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Loopholes in the control of online alcohol marketing in Thailand: Analysis of alcohol-related internet content for Thai audiences extracted by artificial intelligence

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Abstract

Introduction: Thailand's alcohol control laws include an extensive ban on alcohol marketing. However, loopholes exist in online marketing, and online marketing of alcohol targeting audiences in Thailand has not yet been systematically described. The objective of this study was to describe online alcohol marketing activities in the Thai language.

Methods: We used an artificial intelligence (AI) platform to collect alcohol marketing content on the internet. We prepared a database of search terms related to alcohol marketing. The platform automatically searched and filtered alcohol marketing content that violated control and regulatory measures. We analyzed data using descriptive statistics.

Results: Our analyses included data from 13,301 posts generated by 4,638 users. The most common violation of the Alcoholic Beverage Control Act of 2008 was the use of alcohol brand trademarks or symbols (70%). The most common content producers were restaurants, pubs, and bars, followed by wholesale/retail stores and influencers. Content materials focused on driving awareness and drinking methods. Content materials did not mention the location of sales, shipping methods, discounts, free products, or giveaways.

Discussion: We found violations of regulations for alcohol control measures in Thailand among online media posts in the Thai language. Potential selection bias from search engine algorithms and the limited generalizability should be considered as caveats in the interpretation of the study findings.

Introduction

Thailand is an emerging economy in Southeast Asia where alcohol consumption is approximately seven to eight liters per person per year (Pongutta et al., 2019; Wichaidit et al., 2019). Beer is the most commonly consumed alcoholic beverage in Thailand, particularly among youths and young adults (Statista, 2025; Wichaidit et al., 2019). Thailand uses the Alcoholic Beverage Control Act of 2008 (the Act) as the primary legislative tool for alcohol control, including controlling access to alcohol by limiting the hours for alcohol sales from 11:00–14:00 and 17:00–24:00, prohibiting sale to minors under 20 years of age, prohibiting marketing promotions, and prohibiting alcohol advertisements or marketing activities that display logos, trademarks, and images of alcoholic beverages (Department of Disease Control, 2008). The Royal Thai Government has prohibited online sales of alcoholic beverages since 2020 (Office of the Prime Minister, 2020).

Thailand's alcohol control laws take effect only in Thai territory. Furthermore, the Act was passed in 2008, and thus does not extensively cover online marketing, social media-based marketing, and the use of social media influencers (Department of Disease Control, 2008), which can increase drinking and alcohol-related problems (Curtis et al., 2018). The limited jurisdiction within domestic territories also created loopholes. One notable example of this was a whiskey promotion campaign with a global pop star of Thai origin as the presenter (Leelasestaporn, 2022). Thai authorities could not impose advertising restrictions as the campaign was conducted outside of the Kingdom.

Online alcohol marketing has increased since the COVID-19 pandemic worldwide. Online alcohol-delivery marketing

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increased by 20% in 2020 in South Africa (Theron et al., 2023), and alcohol businesses worldwide developed marketing strategies to recreate drinking activities in online spaces during the pandemic (Plata et al., 2022). Businesses and alcohol marketers engaged in "Online Merged with Offline" (OMO) marketing to create an experience and impression of being a part of the social activity, despite being at home (Noel et al., 2020).

Consumers in Thailand can purchase alcohol (both within and outside the excise tax system) at low prices. Also available are discounts, gifts, giveaways, drinking instructions, recipes, and displays of brands and logos with claims for benefits; as well as indirect enticements to drink through information, images, video clips, shared content, ordering systems, seat reservations, and payment through a drinking venue's online platform. Social media technology is an important online marketing tool that eases the direct promotion of sales and creates additional channels to access alcohol. It does not restrict the age of the buyer, particularly those under 20 years of age (McClure et al., 2020; Radoš Krnel et al., 2023). Online marketing is not limited by hours of sales, thus increasing drinking behavior (Noel et al., 2020).

Although studies on exposure to online alcohol marketing have included surveys in the USA (Jernigan et al., 2017; Zhang & Esser, 2024), China (Chan et al., 2024), and South Africa (Osuafor et al., 2023), online alcohol marketing activities targeting Thai audiences have not been systematically described. There are no data available to illustrate the scale and characteristics of online alcohol marketing in the Thai language. Due to the large volume of texts and content online, manual extraction and analysis would be a very difficult and resource-intensive task. Big data and artificial intelligence (AI) can provide solutions for these issues. Marketing researchers and professionals have used web scraping to collect data from the internet (Boegershausen et al., 2022), and such data can be analyzed using content analysis or sentiment analysis to keep track of online marketing exposure and consumer sentiments (Kumar et al., 2021). Although deep learning (Bonela et al., 2022) and machine learning algorithms (Lee et al., 2024) have been used to identify beverage types and brands by images and quantify alcohol exposure in electronic images, no study has assessed the feasibility of using AI to detect alcohol marketing violations. The findings from such a study could offer useful empirical data for stakeholders in alcohol control, such as public health agencies, policymakers, and behavioral health practitioners. The objective of this study was to describe existing online alcohol marketing activities in the Thai language, as extracted by an AI system.

Methods

Study Design and Setting

We conducted a content analysis of online media posts made during the year 2023 related to alcoholic beverage marketing in the Thai language.

Study Instruments

Our study instruments included: (a) learning model tools (e.g., language, slogans, keywords, logos, and alcohol advertising messages) obtained from the use of AI systems to monitor trends in the online alcoholic beverage market; and (b) a web scraping system to query online public posts pertaining to alcohol marketing.

Data Collection

First, the research team performed web scraping of online content by conducting organic searches of alcoholic beverages marketing using search engines that supported queries through APIs (Application Programming Interfaces; Figure 1). The web scraping tools included Beautiful Soup and Scrapy for Python. Beautiful Soup was used to pull data out of webpages (Richardson, 2015), and Scrapy was used as a web crawler that extract data from websites (Scrapy developers, 2025). The research team then used Selenium (Software Freedom Conservancy, 2025) for dynamic content retrieval. The research team also developed a custom search query management system on a MySQL database using PHP Hypertext Preprocessor (PHP). The query management system contained common words, phrases, and slang for alcoholic beverage brands, marketing, and sales. This system enabled the database administrators to add, delete, and enable or disable specific search terms based on contextual needs. The system also automated the search process by executing searches for all predefined terms in a single operation, significantly reducing manual labor. Research team members then copied messages, images, jargon, and words in the posts deemed to be relevant, and stored the retrieved data for further processing by AI. Before entering the data analytics process, the research team members removed posts with data quality issues, namely: (a) posts that were duplicate entries; (b) posts with incomplete or corrupted data (containing only hashtags or images that could not be processed); and (c) posts with irrelevant content.

Data Processing

The research team sorted the collected data into four main types (factors): (a) texts; (b) emojis; (c) hashtags, and (d) keywords/slang words. Team members then triangulated the study data against a database of online alcohol marketing communication materials (containing vocabularies, phrases, slang, and emojis) and a database of alcohol control measures. Team members compiled and indexed a glossary of terms and added descriptions to all labeled posts to identify and categorize posts related to alcoholic beverage marketing and sales.

The MAO Engine

In order to process the collected data, the research team designed a processing mechanism known as the *MAO engine* as a modular system (Figure 2). The system included input of data, data processing, and data weighting. Team members processed each data type (factor) separately and independently of one another, namely:

(a) Texts models, processed using machine learning models (P1),
(b) Emojis models, processed using machine learning models (P2),
(c) Hashtags models, processed based on the ratio of alcohol-related hashtags to the total number of hashtags in the dataset (R1), and

(d) Keywords/slang models, processed based on the ratio of the total length (in characters) of all identified keywords/slang terms to the overall length of the dataset (R2)

Figure 1

Conceptual Diagram of the Artificial Intelligence-Based Web Scraping Platform used in the Study

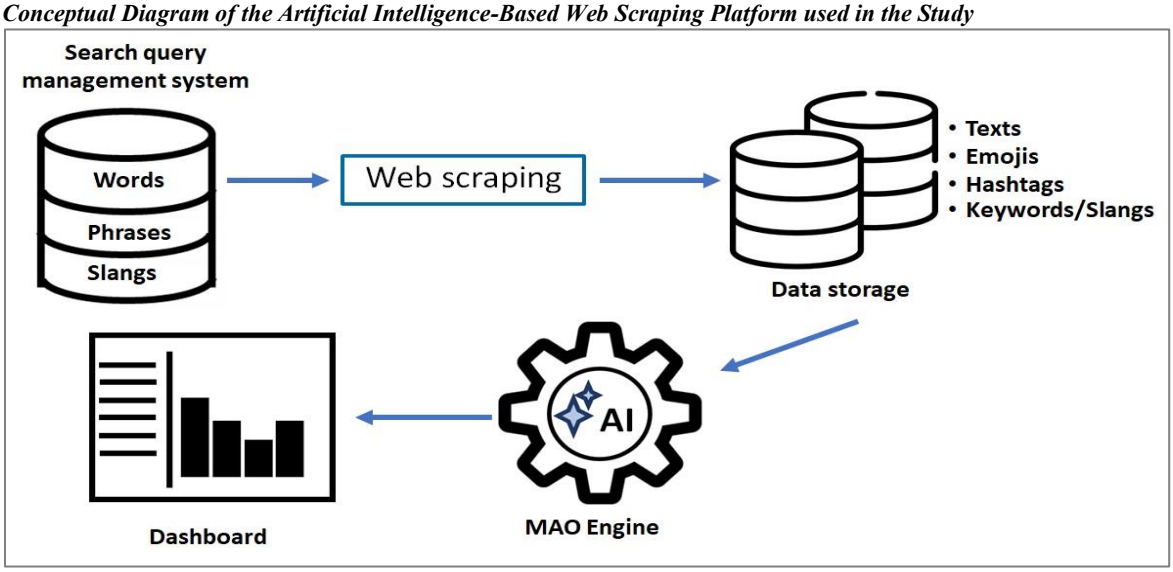
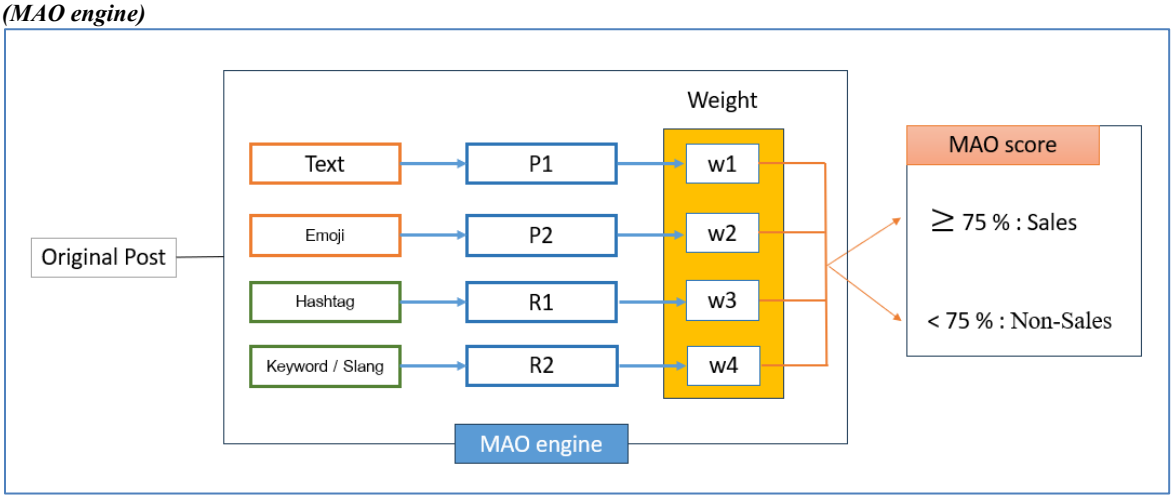


Figure 2

Schematic Diagram of Analysis of Unstructured Data and Classification of the Content using a Processing Mechanism (MAO engine)



Note: Classification of content as being related vs. unrelated to alcohol sales, developed by the lead investigator (KT) and colleagues

The machine learning models for analyses of texts and emojis used neural networks with an embedding bag layer, a technique for generating vectors to enhance the semantic representation of words in the dataset (Machine Learning in Plain English, 2023). The research team used the BERT (Bidirectional Encoder Representations from Transformers; Devlin et al., 2019) for text classification and sentiment analysis. We used convolutional neural networks (CNN) for image recognition and logo detection tasks. We further fine-tuned the model using labeled datasets of alcohol-related content to improve classification accuracy in the context of alcohol marketing on social media. We developed the models using Python along with PyTorch, and used PyThaiNLP for tasks specific to Thai text processing. Both analysis models (P1 and P2) had an accuracy of more than 80%.

Team members fed each factor into the MAO engine processing mechanism. The MAO engine processing mechanism then yielded a score (i.e., the MAO score) for each piece of content that indicated the probability that the content involved the sale or promotion of alcoholic beverages. Investigators arbitrarily considered posts with a 75% or higher MAO score (probability) to potentially involve alcohol advertisement, sales, or control laws violations. We validated the outputs from the AI algorithm with the outputs from a manual review by human experts. We used precision

indicators, recall, and F1-score to measure the occurrence of false-positive and false-negative results. The model had an average F1-score of 0.77.

Study Variables

User

We categorized users who made the posts or content into ten categories and included business/organizational level users (e.g., drinking venues, wholesalers, or retailers), individual level users (e.g., influencers, personal profiles and sites, vendors), and others.

Platform for Online Media Posts

We categorized the platforms according to commonly used social media in Thailand, including Facebook, Instagram, LINE, TikTok, X(Twitter), Thai e-commerce websites, and others.

Violation of Alcohol Control Measures

We categorized each post according to whether the post violated the Alcoholic Beverage Control Act of 2008, Section 30 (prohibition of alcohol sales using automatic machines, peddling, discounts, raffles, giveaways, samples, or complementary gifts) and Section 32 (ban on alcohol advertisement, including display of the product or containers of the beverage) by analyzing the four factors separately as per the above-mentioned data processing procedures. We considered a presentation of alcohol brand identity (known in Thailand and hereinafter referred to as *Brand DNA*) to fall under Section 32 and made *Brand DNA presentation* a separate category.

Objective of Posts

We categorized each post with regard to its objective based on the concept of customer journey. In our study, we used the following categorization of the objective of online media posts: (a) creating product awareness (presenting text-image of alcoholic beverage, drinking methods, new mixing techniques, types of containers used for drinking, etc.); (b) reviews from influencers (content providing comparative information for decision-making); (c) emphasizing purchase generation (indicating sales locations, product facilities, price, and delivery); (d) customer retention through price reductions, exchanges, giveaways, free shipping, loyalty points, etc.); and (e) support, word of mouth, sharing of contents.

Data Management

We used several data transformation techniques to handle the mixed dataset of images and texts. For texts, we compiled and processed the data using a structured natural language processing (NLP) pipeline tailored to Thai language. We cleaned and tokenized the texts using PyThaiNLP, lemmatization (reducing a word to its base form), and removal of noise such as emojis, URLs, and punctuation, then normalized the text to standardize the data for analysis. We used a custom alcohol-related keyword list to retain only relevant content. Examples of these keywords in Thai included *pro lao* (booze promotion), *pro beer* (beer promotion), *beer took* (cheap beer), *ran lao* (bars), etc. Subsequently, the cleaned text was transformed into numerical features using Term Frequency–Inverse Document Frequency (TF-IDF). For images, we extracted the embedded text using optical character recognition (OCR) and used image metadata analysis to check for data redundancy. We used techniques such as duplicate content detection based on text similarity and image hashing (e.g., perceptual hashing) to identify nearly duplicate images. In addition, we used data mining algorithms to analyze and understand the language usage patterns and behaviors of sellers. In particular, we used unsupervised clustering techniques such as K-means clustering and hierarchical clustering (Han et al., 2011) to group similar communication patterns. We also used the Latent Dirichlet Allocation (LDA) technique (Blei et al., 2003) for topic modeling, i.e. to identify common topics and themes in marketing content related to alcohol sales. The LDA algorithm was implemented with the Gensim library (Řehůřek & Sojka, 2010), which allowed identification of underlying themes in alcohol marketing strategies, such as price, promotions, and youth-oriented language. We then created a dictionary to index and label all posts found (including texts and images) to classify posts as those concerning marketing and sales of alcoholic beverages. The data was then aggregated for the final analyses.

Data Analyses

To safeguard the privacy and confidentiality of user-generated content, we removed the username and other personally identifiable information from the study dataset prior to conducting analyses and presenting the findings. We used sentiment analysis as a complementary technique to capture the emotional tone of the posts to help identify potential alcohol marketing-oriented content on social media platforms. Sentiment analysis refers to the computational process of detecting and classifying emotions, opinions, or attitudes expressed in textual data, including but not limited to texts and emojis (Liu, 2012). The sentiment scores were interpreted within the context of alcohol-related communication. Posts with positive sentiment scores combined with alcohol-related keywords, hashtags, or promotional visual content were treated as strong indicators of marketing messages. On the other hand, posts with negative sentiment scores were often associated with warnings, risks, or critiques of alcohol consumption and were classified as deterrents of alcohol consumption. Based on the sentiment analysis output, we assigned a score (probability) of each piece of text or emoji being associated with online alcohol marketing at an arbitrary cut-off point of 75%. Descriptive statistics were used to summarize the overall online alcohol marketing activities by platforms, user categories, apparent primary objectives, and marketing strategies. The sentiment-analysis-related findings will be published separately in the future.

Ethical Considerations

This study was deemed to be unrelated to human research by the institutional review board (IRB) of the lead author (KT). Nonetheless, to safeguard the privacy and confidentiality of users who generated the content, the investigators did not include the username or other personally identifiable information in the analysis of the study data. The investigators only included the analysis outputs in the presentation of the study findings.

Results

We collected data from a total of 13,301 posts generated by 4,638 users. Facebook was the most common platform for alcoholic beverage marketing (53.6%), followed by TikTok, LINE, and Instagram. Most posts came from clubs, bars, and restaurants (38.8%), followed by influencers, wholesalers, retailers, and official brand pages (Table 1).

Table 1

Distribution of Posts Classified by User Category and Platform

User category (number of posts)	Facebook	Instagram	Line	Tiktok	E-Commerce websites	X (Twitter)	Others
Clubs, bars, and restaurants (5156)	3632 (70.4%)	474 (9.2%)	599 (11.6%)	438 (8.5%)	0 (0%)	10 (0.2%)	3 (0.1%)
E-marketplaces (14)	3 (21.4%)	0 (0%)	5 (35.7%)	0 (0%)	6 (42.9%)	0 (0%)	0 (0%)
Grocery stores/convenience stores (133)	44 (33.1%)	0 (0%)	83 (62.4%)	6 (4.5%)	0 (0%)	0 (0%)	0 (0%)
Influencers (3279)	639 (19.5%)	308 (9.4%)	7 (0.2%)	2267 (69.1%)	0 (0%)	31 (0.9%)	27 (0.8%)
Manufacturers/distributors (73)	8 (11%)	1 (1.4%)	40 (54.8%)	13 (17.8%)	11 (15.1%)	0 (0%)	0 (0%)
Official brand pages (1946)	1636 (84.1%)	216 (11.1%)	26 (1.3%)	55 (2.8%)	11 (0.6%)	2 (0.1%)	0 (0%)
Personal profiles and sites (282)	141 (50.0%)	5 (1.8%)	4 (1.4%)	132 (46.8%)	0 (0%)	0 (0%)	0 (0%)
Smuggled/duty-free vendors (212)	28 (13.2%)	1 (0.5%)	119 (56.1%)	0 (0%)	55 (25.9%)	9 (4.2%)	0 (0%)
Wholesalers/retailers (2187)	1000 (45.7%)	126 (5.8%)	505 (23.1%)	282 (12.9%)	117 (5.3%)	157 (7.2%)	0 (0%)
Other (19)	4 (21.1%)	2 (10.5%)	0 (0%)	13 (68.4%)	0 (0%)	0 (0%)	0 (0%)
Total (13301)	**7135 (53.6%)**	**1133 (8.5%)**	**1388 (10.4%)**	**3206 (24.1%)**	**200 (1.5%)**	**209 (1.6%)**	**30 (0.2%)**

Table 2

Distribution of Posts that used Alcohol Brand Trademarks or Symbols Classified by User Category

User Category (Number of Posts)	*n* (%)
Clubs, bars, and restaurants (5156)	4219 (81.8%)
E-marketplaces (14)	13 (92.9%)
Grocery stores/convenience stores (133)	129 (97.0%)
Influencers (3279)	2354 (71.8%)
Manufacturers/distributors (73)	68 (93.2%)
Official brand pages (1946)	865 (44.4%)
Personal profiles and sites (282)	152 (53.9%)
Smuggled/duty-free vendors (212)	210 (99.1%)
Wholesalers/retailers (2187)	2050 (93.7%)
Other (19)	11 (57.9%)
Total (13301)	**10071 (75.7%)**

Approximately three-fourths of posts by users in all categories included alcohol brand trademarks or symbols (Table 2). Posts from smuggled or duty-free vendors, grocery or convenience stores, wholesalers or retailers, manufacturers or distributors, and e-marketplaces commonly contained trademarks or symbols (a proportion of more than 90% in all categories), whereas posts from official brand pages were the least likely to do so. The most common type of violation was that of Section 32 (advertising alcoholic beverages or displaying the name or trademark of alcoholic beverages), found in 37.5% of all posts. This violation was most common among wholesalers and retailers, grocery stores, and convenience stores (Table 3). Posts also violated Section 30, either alone (24% of all posts) or in combination with Section 32. Violation of Section 30 was most common among smuggled or duty-free vendors, e-marketplaces, manufacturers, and clubs, bars, and restaurants. About one-quarter of posts also presented Brand DNA (brand identity) using emoji symbols with similar images to the trademark of the alcoholic beverages (e.g., 🐘🦁🐅🐖🌞🦢, etc.). Creating product awareness was the most common apparent objective of the posts among all user groups (Table 4). However, emphasizing purchase generation also appeared to be a common objective, particularly among grocery stores/convenience stores, smuggled/duty-free vendors, and electronic marketplaces.

Table 3

Distribution of Violations of the Alcoholic Beverage Control Act of 2008 classified by User Category

User Category (Number of Posts)	Violated Section 32	Brand DNA, Emoji	Violated Sections 30 and 32 and Brand DNA	Violated Sections 30 and 32	Violated Section 32 Brand DNA	Violated Section 30
Clubs, bars, and restaurants (5156)	1130 (21.9%)	936 (18.2%)	1462 (28.4%)	1534 (29.8%)	93 (1.8%)	2504 (48.6%)
E-marketplaces (14)	10 (71.4%)	1 (7.1%)	0 (0%)	2 (14.3%)	1 (7.1%)	3 (21.4%)
Grocery stores/convenience stores (133)	111 (83.5%)	4 (3%)	5 (3.8%)	13 (9.8%)	0 (0%)	16 (12%)
Influencers (3279)	1328 (40.5%)	896 (27.3%)	772 (23.5%)	14 (0.4%)	240 (7.3%)	114 (3.5%)
Manufacturers/distributors (73)	51 (69.9%)	(0%)	4 (5.5%)	12 (16.4%)	1 (1.4%)	12 (16.4%)
Official brand pages (1946)	564 (29%)	1071 (55%)	170 (8.7%)	35 (1.8%)	96 (4.9%)	209 (10.7%)
Personal profiles and sites (282)	113 (40.1%)	51 (18.1%)	20 (7.1%)	8 (2.8%)	11 (3.9%)	7 (2.5%)
Smuggled/duty-free vendors (212)	78 (36.8%)	2 (0.9%)	8 (3.8%)	124 (58.5%)	(0%)	99 (46.7%)
Wholesalers/retailers (2187)	1604 (73.3%)	137 (6.3%)	23 (1.1%)	371 (17%)	52 (2.4%)	230 (10.5%)
Other (19)	3 (15.8%)	8 (42.1%)	8 (42.1%)	0 (0%)	0 (0%)	3 (15.8%)
Total (13301)	**4992 (37.5%)**	**3106 (23.4%)**	**2472 (18.6%)**	**2113 (15.9%)**	**494 (3.7%)**	**3197 (24%)**

Table 4

Distribution of the Objectives of Posts, Classified by User Category

User Category (Number of Posts)	Creating Product Awareness[a]	Reviews from Influencers[b]	Emphasizing Purchase Generation[c]	Customer Retention[d]	Support, Word of Mouth, Share
Clubs, bars, and restaurants (5156)	4846 (94%)	4 (0.1%)	3622 (70.2%)	2425 (47%)	109 (2.1%)
E-marketplaces (14)	14 (100%)	0 (0%)	12 (85.7%)	1 (7.1%)	1 (7.1%)
Grocery stores/convenience stores (133)	133 (100%)	0 (0%)	130 (97.7%)	15 (11.3%)	1 (0.8%)
Influencers (3279)	3119 (95.1%)	558 (17%)	1137 (34.7%)	37 (1.1%)	1573 (48%)
Manufacturers/distributors (73)	72 (98.6%)	0 (0%)	62 (84.9%)	11 (15.1%)	0 (0%)
Official brand pages (1946)	1910 (98.2%)	9 (0.5%)	380 (19.5%)	215 (11%)	163 (8.4%)
Personal profiles and sites (282)	261 (92.6%)	0 (0%)	63 (22.3%)	11 (3.9%)	91 (32.3%)
Smuggled/duty-free vendors (212)	212 (100%)	0 (0%)	201 (94.8%)	128 (60.4%)	5 (2.4%)
Wholesalers/retailers (2187)	2162 (98.9%)	15 (0.7%)	1514 (69.2%)	362 (16.6%)	157 (7.2%)
Other (19)	17 (89.5%)	0 (0%)	4 (21.1%)	3 (15.8%)	13 (68.4%)
Total (13301)	**12746 (95.8%)**	**586 (4.4%)**	**7125 (53.6%)**	**3208 (24.1%)**	**2113 (15.9%)**

[a]Text image of alcoholic beverage, drinking methods, new mixing techniques, types of containers used for drinking, etc.;
[b] Content providing comparative information for decision-making; [c]Indicating sales locations, production facilities, price, and delivery; [d] Achieved through price reductions, exchanges, giveaways, free shipping, loyalty points, etc..

Discussion

In this study, we used artificial intelligence (AI) to analyze the overall online marketing and sales of alcoholic beverages in Thailand. The objective was to describe online alcohol marketing activities in the Thai language. We found that the most common violation of alcohol control laws was using alcohol brand trademarks or symbols in online content, and content that commonly focused on creating product awareness. The study findings may be of interest to stakeholders in alcohol control, particularly those working on the control of alcohol marketing.

The uncontrolled expansion of the online alcoholic beverage market poses significant public health risks, particularly among youth (Noel et al., 2020). Although Thailand's Alcoholic Beverage Control Act of 2008 prohibits online alcohol marketing and advertising, many online media platforms lack rigorous oversight, leading to the promotion of alcoholic beverage sales through various channels. This has made it easy for children and youth to access alcoholic beverages with many online sales promotions (Pierce et al., 2022), potentially increasing drinking initiation. Exposure to alcohol-related content online is associated with higher consumption of alcohol (Strowger et al., 2024) and alcohol-related problems (Curtis et al., 2018). The exemption to the enforcement of Section 32 of the Alcoholic Beverage Control Act of 2008 regarding advertisements originating from outside the Kingdom of Thailand, such as live broadcasts of sports where athletes wear symbols or logos of alcoholic beverages (Department of Disease Control, 2008), also represented a key loophole that could be further complicated by the ubiquity of internet-based marketing. In March 2025, the House of Representatives passed the new version of the Alcoholic Beverage Control Act that enables individuals to display alcoholic products for non-commercial purposes, and allows businesses more freedom to publicize the name and details of the products on the condition of not inviting others to drink, claiming benefits, or using surrogate logos (Money and Banking Magazine, 2025). The techniques described in this study have potential for further applications in an evolving policy environment.

Alcohol-related content was distributed through three main platforms: (a) Facebook (for clubs, brand pages, and personal profiles); (b) LINE (for grocery stores, manufacturers or distributors, and smuggled or duty-free vendors); and (c) TikTok (for influencers, personal profiles, and others). Users might have chosen these platforms based on convention as they are the three most commonly used social media applications in Thailand (Pinchuck, 2024). Businesses in Thailand generally use Facebook for marketing and promotion and LINE to communicate with customers, while Thai influencers use TikTok to distribute their content. However, creating product awareness, which violated Section 32 of the Alcohol Beverage Control Act, was very common (i.e., found in more than 95% of all posts). This high prevalence could have been attributed to the wide variety of content that the investigators considered as creating product awareness (text-images of alcohol, drinking methods and techniques, containers, etc.). These broad inclusion criteria might have been oversensitive, considering the highly complex psychological mechanisms between exposure to advertising content and drinking (Jackson & Bartholow, 2020), which implies that not all content actually induces product awareness that leads to behavioral changes. The AI algorithm yielded errors in certain cases, particularly in ambiguous categories. Those who work on this system and other systems employing similar algorithms should consider making further changes to improve the system's efficiency.

The posts that we analyzed commonly contained emojis and Brand DNA. The use of AI systems to identify Brand DNA involves natural language processing (NLP) techniques and computer vision models to extract and recognize components of online posts, as well as the use of supervised machine learning models to categorize the posts (Ho & Chow, 2024). The use of emojis to represent certain brands of alcohol might have been motivated by the desire to circumvent beverage control laws and avoid scrutiny by the authorities, similar to the way they are used for other illegal activities (Albanella, 2018; Taylor, 2024). Marketing strategies for alcoholic beverages are complex and include the use of brand logos on social media platforms and campaigns and interactive content from influencers (Hendriks et al., 2019). This has created widespread online brand identities, and new creative content has made alcoholic beverage brands more recognizable. While some platforms have clear alcoholic beverage policies, many are unable to enforce them completely (Carah & Brodmerkel, 2021), resulting in the exploitation of loopholes to avoid strict regulatory compliance. Policy makers should consider adapting measures such as increasing regulatory oversight and establishing a digital regulatory framework to help close these loopholes. The application of new machine-learning approaches, such as 'zero-shot learning', can enable regulatory agencies to analyze large text data without substantial resources and should be considered accordingly (Riordan et al., 2024). Policymakers should also consider using AI-assisted digital forensics (Sáez-Ortuño et al., 2024; Spies et al., 2024) to detect and quantify the presence of cross-border marketing and raise attention regarding the issue.

One strength of our study was the use of an AI system for content analysis, which helped us to quickly categorize a large number of online media posts. However, our study had a number of limitations. Firstly, the use of automated searches via search engines could have introduced selection bias to our study findings from the search engine algorithms. Secondly, we only performed the searches in the year 2023, thus the findings of the study may not be generalizable to other periods. These limitations should be considered in as caveats in the interpretation of the study findings.

Conclusion

We used an AI platform to perform content analysis of web-scraped online media posts in the Thai language and assessed the extent to which they violated Thailand's alcohol control measures. We found that the majority of posts contained alcohol brand trademarks or symbols, and that a large number of posts violated Sections 30 and 32 of the

Alcoholic Beverage Control Act of 2008. The findings of this study can be used as empirical evidence to support debates regarding the need to control online marketing of alcohol. Future studies should consider expanding the variety of search engines and data scraping algorithms used, and extending the timespan of the searches undertaken. Future studies should also consider applying algorithms to detect cross-border alcohol marketing and other legal loopholes.

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