Original Paper

How Message Construal Level and Outcome Framing Relate to Likes on TikTok Videos About Alcohol Reduction and Cessation: Computational Content Analysis

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Abstract

Background: Social media has transformed the public health communication landscape, giving rise to competing narratives around alcohol use and creating new opportunities for health messaging. On TikTok, short-form videos promoting alcohol reduction and cessation through hashtags such as #sobercurious and #dryjanuary have gained considerable traction. However, existing research has primarily described alcohol-related social media discourse, leaving limited theory-driven evidence about which message characteristics and communication strategies are associated with positive audience engagement, and whether these associations differ between expert and lay creators. Addressing this gap can inform the development of public health messages suited to algorithmically curated social media platforms.

Objective: Drawing on construal level theory and outcome expectancy theory, this study examined how message construal level and alcohol-related outcome framing were associated with positive audience engagement, operationalized as video likes, and whether these associations varied between experts and lay content creators.

Methods: We collected and analyzed a stratified sample of 1950 US-based TikTok videos about alcohol reduction and cessation posted between 2018 and 2025. Videos were identified through systematic hashtag curation and large language model (LLM)–assisted relevance screening. Audio was transcribed using the Whisper API, and video metadata and creator information were obtained through the TikTok Research API. Message construal level was measured using the Medical Research Council psycholinguistic dictionary, which quantifies language concreteness, while AI-assisted text annotation (GPT-4o) was used to identify the presence and valence of alcohol-related outcomes and creators' presented professional expertise. Linear mixed-effects regression models examined associations between these characteristics and log-transformed video likes, adjusting for video views, creator follower counts, and repeated observations within creators.

Results: Greater language concreteness (ie, lower construal level) was associated with more video likes (b=0.04, 95% CI 0.01-0.08; *P*=.005). This association was stronger among expert creators than lay creators, as indicated by a significant interaction (b=0.15, 95% CI 0.01-0.28; *P*=.03). Videos mentioning alcohol-related outcomes received more likes than those without such mentions (b=0.07, 95% CI 0.00-0.14; *P*=.04). Among videos mentioning outcomes, those focusing exclusively on the harms of alcohol consumption received fewer likes than those highlighting the benefits of alcohol reduction or cessation (b=–0.18, 95% CI –0.30 to –0.07; *P*=.002). The interaction between creator type and the presence of outcome framing was not statistically significant.

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Conclusions: This study extends established communication and behavioral theories to observable audience engagement with alcohol reduction and cessation content on TikTok. Our findings offer practical insights for designing public health messages suited to algorithmically curated platforms. The study also demonstrates the potential of LLM-assisted annotation for scalable health communication research.

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KEYWORDS

alcohol reduction; alcohol cessation; TikTok; outcome expectancy; construal level; source type; AI-assisted text annotation

Introduction

Background

Alcohol consumption poses substantial public health risks; yet, public awareness of these risks remains limited and uneven. Despite extensive scientific evidence linking alcohol consumption to numerous diseases [1] and sustained health communication efforts to increase awareness of these links, public understanding of alcohol-related harms and the benefits of reducing or quitting alcohol remains fragmented. Recent research suggests that individuals rarely associate alcohol consumption with serious long-term health conditions, such as cancer [2-4].

Prior work has examined the effectiveness of public health communication efforts to reduce alcohol consumption. Systematic reviews suggest that while mass media campaigns can improve knowledge, attitudes, and beliefs about alcohol-related harms, translating such awareness into behavioral change remains challenging [5,6]. One potential barrier is the disconnect between expert-driven health messages and individuals' lived experiences. Qualitative studies have found that drinkers often perceive expert recommendations as irrelevant, impractical [7], overly simplistic, or inattentive to the contextual challenges they face [8]. These findings highlight a persistent gap between expert communication and lay understanding of alcohol-related risks.

Against this backdrop, social media has emerged as a major source of health information [9] and a space where competing narratives about alcohol consumption circulate [10,11]. Extensive research has documented the prevalence of proalcohol content, including alcohol marketing and portrayals of drinking as socially desirable or normative [12-14]. Yet, social media also provides opportunities for lay-driven health communication and prevention efforts. For example, the *Dry January* movement, which encourages abstinence from alcohol throughout January, has gained substantial traction and participation on social media [15,16]. These diverse narratives offer valuable insights into how alcohol consumption is socially constructed, normalized, promoted, and problematized in digital environments, while potentially shaping perceptions and behaviors beyond social media. Recent meta-analytical evidence suggests that social media use is associated with greater alcohol consumption and engagement in risky behaviors, with user-generated content showing particularly strong associations [17].

Given evidence on the potential influence of alcohol-related content on social media, understanding what drives positive audience engagement with competing narratives about alcohol consumption, reduction, and cessation is valuable for developing public health messages and campaigns that resonate with and potentially reach broader audiences. In response, a growing body of work has examined how alcohol is discussed and portrayed on social media [10,11,13,15,16,18,19]. However, 3 important limitations remain. First, prior research has often focused on specific public health campaigns, offering limited insight into the broader landscape of organically occurring discourse surrounding alcohol reduction and cessation. This focus may overlook the substantial volume of user-generated content that circulates beyond formal campaigns and shapes everyday exposure to alcohol-related narratives. Second, much of the existing research remains descriptive, identifying recurring themes and sentiments without drawing on established theoretical frameworks. This limits our understanding of the content characteristics and communication strategies underlying these narratives, as well as opportunities to examine the applicability of communication and behavior change theories in naturalistic social media environments. Third, relatively little research has examined how theoretically meaningful content characteristics relate to positive audience engagement. Consequently, we know less about which features of alcohol-related messages are more likely to receive positive engagement from social media audiences and may contribute to their visibility and reach on algorithmically curated platforms such as TikTok.

This study addresses these gaps by drawing on construal level theory (CLT) and outcome expectancy theory to examine how message concreteness and outcome framing in TikTok videos about alcohol reduction and cessation are associated with positive audience engagement (ie, likes), and whether these associations vary between expert and lay content creators. Likes provide an observable indicator of positive audience engagement, although their frequency may also be shaped by factors beyond message content, such as audience exposure and creator reach. Beyond reflecting favorable reactions, likes also contribute to a video's visibility, reach, and reception [20].

Our contributions are threefold. First, by examining how content characteristics of naturally occurring narratives about alcohol cessation and reduction are associated with positive audience engagement, we provide empirical insights to inform strategic design of public health messages and campaigns that may attract greater positive engagement and potentially achieve broader visibility on algorithmically curated social media platforms. Second, by applying established communication and behavioral theories to real-world user-generated content, we extend their explanatory scope to observable audience engagement in social media environments, advancing a more contextualized

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understanding of how content and source characteristics jointly shape audience responses to health communication. Third, by demonstrating the potential of large language models (LLMs) to achieve coding accuracy comparable to human annotation in analyzing alcohol-related narratives, we highlight the methodological value of LLM-assisted content analysis for scalable and systematic public health infoveillance and communication research.

Theoretical Framework

CLT posits that individuals mentally represent events, objects, or actions at different levels of abstraction depending on their psychological distance [21]. Psychologically distant entities tend to be construed in abstract, broad terms (high-level construal), whereas psychologically proximal entities are represented in concrete, detailed terms (low-level construal). CLT is particularly pertinent to health communication, where messages often concern psychologically distant or proximal experiences, such as long-term health consequences versus immediate behavioral outcomes and abstract health goals versus concrete everyday practices [22]. Prior research suggests that abstract, why-oriented messages can enhance message satisfaction, efficacy beliefs, and behavioral intentions in contexts, such as hypertension prevention and COVID-19 vaccination, compared to concrete, how-oriented messages [23,24]. Beyond health communication, recent research has found that concrete language is associated with greater sharing and liking of text-based posts on Twitter and Reddit, suggesting that message concreteness may also shape audience engagement on social media [25].

Outcome expectancy theory provides another theoretical lens for understanding how health messages shape audiences' beliefs and behaviors. Rooted in social cognitive theory, it posits that individuals' behavioral decisions are influenced by the consequences they anticipate from performing or not performing a particular behavior [26]. These outcome expectancies encompass both beliefs about the likelihood of specific consequences and evaluations of their desirability. In the context of alcohol consumption, outcome expectancies include anticipated benefits and harms of drinking [27], which play an important role in shaping drinking behaviors [28]. Empirical research suggests that exposure to messages highlighting negative alcohol-related consequences is associated with greater treatment-seeking intention among heavy drinkers [29]. Similarly, Vranken et al [30] found that depictions emphasizing short-term adverse physical consequences of alcohol consumption can foster more negative attitudes toward drinking.

Such outcome expectancy framing is evident in how alcohol consumption, reduction, and cessation are portrayed on social media. For example, Russell et al [15,16] identified the health benefits of temporal abstinence as a recurring theme in *Dry January* discussions, while Clement et al [31] found that nearly half of TikTok videos retrieved using the hashtag #alcohol portrayed alcohol negatively, often highlighting alcohol-related problems and dependence. Conversely, Instagram influencers frequently emphasize the positive consequences of drinking to attract audience attention [32]. The presence and valence of outcome framing may shape audiences' expectations about the consequences of alcohol consumption, reduction, or cessation [33,34].

Beyond what health messages communicate, who delivers them may also shape how audiences perceive and respond to their content. Extensive research has demonstrated the influence of source characteristics on audiences' attitudes and behaviors in health promotion and public service campaigns [35-38], with a seminal meta-analysis highlighting substantial differences in the persuasive effects of expert and nonexpert sources [39]. Such effects extend to video-based health communication. Experimental studies using TikTok videos as stimuli have found that doctor-sourced messages are perceived as more credible than peer-sourced messages, while source cues interact with message characteristics to shape attitudes and behavioral intentions [40,41]. Notably, Lee et al [41] found that peer-sourced videos were more effective in increasing participation intentions. These findings suggest that source type may shape audience responses both independently and in conjunction with message characteristics. Of particular relevance to this study is the potential interplay between source type and message construal level. Lay creators often use first-person narratives grounded in concrete personal experiences, specific events, and everyday actions [42], whereas experts tend to rely more on scientific reasoning, professional terminology, and generalized recommendations [43,44].

Building on this literature, we propose a theoretical framework examining how message construal level and outcome framing are associated with positive audience engagement on TikTok, and whether these associations vary by source type. Accordingly, we ask the following research questions (RQs):

- RQ1: How is message construal level associated with positive audience engagement with TikTok videos about alcohol reduction and cessation?
- RQ2(a): How does positive audience engagement differ between videos that mention alcohol-related outcomes and those that do not?
- RQ2(b): Among videos mentioning alcohol-related outcomes, how does positive audience engagement differ between those highlighting the benefits of alcohol reduction or cessation and those highlighting the harms of alcohol consumption?
- RQ3(a): How does the association between message construal level and positive audience engagement vary between expert- and lay-sourced videos?
- RQ3(b): How does the association between outcome framing and positive audience engagement vary between expert- and lay-sourced videos?

Methods

Reasons for Selecting TikTok as Research Site

We selected TikTok as the research site, focusing on short-form videos about alcohol reduction and cessation. Despite TikTok's rapid growth and widespread popularity, particularly among younger populations worldwide [45], and the broader proliferation of short-form video content across social media platforms [46], visual- and video-centric platforms remain

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relatively understudied in research on alcohol-related public discourse. This gap is important, given TikTok's distinctive communication environment, characterized by lifestyle and trend-driven content, influential creators, and algorithmic content curation. These platform characteristics may shape how health-related narratives are constructed, circulated, and received, making TikTok a critical context for examining alcohol reduction and cessation discourse and its associations with positive audience engagement.

TikTok has also emerged as an important platform for public health communication [47,48], bringing together lay creators and domain experts who share diverse perspectives on alcohol consumption and behavioral change. Content ranges from personal recovery journeys and everyday experiences of sobriety to professional health guidance and evidence-based recommendations. The growing visibility of sobriety culture further underscores the relevance of this context. For example, the hashtag #sobercurious alone has been associated with more than 160,000 videos on TikTok, reflecting substantial public interest in alcohol reduction and cessation and providing opportunities to examine how these narratives are framed and positively engaged with by audiences.

Ethical Considerations

Our data were collected through the TikTok Research API, which provides approved researchers with access to publicly accessible videos and associated metadata. We obtained access to the TikTok Research API through an application process that involved submitting a research proposal outlining the study objectives, intended use of the data, and the data protection plan. Following approval of our application, we collected publicly accessible TikTok videos and associated metadata through the authorized TikTok Research API, without accessing private or restricted content. The study involved no direct interaction or intervention with TikTok users. According to Cornell University's Institutional Review Board policy #20 [49], research involving passive collection and analysis of publicly accessible social media content generally does not constitute human participant research. To safeguard user privacy and data confidentiality, all collected data were stored on secure servers provided by the university's cloud services, with access to raw data restricted to authorized research team members. All research results were reported in aggregate, thereby minimizing the risk of identifying individual users.

Data Collection and Annotation

Phase 1: Curation of Alcohol Cessation and Reduction Hashtags

On TikTok, short-form videos serve as the primary medium for content creation and sharing, with hashtags in video descriptions often used to categorize content, signal key themes, and enhance discoverability. Accordingly, prior research has commonly adopted hashtag-based searches to identify and retrieve thematically relevant TikTok videos [12,31,48,50]. We began with 2 widely used seed hashtags related to alcohol reduction and cessation (#dryjanuary and #sobercurious) and collected 1 year of metadata (August 2024 to August 2025), yielding 71,636 unique co-occurring hashtags.

We manually reviewed hashtags that appeared more than 500 times and identified 51 additional hashtags for inclusion. The inclusion criterion was that hashtags explicitly referred to alcohol cessation or reduction, including sobriety-related hashtags (eg, #sobercurious and #soberjourney), alcohol-free lifestyle hashtags (eg, #alcoholfree and #boozefree), and alcohol moderation/reduction hashtags (eg, #mindfuldrinking). We also identified several categories of hashtags that were excluded because they did not explicitly indicate alcohol reduction or cessation. These included addiction-related hashtags (eg, #addict), general drinking terms (eg, #drinks and #alcohol), health-related hashtags (eg, #mentalhealth and #wellness), nonalcoholic beverage-related hashtags (eg, #mocktailrecipe and #nonalcoholicdrink), general recovery terms (eg, #recovery and #overcomingaddiction), self-care and self-management hashtags (eg, #healingjourney and #selflove), and generic platform or seasonal hashtags (eg, #foryoupage and #newyear).

Among the 152 hashtags reviewed, only 1 hashtag ("#mindfuldrinking") was identified as specifically referring to alcohol reduction rather than complete cessation and was therefore selected as an additional seed hashtag. By repeating the same hashtag snowballing procedure, we compiled a final list of 73 hashtags lexically relevant to alcohol reduction and cessation (see Multimedia Appendix 1 for the hashtag list).

Phase 2: Data Collection and Stratified Sampling

Based on this list, we collected metadata for all videos posted in the United States between August 2018 and 2025, resulting in 1,369,452 unique videos from cessation-related hashtags and 35,790 from reduction-related hashtags. Specifically, we retrieved video metadata using the final list of 73 hashtags. Videos containing at least 1 of these hashtags were included in the retrieval process, and duplicate videos retrieved through multiple hashtags were identified by their unique video IDs and retained only once.

Given the substantial scale of the raw dataset (N=1,405,242) and constraints related to computational cost and TikTok Research API access, we used a stratified sampling procedure to construct a manageable analytical sample. The sampling strata were defined by the cross-classification of hashtag type (alcohol reduction vs alcohol reduction), year, and video length category (short: <15 seconds; medium: 15-60 seconds; long: 1-5 minutes). Extra-long videos longer than 5 minutes were excluded from the sampling frame. Within each stratum, videos were randomly sampled in proportion to the stratum's size in the full corpus until the target sample size of 20,000 (~1%) videos was reached. This approach preserved the temporal, topical, and structural distribution of the original corpus while enabling cost-efficient computational analysis.

Phase 3: LLM-Assisted Text Annotation

Following the hashtag-based search, we used LLM-assisted coding to assess content relevance, striking a balance between classification accuracy and the labor demands of large-scale human annotation. Recent advances in LLMs have enabled scalable text annotation for tasks requiring nuanced contextual understanding. Prior studies have demonstrated strong LLM performance across various annotation tasks [51-53], sometimes

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surpassing that of human crowd workers [53]. Emerging research in public health communication further suggests that LLM-generated annotations can achieve levels of accuracy comparable to those of trained human coders when analyzing social media discourse [54-56]. For example, LLMs have demonstrated promising performance in analyzing public sentiment toward tobacco products [55], distinguishing pro- and antivaccination messages [56], classifying epidemiological characteristics of conjunctivitis-related discussions [57], and detecting adverse events [58], with all these studies drawing on social media posts as their primary sources of data. Following these validated practices, we used one of the widely used LLMs (GPT-4o) as our AI coder, guided by a carefully curated, expert-informed prompt to determine whether a given video was relevant to alcohol reduction or cessation (see Multimedia Appendix 2 for detailed prompts that guide LLM annotation).

The input provided to the LLMs included two textual components: (1) transcripts extracted from video audio and (2) video descriptions. Transcripts captured the spoken content, whereas descriptions served as a complementary source, especially for videos with minimal or no speech. To scale transcript extraction, we first used the voice_to_text field from the TikTok Research API, which yielded transcripts for 1956 videos, representing approximately 10% of the 20,000 videos analyzed. To address this gap, we supplemented OpenAI's automatic speech recognition system Whisper, enabling transcript extraction for videos not covered by the TikTok Research API. Combining both sources, we obtained transcripts for 14,648 (73%) short videos in our dataset.

AI-assisted annotation is an iterative process involving prompt refinement, testing, and validation [59]. In this study, we used a zero-shot prompting strategy, providing the LLM with detailed definitions of alcohol reduction and cessation content, as well as clear annotation guidelines for ambiguous and edge cases. To evaluate AI performance, we created a ground-truth dataset of 500 randomly sampled videos from our corpus (n=20,000), independently annotated by 2 authors (HL and JL) using the same prompt provided to the AI. Videos were classified into 1 of 3 categories: alcohol cessation, alcohol reduction, or nonrelevant. Discrepancies were resolved through group discussion with a third author (DM). Human annotation identified 22 (4%) alcohol reduction videos, 73 (15%) alcohol cessation videos, and 405 (81%) nonrelevant videos, forming the benchmark dataset used to evaluate LLM performance.

We evaluated LLM performance on the text classification tasks using precision, recall, macro F_1-score [60], and Cohen κ [61]. To minimize randomness, the model's temperature was set to 0. For transparency, the AI coder was instructed to generate a brief justification for each coding decision. Once the AI coder demonstrated satisfactory accuracy (>0.80) and interrater reliability (>0.66), it was deployed to annotate the remaining dataset.

Measures

Message Construal Level

Following prior research on construal level analysis of online text [62,63], we used natural language processing techniques to gauge the language concreteness of video transcripts, which reflects the level of construal expressed in written language. Transcript words were assigned concreteness ratings ranging from 0=most abstract to 5=most concrete based on the Medical Research Council psycholinguistic database, which provides perceived concreteness scores for over 85,000 modern English words [64]. Words referring to more tangible and specific objects, processes, or relationships were rated as more concrete, whereas words referring to abstract concepts, processes, or relationships were rated as less concrete. Transcript-level concreteness scores were then calculated by averaging the concreteness ratings of all matched words within each transcript.

Outcome Framing

To examine whether content creators refer to positive or beneficial outcomes of reducing or quitting drinking, the negative or harmful outcomes associated with drinking, or both, when describing alcohol cessation or reduction, we used an AI-assisted text annotation approach described earlier to classify each video into 4 outcome categories: benefit-only, harm-only, both, and none. Benefit-only videos refer to those that describe only positive outcomes of alcohol reduction or cessation. Harm-only videos refer to those that describe only negative outcomes associated with alcohol consumption. Videos coded as both include references to both benefits of alcohol reduction or cessation and harms of alcohol use within the same video. Videos that do not have outcome-related descriptions are coded as none.

Expert Versus Lay Creator

To distinguish between expert and lay creators on TikTok, we used AI-assisted text annotation using video transcripts and creators' profile biographies. Creator type was classified based on observable indicators of health-related professional expertise, without requiring independent verification of professional qualifications. Specifically, expert sources were defined as creator-signaled relevant expertise through self-reported medical or public health credentials (eg, MD, RN, PhD, and MPH), professional roles involving health or behavioral science practice or research (eg, doctor, nurse, epidemiologist, and health coach), institutional affiliations (eg, hospital, clinic, and university), or claims of expertise grounded in professional practice (eg, references to evidence-based guidelines). In contrast, lay sources were defined as creators without identifiable indicators of relevant health-related professional expertise, including those sharing personal opinions, experiences, anecdotes, or advice without claiming professional authority.

A random sample of 100 videos, representing approximately 5% (n=1950) of the analytical dataset, was coded by a human coder (HL) to establish ground-truth labels for benchmarking LLM performance in outcome framing and creator type annotation. The remaining videos were then annotated using GPT-4o. All prompts used for AI-assisted annotation are provided in Multimedia Appendix 2.

Positive Audience Engagement

On social media platforms, such as TikTok, like count serves as the most direct and immediate platform-based indicator of favorable audience response. Unlike comments or shares, which

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may reflect mixed reactions and motivations, liking is generally considered a positive action through which audiences signal approval or appreciation of content. Accordingly, we collected the number of likes each video received using the TikTok Research API.

Covariates

We included video view counts and creators' follower counts as covariates to account for differences in content exposure and potential audience reach. Videos with more views have greater opportunities to accumulate likes, while creators with larger follower bases may benefit from greater initial visibility and established audiences.

Data Analysis

Main Analyses

We conducted linear mixed-effects regression analyses using the lmer function from the *lme4* package in R (version 4.2.0; R Foundation for Statistical Computing). All count variables, including video likes, views, and creators' follower counts, were log-transformed to account for their skewed distribution. To account for the nonindependence of observations posted by the same creator, we included creator-level random intercepts in all models. In all main analyses, video likes served as the outcome variable, with view counts and follower counts included as covariates. The focal predictors included message construal level, operationalized as transcript-level language concreteness, and alcohol-related outcome framing, operationalized in terms of outcome presence (mentioned vs not mentioned) and valence (benefit-only, harm-only, and both). Separate models were estimated to examine these associations and their interactions with creator type (lay vs expert). Continuous predictors were mean-centered where applicable in the interaction analyses. Statistical significance was evaluated at $P<.05$, with 95% CIs reported for regression estimates.

Follow-Up Analyses

We conducted 2 additional analyses to further examine the relationship between outcome framing, language concreteness, and positive audience engagement. First, we fitted a mixed-effects model to assess whether videos mentioning alcohol-related outcomes differed in language concreteness from those without such mentions. Second, we conducted nested model comparisons to assess the incremental explanatory contributions of outcome presence and language concreteness to audience likes. Specifically, we compared models that included either outcome presence or language concreteness, along with their respective interactions with creator type, against models incorporating both predictors and their interactions. Improvements in model fit were evaluated using likelihood ratio tests.

Results

RQ1: Message Construal Level and Positive Audience Engagement With Alcohol Reduction and Cessation Videos on TikTok

As shown in Table 1, GPT-4o demonstrated strong performance in the relevance check across multiple evaluation metrics. Among the 20,000 videos analyzed, we identified 1950 relevant videos and categorized 300 (2%) videos as alcohol-reduction content and 1650 (8%) videos as alcohol-cessation content. The remaining 18,050 (90%) videos were nonrelevant and not included in our analyses.

Table 1. Performance of large language model (GPT-4o)–assisted classification of TikTok videos about alcohol cessation and reduction against human annotations[a].

Topic	Precision	Recall	Macro F_1	Cohen κ
Alcohol-reduction	1.00	0.98	0.99	0.98
Alcohol-cessation	0.95	0.97	0.96	0.92
Nonrelevant	0.97	0.98	0.97	0.94

[a]Precision, recall, and macro F_1-scores indicate classification performance for each category, with values closer to 1 reflecting better performance. Cohen κ measures agreement between the large language model and human annotations beyond chance, with values above 0.80 generally indicating almost perfect agreement.

To address RQ1, we examined the association between message construal level, operationalized as language concreteness, and positive audience engagement. Controlling for video view counts and creators' follower counts, language concreteness was positively associated with video likes (b=0.04, 95% CI 0.01-0.08; P=.005). This suggests that videos expressed at a lower level of construal (ie, use of more concrete language) were associated with more likes on TikTok.

RQ2: Outcome Framing and Positive Audience Engagement With Alcohol Reduction and Cessation Videos on TikTok

GPT-4o also demonstrated strong performance in classifying outcome framing and creator type (Table 2). RQ2 examined the association between alcohol-related outcome framing and positive audience engagement with the content. Of the 1950 videos analyzed, 59% (n=1154) did not mention any alcohol-related outcomes. Among those that did (n=796), nearly two-thirds (n=486, 61%) mentioned only the benefits of alcohol reduction or cessation (eg, clearer skin and increased energy), 21% (n=166) mentioned only the harms of alcohol consumption (eg, cancer risk and liver disease), and 18% (n=144) mentioned both.

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Table 2. Performance of large language model (GPT-4o)–assisted classification of outcome framing and creator type against human annotations[a].

Variable	Precision	Recall	Macro F_1	Cohen κ
Outcome framing	0.96	0.96	0.96	0.93
Creator type	0.99	0.99	0.99	0.88

[a]Precision, recall, and macro F_1-scores indicate classification performance for each category, with values closer to 1 reflecting better performance. Cohen κ measures agreement between large language model and human annotations beyond chance, with values above 0.80 generally indicating almost perfect agreement.

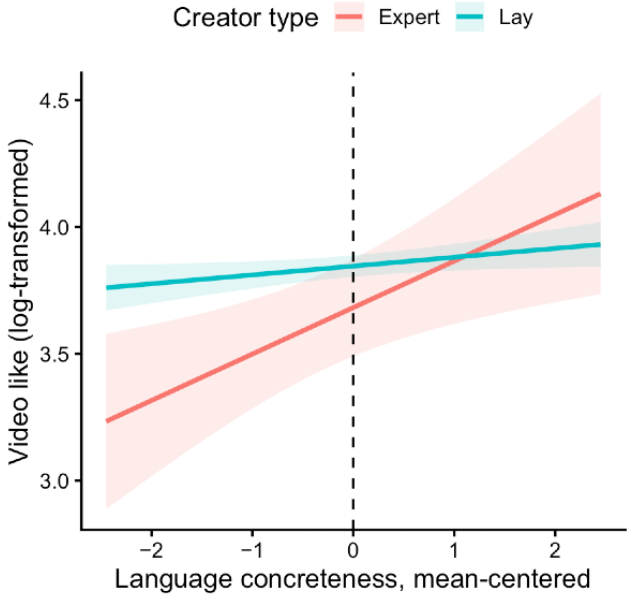
To address RQ2(a), we examined whether positive audience engagement differed based on the presence of alcohol-related outcome framing. Controlling for video view counts and creators' follower counts, videos mentioning alcohol-related outcomes received significantly more likes than those without such mentions (b=0.07, 95% CI 0.00-0.14; *P*=.04). To address RQ2(b), we further examined the association between outcome valence and positive audience engagement among videos mentioning alcohol-related outcomes, using benefit-only videos as the reference group. Compared with benefit-only videos, harm-only videos received significantly fewer likes (b=–0.18, 95% CI –0.30 to –0.07; *P*=.002), whereas videos mentioning both benefits and harms did not differ significantly from benefit-only videos (*P*=.23).

RQ3: Interaction Between Creator Type and Content Characteristics

Finally, RQ3 examined whether the associations between content characteristics and positive audience engagement varied by creator type (expert vs lay). Of the 1950 videos analyzed, 96% (n=1876) were produced by 1371 lay creators, whereas the remaining 4% (n=74) were produced by 52 expert creators who indicated relevant health-related expertise through professional credentials, roles, and affiliations or demonstrated domain knowledge.

For RQ3(a), we found a significant interaction between creator type and language concreteness (b=0.15, 95% CI 0.01-0.28; *P*=.03). As shown in Figure 1, the positive association between language concreteness and video likes was more pronounced for expert-sourced videos than for lay-sourced videos. Specifically, expert-sourced videos tended to receive fewer likes at lower levels of language concreteness, but this gap narrowed as language concreteness increased. For RQ3(b), the interaction between creator type and the presence of alcohol-related outcome framing was not statistically significant (*P*>.05), providing no evidence that the association between outcome framing and positive audience engagement differed between lay and expert creators.

Figure 1. Interaction between creator type and language concreteness in predicting positive audience engagement on TikTok. Lines represent predicted log-transformed video like counts for expert-sourced and lay-sourced videos, holding log-transformed video view counts and creators' follower counts at their sample means. Shaded areas represent 95% CIs. Language concreteness was mean-centered, with 0 indicating the sample mean.



Discussion

Principal Findings

This study examines public discourse surrounding alcohol reduction and cessation from everyday TikTok content creators, with a particular focus on the content characteristics that make such videos more likely to be positively engaged with on the platform. To the best of our knowledge, this study represents the first empirical effort to integrate CLT and outcome expectancy theory into the study of naturally occurring alcohol-related content on social media platforms. Furthermore, this study foregrounds the expert-lay distinction as a central

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moderator shaping the relationship between content characteristics and positive audience engagement.

First, we find that short-form videos articulated in more concrete language were associated with higher levels of positive audience engagement. This pattern suggests that audiences may be more responsive to alcohol-related messages conveyed through tangible, specific details than to those expressed in abstract or broadly framed terms. This finding aligns with the concreteness-engagement dynamics identified in prior work [25] and echoes literature emphasizing the importance of grounding public health communication in lay audiences' everyday experiences and contexts [7,8]. For instance, creators in our dataset described how reducing alcohol consumption could improve concrete aspects of daily life, such as "clearer dream recall" or "enjoyable concert experiences." One potential explanation can be drawn from CLT. Concrete language may make the experiences and consequences of alcohol reduction or cessation feel more psychologically proximate by translating abstract health outcomes into vivid, recognizable aspects of everyday life. Such details may help viewers more readily envision how changes in drinking behavior could manifest in their own lives, potentially reducing psychological distance and enhancing emotional resonance [21]. Furthermore, within the fast-paced communication environment of short-form video platforms, where audiences encounter and process content rapidly, concrete language may be particularly effective in making health messages immediately accessible and interpretable. By grounding broad health claims in familiar situations and experiences, creators may communicate alcohol-related information in ways that resonate more readily with viewers. This interpretation is consistent with prior research [65], showing that authentic stories grounded in lived experiences generated greater positive engagement on TikTok than health-related educational videos primarily featuring creators' opinions.

Importantly, our findings suggest that expert creators may benefit more from using concrete language than lay creators in terms of positive audience engagement. Although experts may be accustomed to technical and abstract language as a result of their professional training and familiarity with specialized knowledge and clinical discourse, such communication styles may be less effective in engaging audiences on social media platforms. Our findings therefore lend empirical support to plain-language recommendations in public health communication, which encourage health professionals to communicate complex health information using familiar, everyday language to enhance its accessibility and relevance to broader audiences [66]. Given TikTok's engagement-driven algorithm, concrete communication may also enhance the visibility of expert-generated content, potentially expanding its reach and influence in public health communication. However, our study relies on like counts as an indicator of positive audience engagement, capturing only one dimension of the diverse ways audiences engage with and respond to health promotion content on TikTok. Moreover, highly concrete language or overly specific exemplars may, in certain contexts, undermine perceived credibility or weaken the authoritative stance of experts [67]. Future research should therefore examine a broader range of audience responses to experts' use of concrete language to better understand the potential trade-offs between accessibility and perceived authority.

Beyond the message construal level, our study highlights the role of outcome framing as another important communication strategy associated with positive audience engagement. At a fundamental level, we found that videos explicitly mentioning the consequences of alcohol use, reduction, or cessation received more likes than those without such references. This finding aligns with a recent systematic review identifying behavior change–oriented content as a reliable predictor of positive user engagement with social media posts addressing lifestyle risk factors [68]. One plausible explanation is that explicitly communicating behavioral outcomes provides alcohol reduction and cessation messages with a clearer motivational structure. By highlighting what individuals may gain, avoid, or experience through their drinking behaviors or changing their drinking behaviors, outcome-framed messages make the potential consequences more salient and personally relevant.

Consistent with this account, our follow-up analysis revealed that videos explicitly mentioning alcohol reduction or cessation outcomes used significantly more concrete language (b=0.21, 95% CI 0.11-0.31; $P<.001$), suggesting that articulating consequences may draw creators toward the specific and concrete linguistic register. Further nested model comparisons showed that adding language concreteness and its interaction with creator type significantly improved model fit beyond outcome presence ($P=.003$), whereas adding outcome presence and its interaction with creator type did not significantly improve model fit beyond language concreteness ($P=.18$). Overall, these findings suggest that language concreteness, considered jointly with its interaction with creator type, provides additional explanatory value for positive audience engagement beyond the presence of outcome framing.

We also observed that the valence of outcome framing was associated with positive audience engagement. Videos exclusively foreground the benefits of alcohol reduction, and cessation garnered the highest levels of likes, particularly outperforming harm-focused content. This finding aligns with prior evidence [50], which showed that vaping cessation videos featuring a higher proportion of gain-framed messages received significantly more likes and shares on TikTok. One possible explanation lies in the distinctive cultural and communicative norms of TikTok. As a platform often characterized by positive self-expression, entertainment, and emotionally affirmative storytelling, TikTok may foster normative expectations for content that feels uplifting and authentic [69]. In this sense, our findings point to an underexplored yet consequential external factor in the design and evaluation of public health messaging on social media: the effectiveness of message strategies may depend not solely on their content or source characteristics, but also on the cultural and affective environments of the platforms through which they circulate. Future research should therefore adopt comparable, cross-platform approaches to examine how similar public health messages are received and engaged with across different social media environments. From a practical perspective, public health campaigns may benefit from considering the distinct culture and norms of their target

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platforms when developing communication strategies that are contextually appropriate and engaging.

Limitations

This study has several limitations that merit consideration. First, our sample included a disproportionately small number of expert creators, who accounted for less than 5% of the videos. This imbalance may reflect the relatively limited presence of health professionals producing alcohol-related content on TikTok, although it may also have been influenced by our stratified sampling strategy, which did not explicitly account for creator type. Given the limited creator-level information available through the TikTok Research API, future research examining source effects could consider using purposive sampling strategies to obtain a more balanced representation of expert and lay creators. Moreover, our classification of expert creators relied on observable signals of professional expertise rather than verified qualifications. Accordingly, creators presenting themselves as health professionals or domain experts may not necessarily possess formal credentials, potentially overestimating the prevalence of credentialed professionals in our sample. Although such cues may shape perceptions of source credibility, we did not directly assess how audiences interpreted them. These considerations warrant caution when generalizing our findings to differences between objectively verified expert and lay sources.

Second, although this study examined short-form videos, our analysis primarily focused on textual data extracted from audio transcripts and video descriptions. We did not systematically analyze visual elements, as many videos featured on-screen captions or subtitles that largely mirrored the spoken content captured in the transcripts, offering limited additional information relevant to our RQs. Nevertheless, this text-centered approach does not fully capture the multimodal nature of TikTok content, where meaning and audience engagement may emerge from the interplay of linguistic, visual, and auditory elements. Future research could extend our findings by incorporating visual presentation, background music, facial expressions, and embodied storytelling to examine how these multimodal cues independently and jointly relate to positive audience engagement with public health messages.

Third, our measurement of language concreteness relied on a validated dictionary-based approach that aggregates word-level ratings into transcript-level averages. Although this approach has been widely adopted in prior research, averaging may obscure within-transcript variation, and fixed word-level ratings cannot fully capture contextual differences in meaning. Transformer-based models may offer more context-sensitive assessments, and future research could explore such approaches to provide a more nuanced assessment of language concreteness.

Fourth, the observational nature of our study limits causal interpretations of the associations between message characteristics, creator type, and positive audience engagement. Although our findings provide empirical evidence relevant to CLT and outcome expectancy theory in naturalistic social media environments, they cannot establish whether these content characteristics directly influence audience responses or through which psychological mechanisms such effects may occur. Future experimental research could systematically manipulate message concreteness, outcome framing, and source cues to examine their causal effects on audience engagement and related psychological processes.

Fifth, our analysis of outcome framing was limited to the presence and valence of alcohol-related outcomes, without distinguishing the specific types of consequences highlighted in these narratives. Future research could further examine the diversity of outcomes emphasized by expert and lay creators to develop a more nuanced understanding of how different consequences are communicated and associated with audience engagement. Indeed, outcomes may vary in their perceived psychological distance and personal relevance. For instance, long-term health risks, such as cancer, may be perceived as temporally distant, whereas more immediate benefits, such as improved sleep, may feel more psychologically proximate and tangible to audiences. An outcome-specific approach could therefore help clarify the boundary conditions under which outcome-framed health messages become engaging and effective.

Conclusions

Echoing calls for theory-driven and ecologically grounded approaches to health communication research [70,71], this study contributes to understanding how naturally occurring health messages are constructed by everyday lay and expert creators and received by audiences on social media. By examining these messages in their naturalistic communication environments, our research also offers insights into the applicability of established communication and behavioral theories to real-world patterns of audience engagement.

More broadly, we highlight the need for continued theory-driven research into the content characteristics and communication strategies associated with audience engagement and circulation of public health messages across social media platforms. Such efforts should pay greater attention to individuals' concrete, lived experiences and the ways they make sense of health behavior change in their own terms. Bridging the gap between institutionally informed public health frameworks and lay narratives presents both a critical challenge and a promising opportunity to develop health messages that are more accessible, relatable, and responsive to diverse audiences. As everyday content creators and social media personalities increasingly participate in public health discourse, understanding how their communication practices engage audiences may offer valuable insights into contextually grounded health communication strategies, with potential implications for broader health promotion efforts.

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Data Availability

The datasets generated or analyzed during this study are available from the corresponding author on reasonable request.

Generative AI Use

Generative AI tools developed by OpenAI were used in the study. Specifically, GPT-4o was accessed through the OpenAI API for AI-assisted text annotation, while Whisper was accessed through its API for automated audio transcription. Both applications are described in detail in the Methods section. ChatGPT was also used to assist with language editing and refinement. All AI-assisted outputs were critically reviewed, verified, and, where necessary, revised by the authors. The authors take full responsibility for the accuracy, validity, integrity, and final content of the work.

Conflicts of Interest

None declared.

Multimedia Appendix 1

List of TikTok hashtags.
[PDF File (Adobe PDF File), 63 KB-Multimedia Appendix 1]

Multimedia Appendix 2

Large language model prompts for text annotation.
[PDF File (Adobe PDF File), 63 KB-Multimedia Appendix 2]

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Abbreviations

CLT: construal level theory
LLM: large language model
RQ: research question

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