Temporal and Sentiment Analysis of Alcohol-Related Tweets in Thailand During 2023: Patterns and Trends in Online Discourse

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Abstract

There is a paucity of research concerning the content and temporalities of alcohol-related social media texts posted in the Thai language. A total of 12,065,726 tweets were collected between January 1, 2023, and May 23, 2023, based on thirteen alcohol-related keywords. Three native Thai speakers manually coded 15,000 random tweets to explore the type, sentiment, and content of collected tweets. "Personal communications" represented 49.1% of the sample, 15.3% were coded as "Pornography-related," and 35.6% as "Irrelevant." Among the personal communication tweets, 81.1% were coded as Neutral, 4.9% as Positive, and 14.0% as Negative. Despite a higher volume of negative tweets, only one prevention-oriented tweet was found during the qualitative content analysis. The coded tweets were further used to train supervised machine learning algorithms to identify posts labelled as positive, neutral, and negative within the whole dataset. Temporal heatmaps of positive, neutral, and negative personal communication tweets were then generated. Negative tweets were more likely to be posted on Sunday evening (from 17:00 to midnight) and Monday early afternoon (13:00 to 15:00), while positive tweets were frequently posted on the evenings (after 20:00), especially Monday. Our results can be used to disseminate alcohol-related health prevention messages at the time and day(s) of the week when such messages would be most read on X.

Keywords

Alcohol; sentiment analysis; temporal heatmap; Thailand; X/Twitter

Introduction

The harmful consumption of alcohol is linked to over 200 diseases and injuries and is responsible for up to 5.1% of yearly deaths worldwide (World Health Organization [WHO], 2018). In addition, alcohol consumption remains the leading risk factor for premature death and disability among those aged 25 to 49 years (Murray et al., 2020). Alcohol use is likewise linked to several adverse behaviors such as pedestrian accidents (Öström & Eriksson, 2001) and unsafe sex (Chersich & Rees, 2010; Staines et al., 2001), but also domestic violence (Bègue et al., 2012; Curtis et al., 2019), criminal behaviors (Dingwall, 2013), and drunk driving, which can lead to vehicle accidents (Tulloh & Collopy, 1994).

Despite the Thailand's Alcoholic Beverage Control Act B.E. 2551 (2008), which strictly prohibits alcohol-related advertisements and limits alcohol purchases to specific hours of the day, Thailand has the third highest total alcohol per capita consumption of the South East Asian Region (SEAR) with 7.99 liters of pure ethanol per year among Thais older than 15 years old (Data Commons, 2025). In addition, an estimate of 5.4% of the Thai population displays signs of alcohol use disorders (compared to 3.9% in SEAR), and, in 2019, alcohol was responsible for 4.5% of yearly deaths, with 2% linked to liver cirrhosis, 1.4% related to road traffic accidents, and 1.1% linked to cancers (WHO, 2019). Thailand has also the second highest rate of Heavy Episode of Drinking (i.e., HED - consumption of 6 or more standard alcoholic beverages in a single occasion over the last 30 days) in the SEAR with 42.8% of the respondents of the Smoking and Drinking Behavior Survey 2017 declaring they had such an episode yearly and 10.3% binge drinking one or several days per week (Vichitkunakorn et al., 2021).

Numerous Thai studies have assessed the prevalence and patterns of alcohol use (Assanangkornchai et al., 2010; Chaveepojnkamjorn, 2012; Chaveepojnkamjorn & Pichainarong, 2009, 2011; Hongthong et al., 2012; McNeil et al., 2016; Pichainarong & Chaveepojnkamjorn, 2010; Saingam et al., 2012; Thailand National Statistical Office, 2017), risk/protective factors influencing drinking behavior (Assanangkornchai et al., 2018; Assanangkornchai et al., 2010; Boonchooduang et al., 2017; Chaveepojnkamjorn & Pichainarong, 2010; Khondok et al., 2012; Luecha et al., 2020; Pengpid & Peltzer, 2012; Tantirangsee et al., 2014; Thonponkrang et al., 2016; Vantamay, 2012; Vantamay, 2009), attitudes toward alcohol (McNeil et al., 2016; Siviroj et al., 2012), as well as the beliefs that youth associated to alcohol among the general Thai population (Vantamay, 2009). Social media was also used to investigate alcohol marketing strategies and advertisements and their impacts on alcohol consumption in the country (Kaewpramkusol, 2018). More recently, one study assessed the effectiveness of alcohol prevention campaigns using Facebook and Line among Thai entertainment girls in Bangkok and found a long-lasting effect of such online campaigns (Sakulthanit et al., 2024).

Over the past two decades, social media have played an increasingly important role in disseminating information among the younger sections of the population, impacting the way people perceive alcohol, which ultimately affects their consumption patterns and behaviors. Studies have consistently shown that social media platforms play a crucial role in shaping individuals' attitudes, behaviors, and perceptions related to alcohol consumption (Curtis, Lookatch, et al., 2018; Westgate & Holliday, 2016). These media often glamorize alcohol drinking by associating its consumption with social success and enjoyment: this specific form of peer pressure through social media can encourage individuals to join in drinking activities to fit in or conform to perceived (group) norms (Boyle et al., 2017; Hendriks et al., 2018). Furthermore, the pervasive presence of alcohol-related content on social media can contribute to the normalization of excessive drinking and may potentially exacerbate issues related to alcohol abuse, particularly among vulnerable populations such as young adults (Ridout et al., 2012; Vanherle et al., 2023). Conversely, social media can also serve as a platform for alcohol harm reduction campaigns by providing information regarding alcohol-related harms (Sakulthanit et al., 2024). The authors of a recent systematic review examining the effectiveness of social media campaigns in influencing alcohol consumption, related harms, attitudes, and awareness concluded that social media campaigns can positively affect the outcomes of alcohol-related practices in specific populations. However, their findings tend to indicate limited and inconclusive results, calling for additional rigorous assessments of the potential impacts of social media-based public health alcohol interventions (Yeh et al., 2023).

Among the various social media platforms, Twitter (now "X") data has been frequently analyzed to understand alcohol use patterns and perceptions. Most of Twitter-based research tends to use large datasets and computational techniques (e.g., Natural Language Processing, Machine Learning) and has been successful in investigating various aspects of alcohol use. For example, a quantitative analysis of 47.5 million tweets posted in 2015 from the United States estimated that about 2% of collected tweets mentioned alcohol, with a majority referring to intoxication (Alhabash et al., 2018), still in the United States, a study used differential language analysis of 138 million alcohol-related tweets at the county level to show that communities with higher numbers of alcohol-themed tweets also tend to report accrued drinking behaviors (Curtis, Giorgi, et al., 2018). Similar work was conducted by Ricard and Hassanpour (2021), who developed a deep learning pipeline using BERT trained on 1,302,524 Reddit posts from 18 alcohol-related subreddits to identify alcohol-related hashtags in 25,558,846 tweets on Twitter and analyze their geographic distribution. Their results indicate that alcohol-associated hashtags were significantly correlated with several alcohol-related outcomes (e.g., consumption rates, outlet density). In the same vein, Crocamo et al. (2020) filtered over 1 million tweets to detect binge drinking discussions in Italy. They used supervised machine learning classifiers to distinguish human users from bots to identify binge drinkers potentially at risk.

Several studies have examined alcohol-related tweets using qualitative methods. For instance, a content analysis of 5,000 tweets conducted by Cavazos-Rehg et al. (2015) indicated that positive messages about alcohol drinking outnumbered anti-drinking messages by a factor of 10. Common tweet themes included descriptions of HED and drinking intention/planning. Another qualitative content analysis conducted by Litt et al. (2018) found that young adults who frequently tweet about alcohol were more likely to display higher alcohol consumption and experience more alcohol-related harms.

X/Twitter data was also used to identify the temporal relationship between alcohol-tweeting and alcohol-drinking activities. Ranney et al. (2016) found a temporal correlation between alcohol-related tweet volume and alcohol-related emergency department visits. Similarly, Merrill et al. (2023) analyzed 3.5 million alcohol-related "blackout" tweets geotagged in the United States and found that 73% of these tweets expressed positive sentiment: using machine learning algorithms, they observed that positivity increased during weekends, but was higher during holidays like Thanksgiving and New Year's Eve, but not during events like the Super Bowl.

These various studies exemplify how X/Twitter data can be leveraged to inform public health agencies on alcohol use. However, to the best of our knowledge, there is no X/Twitter-based research focusing on alcohol usage in an Asian setting. More specifically, no study has assessed the content of alcohol-related social media posts within the Thai context, nor is there any research focusing on the temporalities (i.e., time of the day, day of the week) when social media users post content about alcohol in Thailand. Identifying such temporalities could help to post prevention messages at the right time, increasing the likelihood of reaching the targeted audience and limiting, in turn, the cost of such a social media-based prevention messaging campaign.

This study collected alcohol-related tweets from the X platform to provide initial insights about the sentiments and perceptions of Thai X chatter about alcohol, the themes attached to positive and negative alcohol-related tweets, and when people tweeting about alcohol are more likely to post alcohol-related tweets. These sets of information could provide valuable insights for developing social media-based interventions through prevention messages posted at the most beneficial time of the day and day of the week.

Method

The research protocol described thereafter was considered as exempt by the Mahidol University Social Sciences Institutional Review Board (MUSSIRB) (Certificate 2022/019.1912). Although this study was considered exempt, only publicly available tweets were collected. All personally identifiable information was removed from this analysis. Tweets displayed as examples in this manuscript have been slightly modified to avoid potential reidentification. All collected tweets were stored in an external hard drive used only during data analysis and will be safely erased after publication of the results.

Data collection

Twitter (now X) is a micro-blogging service provider and social network platform that was launched in 2006. There were over 250 million X daily users (Dean, 2025), generating over 500 million tweets per day (Aslam, 2024) at the time this research was submitted for consideration.

Tweets are limited to 280 characters and thus contain very brief information. However, because of the large volume of data generated by Twitter users, analysis of tweets can provide valuable population-level metrics as well as geolocation of Twitter users. Tweets were collected continuously via the Twitter's streaming Application Programming Interface (API) using the "tweepy" Python library filtered by twelve generic Thai search terms related to alcohol use: 'ดื่มเหล้า' ("drink liquor," where *เหล้า* can denote any alcoholic beverage); 'แดกเหล้า' (chug or slam liquor); 'ดื่มเบียร์' (drink beer); 'แดกเบียร์' (chug beer); 'ไวน์' (wine); 'ดื่มไวน์' (drink wine); 'นักดื่ม' (drinkers); 'ขี้เหล้า'/'ขี้เมา' (alcoholic/boozehound); 'มึนเมา' (intoxicated); 'เมาเหล้า' (drunk from alcohol); 'เมา' (drunk); 'เบียร์' (beer); and 'เหล้า' (liquor/any alcohol). For each matching tweet, the following metadata were stored for analysis: the tweet's unique identifier, timestamp, user-reported location (if available), full text, and the user's unique screen name/handle. No tweet content was altered, and only publicly available data was captured. Tweet unique identity, timestamp, location, text, and X/Twitter user unique "screen name" were collected and stored for analysis.

The data collection started on January 1, 2023, and was stopped on May 23, 2023, when all X developer academic accounts were revoked.

Qualitative content analysis

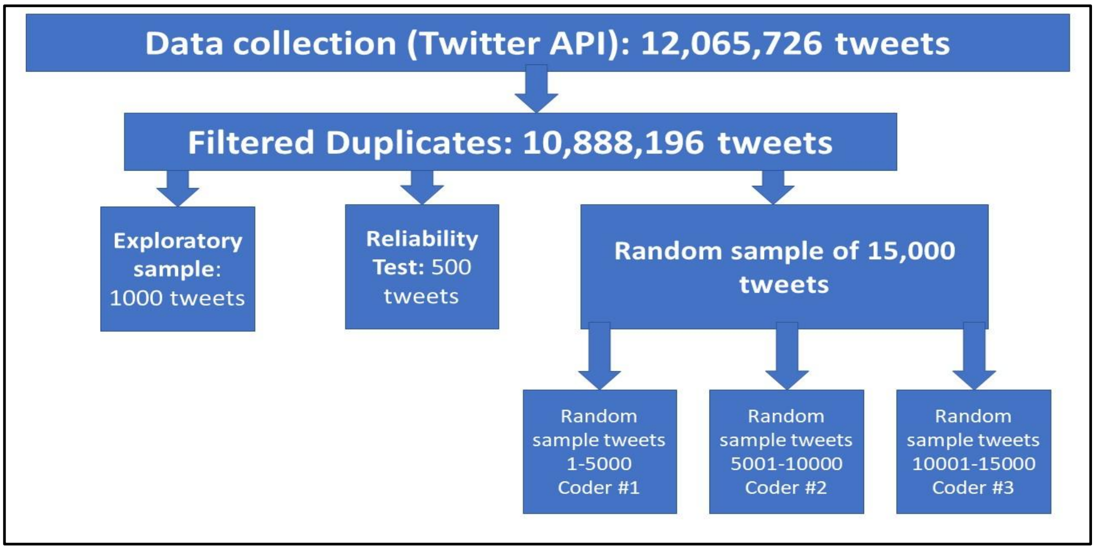
Qualitative content analysis is designed to analyze and group data into topics/themes generated inductively. The inductive approach in qualitative coding, which is also referred to as open coding (Straus & Corbin, 1990), moves from the specific to the general (bottom-up approach) and examines a given phenomenon in its context rather than from a set of predetermined concepts. In other words, themes, categories, and codes emerge from the raw data examined by a team of several researchers, iteratively comparing and contrasting their interpretations. However, the large number of tweets collected during the data collection prevents the manual coding of the full dataset. It is a common strategy to code a portion of random tweets in the field of social media data analysis (Lamy et al., 2016; McNaughton et al., 2014; Pang et al., 2021).

First, 1,000 tweets were randomly selected from the whole dataset using the "pandas" Python library (i.e., df.sample (n = 1000)) and then openly coded by three Thai native speakers to explore emerging themes. The three coders are postgraduate research assistants, whose research subjects are related to alcohol and substance use, and who have already participated in research involving qualitative content analysis of substance-related tweets (references are not added at this time to guarantee anonymity). The coding scheme was inductively developed, and codes were created based on a consensual agreement among the three coders.

Second, another sub-sample of 500 random tweets was coded by all three coders to evaluate the reliability of the coding scheme rules. This subset was then used to discuss discrepancies and develop and refine the coding rules. The intercoder reliability was calculated using Krippendorff's Alpha coefficient (Krippendorff, 2004; Neuendorf, 2009). Krippendorff's Alpha score of 0.67–0.79 indicates moderate to substantial agreement, with scores of 0.8 or higher indicating substantial agreement (Marzi et al., 2024). Themes with a score below 0.7 were redefined and retested to ensure the cohesion of coder results.

Third, a random sample of 15,000 Thai tweets related to alcohol was created based on the full dataset using the "pandas" Python library (i.e., df.sample (n = 15000)). Each tweet was paired with a randomly generated number in Excel, and the column of random numbers was repeatedly sorted to ensure a varied and randomized sequence of tweets. The sample was then manually coded using Excel tabs, with each column corresponding to a code. Each coder manually coded 5,000 distinct tweets from the random sample of 15,000 tweets using the developed coding scheme (see Figure 1).

Figure 1: Qualitative Content Analysis Dataflow



Coding scheme and reliability

The coding scheme included the following codes, with examples for each relevant category, and the codes can be found in Table 1:

1) All tweets that were not directly related to alcohol were coded Irrelevant.

2) The team of coders initially differentiated four types of tweet sources: “News:” media tweets encompassed all news-related tweets, including retweets of news stories, political debates, scientific study results, and other reports (e.g., “พี่เขยใช้ 9 มม.จ่อยิงน้องเมียดับ คาสวนรถไฟ ปมเขม่นกันมานานนับ 10 ปี เรื่องเมาแล้วชอบเปิดเพลงเสียงดัง หลังก่อเหตุ ไม่หนี รอมอบตัวตำรวจบางซื่อ #ไทยรัฐออนไลน์ https://t.co/8CxxxxxiS6” [“A man shot and killed his brother-in-law with a 9mm pistol at a public park, following a long-standing feud of over 10 years—mainly over drinking and playing loud music. After the shooting, he didn’t flee and waited to turn himself in to the Bang Sue police. #ThaiRathOnline”]); tweets that promote the sales of alcohol or events/restaurants with promotion on alcohol were categorized as “Ads”; tweets categorized as “Pornography-related” had to contain a mention of alcohol/drunkenness associated with a sexual act, plus a link to a book, videos or pictures and “Personal communication” were tweets posted within the Thai X chatter providing their opinions on alcohol, describing experiences of consumption, intention of use, or asking questions regarding alcohol. Due to their minimal number, “News” and “Ads” tweets were combined with “Irrelevant” tweets to allow for the calculation of the intercoder reliability test and were not further analyzed.

3) Tweets categorized as Personal Communications were further coded by associated sentiment: Positive, Neutral, and Negative.

Table 1: Examples of Tweets Per Category and Sentiment

Thai tweet	English translation
Irrelevant	
ก หยุดทำตัวหน้าเบื่อได้แล้ว ทุกคนในจังหวัดเมากัญชากันหมดแล้ว	A, could you stop being so annoying? All people in this province has already been drunk by Kanja.
ไม่ได้กลัวเมา แต่กลัวอ้วน	Never been scared of getting drunk, but getting fat!
วันนี้เหนื่อยมาก สอบเสร็จละจะไปอยู่ซุ้มต่อ โคตรร้อนเลย เมาแดดสุด	I'm so exhausted today. Just finished my exam and now heading to the event booth. It's insanely hot—I'm totally sun-drunk.
Personal communications	
ระวังเมานะ	Be careful of getting drunk.
หลงรักตัวเองเวลาเมา	I am falling in love with myself when I am drunk.
เอาจริงหลังๆ มานี่กูเมาทุกวัน ทุกวันแบบทุกวันจริงๆ อะ เมาจนแม่งสติหลุดอะ บางคืนอยู่ยันเช้า กูยังไม่รู้ตัวเลยว่ากูทำไรลงไปบ้าง	Honestly, lately I've been drunk every day—literally every single day. So drunk I totally lose control. Some nights I'm out until morning and have no idea what I've done.
Pornography-related	
แอบถ่ายรูปช่องคลอดน้องสะใภ้ตอนเมาหลับ อยากดูไหมจ๊ะ	I secretly took a picture of my sister-in-law's vagina while she was drunk and asleep, want to see?
ในหนังโป๊ดาวรังสิตเมาแล้วเสร็จกับรุ่นพี่ เสียวสุดๆ พากษ์ไทยด้วย	In the porn movie, the cutest fresher got drunk with her senior. It was passionate with Thai subtitle.
คลิปนี้...ถ่ายตอนกลับบ้านที่ศรีสะเกษ เพื่อนชวนไปดูหมอลำแล้วไปดูผู้ชายหน้าเวทีหมอลำหมดเหล้าไปเกือบ 3 กลม เลยดึงผู้ชายออกมาขึ้นรถ ไปกินกันที่เถียงนากลางทุ่งนา(ของใครไม่รู้) สรุป..ผู้ชายเมาว่ะทำเหี้ยอะไรไม่ได้ ผมก็เลยจับเยสแม่งเลย..(มีต่อนะ)	This clip… was recorded when I went back home to Sisaket. A friend invited me to a Molam concert, and we were watching the guys at the front of the stage. After nearly finishing three bottles of liquor, I pulled one of the guys into the car, and we went to drink more at a hut in the middle of a rice field (not sure whose it was). In the end, the guy was too drunk to do anything, so I just forced myself on him... (to be continued)
Personal communications - Positive	
เพิ่มความเมาอีกนิด เธอจะยิ่งเป็นขวัญใจคนวัยทำงานแห่งนี้	With little more drunkenness, you would become most charming lady in this department.
เมาแล้วเธอมั่นมาก	When drunk, you are so confident!
เวลาที่สงบที่สุดคือเมาเบียร์แล้วหลับ	The most peaceful time is when I get drunk on beer and fall asleep
Personal communications - Negative	
กินเหล้าจนเมา เป็นตัวอย่างที่ไม่ดีแก่เยาวชน	Drink and drunk is bad example for younger generation.
รู้ว่าเมาเมื่อคืน แต่ไม่คิดว่าจะแย่มากจนกระทั่งได้เห็นสภาพตัวเองในสตอรี่ไอจี	I kinda know I was drunk. After checking story IG, didn't realized it was all fucked up.

Thai tweet	English translation
พึ่งเข้าใจการเมาแล้วอ้วกพุ่ง หลับเป็นตายตื่นมาปวดหัวอีก	Now I finally understand what it's like to get so drunk you vomit violently, pass out like the dead, and wake up with a splitting headache.
Personal communications - Neutral	
เมาพรุ่งนี้ไม่ไปเรียนนะ	I am drunk and not capable of going to study tomorrow.
ผมเมา อย่าให้ต้องถึงขีดสุด	I am drunk, do not test my limit.
มาตอนแรกดเบียร์ 6 ป๋อง เมาแบบไม่รู้เรื่องรู้ราว ผ่านไป 4 ปี เบียร์ 6 ป๋อง ทำไรไม่ได้เลย	When I first started, six cans of beer would get me totally wasted. Four years later, six beers don't even affect me anymore.

In addition, an open coding of positive and negative Personal communication tweets was performed to obtain a better understanding of the themes associated with each sentiment. Understanding what X users tweeting about alcohol perceive as positive and negative about alcohol can help target specific aspects of alcohol usage in prevention messages (e.g., alcohol makes people less shy but can also be linked to obnoxious and/or violent behaviors).

Machine Learning Classifiers

Although Machine Learning (ML) has been widely used in consumer research, its application in public health is still recent (Kursuncu et al., 2019), with some research concerning alcohol on X using such a technique (Hasan et al., 2018). Given the large volume of tweets collected during this research, manual classification of all tweets per sentiment is impossible. We mitigated this problem by using the results from the qualitative content analysis to create training datasets for two supervised ML classifiers: the first model aimed at predicting the type of tweet per source (i.e., Personal communication, Pornographic content, or Irrelevant); the second aimed at predicting the sentiment expressed in each tweet labeled as Personal communications. The classification of tweets by type reduced the "noise" from irrelevant tweets, limiting the analysis to tweets sent by X users who post about alcohol. Sentiment analysis helps convey information about the attitudes and opinions of alcohol users towards alcohol, drunkenness, and other relevant issues (e.g., alcohol in society, alcoholism). This type of analysis relies on Natural Language Processing (NLP) and ML to automatically identify and extract positive, negative, or neutral sentiment associated with some topics.

Complement Naïve Bayes (CNB), Support Vector Machine (SVM), and K-nearest Neighbors (KNN) supervised ML algorithms were implemented in Python language (v.3.11) using the "scikit-learn" library. Classifiers were trained with 80% of their respective datasets and tested on the remaining 20%. To identify the most effective supervised classifier for categorizing Thai-language tweets, we conducted a grid search with stratified 5-fold cross-validation for CNB, SVM, and KNN. The set of hyperparameter combinations used for the grid search optimization can be found in Table 2:

Table 2: Grid Search Parameter Values Per Classifier

Model	Hyperparameter	Value
Complement Naïve Bayes (CNB)	ngram_range	(1,1), (1,2)
	min_df	1, 3, 5
	alpha	0.1, 0.5, 1.0

Model	Hyperparameter	Value
	normalized	True, False
Support Vector Machine (SVM)	ngram_range	(1,1), (1,2)
	min_df	1, 3, 5
	C	0.1, 1, 4, 10
	kernel	'linear', 'rbf'
	gamma	'scale', 'auto', 0.1
K-nearest Neighbors (KNN)	ngram_range	(1,1), (1,2)
	min_df	1, 3, 5
	n_neighbors	3, 6, 10

The weighted F1 score was used as the evaluation metric to account for potential class imbalance. The F1 score is a weighted average of precision and recall measures. Precision is defined as the number of correctly classified positive examples divided by the number of examples labeled by the system as positive. Recall is defined as the number of correctly classified positive examples divided by the number of positive examples in the manually coded data. An F1 score of 0.8 or above is considered to be satisfactory. The best model for each classification was selected based on the grid-search cross-validation scores run for each model.

Cross-validation results showed that for category classification, the SVM with a linear kernel, a scale hinge loss, and C = 1.0 consistently achieved the highest mean F1 score (0.806), outperforming CNB (0.784) and KNN (0.739). Concerning the sentiment classification, SVM with a linear kernel, a scale hinge loss, and C = 10.0 displayed the highest mean F1 score (0.816), outperforming CNB (0.774) and KNN (0.764). Based on these results, the SVM model was selected for further classification of the whole dataset and sentiment classification. The performance and cross-validation scores for each classifier can be found in Supplementary Material 1.

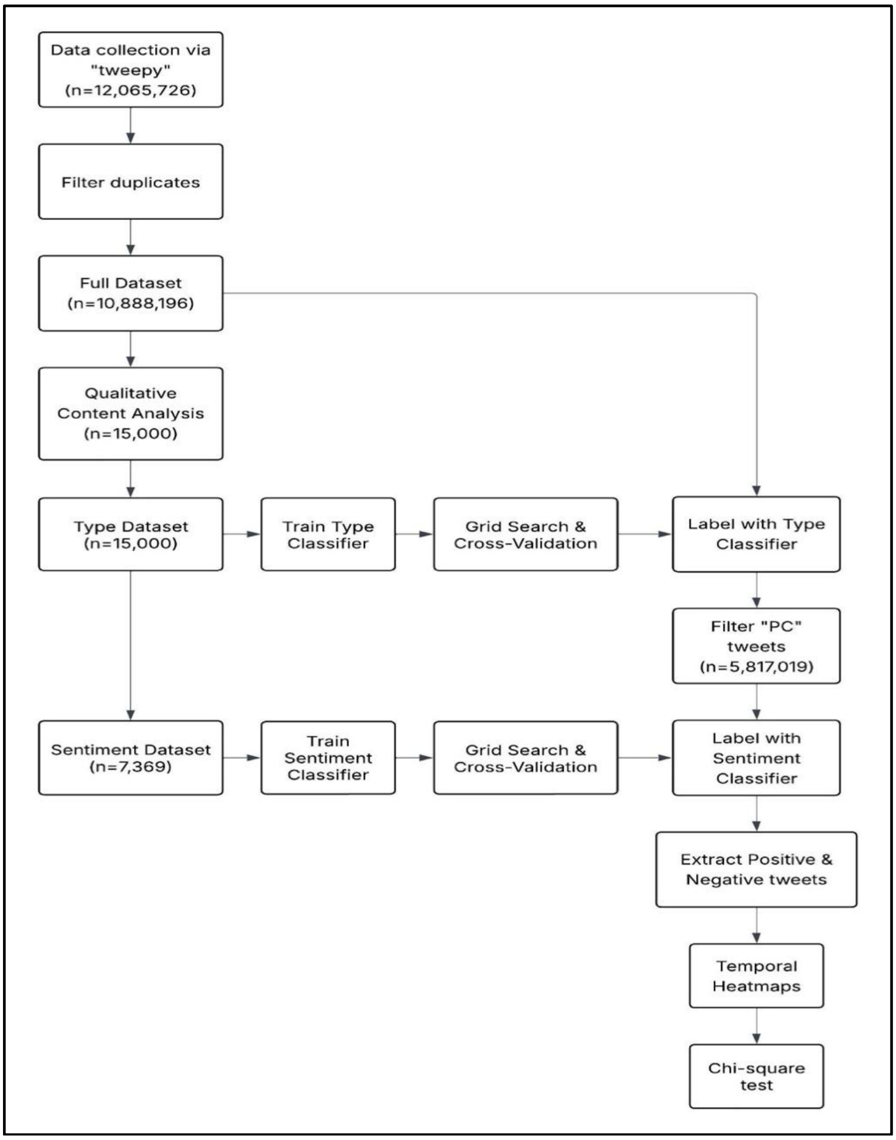
Temporal heatmap construction

Tweet metadata concerning time and date was also collected. Personal communication tweets with erroneous timestamp data were filtered before the generation of temporal heatmaps. The frequency of alcohol-related tweets over time was calculated with an emphasis on the precise day and time within each week to generate temporal heatmaps of alcohol-related tweeting activity. Positive, neutral, and negative tweets identified through the sentiment classifier were isolated to create separate temporal heatmaps to determine when neutral, negative, and positive tweets about alcohol were posted on the Thai X chatter. These heatmaps were created using the "seaborn" Python library (Waskom, 2021). As tweet timestamps are all indexed using Coordinated Universal Time (UTC), the date and time of each tweet were adjusted to Thai time (UTC+7) using the "pandas" Python library (specifically, tz_convert ('Asia/Bangkok')). Days of the week were also rearranged using the "pandas" Python library (specifically, pd.Categorical (ordered=True)).

We then constructed a 3 × 168 contingency table with "neutral tweets," "positive tweets," and "negative tweets" as columns, and rows representing each hour by day combination (24 hours × 7 days). A chi-square test of independence was run to assess whether sentiment distribution differed by time slot. Because all three sentiment groups contain hundreds of thousands of tweets, a standard chi-square test is almost guaranteed to produce exceedingly small p values;

therefore, we also quantified effect size using Cramér's V scores. The chi-square test was conducted using the "scipy" Python library (specifically the "chi2_contingency" function). The overall process for the computational arm of this research could be summarized with the following flowchart diagram (Figure 2):

Figure 2: Computational Section Flowchart



Results

A total of 12,065,726 tweets were collected between January 1, 2023, and May 23, 2023. After data curation and filtering of duplicated tweets, the final dataset equaled 10,888,196 tweets. The results from the manual and computational analysis are presented below.

Manual Qualitative Content Analysis: Intercoder reliability agreements

Krippendorff's Alpha (KA) intercoder reliability assessment of the random sample of 500 tweets shows substantial agreement for "Category" (Percentage Agreement = 93.2%, KA = 0.90) and moderate agreement for "Sentiment" (Percentage Agreement = 88.4%, KA = 0.78) codes.

Manual Qualitative Content Analysis: Results

"Personal communications" represented 49.1% of the 15,000 random sample of tweets (*n* = 7,368), 15.3% (*n* = 2,296) were "Pornography-related", and 35.6% (*n* = 5,336) were coded as "Irrelevant." Concerning the sentiment of Personal communication tweets, 81.1% were coded as Neutral (*n* = 5,980), 4.9% (*n* = 359) as Positive, and 14.0% (*n* = 1,030) as Negative. Results of the Qualitative Content Analysis are displayed in Table 3:

Table 3: Results From Qualitative Content Analysis

Category of Tweets (*N* = 15,000)	**Percentage of coded tweets**
Personal communications (PC)	49.1% (*N* = 7,369)
Pornography-related (S)	15.3% (*N* = 2,296)
Irrelevant (I)	35.6% (*N* = 5,335)
Sentiment in Personal communications (*N* = 7,369)	**Percentage of coded tweets**
Positive (P)	4.9% (*N* = 359)
Neutral (NT)	81.1% (*N* = 5,980)
Negative (NG)	14.0% (*N* = 1,030)

These results were further used to create the two training datasets for classification: the type of tweets dataset comprises the 15,000 tweets labeled as Personal communications (PC), Pornography-related (S) and Irrelevant (I); the second dataset for sentiment classification was constituted of the 7,369 Personal communications tweets labeled as Positive (P), Neutral (NT) and Negative (NG).

The open coding of Personal communication tweets labeled as Positive revealed five main themes expressed within the Thai X chatter about alcohol (Table 4):

Table 4: Positive Tweets Open Coding Results

Theme	Example (Thai)	Example (Translation)
Individuals appear relax and displaying amusing/charming behaviors while inebriated	นึกภาพไปเดทแล้วพี่เมาๆทำหน้างี้ กุเป็นคู่เดทคือหลงแย่	Just imagine going on a date and he's tipsy and makes this kind of face—if I were his date, I'd totally fall for him.
Alcohol boost self-confidence or boldness (e.g., improved sense of humor/being more sociable/be outgoing)	สรุปคือเด็กสินสาดแบบกู เมาแล้วพูดแต่อิ้งค่ะ ครูต้องภูมิใจ ใครมาทักกู มาคุยด้วย ต้องสลับมาคุยอิ้งกับกูหมด เมาแล้ว fluent อะค่ะ	So basically, a liberal arts kid like me gets drunk and speaks only English. My teachers would be proud. Anyone who talks to me has to switch to English. I get fluent when I'm drunk.
Alcohol provides some emotional/psychological benefits (e.g., more relax, help to relieve stress, increase happiness):	ชอบดื่มไวน์ อย่าถามว่าดื่มตัวไหนยี่ห้ออะไร เพราะผมแค่รู้สึกมีความสุขที่ได้ดื่ม ได้เสพบรรยากาศก็พอ	I like drinking wine—don't ask me what kind or brand. I just enjoy drinking and soaking in the atmosphere. That's enough for me.

Theme	Example (Thai)	Example (Translation)
Alcohol improves sexual experience/performance	ผมชอบเวลาเมียเมานิดๆ แล้วนัวเนียกับชายเดี่ยว เทอจะใส่ไม่ยั้ง อารมณ์จะพาไปในช่วงที่สนุกและมีความสนุกเสมอ	I like it when my wife gets a little tipsy and gets touchy. She really goes all in—her mood takes over, and it always turns into something fun and enjoyable.
Alcohol is linked to a sense of reward and pleasure (e.g., reward after hard day of work, drink with friends after work)	ช่วงนี้ทำงานส่งอาจารย์ทุกวันงานเยอะมากๆมีแค่ช่วงพักสั้นๆอยากจะมีเวลาออกไป นั่งที่บาร์ สูบบุหรี่ ดื่มไวน์ ฟังเพลง ชิวๆ อัพเดทข่าวสาร แลกเปลี่ยนความคิดกับเพื่อน. work hard play hard	These days I've been working on assignments for my professors every single day—so much work, and only short breaks. I just want to have some time to sit at a bar, smoke, drink wine, listen to music, chill out, catch up on news, and exchange thoughts with friends. Work hard, play hard.

Four main themes emerged from the open coding of Personal communication tweets labeled as Negative (Table 5):

Table 5: Negative Tweets Open Coding Results

Theme	Example (Thai)	Example (Translation)
Difficulties in handling drunk persons (e.g., fight, unpredictable behavior):	ครั้งแรกเลย เจอคนเมามาขอตัง 42 kr บอกจะคืนให้ 100 kr พรุ่งนี้ นี่ปฏิเสธไปว่าไม่มี ตามขึ้นบัสไปนั่งข้างๆ ขออีกรอบ บอกไม่มี ขออีกที นี่ไม่มองหน้าแล้วส่ายหัวจนเค้ายอมแพ้ เดินลงรถไป	For the first time, I encountered a drunk guy who asked me for 42 kr, saying he'd pay back 100 kr tomorrow. I said I didn't have any. He followed me onto the bus, sat next to me, and asked again. I said no. He asked one more time—I didn't even look at him and just shook my head until he gave up and got off the bus.
Drunkenness caused undesirable behaviors a) to others, e.g., violence, rudeness, aggressiveness, burden placed on others:	เข้าใจว่าเมาเพราะเพิ่งกลับจากร้านเหล้า แต่มารยาทกับความเกรงใจควรมีนะคะ มาโวยวายมันไม่ใช่แล้วอ่ะ เมาได้ แต่ต้องรับผิดชอบตัวเองอย่าสร้างความเดือดร้อนให้คนอื่นค้าาา	I get that he was drunk after coming back from a bar, but basic manners and consideration for others are still necessary. Causing a scene like that is just not okay. Sure, get drunk—but take responsibility for yourself and don't trouble others, please.
	ถึงแล้วๆๆๆ มะกี้เรย วันนี้เจอคนเมาจะต่อยคนบนรถ กุงงมากคะ เมาได้แต่ทำไมต้องทำเหี้ยคะ	Just arrived—literally just now, I saw a drunk guy trying to punch someone on the bus. I was so confused. You can drink, but why act like such an asshole?
Drunkenness caused undesirable behaviors b) to oneself, e.g., losing belongings, fall, shameful or embarrassing behaviors in public	ช่วยด้วยกุอายคน กุไม่เคยเมาขนาดนี้มาก่อน กุอายเพื่อนไอเหี้ย	Help, I'm so embarrassed. I've never been this drunk before. I'm so ashamed in front of my friends—what the hell.
	ไม่ชอบเวลาเห็นคนอื่นเมาไม่รู้เรื่องแต่ตัวเองก็ทำ ภาระคนอื่น แล้วกุนั่งร้องไห้กระเป๋าตังหาย ที่แท้วางไว้ในห้องน้ำ	I hate seeing people get blackout drunk and burden others, but I ended up doing the same. Then I sat there

Theme	Example (Thai)	Example (Translation)
		crying because I lost my wallet—turned out I left it in the bathroom.
Health-related problems: a) physical: i.e., hangovers, vomiting, headaches, muscle pain	ส่วนตัวเป็นเบียร์ที่รสชาติดีที่สุดแล้ว ตอนดื่มอร่อยยกเอาๆ ตอนเช้ามาเท่านั้นแหละ ทั้งท้องเสีย ทั้งมึนหัวกว่าจะหายจากอาการมึนเมา ก็เกือบเย็น จะเลิกดื่มเหล้า เบียร์ของมึนเมาแล้วคือแพ้อะ เมื่อคืนก็เพิ่งแพ้มาหมดสภาพยันตอนนี้ ไม่เอาแล้วค้าบ	Personally, it's the best-tasting beer I've ever had. I kept drinking it because it was so good. But the next morning—ugh—diarrhea, dizziness, and I didn't feel sober until almost evening. I'm quitting alcohol—liquor, beer, anything that gets you drunk. Last night I had a bad reaction again, and I'm still out of it. I'm done with it now, seriously.
Health-related problems: b) mental: i.e., feeling ashamed, dysphoria, anxiety	เมาแล้วร้องไห้ เมื่อไรจะเลิกเป็นแบบนี้	I cry every time I get drunk. When will I stop being like this?
Vehicle accidents linked to alcohol consumption	เวรเหอะ รถจอดอยู่หน้าบ้านโดนคนเมามาชนท้ายตอนตี 2	What the hell—my car was parked in front of the house, and a drunk person rear-ended it at 2 a.m.

Overall, the themes discussed within the Thai X chatter are directly related to the most frequent positive and negative outcomes of alcohol consumption. Positive tweets tend to describe alcohol as a "social lubricant" facilitating social activities and bolstering self-confidence, while the negative tweets depict the behaviors of individuals who consumed alcohol in large quantities and who tend to be challenging to handle and/or exhibit violent behaviors.

Computational Data Analysis Results

Source and sentiment classifier results

The tweets labeled during the qualitative content analysis were then utilized to train the ML classifiers. Once the Support Vector Machine algorithms were trained, the full dataset of collected tweets was then labeled. Tweets labeled as Personal Communications were then labeled per sentiment. Table 6 displays the results for both classifications:

Table 6: Frequency of Labels Based on Supervised Classifications

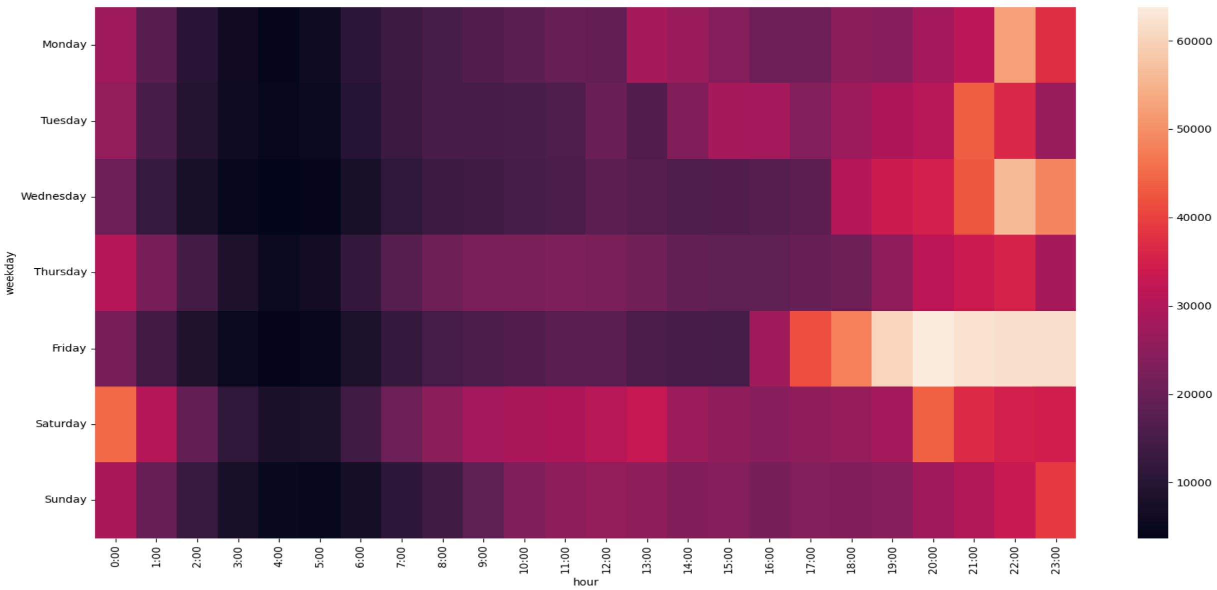
Category of tweets (*N* = 10,888,196)	**Percentage of coded tweets**
Personal communications (PC)	47.6% (*N* = 5,187,220)
Pornography-related (S)	15.2% (*N* = 1,656,113)
Irrelevant (I)	37.1% (*N* = 4,044,863)
Sentiment in tweets labeled as Personal Communications (*N* = 5,153,677)*	**Percentage of coded tweets**
Positive (P)	2.1% (*N* = 109,315)
Neutral (NT)	72.4% (*N* = 3,729,912)
Negative (NG)	25.5% (*N* = 1,314,450)

*Note: *A total of 33,543 tweets with erroneous timestamp data were discarded.*

Temporal heatmaps of Personal Communication tweets per sentiment

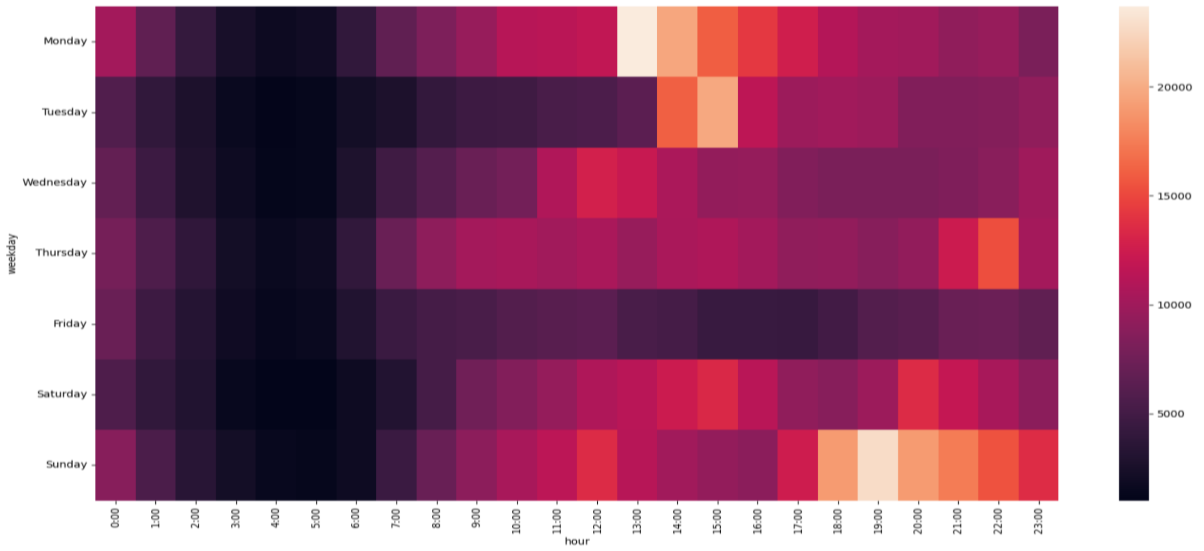
Based on the results of the sentiment tweets classification, three temporal heatmaps were generated to investigate which day(s) of the week and hour(s) of the day, alcohol-related tweets labeled as neutral, negative, and positive, were the most frequently posted by Thai X chatter. Neutral tweets tend to be more frequently posted in the evening (20:00 to midnight) and on Friday from 16:00 to Saturday early morning (until 02:00). As seen in Figure 3, brighter colors indicate a higher number of tweets.

Figure 3: Temporal Heatmap of Neutral Tweets per Weekday and Hour



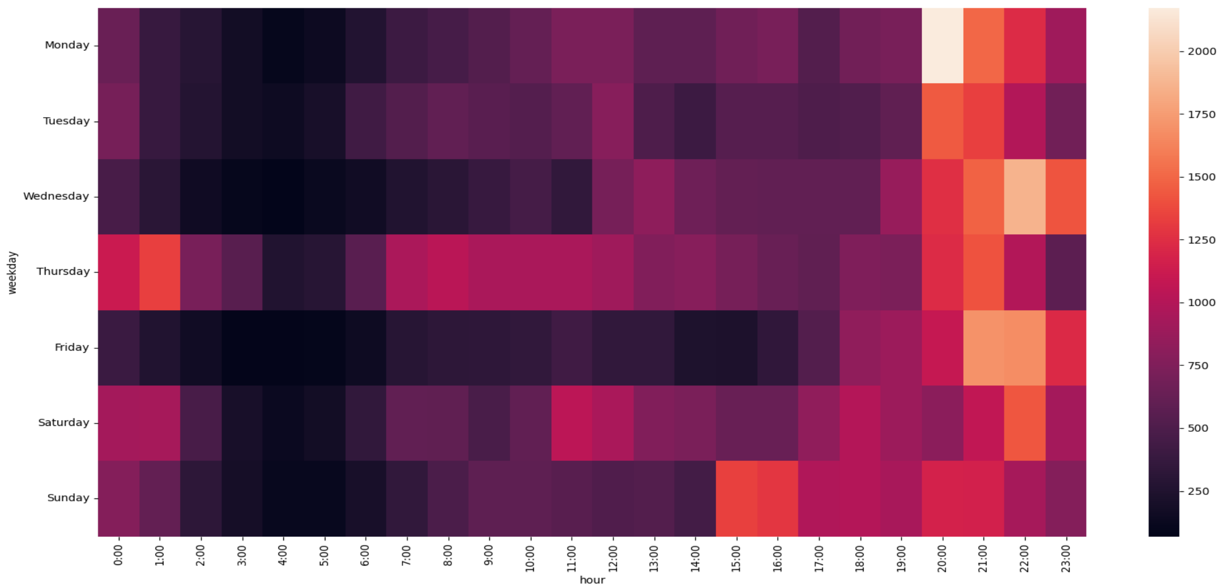
Most negative tweets were posted on Sunday evening (from 17:00 to midnight) and Monday early afternoon (13:00 to 15:00). The lowest number of negative tweets were posted during the night (02:00 to 06:00) but also on Tuesday morning until 13:00 and on Friday afternoon (14:00 to 18:00). The heatmap suggests that adverse events linked to alcohol or about events witnessed/experienced over the weekend were tweeted on the Thai X chatter during Sunday evening and Monday. However, further information is needed to accurately understand why such tweets were posted at these specific times (see Figure 4).

Figure 4: Temporal Heatmap of Negative Tweets per Weekday and Hour



In comparison, Personal communication tweets labeled as Positive were more likely to be posted after 20:00, especially on Monday, and also, but more sporadically, on Thursday early morning (00:00 to 02:00) and Sunday afternoon (Figure 5).

Figure 5: Temporal Heatmap of Positive Tweets per Weekday and Hour



The association between sentiment and time slot was statistically significant, χ^2 (334, N = 5,153,677) = 241,456.61, $p < .001$. Given the large sample size, the effect size was assessed using Cramér's V, which was 0.153, indicating a small-to-moderate association.

Discussion

The main aim of this exploratory research was to describe the sentiments and perceptions expressed in the Thai X chatter regarding alcohol, as well as the temporality of negative and positive tweets related to alcohol consumption in the Thai language. Overall, there were more personal communication tweets coded as negative compared to positive ones. This finding is in opposition to similar studies conducted in Western settings, where tweets positively presenting alcohol were overrepresented compared to negative ones (Cavazos-Rehg et al., 2015; Hendriks et al., 2018). Thailand's cultural attitudes toward alcohol consumption may be more conservative, with family and community values often emphasizing self-discipline and avoiding behaviors seen as harmful to social harmony. In addition, Thai social media users may be more inclined to use platforms like X to discuss social issues or vent frustrations. Negative experiences such as accidents, health problems, or witnessing the consequences of alcohol misuse may prompt users to share their concerns. In contrast, in many Western countries, users may share more celebratory drinking content, reflecting cultural norms that associate alcohol consumption with socializing and leisure activities.

The open coding of tweets labeled as positive and negative reflects perceptions of behaviors that are in line with the neurophysiological effects linked to alcohol consumption. Alcohol, specifically ethanol, is a depressant-type psychoactive substance whose action on dopamine and serotonin provides a sensation of euphoria, increases self-confidence (linked to dopamine), and enhances social behaviors (serotonin), while reducing stress, pain, and inducing a feeling of relaxation (Julien et al., 2023). These positive effects were frequently mentioned in the personal communication tweets labeled as positive. Conversely, individuals who have consumed large quantities of alcohol tend to have reduced cognitive and motor functions, which is expressed in the tweets describing vehicle/pedestrian accidents and the difficulty in handling inebriated individuals. In addition, when the action of ethanol starts to wear off, the inverse neurophysiological actions emerge: hangover (linked to dehydration, but also to the release of large quantity of glutamate), antisocial behaviors (rudeness, brawl, violent behaviors) and a feeling of dysphoria linked to the depletion of the dopamine neuroreceptors, which are side-effects also depicted in the tweets labeled as negative. The personal experiences could serve as powerful examples when designing prevention messages about the harmful effects of excessive drinking.

Our study also mapped the temporal alcohol-related tweeting activities in terms of days of the week and hours of the day when Thai X users are more likely to communicate about alcohol. These types of results can be further used to disseminate health prevention messages to social media users through advertisement campaigns at the right time: social media users tend to post about their actual drinking to share their experiences with others (Erevik et al., 2017; Moewaka Barnes et al., 2016; Moreno et al., 2009). Sending such prevention messages to a targeted population on X can be achieved using the "X Ads" service. These messages should be tagged with relevant hashtag(s) and disseminated via several formats (i.e., image with text, videos, or just text). For instance, some positive tweets in this study conveyed the idea that inebriated people become increasingly sociable and charming. This positive perception of alcohol drinking can be counterbalanced with image plus text on how alcohol abuse is frequently associated with interpersonal violence and sexual abuse in Thailand (Petpailin, 2023; Somhar, 2023) and disseminated on Monday evening (peak positive).

Furthermore, prevention messages linked to national alcohol help lines and/or institutes offering alcohol treatment can be sent on Sunday evenings and Monday early afternoons (peak negative). Limiting the timeframe when these messages are sent will limit the overall cost of such a campaign, while maximizing audience reach. Future research should deepen the exploration of themes and key rationales behind the positive and negative tweets to better inform these potential prevention messages.

Importantly, X was the third most frequently used social media in Thailand in 2023 with 11.45 million users, mostly young and male, which corresponds to the subpopulation with the highest prevalence of alcohol drinking in Thailand (Sitthisongkram et al., 2023). Although the young and middle-aged Thais widely utilize social media and represent an essential channel to disseminate prevention messages regarding a variety of health-risky behaviors, there was only one tweet classified as a prevention message among the 15,000 manually coded tweets. This represents a missed opportunity to increase awareness regarding the adverse outcomes linked to alcohol usage among the Thai population. This scarcity of prevention messages could be partly due to the perception held by some Thai agencies that such messages could inadvertently encourage alcohol consumption. This perception aligns with a more conservative approach, where authorities may prioritize total abstinence over harm reduction strategies and prevention campaigns suggesting moderate or responsible drinking (Kata, 2021). However, this study solely harnessed posts from X/Twitter. Future research should collect and compare alcohol-related content from several social media platforms (e.g., Pantip, Facebook, TikTok) to understand if the lack of prevention messages is limited to X/Twitter or affects a larger number of Thai social media platforms. If the latter, Thai public health institutions should consider developing alcohol-focused prevention messages tailored to the social media environment.

Recently, understanding the impacts of social media on alcohol usage in Thailand has become even more critical, considering that Thailand’s House of Representatives approved the amendment of Thailand’s Alcoholic Beverage Control Act on March 19, 2025. The new bill comprises 38 sections and is set to replace the 2008 Act. Among these sections, amendments to Section 32 would relax the strict bans on alcohol advertising, enabling producers to promote their products following specific guidelines. This initiative is seen as a way to enhance Thailand’s “soft power” by showcasing local beverages to international visitors. This legislative relaxation calls for active monitoring of social media platforms to assess the volume and content of such alcohol ads and their impacts on Thais' alcohol-related practices.

Our findings also revealed a concerning number of tweets linking drunkenness with online pornographic materials, where women were depicted as being sexually abused after heavy alcohol consumption. The frequent exposure to such content among Thai X chatter raises serious public health and safety concerns, particularly in light of the strong association between pornography and violence against women (Malamuth et al., 2000; Wright et al., 2016). This normalization of alcohol-fueled sexual violence in online spaces is alarming, as it may desensitize viewers to these behaviors and contribute to harmful attitudes. Future studies should explore the potential influence on social media users’ attitudes and behaviors.

Moreover, future research should aim to accurately understand the sociodemographic differences between the social media user subpopulation and the general population through an online survey targeting social media users who consume alcohol. Such a survey would not only help to grasp the differences between the social media user subpopulation and the general population, but it would also offer the possibility to assess how social media usage and exposure impact alcohol usage, beliefs, knowledge, and practices compared to non-social media users.

As aforementioned, X/Twitter's drastic changes in their data collection policy have negated the ability to mine tweets for free. In addition, the recent algorithmic change aiming at "penalizing negativity" on the X platform (GVWire, 2025) will most likely restrict the relevance of sentiment analysis based on X chatter data. Given the recent limitation on data collection from X and the aforementioned algorithmic change, future research should explore alcohol-related content on other social media platforms. For example, TikTok may offer information due to its popularity and its video-based format that allows users to share more dynamic, visual representations of their drinking experiences. Exploring how TikTok users described their alcohol experiences could be of interest: a qualitative content analysis of videos related to alcohol combined with an analysis of the metadata of watched videos would provide a substantial understanding of the messages shared by influencers and the beliefs about alcohol expressed online. At least one study conducted by Russell et al. (2021) in the United States has shown promising results.

This study has several limitations, mostly inherent to the field of social media data analysis. First, social media users might only post about the positive aspects of their daily routine, underreport negative behaviors, or refrain from expressing opinions that are considered socially undesirable attitudes (Althubaiti, 2016). Second, social media research solely collects data from digital media. This implies that data are collected only from the subpopulation who have access to the Internet and are using social media, introducing a selection bias (Olteanu et al., 2019). Third, data collection was limited to tweets written in the Thai Language, which does not guarantee that all collected tweets were posted from within the Kingdom of Thailand. Fourth, our exploratory study did not cover a whole year period and is subject to seasonality linked, for example, to the Songkran festival (i.e., Thai New Year celebrations). Fifth, no verification of the final dataset coded by the native coders and used to train the classifiers was conducted, which could influence the consistency of the annotations. Although qualitative content analysis remains potentially the only method allowing the creation of datasets large enough that are not tainted by idiosyncratic annotations, future research using qualitative content analysis results to train supervised machine learning algorithms should proceed to a posteriori cross-checking to strengthen the reliability of the training dataset.

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