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# Cannabis warning labels, sensory marketing, and electronic word-of-mouth: AI-facilitated textual analysis of a randomized experiment among youth and young adults

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## ABSTRACT

Online marketing of recreational cannabis products, particularly edibles, increasingly employs sensory appeals to attract adolescents and young adults (AYAs). Requiring cannabis warning labels (CWLs) on social media marketing posts is a potentially cost-effective intervention to improve health education and influence online word-of-mouth, an understudied outcome in warning label science. This study combined Structural Topic Modeling, supervised machine learning, and AI-facilitated content analysis to investigate potential youth word-of-mouth responding to online edibles marketing posts that systematically varied in the presence of CWLs and social cues. Findings show that both textual and pictorial CWLs effectively reduced pro-cannabis comments, including the mentioning of sensory appeals, while increasing anti-cannabis comments among AYAs. Exogenously manipulated anti-cannabis user-generated comments had similar effects, suggesting a potential feedback loop beneficial to public health. Methodologically, this study illustrates the value of combining qualitative and AI-facilitated quantitative methods in studying health-related online word-of-mouth marketing and interventions.

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electronic word-of-mouth; visual appeal; artificial intelligence; Cannabis marketing; warning labels

## Introduction

Health warning labels are increasingly mandated on the packaging and advertising of a growing list of products to communicate relevant health hazards and risks, improve consumer knowledge, and when justifiable, discourage consumption (Popova, Massey, and Giordano 2024; Purmehdi et al. 2017). In 2009, Congress passed the

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Family Smoking Prevention and Tobacco Control Act to authorize the Food and Drug Administration to mandate warning labels on cigarette packaging and advertising (Popova, Massey, and Giordano 2024). Despite ongoing litigations brought by the tobacco industry, numerous studies have confirmed that tobacco warning labels, especially those deploying graphic visuals, can effectively improve harm perceptions and facilitate quitting behaviors (Brewer et al. 2016; Noar et al. 2016; Popova, Massey, and Giordano 2024). Besides tobacco products, a growing list of hazardous products where cost-effective warning labels are required also includes alcohol, opioid medications, sugary soft drinks, and, more recently, recreational cannabis products (Popova, Massey, and Giordano 2024; Purmehdi et al. 2017).

From the perspective of corporate social responsibility in marketing, prominently displaying health warning labels not only fulfills companies' legal obligations and commitment to social welfare but can also help gain consumer trust and brand favorability (Torres, Sierra, and Heiser 2007). From the perspective of understanding the persuasiveness of online health advertising, health warning labels represent a form of countering messages when juxtaposed with pro-product appeals in the same advertisement (Davis and Burton 2016). This juxtaposition creates the possibility of counter-persuasive resistance. That said, empirical evidence from the advertising literature so far is limited and mixed, documenting both pro-brand favorability and anti-product resistance (Davis and Burton 2016; Purmehdi et al. 2017; Torres, Sierra, and Heiser 2007). Given the expanding requirements for health warning labels on packaging and advertising of a variety of products, it is important to examine whether health warning labels can effectively counter the main advertisement, particularly on consumer-generated online expressions related to the product and consumption, also known as electronic word-of-mouth or eWOM (Babić Rosario, de Valck, and Sotgiu 2020; Berger 2014; Chu and Kim 2018). This outcome is highly relevant for understanding the dynamic influences between online health advertising and social interactions, yet its relationship with warning labels remains understudied in both the advertising and health communication literature.

Fueled by consumer access to a growing list of multi-modal production tools in the social media era, eWOM has become prevalent in today's online information environment. This trend is likely to continue as platforms keep investing in recommendation algorithms and sponsored advertising systems that center online engagement, including eWOM, as the currency of the online attention economy (Gerlitz and Helmond 2013). In a recent review, Rosario and colleagues (Babić Rosario, de Valck, and Sotgiu 2020) define eWOM as 'consumer-generated, consumption-related communication that employs digital tools and is directed primarily to other consumers' (425). They further categorize the existing scholarship on eWOM into three connected processes: eWOM creation, exposure, and evaluation. To date, most research on health-related advertising, campaign, and eWOM focuses on effects related to exposure and evaluation (Dinulescu and Prybutok 2022; Nielsen 2009; Smith, Menon, and Sivakumar 2005; Thrane 2019). Numerous studies have confirmed that eWOM often serves as persuasive messages affecting various consumption behaviors (Anderson and Magruder 2012; Chevalier and Mayzlin 2006; Chintagunta, Gopinath, and Venkataraman 2010; Duan, Gu, and Whinston 2008; Jin and Phua 2014; Ye et al. 2011). In the narrower domain of health campaigns, interpersonal conversations, either offline

or online, are known to mediate or moderate the effects of campaign messages as a social route to campaign effectiveness (Hornik and Yanovitzky 2003; Southwell and Yzer 2009). Beyond intrapersonal consequences, health conversations can also serve as the vehicle for health knowledge to spread and normative influence to accumulate (David, Cappella, and Fishbein 2006; Zhang and Centola 2019).

Given the established roles of interpersonal word-of-mouth in shaping the effectiveness of health advertising and campaigns, it is surprising that few studies have examined communication-related factors that produce such word-of-mouth in the first place. To address this gap, the current study draws on the *motivation, opportunity, and ability* (MOA) framework in eWOM research (Babić Rosario, de Valck, and Sotgiu 2020) to conceptualize health warning labels as a source of both informational and motivational influences that can affect the valence and specific content themes of eWOM. Furthermore, inspired by the dynamic persuasion process perspective (Nowak and Vallacher 1998; see also: Semin and Cacioppo 2008), we experimentally study whether exposure to prior valence-varied eWOM can affect subsequent eWOM. This feedback loop, if confirmed, holds both theoretical and practical significance to help unpack the reproduction of eWOM in online health marketing while testing whether eWOM exposure and creation dynamically influence each other.

Methodologically, drawing upon recent advances in artificial intelligence (AI), large language models (LLMs), and their application in communication research (Törnberg 2024; Zhang et al. 2024), we combine AI-facilitated textual analysis with randomized experimental design to move beyond self-reported measures while improving causal inferences about stances and specific content features of eWOM as outcomes. We thereby showcase an integrated approach that iteratively cycles through inductive analyses (e.g. Structural Topic Modeling) and more theoretically informed deductive analyses (e.g. LLM-facilitated valence and thematic coding) to produce interpretable and causally valid insights about the interplay between warning labels, health advertising, and eWOM in the competitive online informational environment.

### ***E-WOM in the context of cannabis warning labels for adolescents and young adults***

We focus on the rapidly growing online cannabis advertising as a case study to experimentally examine how cannabis warning labels (CWLs) and accompanying eWOM might systematically influence subsequent eWOM produced by adolescents and young adults (AYAs). As of 2025, recreational cannabis use is legalized in 24 states in the U.S. as well as the District of Columbia (Marijuana Policy Project 2025). Cannabis use can have long-term negative impacts on AYAs' cognitive and emotional development (Weinberger et al. 2022) and is associated with a host of health risks, including higher use of other drugs (Macleod et al. 2004), higher likelihood of psychotic outcomes (Moore et al. 2007), increased risk of developing depression and suicidality (Gobbi et al. 2019), and higher likelihood of cannabis use disorder (Leung et al. 2020). As the legalization of recreational cannabis use expands in the United States, online marketing of cannabis products is rising and research suggests that more aggressive advertising is associated with lower harm perceptions and increased cannabis use among AYAs (Firth et al. 2022; Krueger et al. 2021). Social media platforms like

Instagram allow explicit marijuana advertisements and other pro-cannabis content, much of which is created by and for young people (Cavazos-Rehg et al. 2016).

One particularly concerning aspect is the frequent use of sensory appeals in online advertising that promote edible products. Among youth in states that have legalized recreational cannabis products, consumption of edibles increased between 2015 and 2018, while in contrast, consumption through smoking declined (Patrick et al. 2020). Unlike inhalation, consuming psychoactive substances orally typically results in delayed onset of effects with longer duration, which increases the risk of overconsumption and unintentional intoxication (Lin et al. 2022). Despite such heightened health risks, online advertising of edibles often employs sensory marketing tactics (Krishna 2012), utilizing visual, olfactory, and palatability cues (e.g. sweet, fruity, highly saturated colors) to portray edibles as attractive food items (e.g. gummy bears, chocolates) (Luc et al. 2020), known to automatically activate the approach/appetitive motivational system (Samson, Nanne, and Buijzen 2021; Samson and Buijzen 2020). A joint letter from the Attorneys General of 23 U.S. states highlights the striking similarity between tetrahydrocannabinol (THC) edible products portrayed in advertisements and well-established snack brands such as Oreos and Doritos chips (Nevada Attorney General's Office 2022).

One promising cost-effective communication-based intervention is mandating CWLs on online cannabis advertising. As of 2024, no comprehensive regulatory framework in the U.S. governs the requirement of CWLs (Popova, Massey, and Giordano 2024). Although each jurisdiction that allows recreational cannabis use requires CWLs of some sort on product packaging, there is substantial variation in the required format, content, size, and placement, with most falling short of following the best practices in tobacco warning label design and implementation, such as using large-size pictorial warnings (Silver, Naprawa, and Padon 2020). A growing body of research, however, has shown that CWLs, especially those created to follow evidence-based design principles from the tobacco warning labels literature, can effectively reduce product appeal and increase recall and perceived message effectiveness among adolescents and young adults (AYAs) (Goodman, Leos-Toro, and Hammond 2019; Popova, Massey, and Giordano 2024; Yang et al. 2024). The largely unknown question, though, is whether CWLs can counter sensory appeals in advertising and influence eWOM in a direction benefiting AYAs and public health. In the handful of studies that examine warning label-induced conversations, the focus is often on self-reported frequency and valence (Morgan et al. 2018; Thrasher et al. 2016; Tveleneva et al. 2022), with much less attention to more granular features such as thematic specifics. Nor have these studies established the causal impacts of cannabis advertising and CWLs on eWOM generated by AYAs. This study aims to fill these gaps.

### ***The MOA framework: how CWLs and online comments influence motivation and ability in eWOM creation***

Rosario and colleagues (2020) conceptualize eWOM as a communication process, consisting of three distinguishable yet non-linearly interconnected phases—eWOM creation, exposure, and evaluation. Furthermore, they propose an overarching conceptual framework centering around consumers' *motivation, opportunity, and ability*

(MOA) to explain the three eWOM stages and offer recommendations on how marketers may appeal to consumers' MOA to strategically influence eWOM. We agree with Rosario and colleagues' (2020) assessment that there is currently no single theory that can adequately account for the causal precedents and consequences of eWOM. To articulate the theoretical reasoning motivating our hypotheses and research questions, we draw on the MOA framework to make several narrower theoretical arguments specific to the context of CWLs and cannabis-related eWOM from AYAs. Our reasoning assumes that on social media, cannabis marketing posts do not operate in vacuum; instead, they operate with the co-presence of various social cues, including user-generated comments. Therefore, eWOM from AYAs is likely a function of exposure to both cannabis advertising (with or without CWLs) and the accompanying social cues of other social media users. Notably, our study does not address *opportunity*-related factors, which generally concern technological and platform affordances and characteristics (e.g. device, network connectivity, availability of ratings and 'Likes') that influence consumers' access to eWOM.

First, we argue that CWLs influence eWOM creation through improving AYAs' knowledge about the health risks associated with cannabis use and validating their health-related concerns, i.e. enhancing their *ability* to create anti-cannabis eWOMs. Given the declining harm perceptions of cannabis use among AYAs (Harrison et al. 2024; Johnston et al. 2021), unlike tobacco use, many of cannabis products' health risks likely represent novel information, which, once internalized, can expand the knowledge base upon which anti-cannabis word-of-mouth can be built and justified. Such knowledge gain is a prerequisite for anti-cannabis eWOM creation to occur. That said, we acknowledge the possibility of countervailing mechanisms that might limit CWLs' potential to improve the knowledge base for eWOM creation. These factors include the strong pro-cannabis persuasive appeals inherent in online cannabis advertising that CWLs must compete with and overcome, as well as the possibility of inducing perceived freedom threat and psychological reactance—an undesirable outcome reported in literature studying graphic tobacco warning labels (LaVoie et al. 2017). Given the declining trend in baseline knowledge about cannabis products' health risks (Harrison et al. 2024; Johnston et al. 2021), which creates more room for improvement, and the overall positive evidentiary base supporting the effectiveness of health warning labels across various health contexts (Popova, Massey, and Giordano 2024; Purmehdi et al. 2017), we still expect a positive learning effect despite these countervailing mechanisms. It is important to empirically examine whether imposing CWLs on online cannabis commercials is sufficient to overcome pro-cannabis appeals and increase anti-cannabis eWOM, as almost no prior research has studied their net influences on eWOM creation.

Second, online cannabis advertising, particularly for edible products, often employs sensory marketing strategies that use food-related palatability and hedonic cues (e.g. portraying edibles as brownies, fruits, and candies). These strategies can automatically activate recipients' appetitive motivational systems. Sensory marketing is defined as marketing that 'engages the consumers' senses and affects their behaviors' (Krishna 2012, 333). According to the Limited Capacity Model of Motivated Mediated Message Processing (LC4MP, Lang 2000), once activated by message stimuli with evolutionarily adaptive significance—such as food-related cues—the appetitive motivational system

allocates limited cognitive resources toward message processing. Empirical research on sensory marketing in food advertising has shown that commercials with high palatability cues (e.g. color saturation indicating fruit and vegetable ripeness) automatically attract more visual attention than those with lower visual palatability cues (Samson and Buijzen 2020), a pattern consistent with appetitive motivational system activation. Among AYAs, inhibitory neural mechanisms lag behind the development of excitatory systems (Casey, Getz, and Galvan 2008). Therefore, sensory appeals rich in palatability and hedonic cues in cannabis advertising should be particularly powerful in activating the appetitive motivational system among AYAs, which likely motivates pro-cannabis eWOM expression according to the MOA framework.

Following this reasoning, we expect cannabis warning labels (CWLs) to dampen appetitive motivations while activating the *aversive* motivational system. CWLs, particularly those with graphic visuals, vividly address health consequences associated with cannabis consumption (e.g. cognitive function loss, driving risks with depictions of injuries and blood, mental health issues including suicidal ideation), thus signaling risks and danger to the organism. In other health contexts, health warnings have been established to invoke negative emotions (Niederdeppe et al. 2019; Noar et al. 2016), a pattern expected when the aversive motivational system is activated. Therefore, we expect AYAs to process CWLs as motivationally relevant cues that activate the aversive motivational system, thereby countering pro-cannabis sensory appeals, suppressing pro-cannabis eWOM while motivating anti-cannabis eWOM expression.

**H1a-b:** CWLs will (a) increase anti-cannabis and (b) decrease pro-cannabis word-of-mouth among adolescents and young adults.

Since online cannabis advertising often co-appears with eWOM produced by other social media users, it is important to consider how exposure to earlier eWOM dynamically influence subsequent eWOM creation. Rosario and colleagues (2020) argue that consumers can shift between their roles as eWOM receivers and creators. From the perspective of motivational pathways, valenced eWOM, whether pro- or anti-cannabis, constitutes social cues for normative influences that are motivationally relevant. Theories of online interpersonal communication and social contagion have highlighted that social motives including identity-signaling, social bonding, and conformity can influence online message retransmission and eWOM (Berger 2014; Cappella, Yang, and Lee 2015; Goldenberg, Libai, and Muller 2001). Empirically, research has shown that health behavioral cues (e.g. smoking) embedded in online comments causally shape behavior-specific normative perceptions and further modify individual's evaluation of the health campaign messages that co-appear (Liu and Shi 2019; Shi, Poorisat, and Salmon 2018). Pro-nutritional visual messages employing social appeals enhanced attention and recall, consistent with the idea that social cues carry motivational significance essential for human survival (Samson, Nanne, and Buijzen 2021). Neuroimaging evidence further shows that activation of the brain's mentalizing system during exposure to eWOM promoting novel products (i.e. 'social in') predicts subsequent use of social language in product recommendation to others (i.e. 'social out') (O'Donnell, Falk, and Lieberman 2015). Given the cumulated

theoretical reasoning and empirical findings highlighting the motivational relevance of eWOM, we expect a feedback loop where exposure to anti- versus pro-cannabis user-generated comments will encourage the creation of directionally consistent eWOM.

**H2:** (a) Exposure to pro-cannabis comments will increase pro-cannabis word-of-mouth, whereas (b) seeing anti-cannabis comments will increase anti-cannabis word-of-mouth toward cannabis marketing posts.

Lastly, will the effects of CWLs and eWOM interact with each other, and if so, how? On one hand, directional motivational influences from both CWLs and online comments might amplify and reinforce each other, pointing to a positive interaction. AYAs may be particularly susceptible to such positive reinforcement process because they are sensitive to social influences given their psychosocial developmental stage (Franzosi di Riva and Eck 2018). On the other hand, a recent meta-analysis of health warning labels has noted the overall lack of primary studies unpacking social influences in warning label processing, although the authors acknowledge that social influences can serve as an important driver (Purmehdi et al. 2017). Furthermore, although individuals can infer social norms from embedded behavioral cues within eWOM (Liu and Shi 2019), previous research has documented a negativity bias where exposure to *both* positively- and negatively-valenced eWOM undermines the effectiveness of the health campaign messages that co-appear (Shi, Messaris, and Cappella 2014). Given limited prior research and competing theoretical expectations, we pose an exploratory research question:

RQ1: Do social media comments moderate the effects of warning labels on the valence of youth word-of-mouth?

### ***AI-facilitated textual analysis of eWOM: an integrated approach***

Given the known memory and social desirability biases associated with self-reported measures of health-related eWOM, taking advantage of open-ended textual data afford opportunities to explore a wider variety of feature categories beyond the more limited, predetermined options in a survey questionnaire (Ferrario and Stantcheva 2022; Schuldt and Roh 2014). Scholars have emphasized that eWOM research needs to move beyond sentiment expressions to extract more nuanced content features (Babić Rosario, de Valck, and Sotgiu 2020). Recent significant advancements in artificial intelligence, particularly large language models (LLMs), present promising solutions for efficiently and reliably processing and coding unstructured textual data, with performance on par with human coders (Dakhel et al. 2024). When combined with randomized experimental designs, LLMs can facilitate causal inferences about the effects of CWLs and prior eWOM on the valence and thematic variation of subsequent eWOM.

In this paper, we report the procedures and findings of an AI-facilitated integrated approach to extract causally valid insights from unstructured textual data. Our approach started with an initial inductive structural topic modeling (STM)

(Roberts et al. 2014) analysis, including both insights and weaknesses, followed by AI-facilitated supervised coding of content features deemed of high theoretical or practical significance. These categories were selected from the larger pool of topic categories from the initial STM analysis. Given the randomized experimental design, we then attempted to make causal inference by further attributing variations of AI-coded valence and themes back to exogenously manipulated CWLs and prior eWOM conditions. Our approach illustrates the advantages of incorporating LLMs into the analytical workflow of studying open-ended responses in randomized experiments on online health advertising. Several methodological strengths are worth highlighting.

First, our approach integrates both inductive and deductive textual analyses to derive theoretically and practically important thematic categories and employs LLMs for scalable measurement. Inductive analysis allows for the emergence of themes directly from the data, while deductive analysis involves testing content categories derived from pre-existing theories (Fereday and Muir-Cochrane 2006). Researchers such as Hatta et al. (2020) and Onwuegbuzie and Johnson (2021) have emphasized the importance of a hybrid approach to content analysis, which allows researchers to balance data-driven discoveries with theory-informed analysis (Danermark 2019). Whereas popular topic modeling techniques such as STM is designed to inductively identify latent themes and patterns within textual data as a function of document-level structural variables, typically without the need for a predetermined codebook, it may still produce results difficult to interpret from a theoretical perspective. To address this limitation, supervised machine learning is often employed to complement unsupervised approaches like STM, supporting deductive theory testing by further identifying and measuring interpretable content categories and features from the broader, though often noisier, patterns resulting from the unsupervised inductive analysis. This hybrid approach capitalizes on the strengths of both inductive (unsupervised) and deductive (supervised) methods, thereby enhancing the interpretability of results, providing richer insights into the data, and facilitating a more nuanced understanding of communication patterns (Devlin et al. 2019). Recently, scholars have employed LLMs to further accelerate the implementation of this hybrid approach, often at an even lower cost due to the lack of need for extensive human-annotated training data (Chae and Davidson 2023; Fan et al. 2024; Pilny et al. 2019; Toubal et al. 2024). We joined these efforts by incorporating LLMs into our analytical framework to scale up the measurement of significant and interpretable themes from the initial STM analyses.

Second, our approach integrates the AI-facilitated measurement for themes from unstructured textual data with the randomized experimental design to improve causal inference. As Braun and Clarke (2006) suggest, qualitative patterns such as thematic categories discovered through inductive analysis can be quantitatively measured and further linked to structural variables. Given the overarching randomized experimental design under which unstructured textual data are generated, causal validity can be maintained if experimental conditions are analyzed as the primary 'structural variables'. In this sense, our integrated approach can be considered as an 'embedded mixed methods design' (Creswell 2014, 227–228), which preserves causal validity through the randomized data-generation process while allowing the flexible exploration of theoretical nuances *via* hybrid content analyses. In spirit, our approach aligns with Johnson, Russo, and Schoonenboom (2019) 'pluralistic theory of causation'.

To showcase the value of this approach, we report estimated causal effects of CWLs and online comments on one thematic feature: the mentioning of sensory appeals within youth-generated eWOM. In the context of cannabis marketing, sensory cues (e.g. vivid imagery of appealing edibles, enticing flavors) may evoke strong emotional and hedonic responses, enhancing the attractiveness and persuasiveness of cannabis commercials among AYAs (Carlini et al. 2022; Leos-Toro et al. 2019). Importantly, such emotion-laden sensory appeals may drive online retransmission of and engagement with pro-cannabis content (Berger and Milkman 2012), potentially undermining the efficacy of educational and preventive public health messaging among AYAs. Given the public health significance, we focused on the re-production of sensory appeals within youth-generated eWOM. That said, our approach can be employed to examine causal effects on any other content feature deemed of theoretical or practical significance.

RQ2: What are the predominant themes expressed in eWOM among AYAs in response to cannabis marketing posts?

RQ3: Will CWLs and anti-cannabis comments curb the amplification of sensory marketing appeals (e.g. visual aesthetics, flavors) expressed in eWOM among AYAs?

## Methods

### *Sample and experiment design*

We recruited a national sample of U.S. participants aged between 13 and 25 from the Qualtrics panel to participate in an online experiment. Adolescents and young adults (AYAs) within this age group are developmentally sensitive to social influence and digital persuasion, and prior research indicates that cannabis-related attitudes and behaviors often begin to form during this period (SAMHSA. 2022; Whitehill et al. 2020). We adopted a 3 (warning labels: no warning vs. textual warning vs. pictorial warning)  $\times$  3 (social media comments: no comment vs. pro-cannabis comments vs. anti-cannabis comments) between-subjects factorial design, plus a no message condition which was excluded from further analyses. Participants were exposed to three sets of message stimuli randomly sampled from the same condition-specific stimuli pool. Each set consisted of one marketing post promoting marijuana edibles, varying in the presence of CWLs as well as five accompanying comments that all expressed either pro- or anti-cannabis sentiments. CWLs were developed following an established protocol (Kim et al. 2022) to address 10 health risks associated with cannabis use. Pro- and anti-cannabis comments were collected from Twitter, Facebook, Instagram, and Reddit, and the study team verified them for valence. A total of 3,097 participants completed the study. They first viewed treatment stimuli and then were prompted to type a comment in response to the treatment marketing posts. They were instructed to imagine posting it to their own social media timeline. Power analysis indicates that this sample size is sufficient to provide 95% power to detect a small effect size of  $f=0.10$ , assuming  $\alpha = .05$ . Data presented in the current paper were collected from a larger project, with other outcomes including belief, attitudinal, and behavioral intentions about cannabis use reported elsewhere.

*Inductive analysis through Structural Topic Modeling (STM)*

In this study, we first employed Structural Topic Modeling (STM) for exploratory analysis to gain insights into participants’ open-ended answers and to develop a codebook for further classification using large language models (i.e. GPT-4). STM is an unsupervised machine learning technique that identifies latent topic structures within text corpora, by incorporating additional document-level structural variables (Roberts, Stewart, and Tingley 2019). We aggregated the three comments written by each participant into a single ‘document’ to facilitate the STM analysis. We followed standard pre-processing procedures for tokenization, stemming, and removing stop words, and selected  $K=4$  topics based on diagnostic statistics (e.g., held-out likelihood, minimal residuals, semantic coherence) (see [Supplementary Appendixes A and B](#) for details).

STM estimated that the proportions of the four topics T1, T2, T3, and T4 were 25%, 40%, 20%, and 15%, respectively. The details of topics, proportions, top words, and examples are illustrated in [Table 1](#). We manually reviewed examples within each topic and assigned labels based on top words and the context of this study and specifics about treatment conditions: we labeled T1 as ‘Perceived Positive Experiences’, T2 as ‘Anti-Cannabis and Intervention Intention’, T3 as ‘Urge and Attraction’, and T4 as ‘Perceived Risk of Edible Cannabis’.

While each topic represents a distinct aspect, it was clear that the STM analyses largely pointed to a difference in stance, with T1 and T3 largely corresponding to pro-cannabis sentiments and T2 and T4 to anti-cannabis sentiments. However, during our manual review of STM results, we realized that these topics did not clearly distinguish between sentiments towards the edible products versus stances towards the CWLs. Furthermore, the initial topic structure was too general to reveal thematic distinctions. To address these limitations, we followed the inductive STM analyses with an AI-facilitated, supervised stance classification and thematic coding. These procedures are detailed below.

**Table 1.** Inductive analyses through structural topic Modeling.

Topic	Percentage	Top words	Examples
T2 Anti-Cannabis & Intervention Intention	40%	don't, want, not, stop	I don't want anything to do with drugs and this needs to stop. Do not do drugs for fun.
T1 Positive Experience	25%	edible, yummy, delicious	MmmmMmmm!!!! Looks yummy. I would never think that that was an edible!!! Looks very delicious! Hope it taste as good as it looks!
T3 Urge & Attraction	20%	appealing, perfect, good	I think It's appealing and good product. They're extremely good and perfect for you and me.
T4 Perceived Risk	15%	bad, effect, side	Marijuana is a harm drug it's not to be taken lightly, it's bad and can cause serious damage. A lot of people aren't aware of the possible side effects.

### ***Deductive stance and thematic classification through large language models***

Large language models (LLMs) have gained considerable attention in communication research for computational text analysis. Trained on vast datasets, LLMs can be applied to diverse downstream tasks with minimal additional input, making them highly efficient for natural language processing tasks. GPT-4, with 1.76 trillion parameters trained on hundreds of gigabytes of internet text and books, has demonstrated superior performance in text classification compared to traditional supervised machine learning models by capturing nuanced contextual meanings (Fink et al. 2023; Tekumalla and Banda 2023; Törnberg 2024; Zhang et al. 2024). For stance classification, we employed GPT-4 with few-shot learning using human-annotated examples. We improved prompts through multiple experiments to enhance performance (see Table 2), including more negative examples than positive ones given the more implicit nature of negative sentiment.

#### ***Anti-cannabis negative stance***

A random sample of 400 participants' open-ended comments was coded by two trained undergraduate coders and two authors to create a benchmark dataset to validate the performance of LLM classifications. Comments were coded as *anti-cannabis* if they expressed disapproval of the cannabis product or advertisement, or opposed marijuana legalization. All other comments were coded as *others*, including pro-cannabis comments, neutral responses, off-topic remarks, and meaningless text (Krippendorff's  $\alpha = .67$ ).

#### ***Pro-cannabis positive stance***

Comments were coded as *pro-cannabis* if they expressed approval of the cannabis product or the advertisement, or supported marijuana legalization. All other comments were coded as *others*, including negative, neutral, off-topic, or meaningless responses (Krippendorff's  $\alpha = .86$ ).

Validation against human-annotated benchmark data was acceptable. The negative stance classifier achieved precision/recall/F1 scores of .89/.93/.90 while the positive stance classifier achieved .96/.83/.89. Based on these classifications, we created two binary variables representing negative and positive cannabis stance as dependent variables.

#### ***Coding specific themes***

Since RQ2 concerns specific themes expressed in youth-generated eWOM beyond stance detection, we manually coded a subsample of comments to extract more theoretically grounded and interpretable theme categories, building on initial STM results. These categories were identified by manually annotating a stratified random sample of 200 anti- and 200 pro-cannabis comments (see Table 4 for theme labels and examples), based on LLM-detected stances. Krippendorff's alphas range between .73 and .89 for these themes.

#### ***Presence of sensory appeals***

RQ3 examines mentions of sensory appeals as a theoretically and practically significant theme in cannabis marketing. As shown in Table 5, this theme accounts for the highest proportion (70%) of pro-cannabis comments. Two co-authors coded this theme across

**Table 2.** GPT prompts with few-shot learning for stance classification.

Category	GPT prompt
Pro-Cannabis Stance	<p>What is the stance of the text below with respect to 'cannabis'? If we can infer from the text that the text expresses a <b>positive</b> or <b>supportive stance</b> on cannabis, please label it as 'positive'. If we can infer from the text that the text does not express any positive or supportive stance on cannabis, meaning the text does not fall into positive, please label it as 'non-positive'. Please use exactly one word from the following two categories to label it: 'positive' 'non-positive'. Here are some examples of texts. Makes sure to classify the last text correctly.</p> <p>Q: text: this looks interesting. looks cool might want to try this A: positive</p> <p>Q: text: marijuana helps me ease my tension and i love it cannabis makes people feel relaxed and happy, and makes new friends marijuana can lift my mood and make me more productive A: positive</p> <p>Q: text: looks very delicious! hope it taste as good as it looks! wow! i have never seen edibles like this! where i live i've never had the option for a candy bar. does it come in milk chocolate? A: positive</p> <p>Q: text: this is not good nor is it healthy for people! stop this madness! this is harming people!! this is horrible A: non-positive</p> <p>Q: text: ok ok ok A: non-positive</p> <p>Q: text: thanks for helping my education im gon not use weed no more weed A: non-positive</p> <p>Q: text: '{text}' Is this text positive or non-positive? A:</p>
Anti-Cannabis Stance	<p>What is the stance of the text below with respect to 'cannabis'? If we can infer from the text that the text expresses a <b>negative</b> or <b>critical stance</b> on cannabis, please label it as 'negative'. If we can infer from the text that the text does not express any negative or critical stance on cannabis, meaning the text does not fall into negative, please label it as 'non-negative'. Please use exactly one word from the following two categories to label it: 'negative' 'non-negative'. Here are some examples of texts. Makes sure to classify the last text correctly.</p> <p>Q: text: i enjoy feeling at ease myself i do not want to drink thc nothing comes to mind A: non-negative</p> <p>Q: text: marijuana helps me ease my tension and i love it cannabis makes people feel relaxed and happy, and makes new friends marijuana can lift my mood and make me more productive A: non-negative</p> <p>Q: text: can it be used by teenagers and does it have significant harm? did you prove that warning? A: non-negative</p> <p>Q: text: looks very delicious! hope it taste as good as it looks! wow! i have never seen edibles like this! where i live i've never had the option for a candy bar. does it come in milk chocolate? A: non-negative</p> <p>Q: text: this is not good nor is it healthy for people! stop this madness! this is harming people!! this is horrible A: negative</p> <p>Q: text: can't drive after smoking marijuana or it will cause a car accident smoking too much can affect your health long-term smoking affects mental problems A: negative</p> <p>Q: text: thanks for helping my education im gon not use weed no more weed A: negative</p> <p>Q: text: that's bad for you edibles are bad for you. marijuana is a harm drug it's not to be taken lightly, it's bad and can cause serious damage. A: negative</p> <p>Q: text: '{text}' Is this text negative or non-negative? A:</p>

all 200 positive comments, achieving high inter-coder reliability (Krippendorff's  $\alpha = .97$ ). GPT-4 was then used to classify all remaining comments for the presence or absence of sensory appeals. Compared with human-annotated benchmark data, GPT-4 performed well, with precision, recall, and F1 scores of 94%, 95%, and 94%, respectively.

**Statistical analyses**

Consistent with our mixed methods approach, primary quantitative analyses assessed the effects of warning labels and social media comments on cannabis-related stance (H1-2 and RQ1) and specific themes in youth-generated eWOM (RQ3). We performed logistic regression analyses to test main effects of warning label conditions (pictorial vs. textual vs. no warning control), main effects of comments (pro-cannabis vs.

**Table 3.** Effects of CWLs and prior eWOM on stance towards cannabis.

	Pro-cannabis stance		Anti-cannabis stance	
	Main effect	Interaction	Main effect	Interaction
Intercept	0.40*** (0.227)	0.45*** (0.240)	0.26*** (0.346)	0.21*** (0.392)
Pictorial warning	0.54*** (0.107)	0.44*** (0.189)	1.68** (0.169)	2.65** (0.316)
Textual warning	0.58*** (0.108)	0.45*** (0.195)	1.67** (0.172)	1.79 (0.349)
Pro-cannabis comment	0.92 (0.109)	0.73 (0.172)	1.00 (0.177)	1.25 (0.333)
Anti-cannabis comment	0.74*** (0.111)	0.63*** (0.178)	1.50* (0.169)	2.12* (0.316)
Pictorial warning X Pro-cannabis comment		1.57 (0.261)		0.60 (0.437)
Textual warning X Pro-cannabis comment		1.38 (0.263)		0.97 (0.458)
Pictorial warning X Anti-cannabis comment		1.20 (0.266)		0.46 (0.417)
Textual warning X Anti-cannabis comment		1.44 (0.271)		0.87 (0.438)

Note: The values shown are Odds Ratios (OR), with standard errors in parentheses. The logistic regression analysis controlled for 7 covariates such as race, gender, income, sexual orientation, Hispanic, political ideology, and social environment ( $N=2229$ ). \* $p < .05$ , \*\* $p < .01$ , \*\*\* $p < .001$ .

anti-cannabis vs. no comments control), and their interaction effects on AI-coded (a) stance toward cannabis (pro-cannabis vs. others, anti-cannabis vs. others) and (b) presence of sensory appeals. All tests were two-tailed.

The qualitative component used unsupervised Structural Topic Modeling and manual thematic coding on the same dataset to identify emerging themes and provide interpretive depth (see Figure 1.). Descriptive statistics were provided to address RQ2.

## Results

### *Effects of CWLs and prior eWOM on expressed stance towards cannabis*

Results were summarized in Table 3. Regarding H1, logistic regression analysis indicated that participants who viewed pictorial or textual warning labels had lower odds of expressing a pro-cannabis stance compared to those with no warning labels ( $OR_{\text{pictorial vs. no warning}} = 0.54$ , 95% CI [0.439, 0.668],  $p < .001$ ;  $OR_{\text{textual vs. no warning}} = 0.58$ , 95% CI [0.468, 0.714],  $p < .001$ ) and higher odds of expressing an anti-cannabis stance ( $OR_{\text{pictorial vs. no warning}} = 1.68$ , 95% CI [1.206, 2.337],  $p < .01$ ;  $OR_{\text{textual vs. no warning}} = 1.67$ , 95% CI [1.192, 2.342],  $p < .01$ ). H1a-b were supported.

Regarding H2, pro-cannabis comments had no significant effect on participants' pro-cannabis stance ( $OR = 0.92$ , 95% CI [0.744, 1.138],  $p = .443$ ) whereas exposure to anti-cannabis comments increased the odds of expressing anti-cannabis sentiments ( $OR = 1.50$ , 95% CI [1.192, 2.342],  $p < .05$ ). H2a was not supported but H2b was supported. To address RQ1, we conducted interaction analyses but found no significant results.

### *Thematic analysis of eWOM beyond stance detection*

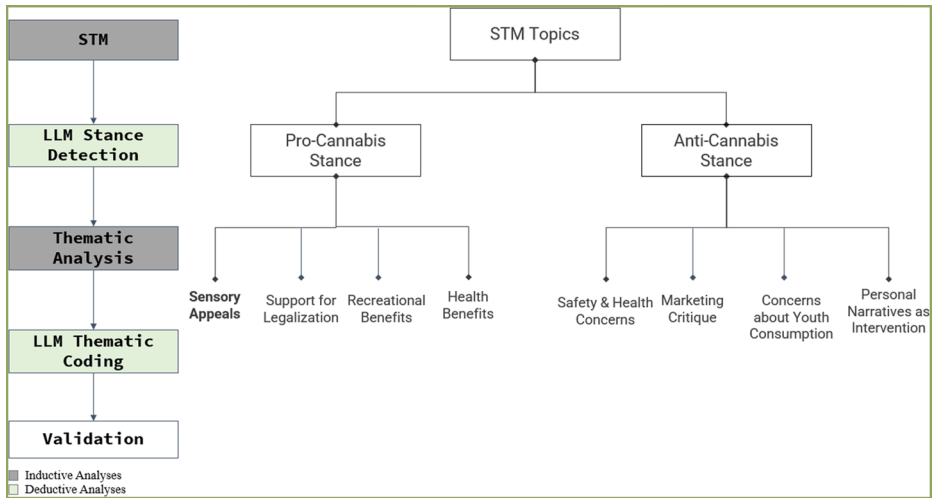
To unpack thematic nuances beyond binary stances, we manually annotated a subsample of 400 comments, equally split between pro- and anti-cannabis stances as

**Table 4.** Thematic analysis for pro- and anti-cannabis comments.

Stance	Theme	Example
Pro-cannabis	Sensory Appeals	how interesting an innovative i like that it is a candy that will mask the flavor of the marijua definitely a product that i would like to try looks good would love to try oh id love to try this because of the popcorn flavor. omg i love snickerdoodles we need more details of the product lol it looks like candy so i lowkey want to try i love chocolate so i might check it out!!!
	Health Benefits of Cannabis	marijua, helps with depression adhd, and many different beneficial factors. if mary jane aka marijua was introduced and cigarettes weren't or any tobacco products there would be alot more healthier births, less drama or violence. plus stores would be helped out more with sales do to the thc factor in marijua. i believe that cigarettes should be banned and to leave mary jane blessing her people. nothing but pros with this topic, marijua helps with a lot of health problems and mental issues. i've never heard anyone i mean nobody having negative effects where they needed medical attention. for the ones that talk bad on it they never tried it and there information is just from other uneducated people that have never tried or did research. if you have the time look up deaths from marijua and that will give your answer on how safe it is to consume or smoke. stay woke and with your mind in the horizons, marijua never hurt people but instead did good inlike cigarettes and alcohol that kills your liver teeth and heart. "i think canbis is medicine. stop calling it marijua i just think you guys seem bias to new information about canbis benefits can't make canbis sound bad to me" i love me some good ol' mary jane. good for anxiety, manic depression, and in my case, schizophrenia. it really really helps my paranoia, but i know that everyone is different. I love the idea. the me, the flavor. all of it looks great. it just looked a little bit boring. I was confused, I thought I was looking at thc infused hand soap.
	Recreational Benefits of Cannabis	I love weed high sex is the best sex high sex is the best sex weed is so good I'd love to have some of this rn having marijua edibles rn would make me feel on top of the world weed and wine would definitely go hand in hand I love the loud smoking keeps me going I like smoking cause it gives me knowledge
	Support for Legalization/Regulation	marijua like alcohol or caffeine can be abused. legalizing marijua is not going to increase abuse however, it will help people that are disproportionately effected by policing to be crimilized. marijua is as addictive as caffeine and alcohol. the effects one person might have from consuming marijua is different to another person. caffeine can cause hypertension and anxiety. alcohol dependence can cause cirosis of the liver. i wonder why only bad comments are being shown. also, the facebook layout makes me think about the demographic they are advertising to. i wish it was legal here if only it was legal in ky warning lable is false! glad to see this is becoming regulated !. glad to see regulation !!! whoooo whoop great to see this on this market regulated ! whoooo hoo
Anti-cannabis	Safety and Health Concern	smoking weed is bad for your brain. looks yummy but is it safe weed will mess you up this is not good nor is it healthy for people! stop this madness! this is harming people!! this is horrible Marijuana is bad for people; it may cause health issues! I do not like anything about marijuana; I hate edibles.
	Marketing Critique	I don't like the marketing and possibly targeting the wrong crowd with the 'appealing' look. Shameful marketing, and sad to see no one else in this comment section sees or understands this. "i'm not a fan of the marketing and possibly targeting the wrong crowd"
	Concerns about Youth Consumption	Marijuana should be targeted towards medical users like me, instead of this kiddish style marketing another "groundbreaking" marijua product brainwashing kids with those bright colors trendy brands trying to make weed cool! i would not use this at all. its stupid its a bad product. and stupid to show a kid. its not a product for kids
	Personal Narratives as Intervention	I have seen the effects happen to people in my own life, and it's not good. I started smoking really young (7th grade) and have an awful memory; sometimes I wonder if my early cannabis usage is the reason for that. My little brother suffers from schizophrenia that was brought on by his first time smoking weed.

**Table 5.** Descriptive statistics about specific themes by stance.

Stance	Theme	Estimate count (%)
Pro-cannabis	Favorable opinion toward the cannabis product shown in the marijuana marketing post	140 (70%)
	Health benefits of cannabis in general	5 (2.5%)
	Recreational benefits of cannabis in general	11 (5.5%)
	Support for legalizing/regulating marijuana	7 (3.5%)
Anti-cannabis	Safety concern and health risk	40 (20%)
	Marketing strategy critique	4 (2%)
	Concerns about Youth/Underage consumption	17 (8.5%)
	Use personal narratives for intervention	10 (5%)

**Figure 1.** AI-facilitated integrated analysis flowchart.

classified by GPT-4. This analysis revealed diverse perspectives on cannabis and provided a more nuanced exploration of both perceived benefits and concerns regarding its use among AYAs. Key themes are detailed below, with estimated proportions and example posts provided in [Tables 4](#) and [5](#).

### ***Pro-cannabis themes***

#### ***Sensory appeals***

A prevalent theme was the mention of sensory attributes of cannabis products, such as portrayals of edible products as candies or highlighting palatability cues like popcorn and snickerdoodle flavors.

#### ***Health benefits***

Participants frequently cited perceived health benefits, asserting cannabis's superiority over substances like tobacco. Comments ranged from general endorsements for depression and ADHD to personal testimonials about managing anxiety and schizophrenia. One participant argued, I think cannabis is medicine...can't make cannabis sound bad to me.

### ***Recreational benefits***

Participants talked about their hedonic experiences with cannabis use, noting its enhancement of intimacy and general well-being.

### ***Support for legalization***

Many advocated for legalization, comparing cannabis to legal substances like alcohol and expressing optimism about reducing cannabis-related criminalization.

### ***Anti-cannabis themes***

#### ***Safety and health concerns***

Anti-cannabis comments emphasized safety and health implications. Participants questioned product safety and expressed fears about potential health issues: “Marijuana is bad for people; it may cause health issues!”

#### ***Marketing critique***

Participants criticized marketing strategies targeting inappropriate audiences, expressing concerns about “appealing” product presentations and describing some marketing as “shameful”.

#### ***Concerns about youth consumption***

Comments reflected concerns about cannabis influence on young people, criticizing youth-oriented marketing with “bright colors” and “trendy brands trying to make weed cool”. Participants argued that products should target medical users rather than using “kiddish style marketing”.

#### ***Personal narratives as intervention***

Some comments included personal accounts of adverse effects, such as memory problems from early use and family members developing mental health issues after cannabis consumption, including one participant whose “little brother suffers from schizophrenia that was brought on by his first time smoking weed”.

### ***Effects on the theme of sensory appeals***

To answer RQ3, logistic regression analysis revealed that participants who viewed pictorial (OR = 0.43,  $p < .001$ ) or textual (OR = 0.53,  $p < .001$ ) warning labels had lower odds of discussing sensory appeals of cannabis products compared to those exposed to no warning labels. Regarding the effects of prior eWOM, participants exposed to anti-cannabis comments had 47% lower odds of describing sensory appeals of cannabis products (OR = 0.53,  $p < .001$ ), while those exposed to pro-cannabis comments had 25% lower odds of mentioning sensory features (OR = 0.75,  $p = .03$ ) (see Table 6).

**Table 6.** Effects of CWLs and prior eWOM on mention of sensory appeals.

	Main effect	Interaction
Intercept	0.33*** (0.288)	0.35*** (0.295)
Pictorial warning	0.43*** (0.141)	0.36*** (0.230)
Textual warning	0.53*** (0.136)	0.45*** (0.226)
Pro-cannabis comment	0.75* (0.132)	0.63* (0.188)
Anti-cannabis comment	0.53*** (0.144)	0.49*** (0.203)
Pictorial warning X Pro-cannabis comment		1.54 (0.326)
Textual warning X Pro-cannabis comment		1.32 (0.319)
Pictorial warning X Anti-cannabis comment		1.04 (0.363)
Textual warning X Anti-cannabis comment		1.24 (0.347)

Note: The values shown are OR, with standard errors in parentheses. For efficient interpretation, it is helpful to transform the OR to a percentage. The logistic regression analysis controlled for 7 covariates such as race, gender, income, sexual orientation, Hispanic, political ideology, and social environment ( $N=2229$ ). \* $p < .05$ , \*\*\* $p < .001$ .

## Discussion

Drawing on the *motivation, opportunity, and ability* theoretical (MOA) framework (Babić Rosario, de Valck, and Sotgiu 2020), this study extends the existing scholarship on health advertising and eWOM by providing the first set of experimental evidence regarding how CWLs interact with valence-varying prior eWOM to shape subsequent eWOM produced by AYAs in the context of online cannabis advertising. Our findings uniquely illuminate how CWLs as a cost-effective communication-based intervention can be leveraged to effectively counter pro-cannabis sensory marketing tactics to shape the valence of youth-generated eWOM in a direction benefiting public health. Furthermore, employing an AI-facilitated integrated approach, we documented the causal impacts of exposure to prior eWOM on subsequent eWOM creation, while noting the differentiable effects of anti- versus pro-cannabis comments. These findings speak to the call for more empirical study on the dynamic relationships between eWOM exposure, creation, and evaluation (Babić Rosario, de Valck, and Sotgiu 2020), while contributing novel insights into the interplay between CWLs, sensory marketing in health advertising, and online social influences.

Although health warning labels are increasingly applied to a wider range of products to communicate health risks and hazards, few experimental studies have shown whether their implementation is sufficient to counter pro-product sensory appeals and influence subsequent eWOM. Extending previous research on warning labels and health advertising where the focus is on intrapersonal persuasive outcomes such as consumer risk perceptions and attitudes (Noar et al. 2016), we found that both textual and pictorial CWLs were effective in curbing pro-cannabis eWOM, including those specifically referring to attractive sensory attributes of edible products, while promoting anti-cannabis eWOM. To the best of our knowledge, these findings represent the first set of experimental evidence documenting CWLs' causal impacts on eWOM that can benefit public health by countering youth-targeted sensory marketing and

curtailing the social diffusion of pro-cannabis information and normative influences. From the perspective of the MOA framework (Babić Rosario, de Valck, and Sotgiu 2020), whereas sensory appeals emphasizing hedonic and palatability cues within cannabis commercials might activate the appetitive motivational system (Samson and Buijzen 2020), our findings are consistent with the expectation that CWLs can activate aversive motivations while providing scientifically validated information on cannabis-related health risks to improve the knowledge base for eWOM creation. Prior advertising research highlights sensory appeals as key emotional triggers enhancing engagement and eWOM (Krishna 2012; Petit, Velasco, and Spence 2019). Our results extend this literature by showing that regulatory interventions, such as CWLs, can effectively disrupt these emotional pathways by diminishing the attractiveness of sensory appeals. These findings provide valuable insights for regulatory entities, emphasizing that strategically deployed warning labels can effectively counter emotionally appealing advertising tactics, which is critical in the context of youth-targeted marketing of risky health products (Carpenter et al. 2005; Leos-Toro et al. 2019). While our current study focused on the behavioral outcome of eWOM creation, further research is encouraged to directly measure and test the mediating mechanisms of positive and negative emotions as well as knowledge gain.

Another key contribution of our research pertains to documenting the nuanced dynamics between eWOM exposure and creation. Drawing on interpersonal communication and advertising literature (Babić Rosario, de Valck, and Sotgiu 2020; Berger 2014; Cappella, Yang, and Lee 2015), we demonstrated that prior anti-cannabis eWOM significantly amplified negative expressions against cannabis products while reducing pro-cannabis expressions. This aligns with existing social contagion research emphasizing the interpersonal dynamics underpinning consumer engagement with advertising content (Goldenberg, Libai, and Muller 2001). However, pro-cannabis comments did not significantly increase positive eWOM and regarding theme-specific effects, exposure to prior pro-cannabis eWOM even reduced the mention of sensory appeals in subsequent eWOM. These findings are consistent with a previous study where exposure to either negative or positive comments undermined the perceived effectiveness of the health campaign message (Shi, Messaris, and Cappella 2014). Taken together, this pattern shows AYAs' general resistance, or at least suspicion, towards overtly promotional eWOM endorsing potentially harmful products like cannabis (Fransen, Smit, and Verlegh 2015; Knowles and Linn 2004; Wojdyski and Evans 2016). These differentiable impacts of pro- versus anti-product eWOM carry important practical implications: Advertisers need to be cautious of employing overly pro-product eWOM as they may be viewed with skepticism, whereas seemingly authentic negative eWOM may be more persuasive.

Methodologically, our innovative integration of AI-based textual analysis within an embedded mixed-methods experimental design contributes a new analytical approach relevant for scholars exploring the causal effects of health advertising on eWOM. The integration of supervised and unsupervised machine-learning techniques (e.g. STM, GPT-4-based stance and theme classification) provided granular and interpretable insights beyond the mere occurrence or binary sentiments of eWOM. Advertising researchers can employ these computational tools to systematically measure a wide range of specific content features and draw credible causal inferences when the outcome eWOM are generated under a randomized study design.

In this study, we acknowledge several limitations. First, our investigation was restricted to marketing posts promoting edible marijuana products, and future research should aim to broaden the scope to cover various types of cannabis products. Second, this study recorded eWOM in a hypothetical setting, which might not generalize to real-world dynamics of eWOM behaviors. Our study design was motivated by a previous study documenting self-selection biases in even large-scale observational research on scraped comments from social media platforms (Kim et al. 2021). Collecting eWOM with a national sample through an online experiment, even in a hypothetical setting, can produce insights more generalizable to the population. That said, future research should investigate real-time commenting to gain a more accurate understanding of AYAs' authentic eWOM behaviors when randomization of treatment is feasible. Finally, it is important to acknowledge that the intercoder reliability for anti-cannabis comments (Krippendorff's  $\alpha = .67$ ) was lower than ideal, potentially introducing noises into the final results. Given the consistent findings regarding the effects on anti-cannabis eWOM, we believe the key takeaways of our findings remain valid. For future studies, it would be beneficial to employ alternative content annotation strategies such as crowdsourcing to improve measurement accuracy.

## Conclusion

This study provides novel experimental evidence that cannabis warning labels (CWLs) effectively counter pro-cannabis sensory marketing by reducing positive electronic word-of-mouth (eWOM) and promoting negative eWOM among adolescents and young adults. Our findings reveal that while anti-cannabis eWOM amplifies negative sentiment, pro-cannabis eWOM does not increase positive responses, suggesting youth resistance to promotional content. Through an innovative AI-facilitated approach, this research contributes novel methodological insights for health advertising and eWOM research. These findings demonstrate that strategically implemented warning labels serve as cost-effective interventions to disrupt emotionally appealing advertising tactics and mitigate the social diffusion of pro-cannabis messaging among vulnerable youth populations.

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## Data availability statement

The data that support the findings of this study are available in OSF via [https://osf.io/54p2m/?view\\_only=3511a68c59d84ee1a3be61c8ba66c761](https://osf.io/54p2m/?view_only=3511a68c59d84ee1a3be61c8ba66c761).

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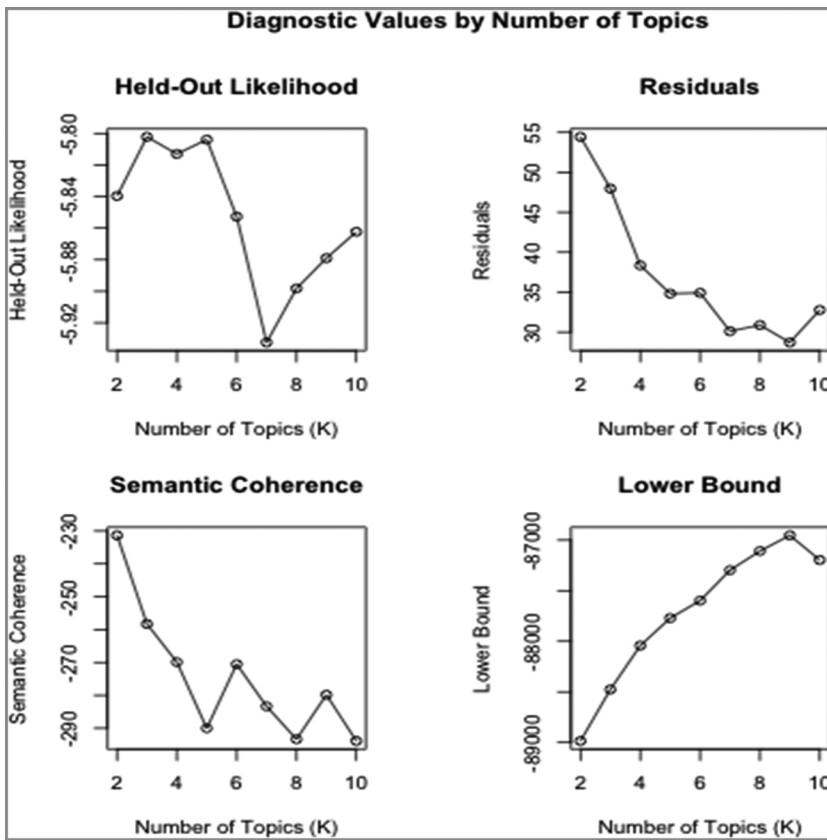
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## Appendix A: Four diagnostic indexes of structural topic models with varying numbers of topics: 2–10 topics



## Appendix B: Experiment stimuli

No warning	Textual CWL		Pictorial CWL		
No Warning		Textual CWL		Pictorial CWL	
No comments					
					
Pro-cannabis comments					
					
Anti-cannabis comments					
