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Emerging poisoning trends on social media: Sodium nitrite and nitrate content on TikTok

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ABSTRACT

Introduction: Sodium nitrite and sodium nitrate have emerged as public health concerns due to their association with severe poisoning and intentional self-harm. As social media increasingly shapes how adolescents and young adults access and share information, platforms such as TikTok may facilitate prevention while also increasing exposure to potentially harmful narratives. This study aimed to investigate sodium nitrite/nitrate-related content on TikTok, focusing on harm-related discourse, suicide-related framing, engagement patterns, and automated harmful-content detection.

Methods: We analyzed metadata from the most-viewed TikTok videos discussing sodium nitrite using discourse analysis, BERTopic, HarmNER, BART-MNLI, DistilBERT, and supervised machine-learning models, including logistic regression and XGBoost, with SHAP-based explainability.

Results: Harm, misuse, overdose, and suicide were prominent themes. Engagement was highly skewed, with a small number of posts receiving disproportionate visibility. Prevention-oriented content was more common than explicitly harmful content, but harmful narratives remained present. Logistic regression showed the best performance for harmful-content detection.

Conclusion: TikTok contains both preventive and potentially harmful narratives related to sodium nitrite/nitrate, underscoring the platform's dual role in self-harm communication. These findings highlight the value of explainable machine-learning approaches for the early identification of high-risk content and for strengthening moderation, suicide prevention, and digital public health responses.

1. Introduction

Sodium nitrate ($NaNO_3$) and sodium nitrite ($NaNO_2$) are inorganic compounds with legitimate industrial, food, and medical uses. Sodium nitrate is commonly used as a food preservative and in industrial processing, and is generally regarded as having low acute toxicity at usual dietary exposure levels (Afonne et al., 2020; Dippong et al., 2020; Hadi et al., 2024; Joosen et al., 2014; Rathod et al., 2024; Santamaria, 2006; van Velzen et al., 2008).

Sodium nitrite is used in cured meat production and as an antidote for cyanide poisoning, but it is also inexpensive, widely accessible, and readily available online (Bloom et al., 2024; Bugelli et al., 2022; Hikin et al., 2023; Mack et al., 2024; Mazzini et al., 2025; Sedhai et al., 2022; Stephenson et al., 2022; Szórádová et al., 2024). Although nitrate and nitrite also participate in normal human physiology through the nitrate–nitrite–nitric oxide pathway, acute exposure to larger amounts, particularly sodium nitrite, can be highly toxic and potentially fatal (Cvetković et al., 2019; Jones et al., 2024; Kapil et al., 2020; Mazzini et al., 2025; Pluta et al., 2011; Rathod et al., 2024).

The toxic effects of sodium nitrite are mainly mediated by oxidation of hemoglobin to methaemoglobin, impairing oxygen transport and causing systemic hypoxia. Clinical deterioration may develop rapidly,

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with manifestations ranging from cyanosis, headache, and tachycardia to seizures, respiratory failure, and death in severe cases (Bugelli et al., 2022; Mazzini et al., 2025; Padovano et al., 2022; Szórádová et al., 2024; Yoshioka et al., 2022). Toxic and lethal thresholds remain difficult to define precisely because reported outcomes vary according to dose, purity, coingestants, timing of treatment, and individual susceptibility (Bloom et al., 2024; Mazzini et al., 2025; Szórádová et al., 2024). Even so, toxicological and forensic reports indicate that ingestion in the low-gram range may be fatal, making sodium nitrite an important substance in both clinical toxicology and suicide prevention (Bloom et al., 2024; Mazzini et al., 2025; Szórádová et al., 2024).

In recent years, sodium nitrite poisoning has become a growing public health concern because of its increasing association with intentional self-harm and suicide (Bottei and Houselog, 2022; Kaubrytė et al., 2025; Padovano et al., 2022). Suicide remains among the leading causes of death worldwide. The World Health Organization (WHO) estimates that more than 700,000 people die by suicide each year (Mazzini et al., 2025; Padovano et al., 2022; WHO, 2025). Socio-economic deprivation, residential care status and pre-existing mental health disorders are consistently associated with higher rates of suicidal behaviour (Burnand and Johnson, 2022; Mazzini et al., 2025; Padovano et al., 2022; Yoshioka et al., 2022).

Globalization and the widespread diffusion of the Internet have facilitated the rapid spread of information about suicide methods, including procurement strategies, dosage discussions, and coadministration of ancillary substances (Bloom et al., 2024; Mack et al., 2024; McCann et al., 2021a; Padovano et al., 2022; Smith, 2023; Szórádová et al., 2024). This mode of exchange of information shifted passive information to actionable knowledge decreasing barriers to sodium nitrite access.

After the first report from New Zealand in 2010, deliberate sodium nitrite self-poisoning has increased steadily since 2017 and is now described internationally as an emerging suicide method, often linked to online communities, “suicide kits,” and e-commerce access to high-purity products at low cost (Durão et al., 2020; Hickey et al., 2021; Padovano et al., 2022; Szórádová et al., 2024; Yoon and Kim, 2022). Epidemiological studies further suggest that many affected individuals are adolescents or young adults, often with mental health disorders or prior self-harm, highlighting the relevance of digital exposure in already vulnerable populations (Bloom et al., 2024; Kaubrytė et al., 2025; Khan et al., 2024; Loiseau et al., 2023; Mack et al., 2024; Smith, 2023).

Social media platforms are now central environments in which harmful and preventive narratives about self-harm can circulate simultaneously. These platforms may provide peer support and recovery-oriented communication, but they may also normalize, sensationalize, or facilitate harmful behaviours through repeated exposure to emotionally charged and method-related content (Davitadze et al., 2020; Tighe et al., 2017). For adolescents and young adults, social media support self-expression, entertainment and socialization in a rapid and accessible format. Its personalized and rapid nature makes it appealing for young adults who are among the heaviest users of social media and may be disproportionately exposed to suicide-related material through platform algorithms, shortform video formats, hashtags, and recommendation systems.

On TikTok, qualitative studies have shown that self-harm and suicide-related videos include both protective and potentially harmful content, including normalization of self-harm, glamorization of suicide, and discussion of methods (García-Fenollar et al., 2025; Grant-Allen et al., 2025; Hamilton et al., 2025; Martínez-Pastor et al., 2025). Exposure to self-harm content on social media has been associated with increased urges and behaviours among adolescents, underscoring the potential role of platform algorithms as proximal risk factors for self-injurious thoughts and behaviours (García-Fenollar et al., 2025; Hamilton et al., 2025). In parallel, sodium nitrite has been explicitly discussed online as a suicide method, and web-based communities appear to contribute to its diffusion, particularly among younger users (McCann et al., 2021b; Smith, 2023).

Despite growing forensic and clinical evidence on sodium nitrite and nitrate poisoning, little is known about how these substances are represented and circulated on TikTok. This gap is important because social media may expose vulnerable users not only to awareness content, but also to practical, ambiguous, or method-related narratives that can increase the visibility and perceived legitimacy of this emerging suicide method. Accordingly, the present study examines TikTok content related to sodium nitrite/nitrate in order to characterize how these substances are framed, how harmful discourse coexists with prevention-oriented messaging, and how computational approaches may help identify high-risk poisoning-related content for digital public health surveillance and suicide prevention.

2. Methods

2.1. Dataset

TikTok metadata related to sodium nitrite were extracted using Apify TikTok scraper that allowed collecting the most viewed videos on TikTok under the *#sodium nitrite* hashtag. The dataset extracted comprised 461 posts that were filtered to 400 posts for modelling. In addition, language distribution was applied to a subsample of 200 posts. Data was exported as .csv, and data analysis was conducted using only anonymised (non-identifiable) data.

2.2. Ethical approvals

The study was approved by the Ethics Committee of the University of Trento (2024–083ESA) and the University of Hertfordshire (PHAEC710-42).

2.3. Data analysis

Data analysis was implemented in Python 3 using the Google Colab environment. Discourse analysis was initially applied to the data to understand dominant trends, engagement and user behaviour. Post-discourse analysis, the dataset was subjected to natural language processing (NLP) algorithms that were implemented in Python 3 using the Google Colab environment. NLP techniques included: Distilled Bidirectional Encoder Representations from Transformers (DistilBERT), Bidirectional and Auto-Regressive Transformers – Multi-Genre Natural Language Inference (BART-MNLI), Time-series analysis and topic modelling. Topic modelling was conducted using BERTopic and named entity recognition with harm-specific models (HarmNER).

DistilBERT is a transformer-based model, that was used to generate semantic representation of the text and classify sentiments into positive, negative or neutral. BART-MNLI model identified outcome-related and harm-associated categories without the need for labelled training data. This was followed by time-series analysis that was in turn applied in order to determine temporal trends in the classified content and engagement patterns. Time series analysis was applied by aggregating posts by date and framing category to generate daily counts of content types. To account for high temporal variability and skewed engagement patterns, a 7-day moving average was applied to smooth fluctuations and reveal underlying trends. This allowed the identification of shifts in prevalence over time and assessing dynamics between harmful and preventive content. Topic modelling undertaken using BERTopic and HarmNER enabled extraction and categorisation of harm-related entities in the text. BERTopic used transformer-based embeddings and density-based clustering to group semantically similar posts into interpretable topic clusters. This enabled identification of dominant themes. HarmNER allowed extraction of harm-related entities from the text and that allowed structured identification of substance-related references associated with harm and preventive discourse.

To complement the transformer-based framing and sentiment

analyses, supervised machine learning models were applied to classify posts as harmful versus non-harmful, using the framing outputs as proxy labels. Posts classified by BART-MNLI as harmful or method-seeking were assigned a positive label (harm = 1), while all other frames were assigned negative label (harm = 0). This two-stage approach enabled interpretable modelling of linguistic and engagement patterns associated with harmful framing.

Text was represented using term frequency–inverse document frequency (TF-IDF) features with unigrams and bigrams, limited to the top 5,000 features after stop-word removal. The top 5,000 features were selected in order to control dimensionality and reduce noise from infrequent words. The dataset was split into training and test sets using stratified sampling (80/20) to preserve class balance. Class imbalance was further addressed through class-weighted loss functions. Logistic regression was implemented with L2 regularisation (max_iter = 2000) and class weights set to "balanced", where weights are inversely proportional to class frequencies in the training data. XGBoost classifier was trained using a binary logistic objective with the following parameters: n_estimators = 400, max_depth = 6, learning_rate = 0.05, subsample = 0.8, colsample_bytree = 0.8, and L2 regularisation (reg_lambda = 1.0). Class imbalance was addressed using the scale_pos_weight parameter, computed as the ratio of negative to positive samples in the training data (≈ 1.69). The model was trained using the histogram-based tree method (tree_method = "hist") with AUC as the evaluation metric.

Model performance was evaluated on a held-out test set using precision, recall, F1-score, and area under the receiver operating characteristic curve (ROC-AUC). Precision reflects the proportion of predicted harmful posts that are truly harmful, while recall captures the proportion of harmful content successfully identified. The F1-score provides a balanced summary of these metrics under class imbalance. ROC-AUC assesses the model's overall discriminative ability across thresholds. Confusion matrices and ROC curves were additionally examined to evaluate trade-offs between false positives and false negatives in the context of safety-critical content detection.

Explainability was incorporated using SHAP (SHapley Additive exPlanations). For logistic regression, feature coefficients provided global interpretability, while SHAP values were computed for the XGBoost model to identify both global and instance-level contributions of lexical features to harm predictions (Fig. 1). This enabled identification of salient linguistic patterns associated with harmful or method-seeking content, supporting transparent and policy-relevant interpretation of automated harm detection.

3. Results

3.1. Data characteristics

The final dataset comprised 461 raw TikTok posts related to sodium nitrite/nitrate, of which a stratified sample of 400 posts was retained following preprocessing. Language distribution was assessed on a subsample of 200 posts. Within this subsample, English was the dominant language (151/200 posts), while the remaining posts were distributed across Norwegian, Slovak, Romanian, Bulgarian, Spanish, German, Estonian, Indonesian, French, and Albanian; a small number could not be classified. Engagement metrics were strongly positively skewed, indicating that most posts received low levels of interaction whereas a small number attracted disproportionately high visibility. Skewness values were 7.21 for play counts, 20.02 for share counts, and 13.74 for comment counts. Because the NLP models used in this study were primarily optimized for English, subsequent text-based analyses focused on English-language posts. The supervised classification models (logistic regression and XGBoost) were trained using labels generated by BART-MNLI rather than human-annotated data. Consequently, model performance should be interpreted with caution, as both models effectively learned the semantic decision boundaries of the underlying language model rather than independently identifying harmful content. This is reflected in the prominence of predictors such as "misuse," "harm," "nitrite," and "commit suicide," suggesting that the models replicate BART-MNLI's linguistic distinctions rather than deriving novel task-specific representations. Furthermore, the extracted metadata did not provide verified individual-level information on concomitant prescription medications, other co-ingested substances, clinical diagnoses, or account holders' demographic characteristics. Therefore, the dataset does not allow reliable estimation of pharmaceutical co-exposure, psychiatric comorbidity, or the prevalence of specific user subgroups. The findings presented below should thus be interpreted as descriptions of textual mentions and inferred content categories rather than clinically confirmed exposures or diagnoses.

The word cloud showed high prominence of harm-related terms including harm, misuse and suicide (Fig. 2). Mental health related terms (mental health, depression and awareness) were also seen frequently. The appearance of these terms indicated that sodium nitrite content was commonly discussed in the context of mental health. Moreover, platform-related terms such as viral, fyp and trending were also prominent, indicating algorithmic amplification of this content. Additionally, food-related terms (e.g., bacon, sausage, preservative) were noticeable

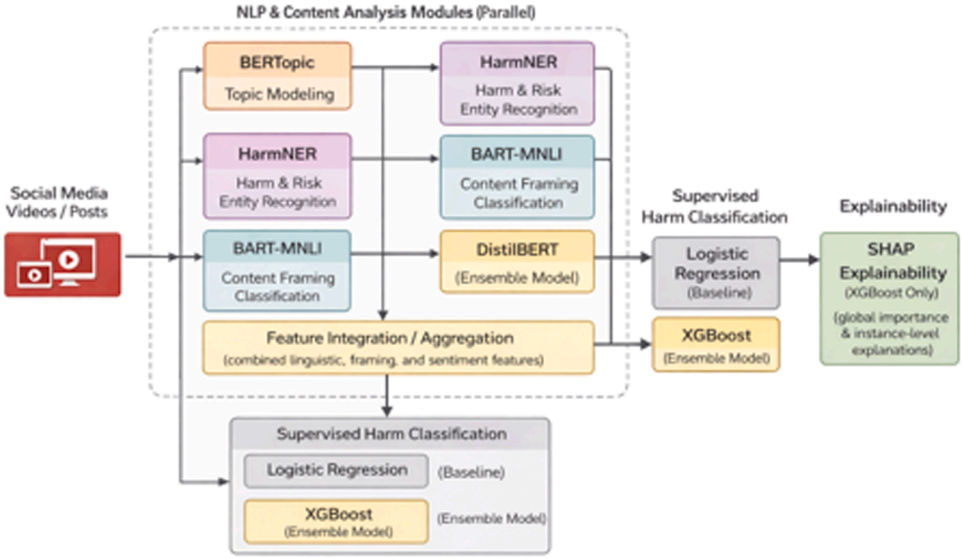


Fig. 1. Methodological approach used in this study: natural language processing and content analysis modules.

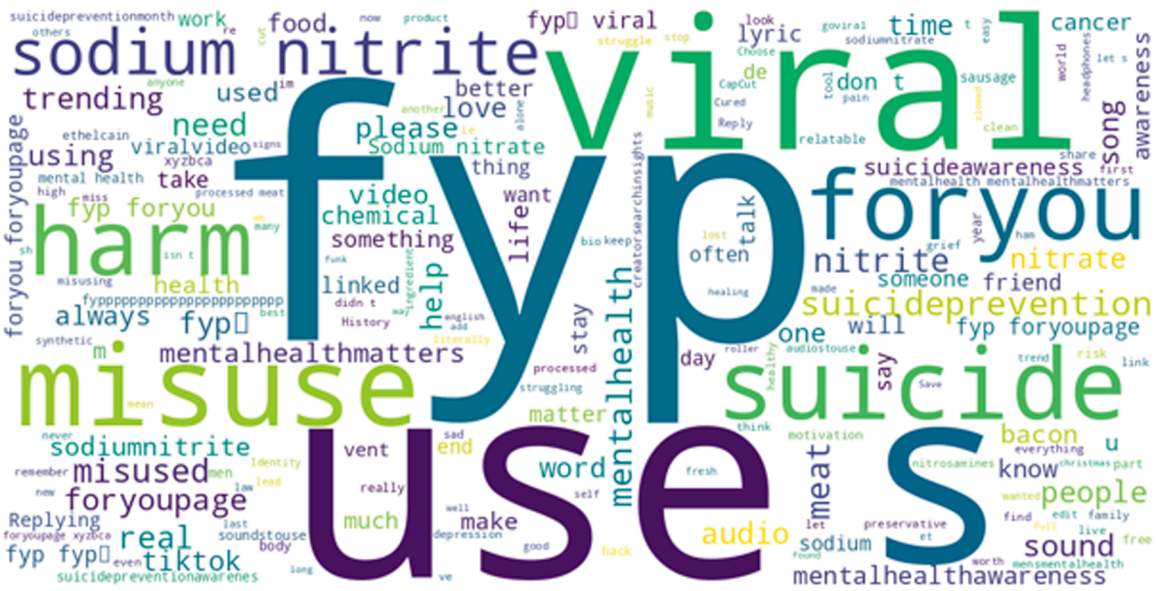


Fig. 2. Word cloud of the top encountered terms in the included videos.

and this suggested overlap between legitimate culinary use and harmful misuse narratives.

3.2. Discourse analysis

Discourse analysis examined themes related to motivation for use, modalities of use, engagement, distribution of engagement, adverse events and toxicity. The most common motivational frame was warning or prevention, which appeared in more than 100 posts. This was followed by belief in effectiveness or certainty, reported in approximately 40 posts. Emotional distress/coping and influence from others or trends were each identified in between 20 and 40 posts, whereas curiosity or information seeking was mentioned in fewer than 10 posts.

In most posts, the exposure context was not clearly specified. Where context was identifiable, it included accidental exposure (n = 125), intentional self-harm (n = 70), medical or food-safety contexts (n = 50), and, less commonly, news/legal and occupational/industrial contexts (n = 5 each). Weekly engagement showed episodic spikes rather than sustained activity across all health-outcome themes (Fig. 3). The largest spikes were observed for posts referring to neurological symptoms or loss of consciousness and breathing or oxygen-related problems. By contrast, posts relating to gastrointestinal symptoms, cardiovascular concerns, and cancer or long-term disease concerns generated lower and less frequent engagement. Posts with no explicit health-outcome framing remained consistently low and stable over time.

Reported adverse events included physical symptoms or distress ($n = 35$), loss of consciousness ($n = 33$), fatal outcomes ($n = 10$), hospitalization ($n = 8$), and psychological distress ($n = 3$). Toxicity-related discourse was dominated by references to neurological symptoms or unconsciousness ($n = 140$) and breathing or hypoxia ($n = 130$), followed by gastrointestinal symptoms ($n = 30$), cardiovascular or circulatory problems ($n = 10$), and cancer or long-term disease concerns ($n = 3$).

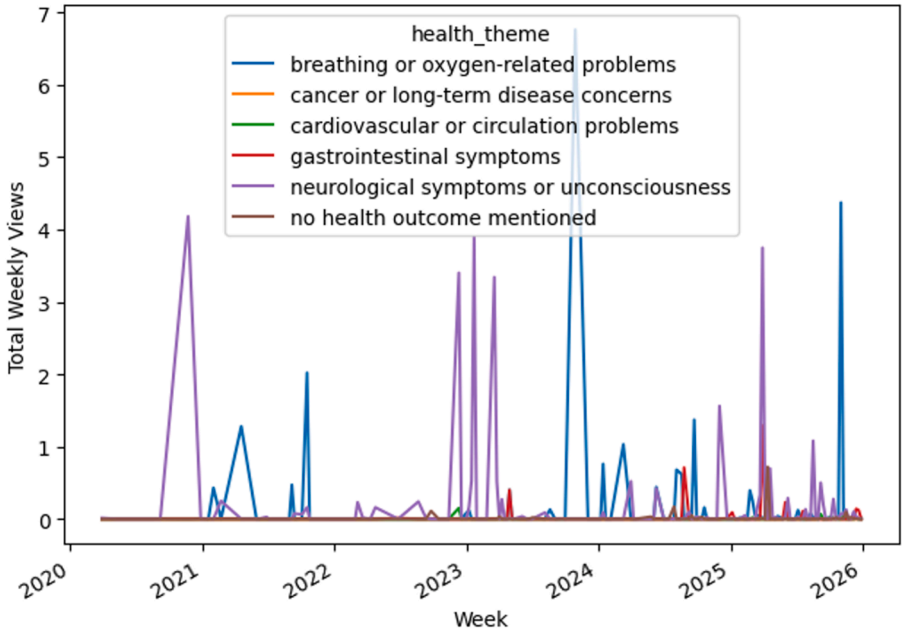


Fig. 3. Weekly engagement for all health outcomes.

3.3. Topic modelling and harm-related entity extraction

BERTopic identified several dominant discourse clusters, including broad conversational content, suicide/help-related discourse, misuse-related language, use/effectiveness narratives, and food-health discussions. Topic activity increased over time, with the highest overall volume observed in 2025.

HarmNER identified overdose and suicide as the most frequent outcome entities, reported in 175 and 125 posts, respectively (Fig. 4). Other outcome-related terms were infrequently observed (each <10 posts) and included *kill, toxic, death, dead, killed,* and *died*. The substances most commonly associated with these outcome terms were nitrite, nitrate, and sodium nitrite. Reported symptom entities included anxiety, headache, weakness, and panic.

Risk-related language was more consistently represented across the corpus, with *misuse* emerging as the dominant risk context, followed by explicit references to *risk and harmful use* (Fig. 4). In contrast, procedural or actionable terms, such as *how to, recipe, instructions,* and *mixing*, were present but remained rare. This pattern suggests that risk framing was more expressed through generalized misuse and harm-related language rather than through detailed or instructional descriptions of use. However, these observations should be interpreted in light of the study's reliance on BART-MNLI-derived labels. The identification and frequency of both outcome- and risk-related terms likely reflect the semantic classification tendencies of the underlying language model, which may preferentially capture explicit harm-related vocabulary over more implicit or nuanced procedural content. Consequently, the apparent predominance of generalized risk framing, and the relative scarcity of actionable content, may partly arise from model-driven detection biases rather than solely from the underlying discourse characteristics.

The substance–outcome/symptom co-occurrence heat map shows that outcome-related terms were co-mentioned with substances more frequently than symptom terms (Fig. 5). The highest co-occurrence was observed for the outcome *kill* (frequency=6), followed by *suicide* (frequency=2) and *killed* (frequency=1). No symptom entities showed measurable co-occurrence with substances in this matrix.

3.4. Content framing, engagement, and sentiment

Zero-shot classification using BART-MNLI identified prevention or education as the most frequent content frame, followed by general discussion and personal experience or bereavement, while news or reporting and harmful or method-seeking frames were least frequent (Fig. 6a top panel). Engagement varied across frames, with higher median play counts for news/reporting, personal experience or bereavement, and prevention/education than for general discussion or harmful/method-seeking posts (Fig. 6b bottom panel).

Within posts classified as harmful or method-seeking, the most common subtypes were seeking instructions or guidance, followed by claims about effects or outcomes. Fewer posts fell into other categories, while discouraging or help-seeking responses and access or availability discussions were rare.

Weekly engagement by frame showed episodic spikes rather than sustained activity over time (Fig. 7a and 7b). Prevention-framed content generated the largest peaks, including the highest weekly engagement observed in the dataset, whereas harmful-framed content showed fewer and smaller spikes with a generally low baseline. Sentiment analysis using DistilBERT indicated that most posts were negative in tone, with fewer posts classified as positive (Fig. 8). Among harmful-framed posts, negative tone predominated over time, while positive-toned posts

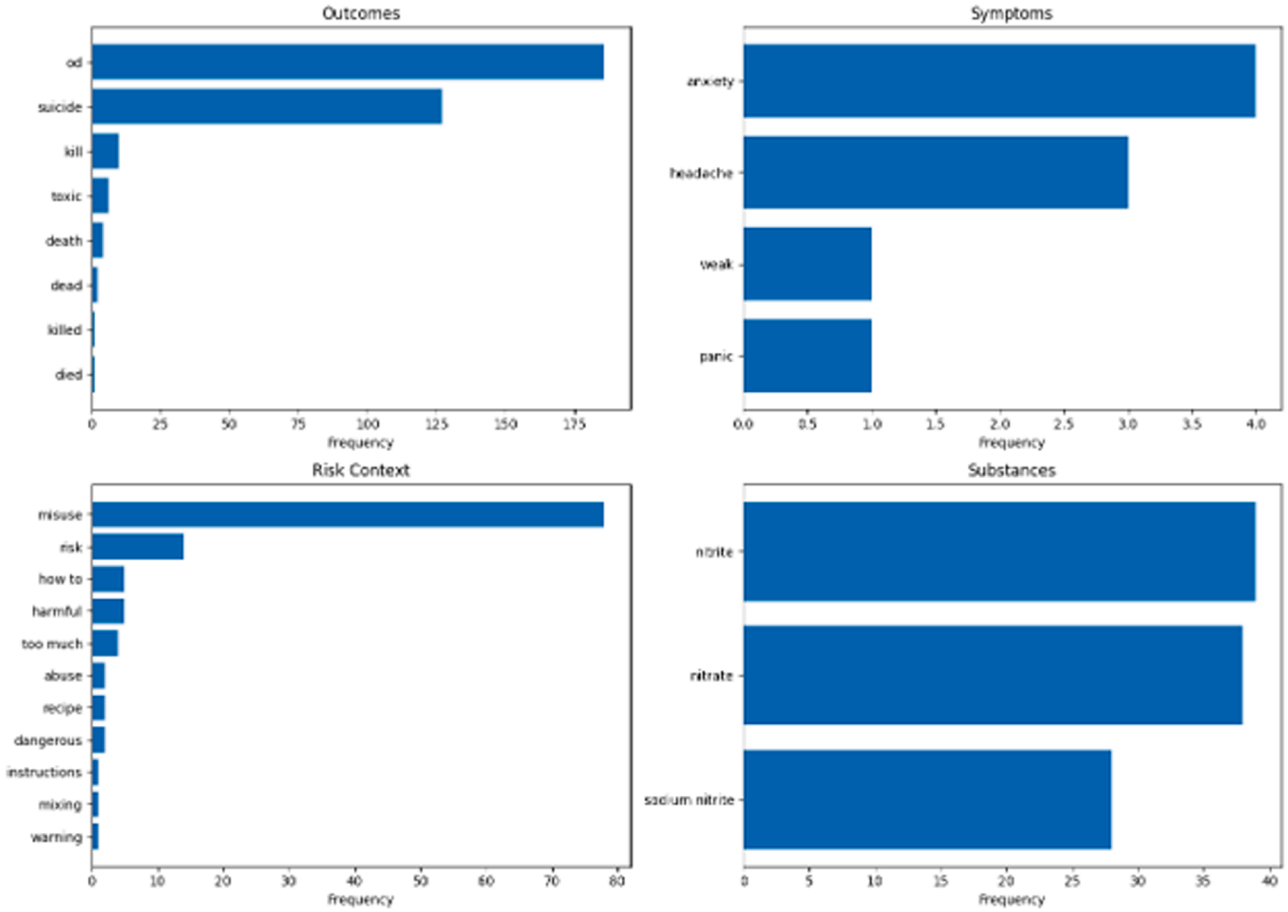


Fig. 4. Most prevalent outcomes, symptoms, risks and substances extracted using HarmNER.

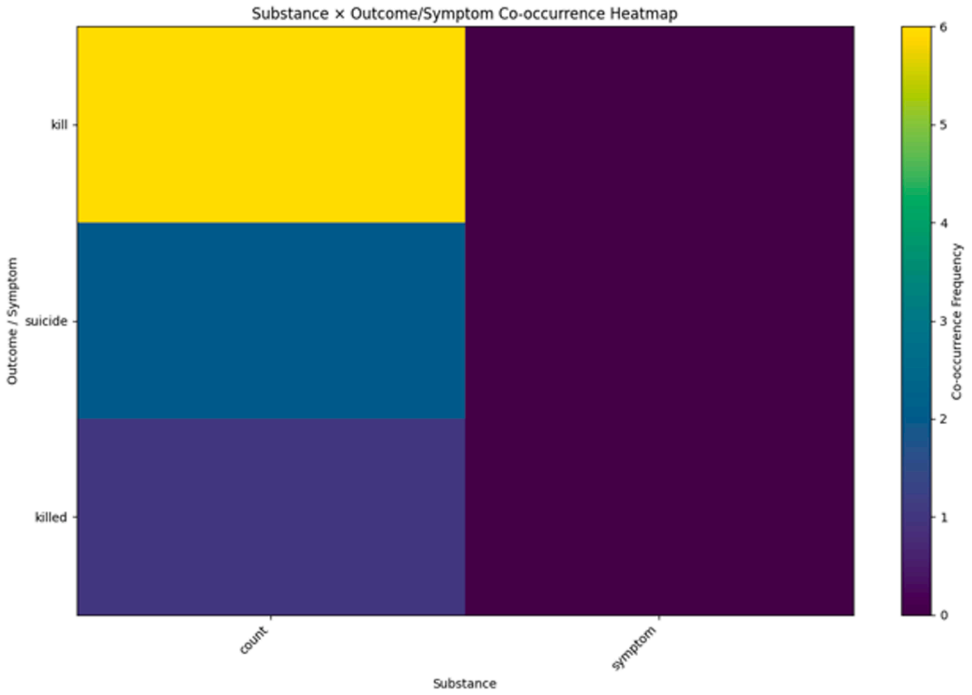


Fig. 5. Substance against outcome heatmap.

appeared only occasionally.

3.5. Harmful-content classification

The logistic regression classifier showed strong discriminatory performance for detecting harmful content (Table 1). On the held-out test set ($n = 80$), the model achieved an accuracy of 0.80 and an AUC of 0.90, indicating good separation between harmful and non-harmful posts. For the harmful class, recall was high (0.87), suggesting that most harmful posts were correctly identified, although precision was lower (0.68), reflecting some false-positive predictions. The confusion matrix indicated that 26 harmful posts were correctly classified, 4 harmful posts were misclassified as non-harmful, and 12 non-harmful posts were incorrectly classified as harmful. XGBoost achieved similar overall accuracy (0.81), with higher precision (0.74) but lower recall (0.77) and a lower AUC (0.85). Overall, logistic regression offered better sensitivity and discrimination, whereas XGBoost provided slightly better precision.

To interpret model behaviour, SHAP was applied to the TF-IDF feature space. Across models, semantically meaningful lexical cues drove harmful-content predictions. Terms such as *misuse, misused, harm, nitrite, suicide*, and *depression* increased the probability of harmful classification, whereas prevention-oriented expressions such as *suicide prevention, mental health matters*, and *stop* shifted predictions toward the non-harmful class (Figs. 9–12). Instance-level SHAP plots further suggested that classifications were influenced by the broader lexical context rather than by isolated keywords alone. Logistic regression provided higher recall and better overall discrimination, making it more suitable when sensitivity is prioritized, whereas XGBoost appeared to capture more complex non-linear interactions at the cost of slightly lower recall.

3.6. Model explainability

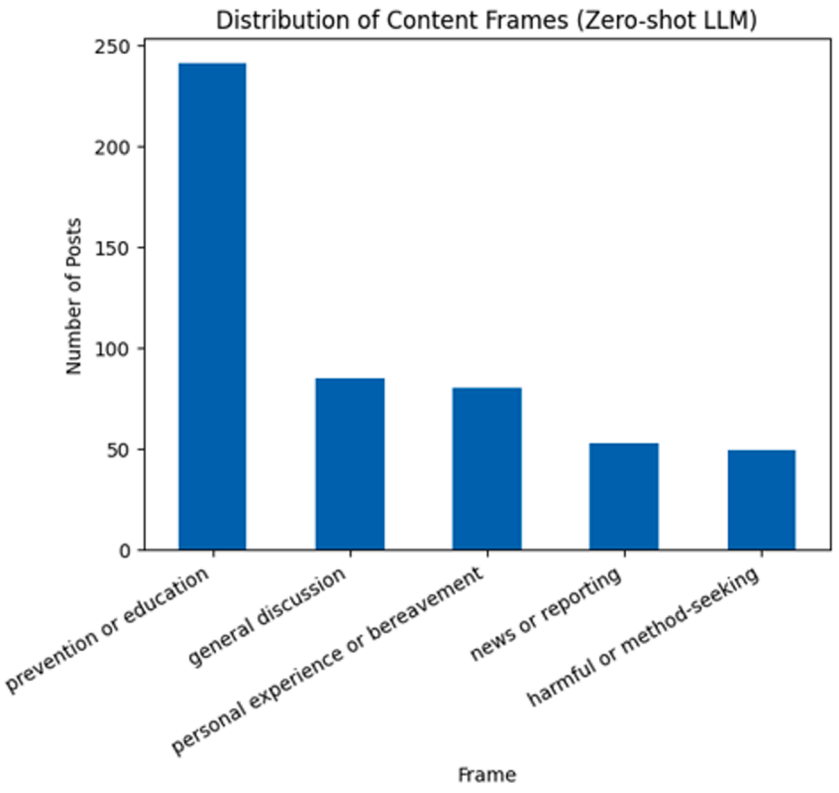
SHAP analyses indicated that semantically meaningful lexical cues drove model predictions. For logistic regression, terms such as *misuse, misused, harm, nitrite, suicide*, and *depression* increased the probability of harmful classification, whereas prevention-oriented expressions such as *suicide prevention* reduced it (Fig. 9). Instance-level SHAP plots showed that prevention-related language could offset smaller positive contributions from ambiguous or sensitive terms, resulting in non-harmful classifications even when certain keywords were present (Fig. 10). This suggests that the model relied on broader lexical context rather than isolated keywords alone.

SHAP analysis similarly identified *harm, misuse, sodium nitrite*, and *suicide* as positive contributors to harmful predictions, while *support-* and *prevention-related terms* such as suicide prevention, mental health matters, and stop shifted predictions toward the non-harmful class (Fig. 11). Instance-level explanations indicated that high-risk predictions emerged from the cumulative effect of multiple lexical signals rather than any single dominant feature (Fig. 12). Protective or awareness-related hashtags could partially offset harmful signals, leading to borderline predictions in mixed-intent posts.

Overall, both models captured semantically meaningful distinctions between harmful and non-harmful content. Logistic regression offered higher recall and better overall discrimination, making it more suitable when sensitivity is the priority, whereas XGBoost captured richer non-linear interactions at the cost of slightly lower recall.

4. Discussion

Our study was designed to characterize TikTok content related to sodium nitrite and sodium nitrate, with a focus on harm-related discourse, suicide-related framing, engagement patterns, and automated harmful-content detection. This study indicates that TikTok hosts a substantial volume of sodium nitrite and nitrate–related content in which harm, misuse and suicide are highly salient themes. Harm-related language dominated the lexical space, with overdose and suicide emerging as the most frequent outcome entities, and most posts being negative in tone. Although only a minority of videos were explicitly classified as harmful or method-seeking, engagement was highly skewed, with a small subset of posts attracting disproportionate attention. Platform-specific terms such as “viral,” “fyp,” and “trending” were also prominent, suggesting that TikTok’s recommendation systems may amplify nitrite-related narratives. In this context, content that normalises or sensationalises sodium nitrite may function as a gateway to off-platform environments where these compounds and related “kits” are marketed, including by commercial actors that profit from their sale



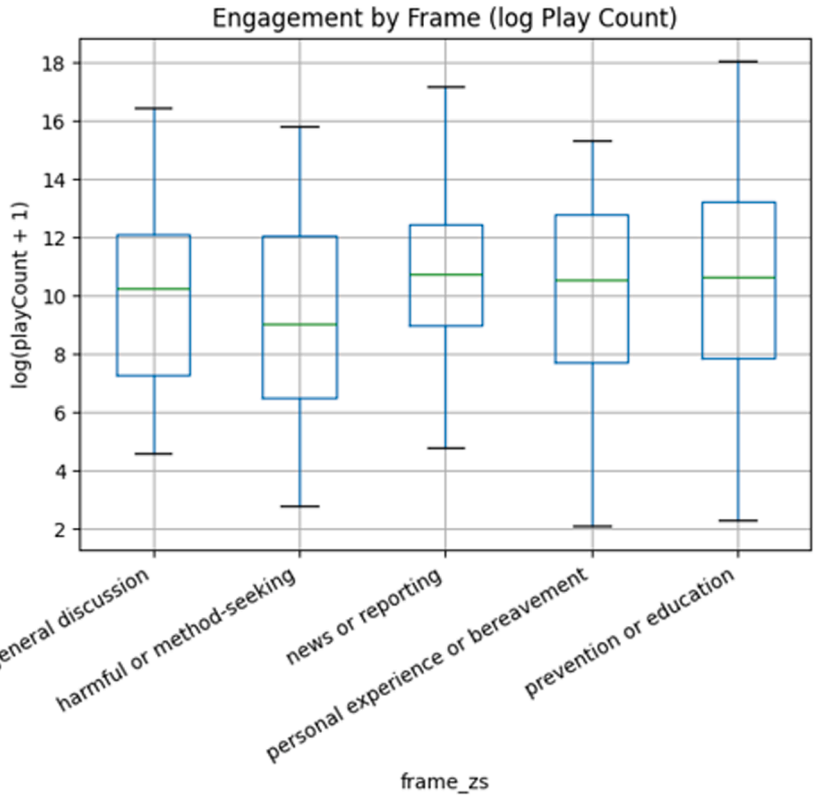


Fig. 6. Distribution frame of zero-shot LLM.

(Bloom et al., 2024; Durão et al., 2020; Kaubrytė et al., 2025; Loiseau et al., 2023; Mack et al., 2024).

These findings should be interpreted alongside the rapidly expanding clinical and forensic literature documenting both suicides and accidental poisonings involving sodium nitrate and nitrite across diverse settings (Das et al., 2024; Hikin et al., 2023; Ječmenica et al., 2025; Kim et al., 2022). These reports consistently describe severe methemoglobinemia with rapid clinical deterioration and high case-fatality rates when

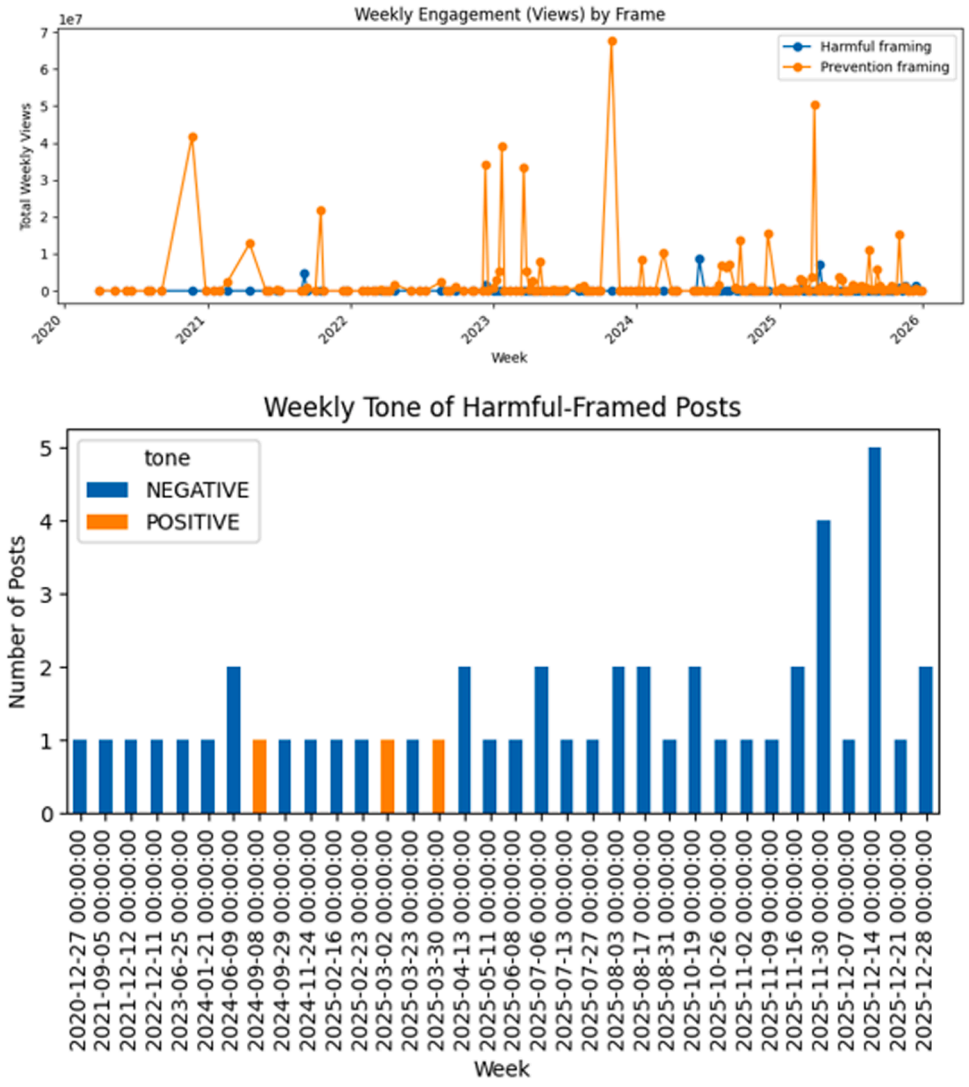


Fig. 7. Temporal trends in weekly engagement and tone of harmful-framed TikTok posts. (a - top panel) Weekly view counts stratified by content frame, displayed over a timeline spanning approximately 2020–2026. (b - bottom panel) Weekly counts of harmful-framed posts classified as having negative or positive tone, with observations extending through December 2025. The panels represent distinct measures (views versus post counts), and therefore their last non-zero observations may differ. Weeks without observations in the bottom panel (b) indicate that no posts in the analysed sample met the corresponding classification criteria during those periods, rather than an absence of related content or broader community interest on TikTok.

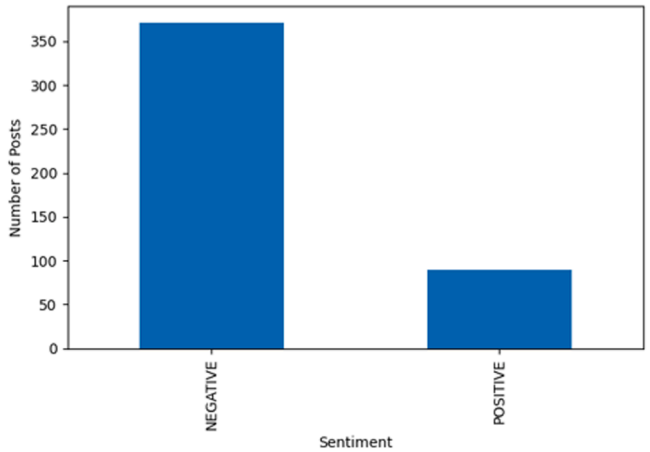


Fig. 8. Overall sentiment distribution (DistilBERT) in the posts.

treatment is delayed (Harvey et al., 2010; Hickey et al., 2021; Mudan et al., 2020; Mun et al., 2022).

Table 1
Performance metrics of LR and XGBoost models.

Model	Accuracy	Precision (Harm)	Recall (Harm)	F1-score (Harm)	AUC
Logistic Regression	0.8	0.68	0.87	0.76	0.9
XGBoost	0.81	0.74	0.77	0.75	0.85

Acute sodium nitrite poisoning can cause severe methemoglobinemia and tissue hypoxia, with cyanosis, altered consciousness, seizures, respiratory compromise, circulatory collapse and potentially hypoxic brain injury. Marked neurological impairment, including weakness or paresis, may follow severe hypoxic injury. However, persistent paralysis should not be presented as a frequent or specifically demonstrated outcome of the TikTok dataset without case-level evidence. Clinicians evaluating a suspected exposure should prioritize emergency toxicology assessment and evidence-based management of methemoglobinemia, alongside psychosocial assessment where

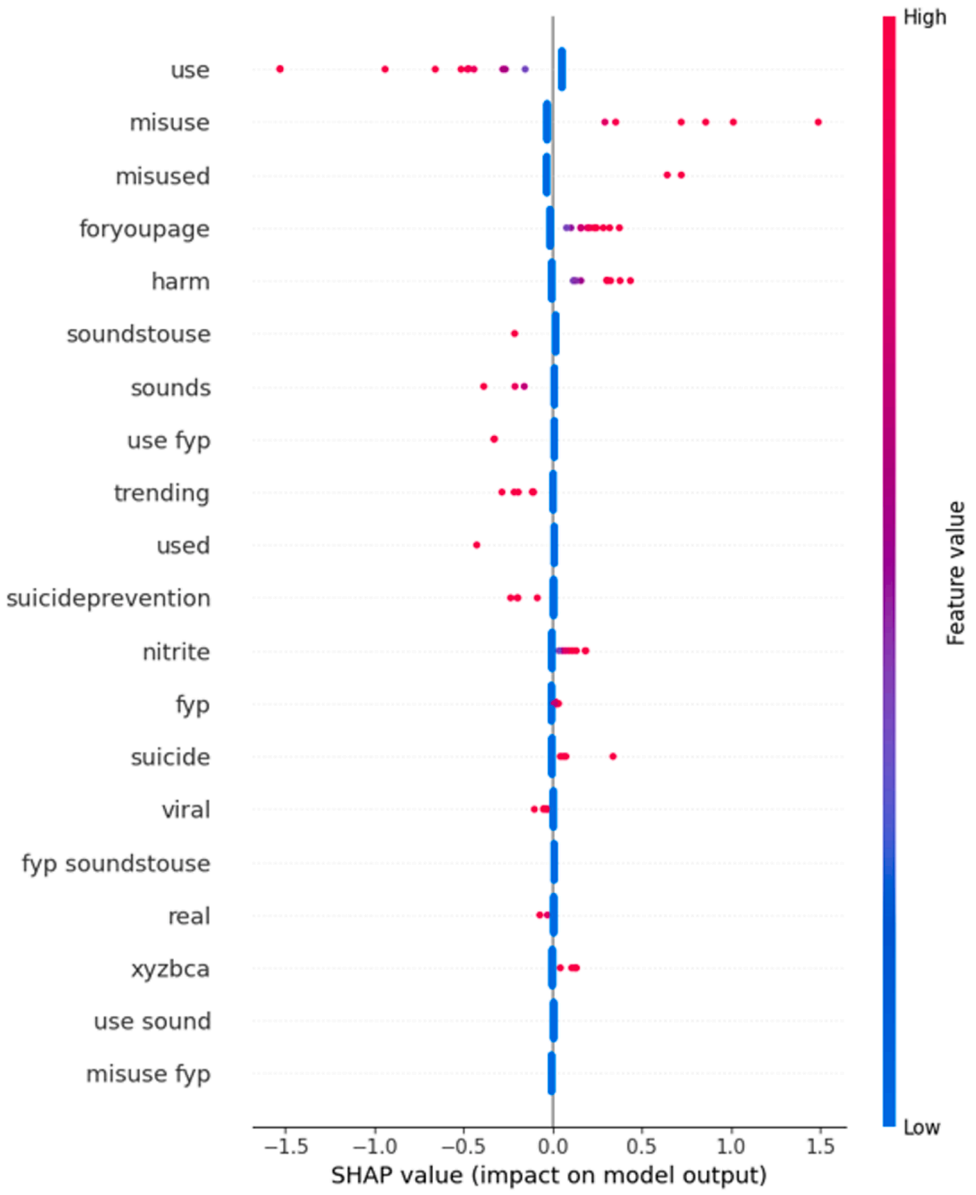


Fig. 9. SHAP summary plot for the harmful content classifier using XGBoost.

intentional self-harm is suspected (Padovano et al., 2022; Matin et al., 2022; Mazzini et al., 2025).

Diagnostic challenges such as pseudohyperchloraemia (Perkins et al., 2022) and non-specific early symptoms further increase the risk of under-recognition. Moreover, concomitant substance use and psychiatric context should be considered. In fact, published forensic case reports document some nitrate/nitrite poisonings with additional drug ingestion (Durão et al., 2021; Kaubrytė et al., 2025), and previous studies describe mental-health vulnerabilities among some affected individuals. However, neither a medication-related causal pathway nor the prevalence of co-ingestion or psychiatric illness can be inferred from hashtag text. Antidepressant or antipsychotic treatment should not be equated with causation of suicidality: confounding by indication, underlying illness and other factors must be considered.

Taken together with the present social-media findings, this wider evidence base suggests that sodium nitrate/nitrite ingestion represents an established and growing source of preventable death and critical illness rather than a theoretical or isolated hazard (Matin et al., 2022; Mazzini et al., 2025).

From a safety and governance perspective, the machine-learning analyses suggest that harmful sodium nitrite/nitrate-related content can be detected with good performance using interpretable lexical features. Logistic regression, in particular, achieved high recall and strong overall discrimination, while SHAP analyses showed that the models learned semantically meaningful patterns linked to misuse, self-harm, and suicidal intent and appropriately down-weighted prevention-oriented language. These properties are important because they support the development of rapid, evidence-enhanced moderation tools that may help identify high-risk content early enough to inform prompt intervention. In safety-critical settings, timely detection may be especially valuable where harmful narratives spread quickly, engagement spikes unpredictably, and exposure may precede help-seeking or crisis escalation.

At the same time, automated detection alone is unlikely to be sufficient. Effective mitigation also requires robust and transparent platform policies that prioritize removal or strong down-ranking of high-risk content, restrict advertising or commercial promotion of nitrite-containing products near suicide-related material, and direct exposed users toward evidence-based mental health and crisis support. As part of the preventive measures, attention should also be focused on causal

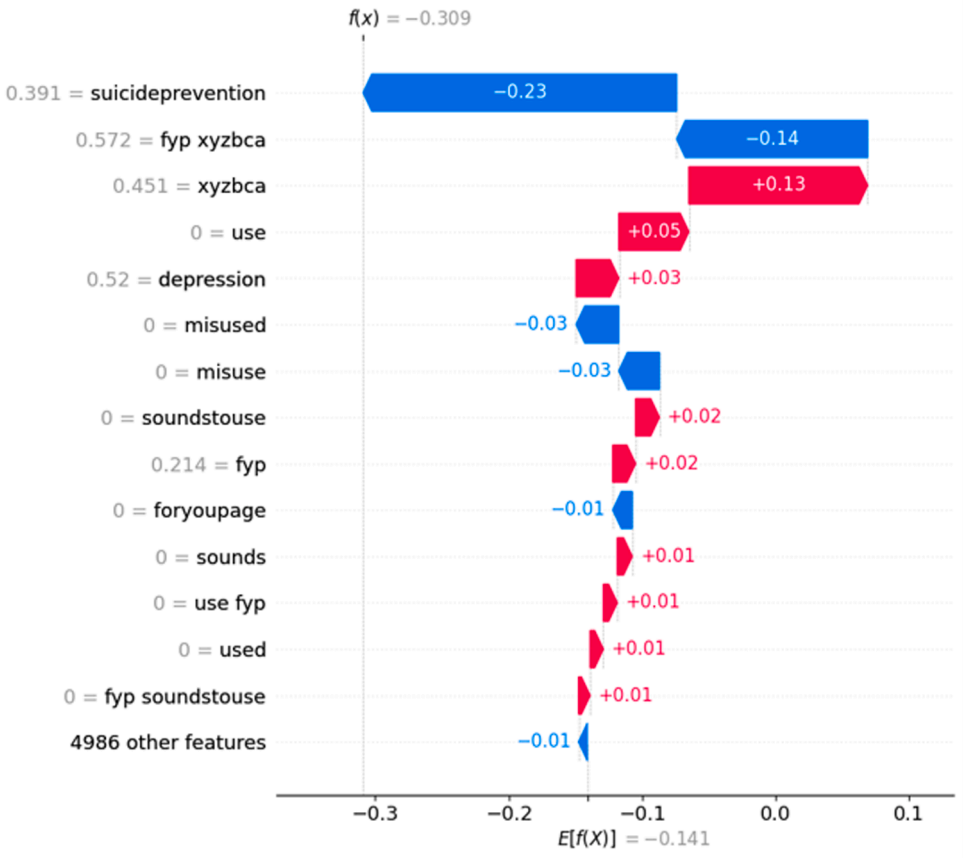


Fig. 10. SHAP analysis.

relationship between depression, use of antidepressants/antipsychotics and suicidal ideation as well as on identifying high risk individuals who would be more vulnerable in terms of using platforms such as TikTok for suicide-related materials.

In terms of safeguards for vulnerable groups, risk mitigation may combine age-appropriate design, better visibility controls for self-harm-related recommendations, friction and down-ranking for method-promoting material, clear reporting pathways, referral links to local crisis services, contextual human review and responsible prevention messaging. Particular attention is warranted for adolescents, people with prior self-harm or mental-health difficulties and those with limited support; these are vulnerability categories from the broader literature, not identified characteristics of accounts in the present sample. Evaluation should measure unintended suppression of help-seeking or recovery content as well as reductions in harmful exposure.

Several international initiatives provide relevant frameworks for addressing suicide-related risks associated with online content. The WHO LIVE LIFE initiative outlines a multisectoral approach to suicide prevention, emphasizing responsible media reporting, the development of socio-emotional skills among adolescents, early identification and follow-up of individuals at risk, and restricting access to means of suicide (WHO, 2021). Complementing this framework, the WHO's updated guidance for media professionals highlights the importance of responsible reporting across traditional and digital media, including social media platforms, while encouraging help-seeking behaviours and recovery-oriented narratives (WHO, 2023). At the European level, the European Union Drugs Agency (EUDA, n.d.) operates an Early Warning System designed to identify, monitor, and assess emerging threats associated with new psychoactive substances. Although sodium nitrite and sodium nitrate do not fall within this category, the system's surveillance and alert mechanisms may offer useful insights for developing cross-sector toxicovigilance strategies targeting emerging poisoning trends. Collectively, these initiatives provide established frameworks that could inform future prevention and monitoring efforts, although they should not be interpreted as evidence of the implementation or effectiveness of TikTok-specific interventions addressing sodium nitrite or nitrate-related harms.

The coexistence of prevention-oriented, awareness-based, and potentially harmful content further complicates moderation, as the same lexical field may contain both protective and risky messages. These concerns may be especially important for adolescents and young adults, who are among the most active users of social media and may be disproportionately exposed to emotionally intense, repetitive, and algorithmically amplified self-harm content. For vulnerable users, particularly those with pre-existing mental health difficulties, histories of self-harm, or limited offline support, repeated exposure to such material may contribute to normalization of harmful behaviours, increased cognitive availability of suicide methods, and greater susceptibility to self-injurious thoughts and behaviours over time, even if these pathways are complex and do not support simple causal interpretations (Marchant et al., 2017; Memon et al., 2018; Nesi et al., 2021; Hamilton et al., 2025).

In this sense, prolonged exposure matters not only because it increases the likelihood of encountering harmful material, but also because it may gradually shape perceptions of the acceptability, feasibility, and immediacy of self-harm methods.

Overall, these findings position TikTok not only as a site of communication about sodium nitrite/nitrate, but also as a potentially consequential environment of exposure in which vulnerable young users may encounter, revisit, and internalize harmful method-related narratives over time, underscoring the need for timely moderation, suicide-prevention safeguards, and digital public health intervention. There is of course a need for further research comparing TikTok with

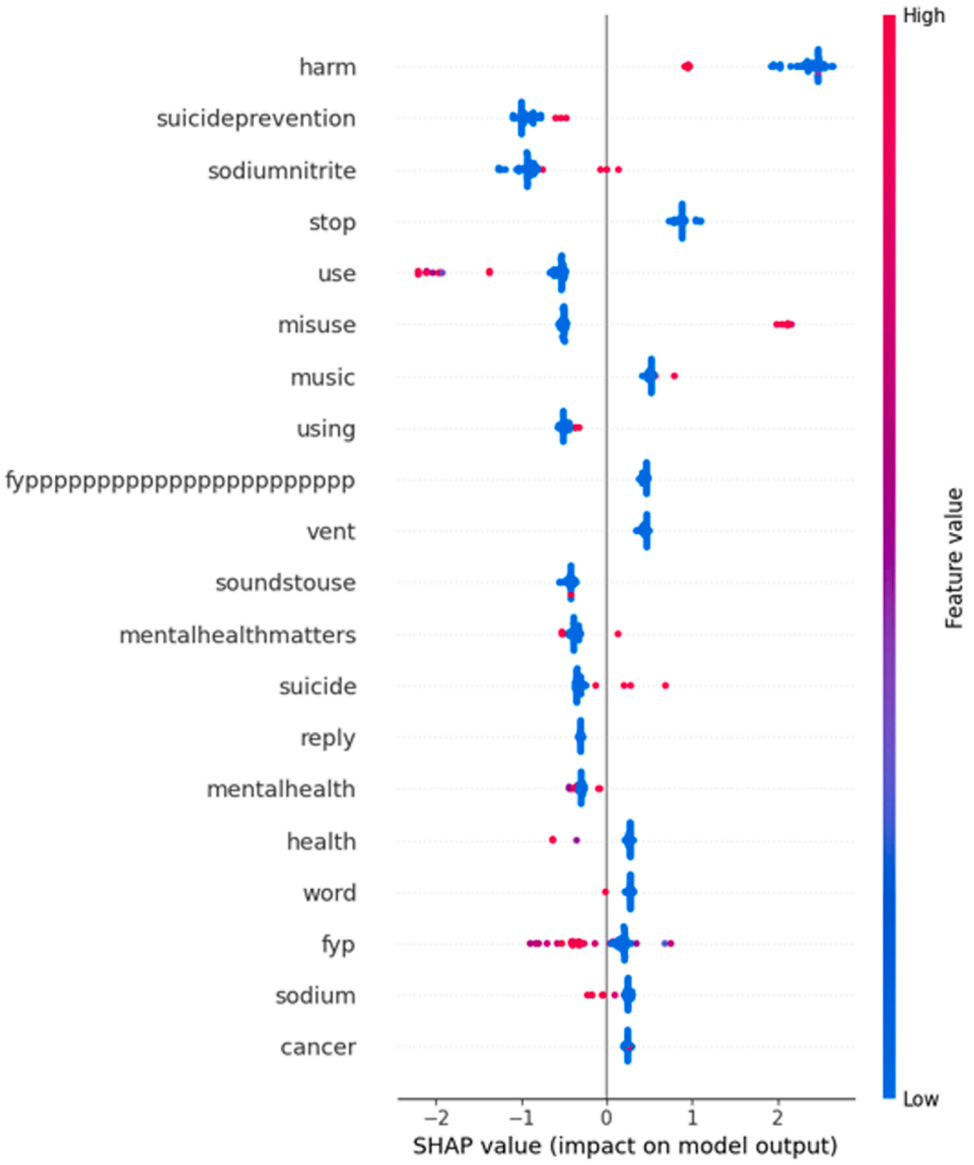


Fig. 11. SHAP summary plot illustrating feature contributions to harmful content predictions using XGBoost.

communication about sodium nitrite/nitrate on other social media platforms. Further, there are a number of social and behavioural factors that may be associated with the tendency of using social media platforms in pursuit of suicide methods.

4.1. Limitations and reproducibility

Our research has some limitations. Selecting highly viewed hashtag posts introduces substantial selection bias: heavily circulated videos may not represent the full population of nitrite/nitrate-related videos, less visible posts, alternative spellings or other platform communities. The recommendation, search-ranking and engagement systems change over time, so the distribution observed at one extraction cannot be assumed stable or nationally representative. Privacy settings, content restrictions, hashtag and language filtering, platform limitations, scraping errors, account settings and geolocation factors can influence which posts appear and which metadata are accessible. Because the source manuscript does not establish the collector's geographic configuration or VPN use, their actual effects here cannot be measured. Automated language models also face ambiguity between prevention messages, personal disclosures, educational discussion and harmful instructions, which may share terms. In addition, supervised models were trained on BART-MNLI proxy labels rather than independent expert annotations; reported discrimination measures performance relative to these proxy labels, rather than validated sensitivity for genuine suicidal intent or individual risk. Accordingly, automated detection should be used for screening and prioritization with expert review, not as a definitive determination of risk or intent. These limits preclude causal inference about algorithmic amplification and inference of wider community interest from weeks with no selected posts.

5. Conclusions

Overall, our results highlight social media and TikTok in particular as a powerful vehicle for the circulation and amplification of high-risk narratives about sodium nitrite and nitrate at a time when real-world poisonings and suicides involving these compounds are increasing. Public health authorities, regulators, platforms and clinicians should recognise this as an emerging online poisoning threat that bridges digital and offline environments.

Coordinated interventions are needed, such as tighter regulation and monitoring of online sales; data-driven, platform-level moderation tools;

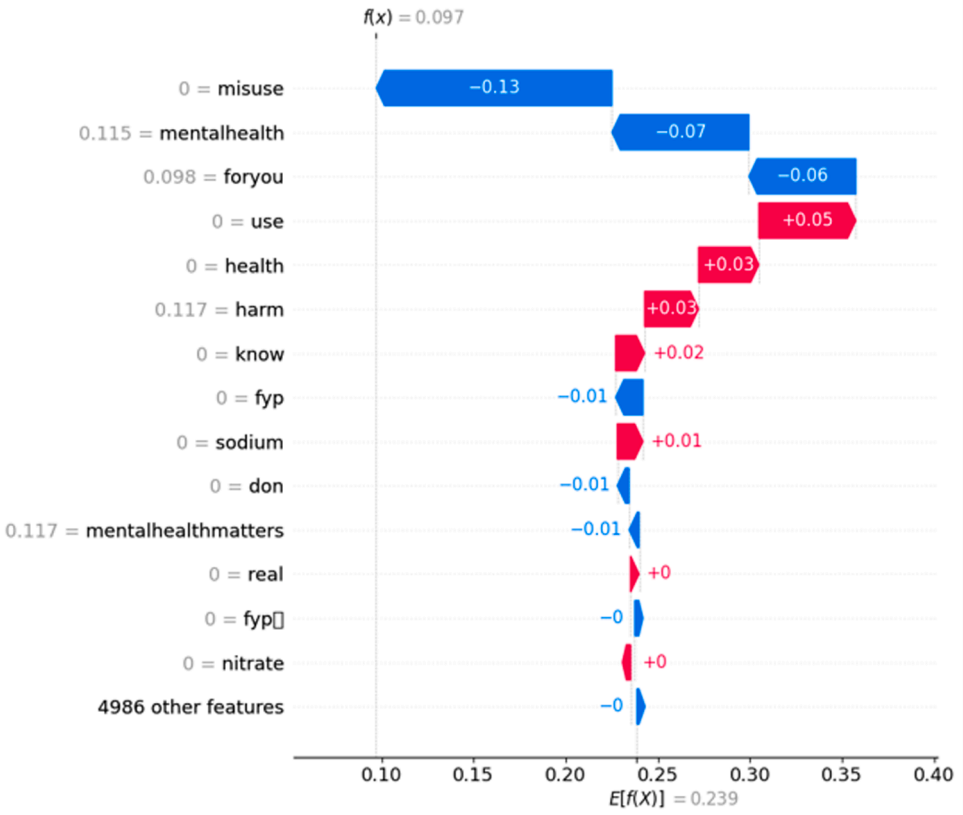


Fig. 12. SHAP analysis for an individual harmful-content prediction using the XGBoost classifier.

cross-sector surveillance linking toxicology and digital signals; and targeted digital literacy and mental-health promotion for young users. Addressing these intersecting commercial, technological and health dimensions is essential to prevent further harm and deaths associated with sodium nitrite and nitrate in the digital era.

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CRediT authorship contribution statement

Ornella Corazza: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Methodology, Investigation, Data curation, Conceptualization. **Sulaf Assi:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Elisabeth Prevete:** Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Data curation, Conceptualization. **Sofia Venturini:** Writing – review & editing, Writing – original draft, Visualization. **Dhiya Al-Jumeily OBE:** Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Formal analysis. **Sam Selek:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Data curation, Conceptualization.

Declaration of interests

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: OC serves as a co-opted member of the Internet-Facilitated Drug Markets Working Group for the Advisory Council on the Misuse of Drugs (ACMD) in the United Kingdom. The remaining authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this manuscript.

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Data availability

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

References

Afonne, O.J., Chukwuka, J.U., Ifediba, E.C., 2020. Evaluation of drinking water quality using heavy metal pollution indexing models in an agrarian, non-industrialised area of South-East Nigeria. J. Env. Sci. Health Tox. Hazard. Subst. Env. Eng. 55 (12), 1406–1414. https://doi.org/10.1080/10934529.2020.1796402.

Bloom, J., Sharpe, A., Nulman, S., Monday, K., Marraffa, J.M., Stayton, C., Clark, C., Slone, M., Cooper, G., Su, M.K., 2024. Comparing confirmed sodium nitrite suicide deaths with poison center surveillance estimates. JAMA Netw. Open 7 (9), e2434192. https://doi.org/10.1001/jamanetworkopen.2024.34192.

Bottei, E.M., Houselog, G.J., 2022. Dramatic increase in deaths from nitrate/nitrite selfpoisonings reported to poison control centers since June 2020. Clin. Toxicol. 60 (1), 139–140.

Bugelli, V., Tarozzi, I., Manetti, A.C., Stefanelli, F., Di Paolo, M., Chericoni, S., 2022. Four cases of sodium nitrite suicidal ingestion: a new trend and a relevant Forensic Pathology and toxicology challenge. Leg. Med. (Tokyo) 59, 102146. https://doi.org/10.1016/j.legalmed.2022.102146.

Burnand, L., Johnson, D., 2022. Self-harm in residential care : a consideration of the evidence and the implications for practice. Scott. J. Resid. Child Care 21 (2). ISSN 2976-9353.

Cvetković, D., Živković, V., Lukić, V., Nikolić, S., 2019. Sodium nitrite food poisoning in one family. Forensic Sci. Med. Pathol. 15 (1), 102–105. https://doi.org/10.1007/s12024-018-00361.

Das, S., Walker, D., Rajwal, S., Lakamana, S., Sumner, S.A., Mack, K.A., Kaczkowski, W., Sarker, A., 2024. Emerging trends of self-harm using sodium nitrite in an online suicide community: observational study using natural language processing analysis. JMIR Ment. Health 11, e53730. https://doi.org/10.2196/53730.

Davitadze, A., Meylakhs, P., Lakhov, A., et al., 2020. Harm reduction via online platforms for people who use drugs in Russia: a qualitative analysis of web outreach work. Harm Reduct. J. 17, 98. https://doi.org/10.1186/s12954-020-00452-6.

Dippong, T., Hoaghia, M.A., Mihali, C., Cical, E., Calugaru, M., 2020. Human health risk assessment of some bottled waters from Romania. Env. Pollut. 267, 115409. https://doi.org/10.1016/j.envpol.2020.115409.

Durão, C., Pedrosa, F., Dinis-Oliveira, R.J., 2020. A fatal case by a suicide kit containing sodium nitrite ordered on the internet. J. Forensic Leg. Med. 73, 101989. https://doi.org/10.1016/j.jflm.2020.101989.

Durão, C., Pedrosa, F., Dinis-Oliveira, R.J., 2021. Another suicide by sodium nitrite and multiple drugs: an alarming trend for "exit"? Forensic Sci. Med. Pathol. 17 (2), 362–366. https://doi.org/10.1007/s12024-020-00340-2.

European Union Drugs Agency (EUDA). The EU Early Warning System on new psychoactive substances (NPS). https://www.euda.europa.eu/activities/eu-early-warning-system-on-nps_en.

García-Fenollar, C., Sánchez-Ortí, J.V., Rojo-Bofill, L.M., Tabarés-Seisdedos, R., 2025. Effect of TikTok on self-harm and suicidal behavior in the adolescent population: protocol for a systematic review. JMIR Res. Protoc. 14, e78600. https://doi.org/10.2196/78600.

Grant-Allen, G., Wang, L., Amini, J., Dhaliwal, S., Sinyor, M., Mitchell, R.H., 2025. Self-harm and suicide-related content on TikTok: thematic analysis. J. Med. Internet. Res. 27, e77828. https://doi.org/10.2196/77828.

Hadi, M., Bashardoust, P., Solaimany Aminabad, M., Nazmara, S., Rezvani Ghalhari, M., Mesdaghinia, A., Hemmati Borji, S., 2024. Exposure assessment of nitrate and phenol derivatives in Tehran's water distribution system. J. Water. Health 22 (1), 147–168. https://doi.org/10.2166/wh.2023.133.

Hamilton, J.L., Untawale, S., Dalack, M.N., Thai, A.B., Kleiman, E.M., Yao, A., 2025. Self-harm content on social Media and proximal risk for Self-injurious thoughts and behaviors among adolescents. JAACAP Open 3 (3), 431–438. https://doi.org/10.1016/j.jaacop.2024.11.008.

Harvey, M., Cave, G., Chanwai, G., 2010. Fatal methaemoglobinaemia induced by self-poisoning with sodium nitrite. Emerg. Med. Australas. 22 (5), 463–465. https://doi.org/10.1111/j.1742-6723.2010.01335.x.

Hickey, T.B.M., MacNeil, J.A., Hansmeyer, C., Pickup, M.J., 2021. Fatal methemoglobinemia: a case series highlighting a new trend in intentional sodium nitrite or sodium nitrate ingestion as a method of suicide. Forensic Sci. Int. 326, 110907. https://doi.org/10.1016/j.forsciint.2021.110907.

Hikin, L.J., Ho, J., Morley, S.R., Ahluwalia, A., Smith, P.R., 2023. Sodium nitrite poisoning: a series of 20 fatalities in which post-mortem blood nitrite and nitrate concentrations are reported. Forensic Sci. Int. 345, 111610. https://doi.org/10.1016/j.forsciint.2023.111610.

Ječmenica, D., Pavlekić, S., Živković, V., Repić, A., Marković, S., Milošević, V., 2025. Suicide by sodium nitrite: autopsy case report. Leg. Med. (Tokyo) 72, 102572. https://doi.org/10.1016/j.legalmed.2025.102572.

Jones, D.A., Beirne, A.M., Kelham, M., Wynne, L., Andiapen, M., Rathod, K.S., Parakaw, T., Adams, J., Learoyd, A., Khan, K., Godec, T., Wright, P., Antoniou, S., Wragg, A., Yaqoob, M., Mathur, A., Ahluwalia, A., 2024. Inorganic nitrate benefits contrast-induced nephropathy after coronary angiography for acute coronary syndromes: the NITRATE-CIN trial. Eur. Heart. J. 45 (18), 1647–1658. https://doi.org/10.1093/eurheartj/ehae100.

Joosen, D., Stolk, L., Henry, R., 2014. A non-fatal intoxication with a high-dose sodium nitrate. BMJ Case Rep. 2014. https://doi.org/10.1136/bcr-2014-204825.

Kapil, V., Khambata, R.S., Jones, D.A., Rathod, K., Primus, C., Massimo, G., Fukuto, J.M., Ahluwalia, A., 2020. The noncanonical pathway for In vivo nitric oxide generation: the nitrate-nitrite-nitric oxide pathway. Pharmacol. Rev. 72 (3), 692–766. https://doi.org/10.1124/pr.120.019240.

Kaubrytė, S.S., Chmieliauskas, S., Salyklytė, G., Laima, S., Vasiljevaitė, D., Stasiūnienė, J., Petreikis, P., Badaras, R., 2025. Fatal outcome of suicidal multi-substance ingestion involving sodium nitrate and nitrite toxicity: a case report and literature review. Acta Med. Litu 32 (1), 160–172. https://doi.org/10.15388/Amed.2025.32.1.11.

Khan, H., Barber, C., Azrael, D., 2024. Suicide by sodium nitrite poisoning: findings from the national violent death reporting system, 2018–2020. Suicide Life Threat. Behav. 54 (2), 310–316. https://doi.org/10.1111/sltb.13043.

Kim, M., Kim, S., Yang, W., Sim, J., 2022. Determination of nitrite and nitrate in postmortem whole blood samples of 10 sodium nitrite poisoning cases: the importance of nitrate in determining nitrite poisoning. Forensic Sci. Int. 335, 111279. https://doi.org/10.1016/j.forsciint.2022.111279.

Loiseau, M., Matheux, A., Sabini, S., Cavard, S., Advenier, A.S., Pasquet, A., François-Purssell, I., Guerard, P., 2023. Suicide of an adolescent girl with sodium nitrite ordered on the internet. J. Forensic Sci. 68 (6), 2200–2204. https://doi.org/10.1111/1556-4029.15350.

Mack, K.A., Kaczkowski, W., Sumner, S., Law, R., Wolkin, A., 2024. Special Report from the CDC: suicide rates, sodium nitrite-related suicides, and online content, United States. J. Saf. Res. 89, 361–368. https://doi.org/10.1016/j.jsr.2024.03.002.

Marchant, A., Hawton, K., Stewart, A., Montgomery, P., Singaravelu, V., Lloyd, K., Purdy, N., Daine, K., John, A., 2017. A systematic review of the relationship between internet use, self-harm and suicidal behaviour in young people: The good, the bad and the unknown. PLOS ONE 12 (8), e0181722. https://doi.org/10.1371/journal.pone.0181722.

Martínez-Pastor, E., Blanco-Ruiz, M., & Feijóo, S. (2025). Digital mental health and hidden support: a qualitative analysis of non-suicidal self-injury communities on TikTok. Front. Digit. Health, 7, 1645276. https://doi.org/10.3389/fdgth.2025.1645276.

Matin, A.M., Boie, E.T., Moore, G.P., 2022. Survival after self-poisoning with sodium nitrite: a case report. J. Am. Coll. Emerg. Phys. Open 3 (2), e12702. https://doi.org/10.1002/emp2.12702.

Mazzini, E., Feola, A., Fracassi, I., Carfora, A., Porzio, A., Severino, S.A., De Simone, M., Campobasso, C.P., 2025. Suicide by sodium nitrite ingestion: a systematic review. Forensic Sci. Med. Pathol. 1–22.

McCann, S.D., Kennedy, J.M., Tweet, M.S., Bryant, S.M., 2021a. Sodium nitrite ingestion: an emerging trend in suicide attempts shared via online communities. J. Emerg. Med. 60 (3), 409–412. https://doi.org/10.1016/j.jemermed.2020.10.021.

McCann, S.D., Tweet, M.S., Wahl, M.S., 2021b. Rising incidence and high mortality in intentional sodium nitrite exposures reported to US poison centers. Clin. Toxicol. (Phila) 59 (12), 1264–1269. https://doi.org/10.1080/15563650.2021.1905162.

Memon, A.M., Sharma, S.G., Mohite, S.S., Jain, S., 2018. The role of online social networking on deliberate self-harm and suicidality in adolescents: A systematized review of literature. Indian J. Psych. 60 (4), 384–392. https://doi.org/10.4103/psychiatry.IndianJPsychiatry.

Mudan, A., Repplinger, D., Lebin, J., Lewis, J., Vohra, R., Smollin, C., 2020. Severe methemoglobinemia and death from intentional sodium nitrite ingestions. J. Emerg. Med. 59 (3), e85–e88. https://doi.org/10.1016/j.jemermed.2020.06.031.

Mun, S.H., Park, G.J., Lee, J.H., Kim, Y.M., Chai, H.S., Kim, S.C., 2022. Two cases of fatal methemoglobinemia caused by self-poisoning with sodium nitrite: a case report. Med. (Baltim.) 101 (7), e28810. https://doi.org/10.1097/md.0000000000028810.

Nesi, J., Burke, T.A., Bettis, A.H., Kudinova, A.Y., Thompson, E.C., MacPherson, H.A., Fox, K.A., Lawrence, H.R., Thomas, S.A., Wolff, J.C., Altemus, M.K., Soriano, S., Liu, R.T., 2021. Social media use and self-injurious thoughts and behaviors: A systematic review and meta-analysis. Clin. Psychol. Rev. 87, 102038. https://doi.org/10.1016/j.cpr.2021.102038.

Padovano, M., Aromatario, M., D'Errico, S., Concato, M., Manetti, F., David, M.C., Scopetti, M., Frati, P., Fineschi, V., 2022. Sodium nitrite intoxication and death: summarizing evidence to facilitate diagnosis. Int. J. Env. Res Public Health 19 (21), 13996. https://doi.org/10.3390/ijerph192113996.

Perkins, C.J., Wahl, G.E., Gillett, M.J., 2022. A case of pseudohyperchloraemia caused by sodium nitrate ingestion. Clin. Toxicol. (Phila) 60 (2), 259–261. https://doi.org/10.1080/15563650.2021.1939882.

Pluta, R.M., Oldfield, E.H., Bakhtian, K.D., Fathi, A.R., Smith, R.K., Devroom, H.L., Nahavandi, M., Woo, S., Figg, W.D., Lonser, R.R., 2011. Safety and feasibility of longterm intravenous sodium nitrite infusion in healthy volunteers. PLoS One 6 (1), e14504. https://doi.org/10.1371/journal.pone.0014504.

Rathod, K.S., Mathur, A., Shabbir, A., Khambata, R.S., Lau, C., Beirne, A.M., Chhetri, I., Ono, M., Belgaid, D.R., Massimo, G., Ramasamy, A., Tufaro, V., Jain, A.K., Poulter, N., Falaschetti, E., Jones, D.A., Garcia-Garcia, H.M., Bourantas, C., Learoyd, A., Ahluwalia, A., 2024. The NITRATE-OCT study-inorganic nitrate reduces in-stent restenosis in patients with stable coronary artery disease: a double-blind, randomised controlled trial. EClinicalMedicine 77, 102885. https://doi.org/10.1016/j.eclinm.2024.102885.

Santamaria, P., 2006. Nitrate in vegetables: toxicity, content, intake and EC regulation. J. Sci. Food Agric. 86 (1), 10–17.

Sedhai, Y.R., Atreya, A., Basnyat, S., Phuyal, P., Pokhrel, S., 2022. The use of sodium nitrite for deliberate self-harm, and the online suicide market: should we care? Med. Leg. J. 90 (2), 79–80. https://doi.org/10.1177/0025817221998119.

Smith, E.M., 2023. Sodium nitrite suicide and social media influence. Nursing 53 (12), 44–47. https://doi.org/10.1097/01.Nurse.0000991568.99431.13.

Stephenson, L., Wills, S., van den Heuvel, C., Humphries, M., Byard, R.W., 2022. Increasing use of sodium nitrite in suicides-an emerging trend. Forensic Sci. Med. Pathol. 18 (3), 311–318. https://doi.org/10.1007/s12024-022-00471-8.

Szórádová, A., Hojsík, D., Zdarílek, M., Valent, D., Nižnanský, Ľ., Kovács, A., Hokša, R., Šidlo, J., 2024. Modern suicide trend from internet. Leg. Med. (Tokyo) 67, 102384. https://doi.org/10.1016/j.legalmed.2023.102384.

Tighe, J., Shand, F., Ridani, R., Mackinnon, A., De La Mata, N., Christensen, H., 2017. iBobbly mobile health intervention for suicide prevention in Australian Indigenous youth: A pilot randomised controlled trial. BMJ Open 7 (1), e013518.

van Velzen, A.G., Sips, A.J., Schothorst, R.C., Lambers, A.C., Meulenbelt, J., 2008. The oral bioavailability of nitrate from nitrate-rich vegetables in humans. Toxicol. Lett. 181 (3), 177–181. https://doi.org/10.1016/j.toxlet.2008.07.019.

World Health Organization (WHO). (2021). LIVE LIFE: an implementation guide for suicide prevention in countries. https://www.who.int/publications-detail-redirect/9789240026629.

World Health Organization (WHO). (2023). Preventing suicide: a resource for media professionals (2023 update). https://www.who.int/publications/i/item/9789240076846.

World Health Organization (2025). World health organisation suicide: key facts. https://www.who.int/news-room/fact-sheets/detail/suicide.

Yoon, J.C., Kim, S.E., 2022. Suicide attempt using sodium nitrite ordered on the internet: two case reports. Med. (Baltim.) 101 (28), e29355. https://doi.org/10.1097/md.0000000000029355.

Yoshioka, E., Hanley, S., Sato, Y., Saijo, Y., 2022. Associations between social fragmentation, socioeconomic deprivation and suicide risk across 1887 municipalities in Japan, 2009–2017: a spatial analysis using the Bayesian hierarchical model. BMJ Open 12 (8), e063255. https://doi.org/10.1136/bmjopen-2022-063255.