Alcohol Information Dynamics During Crisis: A Longitudinal Analysis of Bidirectional Influence Between Alcohol Industry Marketing and User-Generated Content on Twitter During the COVID-19 Pandemic

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ABSTRACT

Introduction: During the COVID-19 pandemic, alcohol consumption and related mortality increased among young adults in the U.S., coinciding with increased social media use. Given the documented influence of alcohol marketing on drinking behaviors, this study examines the bidirectional association between alcohol industry social media marketing and user-generated content related to alcohol delivery and isolation drinking on Twitter during early pandemic lockdowns.

Method: We conducted a longitudinal analysis combining industry tweets from 11 major alcohol brands (n=704 tweets) and user-generated tweets from 66,303 U.S. Twitter users (n=486,786 tweets), collected during two periods: early during the pandemic lockdown (March 25-April 30, 2020) and later in the lockdown (May 1-31, 2020). Tweets were classified using GPT-4o to identify content related to alcohol delivery and isolation drinking. Potential exposure to alcohol brand tweets was quantified as a standardized composite score integrating user friend count, tweet frequency, and alcohol brand tweet volume. A cross-lagged panel model assessed bidirectional temporal associations.

Results: Analysis revealed an asymmetrical association. Early potential exposure to alcohol brand tweets significantly predicted subsequent user-generated content about alcohol delivery and isolation drinking ($\beta = 0.05$, $p<0.01$), indicating each standard deviation increase in potential exposure corresponded to a 5% greater likelihood of generating related content later. Conversely, early user-generated content did not significantly predict subsequent potential exposure to alcohol brand tweets ($\beta = 0.01$, $p=0.639$). High temporal stability emerged for both potential exposure ($\beta = 0.85$, $p<0.01$) and user-generated content ($\beta = 2.76$, $p<0.01$).

Discussion: Findings highlight the unidirectional influence of alcohol industry marketing on user-generated content during crisis periods. The absence of a bidirectional influence underscores industry-driven messaging rather than an industry response to public discourse. Given established links between alcohol marketing and drinking behaviors, these results advocate for strengthened regulatory oversight of digital alcohol advertising during public health crises. Future research should explore the dynamics of alcohol information over extended periods and across diverse crisis contexts.

INTRODUCTION

During the COVID-19 pandemic, alcohol consumption and related mortality increased substantially in the United States, particularly among young adults (Grossman et al., 2020; White et al., 2022). Specifically, from 2019 to 2020, alcohol-related deaths increased by 29.8% among Americans aged 16-20, 25.6% among those aged 21-24, and 37% among individuals aged 25-34 (White et al., 2022). Simultaneously, social media usage intensified as stay at home orders and physical distancing measures (i.e., lockdowns) transformed daily communication patterns (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), with platforms like Twitter (now X) becoming essential channels for pandemic-related information exchange and social connection (Haman et al., 2020; Rufai et al., 2020). Given these intersecting trends, understanding the potential role social media played in shaping drinking behaviors during the pandemic is critical for informing future public health strategies.

The convergence of increased alcohol consumption and heightened social media usage raises important public health concerns regarding alcohol industry marketing practices during this time. Research consistently demonstrates that exposure to alcohol marketing influences drinking behaviors, with young adults being particularly susceptible (Anderson et al., 2009; Smith et al., 2009; Jernigan et al., 2017; Curtis et al., 2018; Hendriks et al., 2021; Alhabash et al., 2022). Furthermore, several studies indicate that the alcohol industry adapted marketing strategies during the early COVID-19 period (March-May 2020), prominently featuring pandemic-related themes such as alcohol delivery services and at-home drinking (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). To this end, our previous research analyzed over 5,000 tweets from major alcohol brands between January 2019 and July 2021, revealing "Alcohol Delivery and Isolation Drinking" as the dominant theme during initial lockdown months, comprising nearly 20% of tweets. Furthermore, sentiment analysis of tweets related to alcohol delivery and isolation drinking revealed high levels of emotionality, suggesting these campaigns may have leveraged emotional vulnerability to promote alcohol consumption during a period of heightened pandemic-related psychological distress (Pfefferbaum et al., 2020; Panchal et al., 2021). This practice is consistent with established tactics among online advertisers who routinely exploit psychological vulnerabilities of consumers in their marketing communication (Strycharz et al., 2021).

Centering marketing campaigns on alcohol delivery and isolation drinking represents a significant public health concern for several reasons. First, messaging that promotes rapid alcohol access could have encouraged or exacerbated problematic drinking behaviors during a period of heightened psychological distress, as increased isolation, anxiety, and economic uncertainty during the COVID-19 pandemic have been consistently linked with greater alcohol use (Clay et al., 2020; Pollard et al., 2020; Barbosa et al., 2021). Further, given that lockdown periods restricted traditional sources for obtaining alcohol, marketing that emphasized alcohol delivery may have encouraged drinking among individuals who would otherwise have abstained.

Second, these marketing strategies could indicate a structural adaptation by the alcohol industry in response to temporary regulatory changes, potentially resulting in permanent shifts in alcohol accessibility. For example, the temporary policy in Texas permitting restaurants and alcohol retailers to offer alcoholic beverages "to-go" was subsequently made permanent (Texas Legislature, 2021), highlighting the enduring impacts of pandemic-era regulatory adjustments on alcohol distribution and consumption norms. These permanent regulatory changes allow increased access to alcohol even in situations where distance or time of day may preclude traveling to an outlet to purchase alcohol.

Third, the industry's marketing shift aligned with documented increases in user-generated social media content that helped to normalize alcohol consumption as a coping mechanism during the pandemic. Multiple studies have reported significant increases in online discussions about problematic drinking and using alcohol as a coping strategy. For example, Wanchoo et al. (2023) identified elevated Reddit activity related to alcohol-based coping mechanisms, and Ward et al. (2021) noted an increase in Twitter discussions concerning alcohol-induced blackouts during the initial lockdown period compared to previous years. Similarly, Stone et al. (2022) observed a shift toward more authentic and emotionally charged tweets about alcohol use, indicating greater openness regarding personal drinking experiences. Litt et al. (2021) further demonstrated that perceiving that peers were posting on social media about using alcohol to cope with the pandemic was associated with both an increased likelihood of making similar posts and increased drinking among adults. Additionally, Ahmed et al. (2024) found that Twitter discussions during the COVID-19 pandemic normalized risky drinking behaviors such as binge drinking, especially among young adult males aged 25-34, and frequently associated alcohol consumption with coping, celebrations, and entertainment.

Collectively, these findings suggest that increased online dialogue about alcohol during COVID-19 may have coincided with alcohol industry marketing adaptations, raising important questions about how changes in alcohol industry marketing practices may have affected social media posts about alcohol use and also how social media posts about alcohol use may have affected alcohol industry marketing practices. Social media activity has been shown to predict drinking behaviors (Young, 2014; Lane et al., 2023); thus, increased online posts during the pandemic may serve as a meaningful proxy for increased alcohol consumption. Understanding the dynamics between industry-driven marketing and user-generated social media content during the pandemic could help

inform the future development of safeguards against potentially exploitative marketing practices during future public health crises.

Media effects theories provide a framework for understanding how industry marketing and user-generated social media content may have bidirectional effects. The Differential Susceptibility to Media Effects Model (DSMM) suggests that media exposure triggers cognitive, emotional, and excitative responses that influence attitudes and behaviors (Valkenburg et al., 2013). Applied to alcohol marketing, exposure to alcohol-related content can inform consumers about drinking options, emotionally engage them through positive associations, and stimulate desire for consumption behaviors. Additionally, the theory of sociogenesis highlights the bidirectional nature of media influence, wherein user-generated content and community trends can shape industry marketing practices (Valsiner et al., 2000; Baker et al., 2020; Walsh et al., 2020; Negowetti, et al, 2022). In this context, user generated content about drinking behaviors may be adapted by industry actors and transformed into a media campaign.

Despite growing evidence of strategic shifts in alcohol marketing and changes in alcohol-related discussions on social media during the pandemic (Foundation for Alcohol Research & Education, 2020; Colbert et al., 2020; Gerritsen et al., 2021; Huckle et al., 2021; Litt et al., 2021; Martino et al., 2021; Ward, et al., 2021; Kennedy et al., 2022; Stone et al., 2022; Ahmed et al., 2024), significant gaps remain in understanding the bidirectional association between alcohol industry messaging and user-generated social media content. While previous research has documented marketing adaptations by the alcohol industry and changes in social media discussions about alcohol, no studies have systematically examined the longitudinal associations between alcohol industry marketing and user-generated content during the pandemic. Therefore, the purpose of the present study is to investigate the bidirectional association between potential exposure to alcohol brand tweets and user-generated content related to alcohol delivery and isolation drinking during COVID-19 lockdown.

To assess the bidirectional association between alcohol brand tweets and user-generated content about alcohol delivery and isolation drinking, the present study employed a longitudinal design using Twitter data collected during two distinct pandemic periods (T1 - early in the pandemic lockdown, March 25-April 30, 2020; and T2 - later in the pandemic lockdown, May 1-May 31, 2020). Using a publicly available dataset of over 19 million tweets with hashtags related to the COVID-19 pandemic (Dashtian et al., 2021) as well as a dataset of tweets from 11 verified alcohol brand Twitter accounts, we identified a sample of 66,303 U.S. Twitter users who posted in English at least once during both time periods. For each user, we quantified: the frequency of posts related to alcohol delivery and isolation drinking during both periods; and a measure of potential exposure to alcohol brand tweets about alcohol delivery and isolation drinking incorporating both individual-level factors (i.e., friend count, overall tweet volume) and industry-level metrics (i.e., frequency of themed marketing messages during respective time periods) during both periods. We then constructed a cross-lagged panel model to assess temporal associations between potential exposure to alcohol brant tweets at T1 and user-generated content at T2, and conversely, between

user content at T1 and subsequent potential exposure to alcohol brand tweets at T2, while controlling for stability paths of both variables as well as cross-sectional correlations between both variables.

We hypothesized positive bidirectional associations, anticipating that increased potential exposure to alcohol brand tweets would predict subsequent increased user-generated content about alcohol delivery and isolation drinking, and conversely, that greater user-generated alcohol content would predict subsequent increased potential exposure to alcohol brand tweets.

METHOD

During the COVID-19 pandemic, Twitter (now, X) became an essential medium for communication, heavily utilized by public health officials, governmental representatives, and prominent public figures to disseminate timely information (Haman et al., 2020; Rufai et al., 2020). In addition to its pandemic-specific significance, Twitter has proven beneficial for sociological research by providing scientists with access to immediate data generated by diverse user groups (Murthy, 2018). The platform's demographics (younger, urban, and digitally proficient) offer advantages for targeted research, especially when studying online communication dynamics (Murthy, 2024). Moreover, Twitter's dual capacity as both a digital public square and an active advertising hub makes it particularly relevant for exploring marketing trends. Given these attributes, Twitter was chosen as the analytical medium for the current research.

Sample and Data Collection

The present study combined user-generated content from the Computational Media Lab COVID-19 Twitter Dataset (CML-COVID; Dashtian et al., 2021) with alcohol brand tweets from the Prevention Research Lab Twitter Marketing Surveillance Study (PRL-TMS; Study 1). The CML-COVID dataset was collected via Netlytic 2 utilizing the Twitter REST API and comprises over 19 million tweets from nearly 6 million global users containing COVID-19-related hashtags, collected between March and July 2020. PRL-TMS data included 5,872 tweets from 11 alcohol companies posted between January 2019 and July 2021, collected as part of a larger study comprising over 20,000 tweets from consumer product companies, aiming to document and describe marketing practices before, during, and after the onset of the COVID-19 pandemic. The PRL-TMS data analyzed here is a subset specifically from alcohol companies. Alcohol companies were selected to represent 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 and systematically documenting each tweet using a standardized data entry form. The present study uses the verbatim text from each tweet.

For user-generated data from CML-COVID, we extracted tweets with the #coronavirus hashtag and filtered to include only English-language content, yielding 3,500,547 tweets. The #coronavirus hashtag was selected because it was the earliest data available in CML-COVID; other pandemic-

related hashtags were added later. We refined this dataset to include only users with at least two tweets (n = 2,665,987), then filtered to retain only U.S.-based accounts based on user location data (n = 1,026,503). We further limited our analysis to tweets posted between March 25 and May 31, 2020, capturing the lockdown period in the United States (n = 823,036 tweets from 88,877 users). To facilitate temporal comparison, we segmented the data into two periods: early lockdown (March 25-April 30, 2020) and later lockdown (May 1-31, 2020). This division allowed us to examine how potential exposure to content in the early lockdown period might influence content generation in the later period, and vice versa.

Bot activity is known to be problematic on Twitter (Fukuda et al., 2022). Because problematic twitter accounts often exhibit distinctive behavioral patterns, such as tweeting extremely frequently (i.e., dozens or hundreds of times per day), tweeting rapidly (i.e., many tweets within the window of several seconds), or tweeting repetitively (i.e., relaying identical content from the same account or across other accounts) (Pastor-Galindo et al., 2022; De Clerck et al., 2024; Mouronte-Lopez et al., 2024), and to enhance data quality, we implemented three complementary strategies. First, we removed users who posted more than twice within the same minute (removing 1,105 users from Time 1 and 844 users from Time 2), Second, we retained only users with at least one tweet in both time periods (n = 66,874). Finally, we excluded users with tweet counts ≥3 standard deviations above the mean (removing 571 users with an average of 161.60 tweets [SD = 204.24]). These procedures yielded a final sample of 66,303 unique users and 486,786 tweets. Average tweet count per user was 7.34 (SD = 9.48) across the study period, and they had an average friend count of 3235.19 (SD = 12824.25). A flow chart of the data collection procedures for user-generated content is shown in Figure 3.

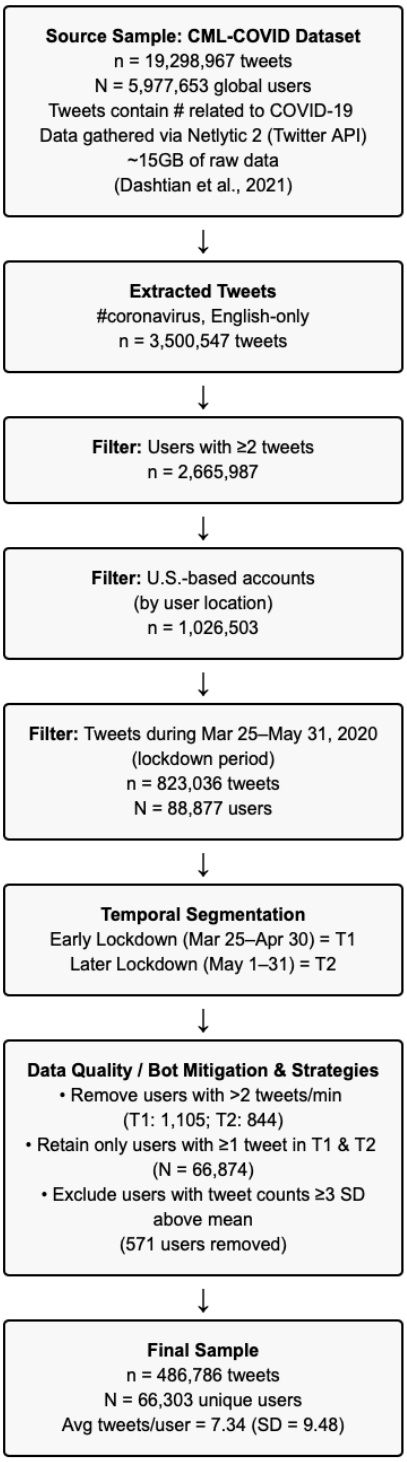


Figure 3. Flow chart of data collection procedures for user-generated content in Study 2

For alcohol brand data, we extracted alcohol company tweets from PRL-TMS posted between March 25 - May 31, 2020 (n=704). The distribution of these alcohol brand tweets is summarized in Table 4. The methods for the present study were reviewed by the UT-Austin institutional review board and determined to be non-human-subjects research.

Brand (n=11)	Number of Tweets (n= 703)	Number of Followers (n=1,199,052) (single cross-section during study period)
Bud Light	193	248,718
Budweiser	148	17,762
Malibu	107	46,824
Truly Hard Seltzer	67	88,688
Jagermeister USA	49	81,707
Jack Daniel's	45	125,605
Samuel Adams Beer	35	198,896
Brooklyn Brewery	30	220,140
White Claw	11	99,687
Absolut Vodka	11	30,526
Bacardi	7	40,499

Table 4. Summary of alcohol brand tweets included in Study 2 (March 25 - May 31, 2020)

Tweet Classification

Given that previous research identified “Alcohol Delivery and Isolation Drinking” as the most prevalent theme tweeted about by alcohol brands during the COVID-19 pandemic lockdowns (e.g., Martino et al., 2021; Study 1), we classified each tweet as related to "Alcohol Delivery and Isolation Drinking,” other prominent themes (see Appendix 3), or “not belonging to any theme” using the Large Language Model (LLM) GPT-4o (OpenAI, 2024). The process - adapted from our previous study (Study 1) - involved prompting the OpenAI API to classify text (i.e., a verbatim tweet) into a list of options (i.e., a list of potential themes + "not belonging to any listed theme"), and looping this procedure through an entire corpus (i.e., the dataset of tweets). LLMs are ideal for text classification with systematic review suggesting excellent performance 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 open source in Appendix 3. There were a total of 126 classifications as related to Alcohol Delivery and Isolation Drinking in the alcohol brand data, and 536 classifications in the user-generated data.

Measures

Potential Exposure to Alcohol Brand Tweets Related to Alcohol Delivery and Isolation Drinking

Given that CML-COVID does not provide direct information about which alcohol brands users followed, we created an index of potential exposure based on established methods in both informatics and public health research (Henrikson et al., 2010; Sasaki et al., 2015; Luarn et al., 2016; Bhattacharya et al., 2023; Pasch et al., 2023). This measure incorporated three components:

(1) the number of friends a user had on Twitter (user_friends_count from the Twitter API), (2) the user's tweet frequency during the relevant period (a proxy for platform engagement), and (3) the total number of alcohol brand tweets about “Alcohol Delivery and Isolation Drinking” during that period (T1=56; T2=70). Multiplying each of these components together creates an index of potential exposure.

The underlying rationale for this approach draws from network density theory, which demonstrates that users with more connections have higher potential exposure to information within their network (Luarn et al., 2016; Bhattacharya et al., 2023). Similarly, research by Sasaki et al. (2015) established that friend count on Twitter correlates with the volume, variety, and velocity of content appearing in a user's feed. Further, this approach also parallels established methodologies in point-of-sale tobacco marketing surveillance (Henriksen, 2010; Pasch et al., 2023), where researchers multiply the self-reported frequency of store visits by the number of objectively audited tobacco advertisements present in a store to create an index of potential tobacco marketing exposure at retail outlets. Our measure of potential exposure to alcohol brand tweets related to alcohol delivery and isolation drinking is adapted from this previous work. The number of tweets that a user generated is analogous to the number of times a participant visited a store. The number of friends that a user has is analogous to the type and size of the store. The number of alcohol brand tweets that were generated during the study period is analogous to the objective count of tobacco ads that existed at the retail stores participants had access to. In both instances, multiplying these components together creates an index of potential exposure. Indeed, social media platforms generate much of their revenue via advertisements (Raffoul et al., 2023), and these platforms have been suggested as "the storefront of the future" (Wiese, 2021). When users visit "the store of Twitter" they are potentially exposed to a pool of advertisements, and the measure herein is a methodological way to quantify potential exposure to a given segment of products (i.e., alcohol).

Therefore, the equation [number of friends * number of tweets from March 25, 2020-April 30, 2020 * number of alcohol brand tweets about alcohol delivery and isolation drinking from March 25, 2020-April 30, 2020] created a variable that represents the potential exposure to alcohol brand tweets related to alcohol delivery and isolation drinking during the early pandemic lockdown period (i.e., T1).

Additionally, the equation [number of friends * number of tweets from May 1, 2020-May 31, 2020 * number of alcohol brand tweets about alcohol delivery and isolation drinking from May 1, 2020-May 31, 2020] created a variable that represents the potential exposure to alcohol brand tweets related to alcohol delivery and isolation drinking later in the pandemic lockdown period (i.e., T2).

To address skewness in these exposure variables while preserving interpretability and fitting convention in the field of public health, potential exposure variables at both time points were standardized using z-score transformation.

User-Generated Tweets Related to Alcohol Delivery and Isolation Drinking

For each user, we calculated the number of tweets classified as related "Alcohol Delivery and Isolation Drinking" during each time period. Due to the highly skewed nature of these variables (most users had zero related tweets), and the fact that very few users produced more than one related tweet, we treated them as binary variables (0 = no related tweets, 1 = one or more related tweets) with the following distributions: T1: 65,984 users with 0 tweets, 319 users with 1 or more tweets; T2: 66,131 users with 0 tweets, 172 users with 1 or more tweets.

Analysis

To examine the bidirectional associations between potential exposure to alcohol brand tweets and user-generated tweets, we employed a cross-lagged panel model using generalized structural equation modeling (GSEM) in Stata 17 (StataCorp, 2021). This analytical approach allows simultaneous modeling of autoregressive effects (i.e., stability of each variable over time), cross-sectional correlations (i.e., associations between variables at each time point), and cross-lagged effects (i.e., the influence of one variable at Time 1 on the other variable at Time 2, and vice versa) of mixed variable types (Rabe-Hesketh et al., 2022).

Given the mixed variable types (standardized continuous potential exposure variables and binary user-generated indicators), we specified appropriate link functions in our model. The continuous variables used identity links (Gaussian family), while the binary variables used logit links (Bernoulli family) to account for their dichotomous nature (Kuiper, 2018; Wooldridge, 2020; StataCorp, 2023). We employed robust standard errors (vce(robust)) to account for potential heteroscedasticity and non-normality in the data (White, 1980). All analyses were conducted in Stata 17, with a significance threshold of $p < 0.05$ for hypothesis testing.

RESULTS

The cross-lagged panel model examining the bidirectional associations between potential exposure to alcohol brand tweets and user-generated content about alcohol delivery and isolation drinking during the COVID-19 pandemic converged to a log pseudolikelihood of -147146.67. The model is visualized in Figure 4.

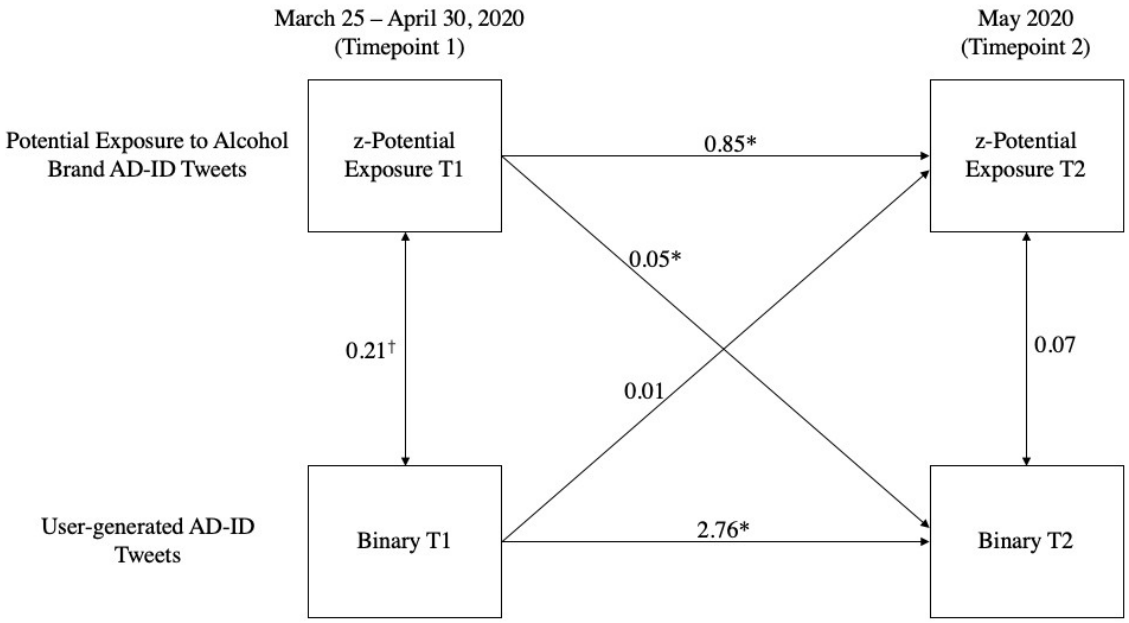


Figure 4. Cross-lagged panel model examining the bidirectional associations between potential exposure to alcohol brand tweets and user-generated content about Alcohol Delivery and Isolation Drinking (AD-ID) during the COVID-19 pandemic. * = $p < 0.05$ † = $p = 0.054$

Cross-Sectional Associations

At Time 1 (early lockdown period), a marginally significant positive association emerged between potential exposure to alcohol brand tweets and user-generated tweets about alcohol delivery and isolation drinking ($\beta = 0.21$, $p = 0.054$). This suggests that individuals with higher potential exposure were potentially more likely to generate related content themselves during the initial pandemic lockdown phase, although the p-value is marginal. At Time 2 (later lockdown period), the cross-sectional association between variables was not statistically significant ($\beta = 0.07$, $p = 0.12$).

Stability over Time

Both variables demonstrated high stability across the study period. Potential exposure exhibited strong temporal consistency ($\beta = 0.85$, $p < 0.01$), indicating that individuals' relative exposure levels remained largely stable from early to later lockdown periods. User-generated content about alcohol delivery and isolation drinking also showed temporal consistency ($\beta = 2.76$, $p < 0.01$), suggesting that individuals who discussed these topics during early lockdown were significantly more likely to continue doing so in the later period (OR=15.8).

Bidirectional Cross-Lagged Effects

The bidirectional pathways between potential exposure and user-generated content revealed an asymmetrical pattern of associations. Potential exposure in the early lockdown period positively predicted subsequent user-generated content about alcohol delivery and isolation drinking ($\beta =$

0.05, $p < 0.01$). This statistically significant effect suggests that higher initial potential exposure was associated with higher odds of generating related content later (OR=1.05), even after controlling for prior content generation patterns. User-generated content related to alcohol delivery and isolation drinking in the early lockdown period did not significantly predict subsequent potential exposure ($\beta = 0.01$, $p = 0.639$).

DISCUSSION

This study investigated the bidirectional association between alcohol brand tweets and user-generated content about alcohol delivery and isolation drinking on Twitter during the COVID-19 pandemic lockdowns. Building on previous research which suggested alcohol companies strategically emphasized these topics during the 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; Study 1), we examined how industry messaging and user-generated content potentially influenced each other over time.

The Industry-to-Public Pathway

Our analysis indicated that potential exposure to alcohol brand tweets promoting alcohol delivery and isolation drinking in the early lockdown period was associated with greater odds of subsequent user-generated content on these topics. In practical terms, each standard deviation increase in potential exposure at T1 corresponded to approximately 5% higher odds of a user generating a tweet about alcohol delivery and isolation drinking at T2. While this effect may appear modest when examining average exposure, it is worth noting that individuals with the highest exposure levels (i.e., > 3 SD above the mean) are at 15%+ greater risk of tweeting about alcohol delivery and isolation drinking compared to those with minimal exposure. These findings align with our hypothesis regarding the prospective association between alcohol brand tweets and user-generated content about alcohol delivery and isolation drinking. The effect persisted after controlling for individuals' baseline tweets about these topics and both variables stability paths, suggesting that industry messaging may contribute to shaping public discourse.

These industry-to-public effects coincided with significant increases in alcohol-related health problems and deaths. White et al. (2022) reported alarming statistics: alcohol-related deaths rose by 25.6% among Americans aged 21-24 and by 37% among those aged 25-34 -demographics that closely align with Twitter's primary user base (Murthy, 2024). Given the established connections between alcohol marketing and consumption (Anderson et al., 2009; Smith et al., 2009; Jernigan et al., 2017; Curtis et al., 2018; Hendriks et al., 2021; Alhabash et al., 2022), as well as between social media posts about drinking and actual alcohol use (Young, 2014; Lane et al., 2023), this study’s findings raise questions about how industry messaging may have contributed to alcohol-related morbidity and mortality during this time.

The industry-to-public pathway identified here exemplifies what Lacy-Nichols et al. (2023) describe as commercial determinants of health: structural factors driven by corporate interests that

shape individual health outcomes beyond personal control. By leveraging crisis conditions to promote potentially harmful consumption patterns, the alcohol industry's marketing strategies reflect broader patterns of corporate exploitation documented during the pandemic (Kim et al., 2020; Rothwell et al,. 2021; McSwane, 2022; Chetty et al., 2024; U.S. House of Representatives, Committee on Oversight and Accountability, Select Subcommittee on the Coronavirus Pandemic, 2024)

The Public-to-Industry Pathway

Contrary to our hypothesis, we did not find statistically significant support for user-generated content about alcohol delivery and isolation drinking being associated with subsequent potential exposure to alcohol brand tweets during the brief timeframe examined. Although these results do not support a clear bidirectional pathway, methodological factors such as strong autoregressive stability and limited temporal scope may have restricted our ability to detect subtle or gradual reciprocal influences. Thus, these findings do not conclusively rule out the possibility of bidirectional dynamics occurring over longer periods or under different conditions.

Several complementary explanations may account for this unexpected finding. First, alcohol companies may have maintained consistent marketing strategies regardless of varying user-generated content about alcohol delivery and isolation drinking, focusing on predetermined campaign schedules rather than adaptively responding. Second, the relatively short timeframe of our study may not have captured longer-term industry responses to user-generated content. Third, while we found no significant evidence of user-generated content influencing subsequent industry exposure in terms of volume, this does not rule out other forms of industry responsiveness not captured by our measures. For example, qualitative aspects of industry messaging might have shifted in response to user-generated content without changing the overall volume or distribution of content reflected in our exposure measure. Finally, the alcohol industry may not have been influenced in regard to this particular theme but may have been influenced by themes in other public tweets related to alcohol. Future research is needed which examines these additional possibilities.

Temporal Associations

The stability coefficients for both variables indicate that individual-level patterns of both exposure and content generation remained highly consistent throughout the study period. The particularly strong autoregressive effect for user-generated content ($\beta = 2.76$, $p < 0.001$) suggests the importance of early intervention in disruptive moments like pandemic onset, as patterns established during initial crisis phases appear to maintain considerable momentum.

Taken together, the autoregressive, cross-sectional, and cross-lagged analyses indicate that users who initially did not tweet about alcohol delivery and isolation drinking early in the pandemic, yet experienced high potential exposure to alcohol brand tweets, subsequently became significantly more likely to engage in tweeting about these topics. This behavioral shift marks an important

consumer conversion - representing a theoretical transition from non-engaged to engaged customer through a novel delivery channel, while possibly adopting the high-risk practice of isolation drinking. In the current study, 160 such conversions occurred (0.24% of the eligible sample), with these converted individuals averaging 3.03 times greater potential exposure at T1 compared to non-converted users. Projecting this conversion rate onto a broader population equates to nearly 2,500 conversions per million individuals exposed. Given that social media advertisements frequently reach audiences numbering in the billions and considering that industry actors continually produce new marketing content, the potential existed for the rapid emergence and expansion of a new commercial sector - the food and beverage delivery application sector - which has proliferated significantly since the onset of the pandemic (Duthie et al., 2023).

Public Health Implications

Our findings have several notable implications for public health. First, the prospective association between potential exposure to alcohol brand tweets and subsequent user-generated content regarding alcohol delivery and isolation drinking supports calls for enhanced regulatory oversight of digital alcohol marketing (World Health Organization, 2021), especially during societal crises. The rapid deployment of marketing emphasizing alcohol delivery and isolation drinking coincided with documented increases in problematic consumption patterns and alcohol-related mortality (White et al., 2022), highlighting the potential public health consequences of opportunistic crisis marketing. Second, while we did not find evidence of a prospective association between user-generated content and subsequent potential exposure to alcohol brand tweets, the strong stability in both variables over time underscores the critical importance of early intervention. Public health messaging should deploy rapidly at crisis onset to establish protective behavioral norms before maladaptive patterns stabilize, as our findings suggest considerable momentum in both potential exposure and user-generated content once established. Finally, our results highlight the need for integrated consideration of both commercial determinants of health and individual behaviors in public health approaches to alcohol harm reduction. While individual-level interventions remain important, our findings demonstrate how corporate marketing strategies may systematically shape the informational environment within which individual choices occur, particularly during periods of heightened vulnerability.

While our analysis specifically examined the COVID-19 pandemic, it is essential to recognize that these findings reflect a broader pattern of marketing practices that may emerge during any public health crisis or major societal disruption. The pandemic provided a distinctive lens through which to observe industry strategies as companies swiftly adapted their messaging to exploit periods of heightened societal vulnerability, shifting consumption patterns, and evolving regulatory environments. Gaining insights into these dynamics is critical, not only for accurately interpreting the immediate impacts of alcohol marketing during COVID-19 but also for guiding the development of proactive regulatory frameworks and targeted public health interventions. Ultimately, the lessons learned from examining alcohol industry behaviors during this crisis offer a

valuable foundation for strengthening public health preparedness and resilience against harmful marketing practices across diverse industries in future emergencies.

Limitations and Future Directions

These findings should be considered in light of several limitations. First, our methodological approach to measuring potential exposure, while conceptually grounded and theoretically informed, represents an approximation based on network characteristics and general engagement rather than direct observation of exposure. Though standardizing these variables improved their distributional properties, this indirect measurement introduces uncertainty that direct tracking would mitigate.

Second, our binary classification of user-generated content, while appropriate given the highly skewed distribution of this variable, may have reduced our ability to detect nuanced patterns among the most active content generators.

Third, our analysis focused specifically on Twitter users in the United States who engaged with COVID-19-related content, limiting generalizability to other populations, contexts, or platforms.

Fourth, our sample of alcohol brand tweets was from 11 alcohol companies with substantial social media followings (>10,000 followers) which were deemed popular by our research group of graduate and undergraduate research assistants, potentially overlooking marketing strategies employed by smaller or regional companies with fewer followers and less broad popularity.

Fifth, there was a relatively low number of tweets related to alcohol delivery and isolation drinking in the user-generated dataset; however, this is somewhat expected, as the sample specifically consisted of tweets related to COVID-19. A more general sample of tweets might yield a higher frequency of content related to these topics.

Sixth, the strong autoregressive (stability) pathways observed in our cross-lagged panel model pose analytical challenges for detecting cross-lagged (bidirectional) effects. Specifically, high stability indicates that individual differences at baseline persist strongly over time, leaving less variance available for cross-lagged relationships to explain. This reduced variance can mask or attenuate potential bidirectional effects, thus complicating the interpretation of causality or mutual influence between variables. Consequently, caution is warranted when interpreting null findings for cross-lagged paths in contexts with high temporal stability.

Lastly, the relatively short timeframe examined in this study (approximately 2.5 months during the early COVID-19 pandemic lockdown) likely limited our ability to detect more gradual or longer-term effects, particularly those associated with industry adaptation (i.e., the public-to-industry pathway). Structural changes within industries, shifts in marketing strategies, and subsequent alterations in consumer behavior could require extended periods to emerge clearly. As a result, longer-term longitudinal research is necessary to capture these slower-developing dynamics fully

and to provide a more comprehensive understanding of the longer-term bidirectional relationship between the public and the alcohol industry.

Future research should address these limitations while expanding investigation into several promising directions. Moderator analyses could identify population subgroups particularly susceptible to industry influence or contextual factors that strengthen or weaken these associations. Longer-term longitudinal studies could track how industry-user-generated content associations evolve beyond initial crisis phases; particularly as temporary regulatory changes become permanent. Additionally, comparative analyses across multiple crisis events could identify consistent patterns in alcohol industry crisis marketing tactics, informing more targeted regulatory approaches. Lastly, comparative analyses across other product types (e.g., tobacco, cannabis, highly processed foods, etc.) could inform broader interpretations of the industry-to-public pathway identified in this study.

Conclusion

This study provides empirical evidence of a unidirectional association between alcohol industry marketing and subsequent user-generated content about alcohol delivery and isolation drinking during the early COVID-19 pandemic. These results contribute to our understanding of how alcohol marketing on social media may influence user-generated content during societal crises, with notable implications for public health. The documented influence of strategically adapted marketing on user-generated content, coupled with the known links between marketing exposure and consumption behaviors, highlights the need for enhanced oversight of digital alcohol marketing during vulnerable periods.

As society faces ongoing and future crises, understanding these associations between industry marketing tactics and public discourse becomes increasingly critical for protecting public health. Our findings suggest that early, sustained public health messaging, coupled with appropriate regulatory guardrails around crisis marketing, may help mitigate the exploitation of vulnerability during periods of societal disruption.

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