mental health problems, including depression, anxiety, and problematic substance use behaviors (U.S. Department of Health and Human Services, 2023). Furthermore, these findings parallel troubling societal trends of declining mental health among youth and young adults (Thomas et al., 2022; Haidt, 2024; McGorry et al., 2024), the demographic most active on social media platforms.

This study also found evidence of themes not previously identified as prominent within alcohol industry marketing the COVID-19 pandemic. Specifically, Gaming and Sports. The identification of Gaming and Sports themes could reflect both platform-specific and regional characteristics. Twitter's young adult user base in the U.S. (Murthy, 2024) combined with the established propensity for alcohol companies to use sports and gaming marketing campaigns make this finding expected (Westberg et al., 2018; Kelly et al., 2021). Nevertheless, this finding highlights the importance of considering platform demographics and regional contexts when studying alcohol marketing adaptations.

The temporal patterns in theme prevalence provide important insights into the alcohol industry's strategic marketing adaptations during the COVID-19 pandemic. The significant increases in Alcohol Delivery and Isolation Drinking (Δ = 91.2%), Restaurant Support (Δ = 189.5%), and Social Media Promotions (Δ = 150%) during the peri-pandemic period demonstrate a clear shift in

marketing focus. While there were subsequent significant decreases in these themes during the post-pandemic period (decreases of 31.6%, 69.1%, and 35.8% respectively), our statistical analyses reveal important long-term changes. Notably, Alcohol Delivery and Isolation Drinking remained significantly higher in the post-pandemic compared to pre-pandemic period ($\Delta = 30.8\%$), as did Social Media Promotions ($\Delta = 60.6\%$). In contrast, Restaurant Support tweets showed no significant difference between post-pandemic and pre-pandemic periods ($\Delta = -30.8\%$). These patterns suggest durable changes in certain marketing strategies even after the acute lockdown phases ended. The magnitude of changes that occurred from the pre- to peri-pandemic response period suggests a deliberate and substantial reallocation of marketing resources in response to pandemic conditions. In contrast, the statistical stability of Sports and Gaming themes throughout the study period indicates these were likely part of ongoing marketing strategies rather than pandemic-specific adaptations. This pattern of selective theme adaptation shows how the alcohol industry maintained certain marketing foundations while strategically amplifying specific messages in response to the unique circumstances of the pandemic, with some of these adaptations persisting well beyond the initial pandemic response. This finding contributes to the existing literature by demonstrating longitudinal patterns of alcohol marketing themes before, during, and after the initial pandemic response period, whereas existing research focuses mostly on the presence of those themes during one period.

The second purpose of this study was to explore the cognitive, emotional, and excitative composition of content related to these themes during the early phases of the COVID-19 pandemic (i.e., March-May 2020). Sentiment analysis suggested that Alcohol Delivery and Isolation Drinking, Restaurant Support, and Social Media Promotions had higher emotionality, whereas Sports and Gaming had higher scores on cognitive dimensions. Restaurant Support and Social Media Promotions had higher scores on excitative dimensions (i.e., calls to action).

The finding that the Alcohol Delivery and Isolation Drinking, Restaurant Support, and Social Media Promotions themes carried stronger emotional appeals is concerning for several reasons. First, these themes emerged during a period of heightened psychological vulnerability brought on by pandemic-related stress (Pfefferbaum et al., 2020; Panchal et al, 2021). Research indicates that emotion-laden advertisements have more persuasive impact (Hamelin et al., 2017), and that online advertisers exploit psychological vulnerabilities of consumers using their marketing communication (Strycharz et al., 2021). Hence, the introduction of these themes during the early phases of the pandemic when stress and anxiety were high - coupled with linguistic structures that engage emotional triggers - raises ethical questions.

Second, the emotional pull of these campaigns often alluded to the hardships faced by essential workers in the restaurant industry. For example, one alcohol company tweeted “Yeah, we miss bars too. But we can still support restaurant and bar workers today. Order takeout and we'll buy your first round when they reopen. Find out more at [link]…” One interpretation of this is that the alcohol industry, consciously or not, harnessed the sympathy generated by restaurant support

messaging to direct attention to other emotionally laden themes (i.e., Alcohol Delivery and Isolation Drinking, Social Media Promotions) aimed at broadening commercial activities.

Furthermore, the Restaurant Support and Social Media Promotions themes contained the strongest calls to action, reminiscent of subverting action towards charitable donation and directing the user towards engaging with their social media page. For example, one alcohol company tweeted "[Brand] Mojito time everyone! Have you put your creative spin on #The CoconutChallenge yet?! @[BrandTwitterProfile] is extending their pledge to support businesses most impacted by COVID-19 and your dancing can do even more good!..." These tactics, in essence, repurpose genuine empathy and goodwill towards struggling businesses to advance corporate interests, ultimately exploiting a population already made vulnerable by the pandemic.

Concurrent to alcohol companies launching these campaigns, alcohol-related deaths among young people increased significantly compared to the previous year. Specifically, deaths among Americans aged 16-20 rose by 29.8%, those aged 21-24 saw a 25.6% increase, and deaths among individuals aged 25-34 increased by 37% (White et al., 2022). Given the link between alcohol marketing exposure and increased alcohol use (Anderson et al., 2009; Smith et al., 2009; Jernigan et al., 2017; Curtis et al., 2018; Hendriks et al., 2021; Alhabash et al., 2022), it is possible that exposure to marketing messages such as the ones found in this study could have been associated with the increased use of alcohol. Future research which objectively identifies exposure to marketing messages and prospectively examines the association with alcohol use is needed.

Beyond conventional public health effects (e.g., increased alcohol use), the marketing strategies employed by the alcohol industry during the early phases of the pandemic could also have economic effects. The food and beverage delivery industry (i.e., delivery apps) has grown immensely since the pandemic, with alcohol delivery commanding a significant market share (Duthie et al., 2023). Delivery apps have been shown to redistribute tips from restaurant workers to gig drivers as well as redistribute thin profit margin from restaurant owners to Big Tech companies (e.g., Uber, DoorDash) (Chen et al., 2022). Thus, while originally marketed alongside supporting restaurants, in the long term, delivery apps could ultimately hurt the restaurant industry. The use of delivery apps has also been linked to unfavorable health behaviors (e.g., eating high-calorie/low-nutrient foods) and is used by vulnerable populations such as those experiencing food insecurity (Buettner et al., 2023); and thus, in the long-term delivery apps could contribute to widening health disparities. This also aligns with the commercial determinants of health framework wherein a significant proportion of individual health outcomes are driven by the activity of commercial entities, which are entirely beyond the person's control (Lacy-Nichols et al., 2023).

A key strength of this study is its longitudinal design, covering extensive 'pre-' (January 2019–January 2020) and 'post-' (June 2020–July 2021) windows surrounding the acute pandemic response period (March–May 2020). This extended observation period allows for more robust identification of thematic shifts in alcohol marketing over time. Specifically, having approximately one full year of baseline (pre-pandemic lockdown) data and over a year of post-pandemic

lockdown data provides a clear context to determine whether observed thematic changes were transient adaptations limited to the early pandemic period or represented longer-term shifts in marketing strategy. This design significantly enhances the study's capacity to draw more confident conclusions regarding the durability and evolution of marketing themes, compared to designs with narrower or non-existent comparative timeframes.

The findings from this study have important implications for contemporary alcohol marketing practices, particularly in the context of evolving digital environments and delivery services. The demonstrated persistence of themes such as Alcohol Delivery and Isolation Drinking and Social Media Promotions beyond the immediate COVID-19 lockdown period suggests a durable shift toward social and direct-to-consumer strategies within the alcohol industry. These insights highlight the necessity for ongoing regulatory attention to social media platforms, where persuasive emotional and action-oriented appeals can rapidly reach and influence consumers, potentially exacerbating problematic drinking behaviors. Furthermore, given the increasing prominence of app-based delivery services that make alcohol readily available, understanding these thematic trends can guide the development of targeted public health interventions and policies designed to mitigate potential harms of alcohol industry marketing, especially strategically adaptive campaigns.

Limitations

This study has several limitations that should be acknowledged. First, the dataset consisted exclusively of tweets from 11 alcohol companies with substantial social media followings (>10,000 followers), potentially overlooking marketing strategies employed by smaller or regional companies with fewer followers and less widespread popularity. Consequently, findings may not be generalizable to the broader alcohol industry, periods beyond the study timeframe, or other digital platforms beyond Twitter. Additionally, Twitter's demographics (typically younger, urban, and technologically adept) may influence the types of themes identified, potentially omitting strategies targeted at older or rural populations.

Second, not all data collection occurred concurrently with the posting of tweets, meaning that any tweets deleted prior to data capture were inevitably missed. This could result in an incomplete representation of the marketing strategies deployed during the study period.

Third, although the BERTopic modeling approach combined with GPT-4o and human interpretation offers a rigorous framework inspired by the Themes and Topics system (Gillies et al., 2022), synthesizing information from topic modeling and AI-generated outputs into themes retains inherent subjectivity. Despite efforts to minimize bias through extensive iterative human-AI validation, subtle biases stemming from language complexity and contextual nuances may still exist.

Fourth, the sentiment analysis tool employed (LIWC; Chung et al., 2012; Boyd et al., 2022), while insightful regarding cognitive, emotional, and excitative dimensions of communication, uses a

dictionary-based approach that might overlook nuanced meanings better captured by alternative sentiment analysis methods. Thus, future research should explore complementary sentiment analysis techniques to validate the present findings. Additionally, the sentiment analysis conducted was exploratory and descriptive, providing aggregate rankings of various linguistic variables rather than statistical tests. More detailed analyses may raise different findings.

Lastly, this study cannot establish associations between exposure to alcohol marketing and subsequent consumption behaviors or health outcomes. Future investigations using longitudinal or experimental designs, along with direct observations of marketing exposure and individual-level data, are essential to empirically test these associations, including examination of potential moderating factors such as psychological vulnerability or preexisting drinking patterns.

Conclusion

This study provides critical insights into the strategic adaptations of alcohol marketing on social media during the COVID-19 pandemic, highlighting significant shifts in themes such as Alcohol Delivery and Isolation Drinking, Restaurant Support, and Social Media Promotions. These adaptations leveraged emotional and excitative appeals, potentially exploiting psychological vulnerabilities heightened during crisis conditions. Understanding these dynamics underscores the need for regulatory scrutiny and public health preparedness to mitigate potentially harmful industry practices during future crises.

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