Information, Communication & Society

ISSN: 1369-118X (Print) 1468-4462 (Online) Journal homepage: www.tandfonline.com/journals/rics20

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To cite this article: Scott Houghton, Frederic Boy, Alexander Bradley, Richard J. E. James, Heather Wardle & Simon Dymond (13 Oct 2025): Adapting in times of crisis: how social media marketing of gambling changed in response to major shifts in the gambling landscape, Information, Communication & Society, DOI: 10.1080/1369118X.2025.2572025

To link to this article: https://doi.org/10.1080/1369118X.2025.2572025

Published online: 13 Oct 2025.

INFORMATION, COMMUNICATION & SOCIETY
https://doi.org/10.1080/1369118X.2025.2572025

Adapting in times of crisis: how social media marketing of gambling changed in response to major shifts in the gambling landscape

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ABSTRACT
Gambling marketing on social media in countries like Great Britain (GB) is relatively well understood. Little is known, however, about how such marketing is impacted by major changes to the gambling landscape, like the COVID-19 pandemic. Here, we assessed changes in the frequency, sentiment, and content of gambling marketing on Twitter by Great Britain (GB) gambling operators and affiliates. We analysed $n = 353{,}134$ tweets from 10 operators and affiliates posted between January 2020 and July 2022. Using machine learning, we categorised tweets based on content and tracked how social media use by operators and affiliates changed during the pandemic. Findings revealed decreases in the frequency of tweets posted during the first national lockdown, particularly for affiliates, and a greater proportion of sports content related tweets, compared to direct advertising, as the pandemic continued. Postings by affiliates tended to include more positive sentiments. Our findings highlight the speed at which gambling operators and affiliates adapted their social media marketing campaigns to large structural changes like the COVID-19 lockdowns.

ARTICLE HISTORY
Received 14 August 2024
Accepted 3 October 2025

KEYWORDS
Gambling marketing; social media; operators; affiliates; machine learning; sentiment analysis

1. Introduction

Gambling is increasingly recognised as a significant public health issue worldwide (David et al., 2020; Wardle et al., 2019, 2024). Harms arising from gambling impact people, their families, and communities often for an extended period of time (Browne & Rockloff, 2018; Tulloch et al., 2022). Harms include, but are not limited to, financial harm,

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emotional distress, relationship breakdown, impacts upon employment and increased suicidality (Wardle et al., 2024). Within Great Britain (GB), the government Gambling Act White Paper (Department for Culture Media & Sport, 2023) proposed regulatory changes to better protect individuals and impacted others from harm. A key legislative focus is the marketing and advertising of gambling, with restrictions proposed for the direct marketing of gambling inducements. There is, however, little focus upon advertising. As such, the gambling industry may choose to redirect spending from the marketing of inducements to other advertising channels. Indeed, a recent umbrella review on the impact of gambling advertising on gambling-related harms found a dose–response effect (McGrane et al., 2023), whereby increased exposure to advertising leads to a greater risk of gambling harms.

The COVID-19 pandemic initiated major changes to the gambling landscape leading to major reductions in the availability of gambling activities, due to both the closing of land gambling venues, the postponement of professional sport (Håkansson et al., 2020), and voluntary reductions in gambling marketing (Betting and Gaming Council, 2020). As such, assessing how the gambling industry responded to such unanticipated changes in the gambling landscape may offer insight into how they may respond in the future to any proposed regulatory change.

A recent study from the UK analysed paid-for advertising of gambling during the three periods of national COVID-19 lockdown (Critchlow et al., 2022). Findings highlighted reductions in advertising spend during the initial lockdown compared to the same time period in the previous year; however, increased advertising expenditure in the second and third lockdowns was evident. This may be explained by the fact that competitions such as the Premier League were available to watch during the second and third lockdowns but were mostly not available during the first lockdown. Whilst this indicates evidence of shifts in marketing behaviour during the pandemic in the UK, the data analysed did not include social media marketing, such as advertising spend on platforms such as Facebook, Twitter/X, and Instagram, and so on. Social media is a particularly attractive marketing platform for companies, as it offers direct access to a global network of users, who can easily access such marketing through their personal devices at any time (Appel et al., 2020). The study of social media gambling marketing is a burgeoning area of research (James & Bradley, 2021). Such marketing includes high levels of brand-building and normalisation of gambling within sports content, such as through sports news services or humour, inducements to gamble, minimal safer gambling content, and content with overly high levels of positive sentiment (Bradley & James, 2019; Gainsbury et al., 2016; Houghton et al., 2019; Killick & Griffiths, 2019). Research has highlighted similar trends in other countries such as Canada (Wheaton et al., 2024) and the United States of America (Rossi et al., 2024). Yet, investigations of whether similar trends were evident during the pandemic are currently lacking.

It is notable that the risky nature of both the frequency and content of social media marketing is well established, with correlational research also demonstrating positive associations between gambling-risk and self-reported exposure to marketing (Gainsbury et al., 2016). Qualitative research with treatment-seeking individuals with experience of harmful gambling has also highlighted the role social media marketing plays in preventing efforts to abstain from gambling (Lopez-Gonzalez et al., 2020). This is not surprising given the reach that social media marketing has on social media, with one study demonstrating that posts from ten selected brands generated 24 million impressions over a single weekend (Rossi et al., 2024). Social media marketing may therefore contribute towards risky and potentially harmful gambling behaviour, help to normalise gambling in people with little or no prior experience of gambling, encourage riskier bets for those who are gambling regularly, and mitigate attempts to reduce or stop gambling (James & Bradley, 2021). However, no research to date has asked how the gambling industry in GB adapted their social media marketing during the pandemic. Better understanding of these possible changes is particularly important given the increased usage of social media in 2020 (Delogu et al., 2025), the unique gambling landscape created by national lockdowns, and the fact that social media marketing was not part of industry-led voluntary advertising reductions during the pandemic.

Notwithstanding this, a relatively understudied type of gambling social media marketing is affiliate marketing. Affiliates are often portrayed as sports betting communities or tipping pages on social media and have a similar reach to gambling operators (Houghton et al., 2019). However, there is a lack of transparency about the nature of the relationship between affiliates and industry operators (Houghton et al., 2020). Affiliates are financially incentivised to attract custom to their gambling industry partners and receive commission for doing so. They also post more content than gambling operators, as well as posting a higher frequency of direct advertising (Houghton et al., 2019). Given there was a reduction in the availability of live sports betting opportunities during the initial lockdown period in the UK (British Foreign Policy Group, 2022), there is a need to investigate how affiliates navigated such changes, to assess whether their marketing strategies changed as a result and, if so, in what way. For instance, despite their portrayal as tipping accounts, affiliate-suggested bets only perform slightly better than the bets advertised by operators and lead to consistent overall losses (Houghton & Moss, 2022). Whilst little research has been conducted assessing how people respond to affiliate marketing, we do know that regular football bettors report increased confidence in certain bets when advertised on an affiliate account compared to an operator account (Houghton & Moss, 2020). Taken together, these studies highlight the potentially concerning nature of affiliate marketing, where the presentation of the accounts is not aligned with the business practices of the accounts, and that this misalignment can impact upon bettors' perceptions of advertised bets.

As such, it is essential to better understand the impact of affiliate marketing. Doing so requires the development and application of sophisticated research practices suitable for these kinds of data. Machine learning, where complex mathematical models are applied to large datasets, is receiving increasing attention within gambling research (Deng et al., 2019). A recent review of data science approaches to safer gambling highlighted 17 studies of supervised machine learning where models are trained to classify unseen content based upon a labelled training dataset, with the main objectives to predict signs of harmful gambling or engagement with safer gambling tools (Ghaharian et al., 2022). Other potential applications of machine learning include assessing and categorising large datasets of online gambling content, which will help overcome limitations inherent with manual content analysis usually restricted to a specific time period or smaller datasets (Gainsbury et al., 2016; Houghton et al., 2019; Killick & Griffiths, 2019). Overcoming such limitations is increasingly important in the case of social media data as social media trends change over time and seasonal trends occur in gambling advertising due to sporting calendars (Houghton et al., 2023).

Researchers in Germany implemented a semi-supervised topic modelling approach to categorise 18,051 tweets from 13 German operators Twitter accounts (Singer et al., 2022). These authors highlighted the usefulness of coding large gambling social media datasets with a machine learning model, demonstrating that news and product advertising were the most common types of content posted by German gambling operators. However, the study did not focus on how such content changed throughout the COVID-19 pandemic and did not investigate any potential differences between operators and affiliates. Similarly, Russell et al. (2022) used frequent keywords to classify tweets from Australian gambling operator Twitter/X accounts between 24th February 2019 and 17th July 2020 into content categories such as sports, racing, responsible gambling, and novelty betting markets. This highlighted that gambling operators moved away from posting content relating to gambling during the initial lockdown and instead posted more on racing, esports, and table tennis. However, patterns of posting returned to their original levels post-lockdown, highlighting temporary changes in social media marketing that were not sustained over time. Further research is therefore needed to assess whether such identified changes can be observed in other countries with high levels of gambling marketing on social media, such as the UK (Rossi et al., 2021).

The current study sought to investigate how gambling was marketed on social media in the UK throughout and since the COVID-19 pandemic up until late 2022. We analysed two and half years' worth of tweet data from five gambling operators and five affiliates between 2020 and 2022 to examine the frequency, sentiment, and content of social media gambling marketing during the pandemic. We also investigated whether there are any differences in the ways in which operators and affiliates marketed on social media throughout pandemic, given the concerns highlighted in previous research around affiliate marketing (Houghton et al., 2020).

2. Method

2.1 Sampling procedure

Twitter data (i.e., original tweets) were purchased from Tweetbinder, a social media analytics platform with access to historical Twitter data, for the five most-followed UK gambling operators and affiliates, as determined in a previous study (Houghton et al., 2019). The time period between 1st January 2020 and 1st July 2022 was chosen to include all three national COVID-19 lockdowns in the UK, as well as periods before and after. Of the initial 494,563 tweets in the dataset provided, 141,429 tweet replies were removed; the final dataset therefore consisted of 353,134 original tweets. This was to ensure that our sample only consisted of Tweets sent to all followers, rather than replies which are directed at an individual user. Information collected for each tweet in the dataset included the account it was tweeted from, the date and time it was tweeted, and the number of retweets and the number of likes it received. The number of followers for each account was identified, and descriptive statistics (mean and median) were calculated on likes and retweets for each account. Table 1 gives the sample characteristics for each of the 10 accounts.

2.2 Data analysis

Throughout the different stages of data analysis, there was a focus on assessing differences across account types and time periods. For account types, averages of key variables were taken across the five affiliate accounts and the five operator accounts. To explore differences over time, four main time periods of interest were identified within the dataset, determined in

Table 1. Sample characteristics for the 10 gambling Twitter accounts (operators and affiliates).

Account	Account type	Followers	Original tweets	Mean likes per tweet	Median likes per tweet	Mean retweets per tweet	Median retweets per tweet
Bet365	Operator	443,065	32,103	64.15	9	7.47	1
Coral	Operator	316,279	4564	4.66	1	1.01	0
Paddy Power	Operator	686,807	40,363	355.85	17	29.23	1
Sky Bet	Operator	410,365	3717	172.05	16	25.35	2
William Hill	Operator	239,111	22,625	104.14	11	15.30	1
Football Tips	Affiliate	200,484	9195	6.67	1	0.77	0
Footy Accumulators	Affiliate	647,473	87,332	308.80	6	23.25	0
Free Super Tips	Affiliate	410,927	22,619	11.73	3	1.29	0
My Racing Tips	Affiliate	247,231	26,625	2.60	0	0.20	0
The Winners Enclosure	Affiliate	212,519	103,991	3.42	0	0.17	0

Football Tips, Footy Accumulators and Free Super Tips are affiliate accounts dedicated to predominantly posting football tips, whereas My Racing Tips and The Winners Enclosure mostly post horse racing tips.

line with key UK government lockdown dates (Institute for Government Analysis, 2022). Time period 1 (T1) covered the pre-lockdown period from 1st January 2020 to 26th March 2020. Time period 2 (T2) covered the period of the first national lockdown from the 27th March 2020 to 4th July 2020. Time period 3 (T3) covered the period between the end of the first national lockdown and the end of the third national lockdown, from the 5th July 2020 to 8th March 2021, and finally, time period 4 (T4) covered the period after the final national lockdown from the 9th March 2021 to 1st July 2022. All analyses were conducted on R. The data and script are openly available on OSF (ANONYMISED LINK – https://osf.io/mv5k6/?view_only=90efe089e9d54e969e4e96d9d556a811).

2.2.1 Stage 1 – frequency

Data were analysed to assess the frequency of posting across the time period to identify the impact of COVID-19 lockdowns. Average number of tweets per week were calculated for each of the 10 accounts and were then averaged across account type to create a weekly average for operators and a weekly average for affiliates. A time-series graph was then produced with the four main time periods of interest.

2.2.2 Stage 2 – sentiment analysis

The next stage was to assess the sentiment of tweets in the dataset using the 'syuzhet' package in R (RStudio Team, 2020). Before conducting the analysis, each tweet needed to be cleaned before analysis to remove punctuation, numbers and emojis. The National Research Council (NRC) Word-Emotion Association Lexicon was then used to carry out the sentiment analysis, counting the number of words in each of the individual emotional categories in each tweet, as well as the overall positive and negative sentiment. Individual emotion categories assessed were anger, anticipation, disgust, fear, joy, sadness, surprise, and trust. Average sentiment per tweet was then calculated for both operators and affiliates, as well as across the four previously identified time periods, and bar graphs were created to illustrate this. A series of 2×4 independent groups ANOVAs were then carried out to assess differences in sentiment and individual emotions between account types and time periods. Effect sizes were also calculated to assist interpretation of findings, given the extremely large sample sizes within the analyses.

2.2.3 Stage 3 – machine learning content analysis

The final stage in the analysis was to use machine learning to apply a simplified version of a coding scheme established in the previous research (Houghton et al., 2019) to analyse the main content of each Tweet within the dataset. The decision to use a simplified version of the coding scheme was made to improve overall model performance. A supervised learning approach was adopted so the model could learn this previously established coding scheme. This differs from an unsupervised approach where the choice of how many topics to extract is somewhat arbitrary and less theory driven. The model chosen within the supervised learning approach was a support vector machine (SVM) since they do well with high dimension (Joachims, 1998) and text typically has a lot features (i.e., words) which are represented by dimensions (vector of numbers) leading to a complex dataset with lots of dimensions. SVM do well with high dimension because they rely on a subset of vectors (features) at the boundary of the categories to help determine how best to separate the different categories (Cervantes et al., 2020). Furthermore, SVM can take account of many relevant features to help separate categories (Joachims, 1998), i.e., it can use words like football or cricket or table tennis to help separate the sports and promotional content category from direct advertising category. The ability of SVM to take a large number of dimension and be able to learn to identify and separate out tweets into different categories made it a good choice for this project.

As such, the lead author (ANONYMISED) coded 1000 tweets from the dataset manually and two co-authors (ANONYMISED) coded 200 of those tweets to assess inter-rater reliability. Tweets were assigned to one of the three following categories: direct advertising and betting assistance, sports and promotional content, and safer gambling. The direct advertising and betting assistance category refers to any tweets where bets are being advertised or discussed. The sports and promotional content category refers to posts made discussing sports, discussing promotional content that increases the brand's visibility, or which aims to be funny. Finally, the safer gambling category represents tweets that encourage followers to gamble safely, give information on how to gamble safely, provide gambling warnings or discuss age restrictions. A Fleiss Kappa of .687 was observed, demonstrating good reliability between researchers.

The sample of 1000 tweets was then split into train ($n = 900$) and test ($n = 100$) samples. In preparation for the machine learning analysis, further cleaning of the text was undertaken through removal of stop words, stemming, converting upper case to lower case, and removing white space from the tweets. A document term matrix (DTM) was then created, analysing the frequency of every word that appeared at least 10 times in the tweets across each of the individual tweets. A support vector machine model, using KSVM classification, was then trained on the training sample to identify the appropriate content category for each of the tweets (i.e., direct advertising and betting assistance, sports and promotional content, and safer gambling).

The model was then assessed on the test sample. Within the process of model training, different parameters within the model were used to produce the best agreement. For example, a range of kernels were applied, as well as a range of values for the cost of violation parameter. A model including the polydot kernel and a cost of violation parameter of '10' was found to give the highest agreement of 85%. To ensure the model was not made overly specific to the test sample, a validation sample of 100 additional tweets was manually coded to assess the model. The model showed 81% agreement with the validation sample; 81% and 85% are thought to be reasonable levels of agreement given the small number of words used in tweets, the class imbalance with safer gambling often appearing far less than sports or direct advertising (Bradley & James, 2019), and the inherently subjective nature of classifying words into subjective categories (Sebastiani, 2002). Due to the reasonable levels of agreement, the model was then used to assign a content category to every tweet in the dataset. Two multinomial logistic regressions were then conducted to assess the likelihood of direct advertising and safer gambling, in relation to the reference category of sports content. Predictors included in each of the models were the main time periods of interest, account type and an interaction term between time period and account type.

3. Results

3.1 Frequency of tweets

Figure 1 shows a clear decrease in the frequency of tweets from both gambling operators and affiliates during the period of the first national lockdown in the UK. This decrease was more pronounced for affiliates than operators. The frequency of affiliates posting increased after the first lockdown but did not return to pre-lockdown levels. Seasonal increases in tweet frequency were also observed in March 2021 and 2022 around major UK horse racing events, as well as a peak in July 2021 coinciding with England reaching the final of the UEFA men's European Championships.

3.2 Sentiment analysis

The sentiment analysis conducted found that tweets across the dataset had more positive sentiment than negative, with an average 1.39 positive words used per tweet, compared

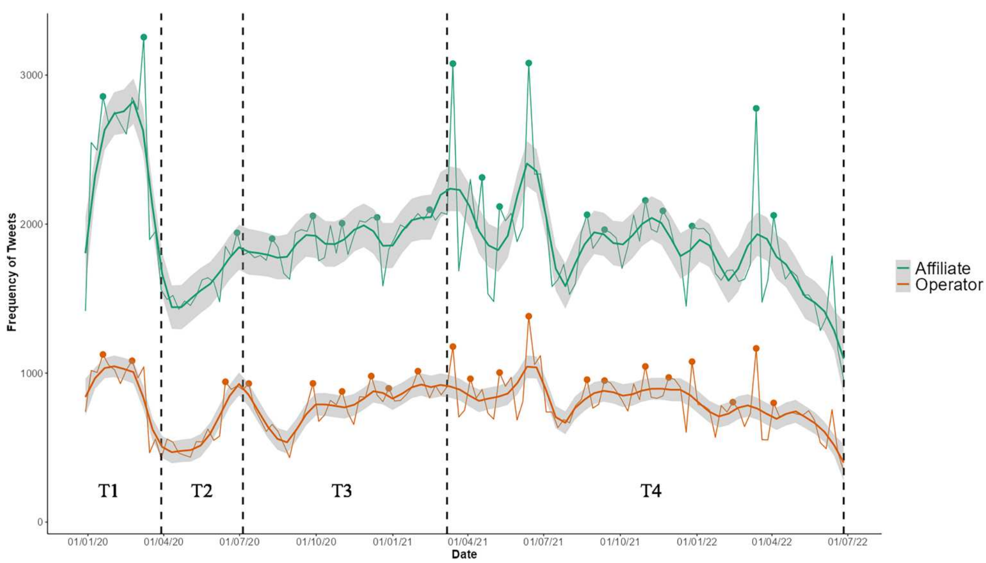

Figure 1. Frequency of Tweets per week for operators and affiliates across T1 (01/01/2020–26/03/2020), T2 (27/03/2020–04/07/2020), T3 (05/07/2020–08/03/2021) and T4 (09/03/2021–01/07/2022).

with just 0.40 negative words per tweets (see Figure 2). The most frequently observed positive emotion was anticipation, with 0.52 words per tweet. The most observed negative emotion was fear, with 0.18 words per tweet. A 2×4 between subjects ANOVA showed a significant small to medium main effect of account type upon positive sentiment, $F(1, 353{,}130) = 1572.02$, $p < .001$, $\eta^2 = .03$, with affiliates posting a higher frequency of positive sentiment ($M = 1.56$, $SD = 1.49$) compared to operators ($M = .99$, $SD = 1.16$). There was also a significant main effect of time period and a significant interaction effect between time period and account type upon positive sentiment (p's $< .001$). However, effect sizes showed these differences to be negligible. Similarly, there were significant main effects and interaction effects for other emotions assessed within the sentiment analysis, however, these were again found to be negligible through interpretation of their effect size and therefore will not be discussed further.

3.3 Machine learning content analysis

A multinomial logistic regression assessed the likelihood of tweets being classified as direct advertising compared to sports content, using time period, account type and an interaction term between time period and account type as predictor variables. A further multinomial regression assessed the likelihood of bets being classified as safer gambling, as compared to sports content, using the same predictor variables. See Table 2 for odds ratios for each predictor within both models.

Time period was a significant predictor of the likelihood of direct advertising, as compared to sports content, with direct advertising being less likely than sports content during the three lock downs (T2 and T3) and afterwards (T4) than pre-lock down

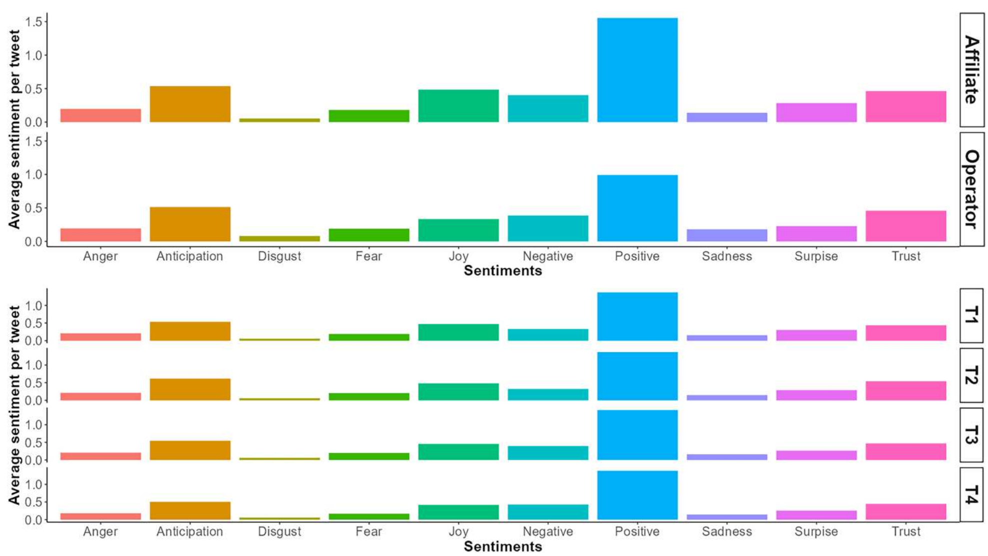

Figure 2. Top two panels: average emotion and sentiment per tweet for both affiliates and operators. Bottom four panels: average emotion and sentiment per tweet for all accounts (affiliates and operators) combined during T1 (01/01/2020–26/03/2020), T2 (27/03/2020–04/07/2020), T3 (05/07/2020–08/03/2021) and T4 (09/03/2021–01/07/2022).

Table 2. Odds ratio and confidence intervals for predictor variable in both multinomial logistic regressions that predict the likelihood of tweets being classified as direct advertising or safer gambling content, as opposed to sports content.

Model	Predictor	Odds ratio	95% CI
1: Likelihood of Direct Advertising vs Sports Content	Time 2 (vs Time 1)**	0.49	0.47, 0.50
	Time 3 (vs Time 1)**	0.67	0.65, 0.69
	Time 4 (vs Time 1) **	0.65	0.63, 0.66
	Operator (vs Affiliate) **	0.17	0.16, 0.18
	Time 2*Operator **	1.82	1.69, 1.96
	Time 3*Operator **	1.16	1.09, 1.23
	Time 4*Operator **	1.16	1.10, 1.22
2: Likelihood of Safer Gambling vs Sports Content	Time 2 (vs Time 1) **	0.92	0.74, 1.14
	Time 3 (vs Time 1) **	0.72	0.59, 0.86
	Time 4 (vs Time 1) **	1.42	1.21, 1.67
	Operator (vs Affiliate) **	0.24	0.17, 0.35
	Time 2*Operator **	2.48	.53, 4.02
	ime 3*Operator **	2.93	1.92, 4.46
	Time 4*Operator **	2.55	1.73, 3.76

Note: $^*p < .05$; $^{**}p < .001$.

(T1). Time period was also a significant predictor of the likelihood of safer gambling against sports content, with it being less likely for tweets to be classified as safer gambling than sports content during the three lockdowns (T2 and T3), as compared to pre-lockdown (T1). However, it was more likely that tweets would be classified as safer gambling than sports content post lockdowns (T4) compared to pre-lockdowns (T1). Account type was a significant predictor of the likelihood of direct advertising compared to sports content, with operators being around five times less likely to post direct advertising compared to sports content than affiliates. Similarly, account type was a significant predictor of the likelihood of safer gambling compared to sports content, with operators also being around five times less likely than affiliates to post safer gambling compared to sports content. The interaction terms between time period and account type were significant for both the likelihood of direct advertising and safer gambling, as compared to sports content. To explore this further, Figure 3 shows the predicted probabilities for each of content types across the four time periods for both operators and affiliates.

Inspection of the predicted probabilities highlights that the observed probability for each of the different content categories remained relatively stable across the four different time periods for gambling operators (Figure 3). However, the predicted probability for sports content was higher for affiliates during the first lockdown (T2) than pre-lockdown (T1). This then decreases during the subsequent lockdowns (T3) but not back to the same level as pre-lockdown (T1). Affiliates also decreased their direct advertising in the first lockdown (T2), as compared to pre-lockdown (T1). This then increased in the later lockdowns (T3) as compared to the first lockdown (T2) but again did not return to similar pre-lockdown levels (T1).

4. Discussion

The current study investigated how the social media marketing of gambling industry operators and affiliates was adapted in response to unprecedented changes in the gambling landscape. We found that the frequency, sentiment and content of tweets differed

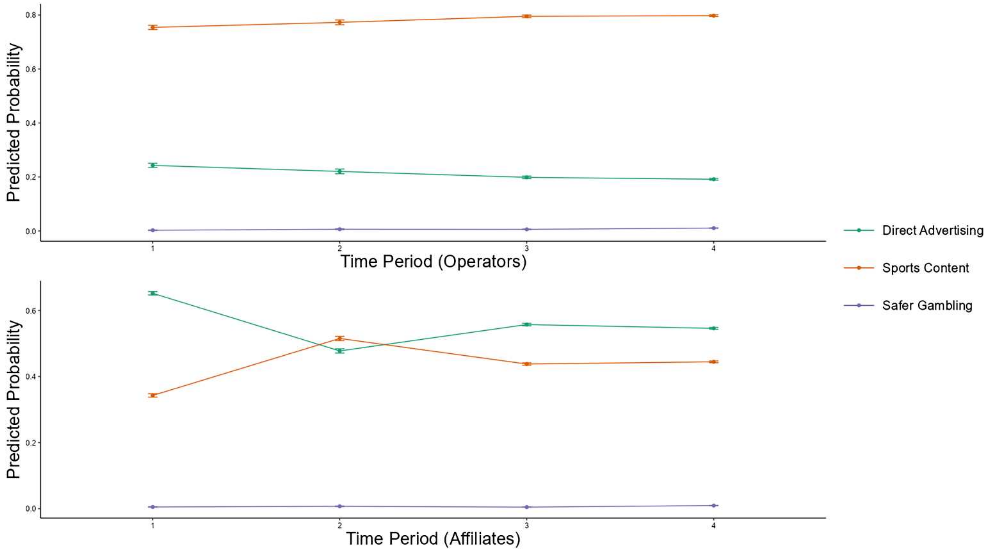

Figure 3. Predicted probabilities of direct advertising, sports content, and safer gambling tweets at each of the different time points for both operators (upper graph) and affiliates (bottom graph).

over the COVID-19 pandemic and between operator and affiliate accounts. Whilst affiliates included larger frequencies of positive sentiment within their tweets compared to operators, the overall sentiment of tweets remained consistent across time. There were fluctuations in the volume of tweets over time, particularly for affiliates, with large decreases noted during the first lockdown. Affiliates also adapted the content of their tweets during the first lockdown, posting a higher amount of sports content then they did previously. This suggests that whilst the sentiment of tweets remains consistent when changes to the gambling landscape occur, affiliates adapt their social media marketing in terms of both frequency and the content of their marketing. As such, it can be expected that affiliates will readily adapt their marketing strategies in response to any future regulatory change. For example, one of the main areas of focus within the Gambling Act White Paper is proposals for the gambling industry to avoid sending direct marketing or bonus offers to those who show strong indicators of harm (Department for Culture Media & Sport, 2023). The industry may therefore place increased focus upon alternative forms of marketing to reach those who engage most with these offers, with affiliate social media marketing being one such channel. As such, continued monitoring of how affiliates react to any changes brought about by the consultations around the White Paper are necessary to protect those at-risk of gambling harm.

The finding that levels of social media marketing dropped during the first UK national lockdown is consistent with research on operator social media use in Australia (Russell et al., 2022), declines in paid-for UK television advertising (Critchlow et al., 2022), and general reductions in gambling behaviour during this period (Brodeur et al., 2021). However, the current study extends these findings to highlight how this reduced marketing was more pronounced for affiliates. Our findings also offer insight into the frequency of marketing during subsequent lockdowns, with neither operator nor affiliate marketing seeing substantial increases during these periods. One possible explanation for this may be the COVID-19 measures introduced by the UK's Gambling Commission in November 2020 stating that operators must not exploit lockdowns for marketing purposes and to ensure their affiliates were conducting themselves appropriately (Gambling Commission, 2020). However, this interestingly does not align with the increased television advertising spend during the second and third lockdowns (Critchlow et al., 2022), despite the availability of sport during these periods. This indicates other factors impacted the volume of social media marketing at that time. Instead, after the end of the initial lockdown large increases in tweet volume seem to be related to seasonal trends and large sporting events, such as the delayed 2020 European men's Football Championships in 2021, where England were co-hosts and reached the final of the competition. Marketing frequency may have been impacted by a complex interplay between market availability, seasonal trends and public interest or mood in a major sporting event. Given that marketing is a risk factor for gamblers across the spectrum of gambling behaviour (Rockloff et al., 2019), future research should explore these factors in relation to gambling marketing in more detail to highlight periods in the year where marketing is most likely to have a negative impact upon individuals, especially those at risk of harmful gambling. This is particularly important given the sheer volume of social media marketing highlighted in the current study, whereby there was an average of around 380 original Tweets per day across the 10 accounts studied.

We also demonstrated a larger volume of positive emotions are included within social media marketing of gambling compared to negative emotions, replicating previous findings (Bradley & James, 2019). To date, the extant literature has highlighted associations between positive emotions and purchasing behaviours (Widayati et al., 2019), and gambling behaviour (Juma & Pandelaere, 2019). As such, it follows that marketing campaigns would use positive language to aim to instil positive emotions within their account followers. The current study expanded on existing findings by revealing that a machine learning approach categorisation of the emotionality of tweets remained consistent across time and did not show similar seasonality as frequency of tweets. It was also found that affiliates used a greater proportion of positive emotion within their tweets compared to operators, providing evidence for a positivity bias seen across affiliate marketing (Guillou-Landreat et al., 2021; Torrance et al., 2021) is even more prominent within affiliate marketing. This adds to a growing evidence base on the risky nature of affiliate marketing of gambling (Houghton et al., 2019; Houghton & Moss, 2020) and is likely attributable to the fact that affiliates over-represent suggested winning bets over losing bets (Houghton & Moss, 2022). This represents a particular risk towards vulnerable audiences, such as children, as it may lead to unrealistic perceptions about the likelihood of making money from gambling. As such, new regulatory approaches are needed to target this element of affiliate marketing. For example, affiliate marketers should be made to accurately report the success of their suggested bets and make it clear to their audience that they receive income from getting people to sign up to a gambling website.

Another major finding of the current study is that while the content of operator marketing remained consistent across time, affiliates adapted their posting during the first lockdown, and this appeared to have a lasting impact. Previous literature has established that operators tend to post more sports content than direct advertising, with the inverse being true of affiliate marketing (Houghton et al., 2019). However, affiliates shifted to posting more sports content than direct advertising during the first lockdown and whilst this reverted during subsequent lockdowns, the disparity between the frequency of each type of content was less pronounced than pre-lockdown. A likely explanation for this change was the reduced availability of professional sport for large periods during the first lockdown (British Foreign Policy Group, 2022). This lack of availability greatly reduced affiliates' opportunities to advertise sports betting – their main, and most profitable, gambling activity they advertise. By the end of the first lockdown, affiliates once again posted more direct advertising than sports content, but not to the same levels as pre-lockdown or those observed in previous studies before the pandemic. This demonstrates the evidence of how the actions of companies involved in gambling are embedded within wider social contexts and will be informed by the prevailing attitudes and social norms (Wardle et al., 2024).

These changes may be explained, at least in part, by these types of marketing being shown to be more appealing to younger audiences and instil positive emotions in them (Rossi & Nairn, 2021). Sometimes referred to as content marketing, posting about sporting events or humorous messages aims to engage and expand their follower base with content that is not necessarily related to the product that the advertiser offers (Rossi & Nairn, 2022). It may therefore be the case that affiliates adapted their content out of necessity but maintained these changes because of increased engagement with their marketing. Certainly, there has been a shift towards content marketing in recent years due to its ability to reach and engage as many potential customers as possible, with the content itself appearing innocuous. Recent research has also shown that people struggle to identify gambling content marketing as advertising (Rossi & Nairn, 2025). As such, any reductions in direct marketing caused by the gambling White Paper may be counteracted by increases in content marketing. Given content marketing now falls under the Advertising Standards Authority nonbroadcast marketing code and is less likely to be recognised as advertising (Rossi & Nairn, 2022), further regulation is needed to ensure that content marketing is clearly labelled as advertising on social media. This is particularly the case for affiliates as their presentation as tipping accounts (Houghton et al., 2020) reduces the clarity of content marketing as a form of marketing even further.

A major strength of the current study is the successful use of a machine learning model to accurately code the content of tweets throughout the COVID-19 pandemic. This allowed for a much larger sample size of tweets to be analysed than previously (Gainsbury et al., 2016; Houghton et al., 2019; Killick & Griffiths, 2019) and therefore to assess how the content of tweets changed over time. More specifically, this facilitated a comparison of social media marketing between the different lockdown periods in the UK, something that is largely absent in existing COVID-19 and gambling literature that instead had largely focused on the initial lockdown (Brodeur et al., 2021). However, to achieve acceptable levels of accuracy within the machine learning model, it was necessary to use a simplified version of the coding scheme established in a previous study (Bradley & James, 2019). As some content categories had to be merged, the resulting content categories were less specific than in the previous studies. Such a trade-off in specificity of content categories versus volume of tweets analysed highlights the importance of both manual and machine modelled content analysis of large datasets.

5. Limitations and future directions

There are several potential limitations of the current study. The sentiment analysis only counted the number of emotional words per tweet and therefore could only infer strength of emotionality through volume rather than global meaning. As a result, the analysis may have missed important context (e.g., sarcasm, irony). In terms of the reach and influence of advertising messages, the number of followers is known, but ultimately no statement can be made about how many users are exposed to the content due to this information not being provided by Tweetbinder. There is also no usage data about the users themselves, or whether they are bots – the users are anonymous. Additionally, only the text included in a tweet was available within the data framework collected and therefore context for some tweets may have been lost (i.e., if the posting included an image). This is particularly important given the increasing focus placed upon visuals within social media marketing. Future research should collate images accompanying the social media marketing of gambling to explore whether this additional context impacts upon categorisation of tweets. Previous research analysed the content of images (Singer et al., 2022), and such methods should now be applied in different countries and on different social media platforms (i.e., Facebook, TikTok, and Instagram) to develop a stronger understanding of social media gambling marketing strategies.

A further limitation of this paper is that is only looked at one social media platform and there is evidence to suggest that people and companies engage differently with different social media companies (Voorveld et al., 2018). Whilst this study was confined to only the English language, a large proportion of the world speak English and the UK is a large gambling market. The inclusion of affiliate accounts was a strength of the current study and permitted the first formal investigation of affiliate marketing during lockdown by revealing potentially concerning features of their marketing practices. Carefully designed experimental research is needed to investigate how affiliate marketing is recognised and responded to by gamblers on social media and to explore whether features of affiliate marketing may increase subsequent risky gambling.

6. Conclusion

Our study demonstrates how quickly social media marketing strategies were adapted by gambling operators and affiliates during COVID-19 lockdowns in the UK. After a substantial decrease in Twitter/X postings during the first lockdown and a shift in affiliate-led content from direct advertising/promotion of betting odds to sports content, subsequent lockdowns saw no further reductions by operator or affiliates. This study also highlights the need to seriously and carefully consider the regulatory framework around the role affiliates play within the gambling marketing sphere. Affiliates post more often, and with high positive sentiment content that is filled with more direct advertising/odds promotions than operators. Crucially, affiliates adapted more quickly to structural changes which can leave gamblers uniquely vulnerable to the influence of social media marketing.

Author contribution statement

SH: Conceptualisation, methodology, data analysis, writing first draft. FB: Conceptualisation. AB: Conceptualisation, methodology, writing – review editing. RJ: Conceptualisation, methodology, writing – review editing. HW: Funding acquisition, writing –

review editing. SD: Funding acquisition, conceptualisation, methodology, writing – review editing.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This work was supported by British Academy: [Grant Number SG2122\211340].

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