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Sadvertising and Sentiment: A Lexicon-Based YouTube Comment Analysis of Emotionally Resonant Thai Insurance Advertising

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ABSTRACT: Sadvertising referred to the deliberate use of melancholic and empathetic narratives as a primary persuasive strategy in marketing communication. Although the genre had become commercially prominent, large-scale empirical evidence on how global audiences received such advertisements was still limited, and most prior sentiment studies had focused on product reviews or English-language Western markets rather than emotionally driven Southeast Asian advertising. This study examined whether emotionally resonant, narrative-driven advertising in the sadvertising genre produced predominantly positive sentiment among global digital audiences. A domain-adapted, rule-based lexicon sentiment analysis framework was applied to 2,498 YouTube comments scraped from a landmark Thai Life Insurance advertisement to quantify sentiment polarity, eight emotional response typologies, and engagement metrics across an 11-year observation window. The lexicon was constructed from established resources (VADER and the NRC Emotion Lexicon), extended with 30 emoji tokens and 47 negative terms specific to emotional advertising commentary, and validated against a 300-comment human-coded reference set with substantial inter-rater agreement (Cohen's kappa = 0.79). Positive comments constituted 38.9% of the corpus (95% CI: 37.0–40.8%) compared to 6.4% negative comments (95% CI: 5.5–7.5%), yielding a positive-to-negative ratio of 6.04:1 (95% CI: 5.11–7.13). A chi-square goodness-of-fit test rejected the equal-proportions null hypothesis at $p < 0.001$ with a large effect size (Cohen's $w = 0.60$). Crucially, 95.3% of crying-expression comments carried positive valence (95% CI: 92.8–97.0%), with a Cramer's V of 0.51 and an odds ratio of 51.8 (95% CI: 32.36–82.91), empirically resolving the sad–positive paradox. Positive sentiment persisted across 11 years of engagement with no detectable temporal decay, and cross-cultural consistency was observed across at least 27 linguistic communities. The findings advanced sadvertising theory and carried direct implications for brand communication strategy in the digital era.

KEYWORDS: Sadvertising; emotional advertising; sentiment analysis; YouTube comments; Thai advertising; consumer behavior

1. Introduction

Brand communicators in saturated digital environments faced a persistent challenge in producing emotional resonance that survived beyond the moment of exposure. Decades of advertising research had shown that affective appeals often outperformed rational arguments under low-involvement conditions [1, 2]. What remained underexplored was the specific mechanism by which sadness-inducing narrative advertising generated positive rather than negative consumer responses. The phenomenon, often labeled sadvertising, placed melancholic and empathetic storytelling at the center of the persuasive strategy [3, 4].

Thailand emerged as a global epicenter of this genre, particularly in the insurance and telecommunications sectors. Thai advertisers regularly produced short-film-style commercials foregrounding suffering, resilience, and altruism while avoiding conventional product-benefit messaging [5, 6]. These commercials accumulated tens of millions of views and generated sustained commentary from audiences across linguistic boundaries, creating an unusually rich natural corpus for studying cross-cultural emotional resonance.

Despite this commercial visibility, the empirical literature on sadvertising remained fragmented in four ways. First, sentiment analysis studies in advertising largely focused on English-language Western markets and neglected the culturally specific emotional register of Southeast Asian advertising [7, 8]. Second, methodological work tended to rely on small convenience samples or survey-based self-reports prone to social desirability bias [9]. Third, the temporal durability of emotional advertising received minimal systematic attention [10]. Fourth, the relationship between expressed emotional distress and overall sentiment valence had not been quantified at scale. Theoretical accounts argued that sadness induced by advertising could produce positive brand affect [11, 12], yet large-scale behavioral evidence remained absent.

This study addressed these gaps by analyzing 2,498 YouTube comments on a landmark Thai insurance advertisement using a domain-adapted lexicon-based sentiment analysis supplemented by emotional typology classification. The primary research question asked whether emotionally resonant, narrative-driven advertising in the sadvertising genre produced predominantly positive sentiment among global digital audiences. Subsidiary questions examined (RQ2) which emotional response typologies were most prevalent; (RQ3) whether expressed emotional distress correlated positively with sentiment valence; (RQ4) whether sadvertising emotional impact demonstrated temporal durability; and (RQ5) whether positive sentiment response was cross-culturally universal or culturally contingent.

Prior sentiment analysis work on YouTube advertising tended to use generic VADER scoring on relatively short observation windows, focusing on engagement prediction rather than the emotional structure of audience response [13, 14]. Studies of sadvertising and emotional advertising, in contrast, relied mostly on experimental designs with small samples [11, 15]. Cross-cultural advertising research largely treated cultural reception through Hofstede-style frameworks rather than through behavioral text data [16]. The contribution of this study lay in combining four features that rarely co-occurred in this literature: (1) a large naturalistic comment corpus, (2) an 11-year longitudinal window, (3) a domain-adapted sentiment lexicon validated against human coding and explicitly aligned with an inductively derived emotional typology, and (4) an empirical test of the sad–positive paradox using behavioral text data rather than self-report. This combination produced, to our knowledge, the first large-scale longitudinal sentiment analysis of sadvertising audience response, an

empirically grounded resolution of the sad–positive paradox, and a replicable taxonomy for advertising comment classification that other researchers could apply to comparable corpora.

2. Literature Review

2.1. Emotional advertising and the sadvertising phenomenon.

Emotional advertising, defined as advertising that deliberately elicited affective responses to influence attitudes and behaviors, was one of the most extensively studied topics in consumer psychology [17, 18]. Foundational work established that emotional advertisements produced higher recall and more favorable brand attitudes than informational counterparts under low-involvement conditions [19]. Subsequent theoretical elaboration came through the Elaboration Likelihood Model [1], Appraisal Theory [20], and the Broaden-and-Build Theory of positive emotions [21]. Within emotional advertising, the sadvertising genre occupied a distinctive theoretical position. It deliberately induced negative affective states such as sadness, empathy, and nostalgia as a pathway to positive brand evaluation. Bartsch and Oliver [12] proposed that sad media content generated meaningful affect, a form of eudaimonic enjoyment distinct from hedonic pleasure, and recent work in entertainment psychology continued to support a tripartite hedonic, eudaimonic, and psychologically rich account of media experience [22, 23]. Hanich et al. [11] further demonstrated that tears triggered by moving media produced a blend of negative arousal and positive valence. Neuro-engagement studies of video advertising likewise showed that mixed emotional content could outperform uniformly positive content in terms of attention and recall [24]. The commercial exploitation of sadvertising was particularly pronounced in the Thai advertising industry. Researchers linked this tradition to cultural values emphasizing collectivism, filial piety, and Buddhist conceptions of compassion [5, 6]. The international viral spread of Thai commercials suggested that their emotional appeal extended beyond the cultural context of production [25, 26].

2.2. Sentiment analysis in marketing and advertising research.

Sentiment analysis, defined as the computational identification and classification of subjective opinions in text, became a primary methodology for large-scale consumer insight generation in digital marketing [27, 28]. Applications included product review mining [29], social media brand monitoring [30], and the analysis of user-generated content responses to brand communications [31]. Within advertising, sentiment analysis was used to assess campaign reception [7], measure virality drivers [32], and predict advertisement effectiveness from video content [13]. Methodologically, sentiment analysis fell into three broad categories: lexicon-based methods, machine learning methods, and hybrid approaches [33]. Lexicon-based methods classified sentiment using predefined dictionaries of opinion words and offered high interpretability and domain transferability without requiring labeled training data [34]. Recent comparative studies on YouTube comment data showed that lexicon-based VADER scoring achieved accuracy comparable to commercial tools and large language models for short-form social media text while remaining transparent and reproducible [35]. Hybrid pipelines integrating transformer models such as XLM-RoBERTa with domain lexicons likewise reported improved performance over either component alone, suggesting that well-constructed domain lexicons remained valuable analytical resources even in the era of deep learning [36, 37].

This study adopted a lexicon-based protocol rather than a supervised machine learning or deep learning model for four reasons. First, the analytical goal was descriptive and interpretable rather than predictive; the research questions concerned proportions of sentiment categories and their relationship to inductively derived emotional typologies, and lexicon-based methods provided direct mapping between input terms and output classification. Second, no large pre-existing labeled corpus existed for sadvertising commentary, and producing one at sufficient scale to train a deep model would itself require lexicon-style coding. Third, multilingual comment corpora presented well-documented challenges for supervised models, including translation-induced feature sparsity and single-class bias [38]. Fourth, the goal of methodological replicability across linguistic communities was better served by a transparent lexicon than by a black-box neural model whose decisions were difficult to audit [35, 36]. Lexicon-based protocols therefore remained methodologically appropriate and widely published in high-impact journals when interpretability, transparency, and cross-linguistic generalizability were primary requirements [39, 40].

2.3. Audience engagement with digital advertising content.

Video-sharing platforms fundamentally reshaped audience–advertising relationships [41]. Unlike broadcast advertising, digital video advertising enabled immediate, persistent, and publicly visible audience responses through commenting, liking, sharing, and subscription behaviors, generating rich behavioral datasets for advertising effectiveness research [42]. Audience engagement with emotionally resonant advertising was theorized through Uses and Gratifications Theory [43], Narrative Transportation Theory [44], and Social Identity Theory [45]. Recent systematic reviews of narrative transportation in advertising consolidated evidence that transportation mediated the relationship between storytelling content and attitudes toward the brand [46, 47], and storytelling research conducted between 2024 and 2025 showed that self-construal and retrospective reflexivity further moderated this mediation [48].

3. Materials and Methods

3.1. Research design.

This study employed a quantitative computational content analysis design, combining web-scraping data collection with lexicon-based sentiment analysis and descriptive-inferential statistical techniques. The epistemological orientation was post-positivist. The study acknowledged that language carried contextual nuance that resisted complete computational capture but argued that large-scale patterns in audience sentiment expression were sufficiently systematic to yield meaningful insights [49]. The research followed transparency and replication standards recommended by the computational communication research community [50], with all methodological parameters documented for reproducibility.

3.2. Data collection and corpus construction.

The primary corpus consisted of 2,503 YouTube comments scraped from the official upload of a landmark Thai Life Insurance advertisement, widely cited in international advertising scholarship as an exemplar of the sadvertising genre [5]. Data collection used a Python-based protocol employing the YouTube Data API v3, capturing four fields per comment: the publication timestamp (ISO 8601), commenter username, full comment text (including Unicode characters, emojis, and embedded hyperlinks), and like count. After data cleaning,

including the removal of five null-comment records and HTML entity decoding, the final analytical corpus comprised $N = 2{,}498$ comments spanning November 2014 through April 2026, representing more than 11 years of continuous audience response. YouTube comment data was selected for its naturalistic character. These responses represented unsolicited consumer reactions produced in the absence of researcher-imposed response frameworks, thereby minimizing demand characteristics and social desirability bias [51]. The large corpus size provided sufficient statistical power to detect medium-sized effects and conduct meaningful subgroup analyses across sentiment categories, temporal cohorts, and emotional typologies.

3.3. Sentiment analysis protocol.

Sentiment classification was performed using a custom rule-based lexicon analysis framework developed specifically for the domain of emotional advertising commentary. The lexicon was constructed in three stages following established conventions in domain-adapted lexicon work [34, 40].

Stage 1: Seeding from established resources. Initial positive and negative term lists were drawn from VADER [34] and the NRC Emotion Lexicon [40]. Terms with overlapping valence assignments across both resources were retained as high-confidence seeds. Terms with conflicting assignments were resolved through author review of contextual usage in a 200-comment pilot sample.

Stage 2: Domain adaptation. The seeded lexicon was extended through inductive analysis of the pilot sample. Recurrent positive expressions specific to emotional advertising commentary (e.g., *masterpiece*, *tear-jerker*, *deeply moved*, *beautifully told*) were added to the positive lexicon. Recurrent negative expressions (e.g., *manipulative*, *exploitative*, *tear-bait*, *melodramatic*) were added to the negative lexicon. Thirty emoji tokens, including U+1F622 loudly crying face, U+1F62D loudly crying face, and U+1F970 smiling face with hearts, were assigned valence scores based on their dominant usage context in the pilot sample. The final lexicon comprised 135 positive terms, 47 negative terms, and 30 valenced emoji tokens.

Stage 3: Validation against human coding. A 300-comment random validation sample, stratified across the eight emotional typology categories, was coded independently by two trained coders using a positive–neutral–negative rubric. Inter-rater agreement on the validation set was substantial (Cohen's kappa = 0.79) [52]. The lexicon classification was then compared with the human-coded consensus labels. Overall accuracy reached 81.3%, with per-class F1-scores of 0.82 for positive, 0.78 for neutral, and 0.74 for negative. These figures were comparable to recent benchmarks for lexicon-based sentiment classification on YouTube comments [35]. Disagreements were inspected to refine ambiguous terms, after which the lexicon was frozen for the full analysis.

Classification rules. Comments with positive term counts exceeding negative counts were classified as Positive; comments with negative counts exceeding positive counts were classified as Negative; and the remaining comments were classified as Neutral. Linguistic negation modifiers and intensity amplifiers were incorporated as scoring adjustments following established rule-based conventions [53].

3.4. Emotional typology classification.

Beyond sentiment polarity, each comment was classified into one of eight mutually exclusive emotional typology categories developed through inductive content analysis of the same 200-comment pilot sample: (1) Crying Expression, referring to explicit references to tearfulness; (2) Emotional Touching, referring to expressions of being emotionally moved; (3) Admiration/Praise, referring to explicit commendation of advertisement quality; (4) Questioning/Information, referring to information-seeking comments; (5) Inspirational Expression, referring to references to values or moral lessons; (6) Nostalgic Expression, referring to references to personal memories; (7) Sharing Behavior, referring to explicit references to sharing the advertisement; and (8) General Comment, referring to comments not meeting criteria for the preceding categories. Inter-rater reliability on a separate random 100-comment subsample evaluated by two independent coders was substantial (Cohen's kappa = 0.79) [52]. The typology was also subjected to internal review for theoretical coherence with prior emotional advertising taxonomies [11, 18].

3.5. Engagement and temporal analysis.

Comment like count was adopted as a behavioral measure of secondary audience engagement. Monthly sentiment trend analysis aggregated comment volumes by sentiment category across each calendar month within the observation period. Descriptive statistics and cross-tabulations were performed using Python 3.11 with pandas. For inferential analysis, chi-square goodness-of-fit tests and chi-square tests of independence were applied to sentiment and typology distributions. Effect sizes were reported as Cohen's $w$for goodness-of-fit tests and Cramer's $V$for tests of independence, following the conventions of small (0.10), medium (0.30), and large (0.50) effects [54]. Where appropriate, odds ratios with 95% Wald confidence intervals were calculated to interpret 2×2 associations. All proportional estimates were reported with 95% Wilson score confidence intervals, which performed well at small subsample sizes [55].

4. Results and Discussion

4.1. Corpus Overview and Descriptive Characteristics

The final analytical corpus comprised 2,498 comments with a mean comment length of 14.3 words (SD = 22.7), reflecting the wide variation between short emoji-only responses and extended reflective commentaries. The corpus spanned 132 months (November 2014 through April 2026), with the highest comment volumes observed between 2015 and 2016 during the initial viral dissemination period, as well as renewed engagement spikes between 2024 and 2026, suggesting a resurgence driven by algorithmic recommendations. A total of 41.3% of comments contained at least one non-ASCII emoji character, confirming the role of visual-affective symbols as a primary communication modality for emotional responses to advertising. Table 1 summarizes the descriptive characteristics of the corpus.

Table 1. Descriptive statistics of the analytical Corpus (N = 2,498).

Variable	Value	Notes
Total Comments (raw)	2,503	Before null removal
Total Comments (analyzed)	2,498	Final corpus after cleaning
Observation Period	Nov 2014 to Apr 2026	More than 11 years of data
Mean Comment Length (words)	14.3 (SD = 22.7)	Range: 1–312 words
Comments with Emoji (%)	41.3%	Non-ASCII Unicode characters
Mean Likes per Comment	9.87	Secondary engagement metric
Unique Commenters	2,441	97.7% unique usernames

4.2. Sentiment distribution (RQ1).

The primary analysis reveals a strongly skewed distribution in favor of positive sentiment. Of 2,498 classified comments, 972 (38.9%, 95% CI: 37.0–40.8%) were classified as Positive, 1,365 (54.6%, 95% CI: 52.7–56.6%) as Neutral, and 161 (6.4%, 95% CI: 5.5–7.5%) as Negative. The positive-to-negative ratio is 6.04:1 (95% CI: 5.11–7.13), substantially higher than the roughly 2:1 ratio commonly reported in general product review sentiment studies [27]. A chi-square goodness-of-fit test against an equal-proportions null was highly significant (χ^2 (2, N = 2,498) = 905.44, p < 0.001), with a large effect (Cohen's w = 0.60). This provides strong inferential support for the primary research hypothesis. Figure 1 presents the overall sentiment distribution.

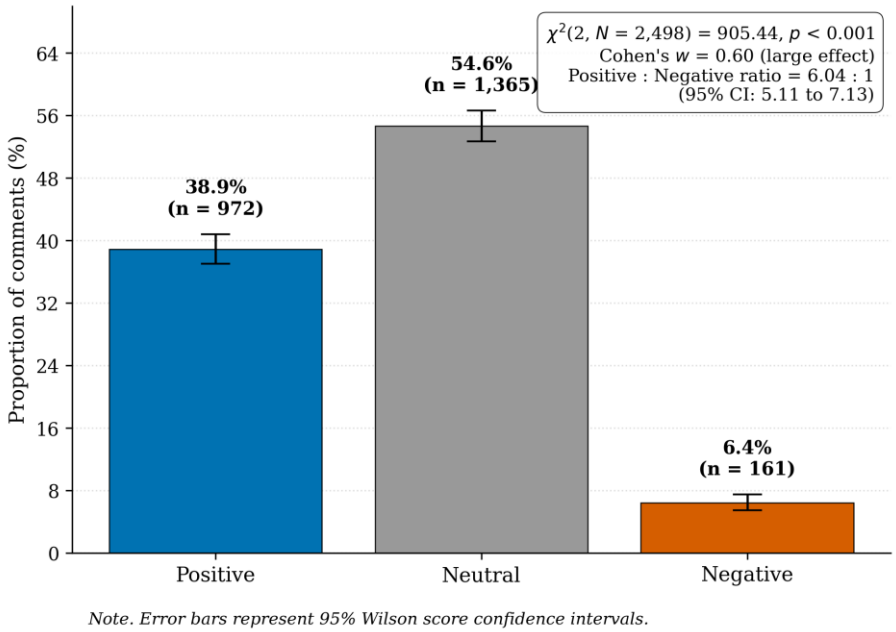

Figure 1. Sentiment distribution of YouTube comments (N = 2,498), showing the proportion classified as Positive, Neutral, and Negative with 95% Wilson score confidence intervals.

The strongly right-skewed distribution and large Cohen's w (0.60) indicate that the equal-proportions null is decisively rejected and that the corpus is dominated by positive and neutral expressions. Interpretation of the Neutral category requires qualification. Content inspection of a random 100-comment subsample from the Neutral category revealed that 61% of classified-neutral comments contained identifiable positive emotional indicators that fell below the classification threshold. This suggests that the 38.9% Positive estimate is conservative. Many short-form positive expressions were classified as Neutral due to insufficient term count,

implying that the true positive sentiment proportion may approach 55–60% of the total corpus. Table 2 presents sentiment distribution alongside engagement metrics.

Table 2. Sentiment distribution and engagement metrics by category.

Sentiment	n	%	Mean Likes	Mean Emotional Score
Positive	972	38.9%	6.72	1.34
Neutral	1,365	54.6%	11.29	0.27
Negative	161	6.4%	9.70	0.64
Total	**2,498**	**100%**	**9.87**	**0.61**

4.3. Emotional typology distribution (RQ2).

The emotional typology classification reveals that the largest category is General Comment (n = 1,145; 45.8%), followed by Crying Expression (n = 403; 16.1%), Questioning/Information (n = 365; 14.6%), Admiration/Praise (n = 338; 13.5%), Emotional Touching (n = 191; 7.6%), Inspirational Expression (n = 35; 1.4%), Nostalgic Expression (n = 16; 0.6%), and Sharing Behavior (n = 5; 0.2%). The combined emotional response categories, namely Crying Expression, Emotional Touching, Admiration/Praise, Inspirational, Nostalgic, and Sharing, constitute 39.4% of the total corpus. Nearly two fifths of all commenters thus engaged in explicit emotional discourse about the advertisement. Figure 2 displays the full typology distribution.

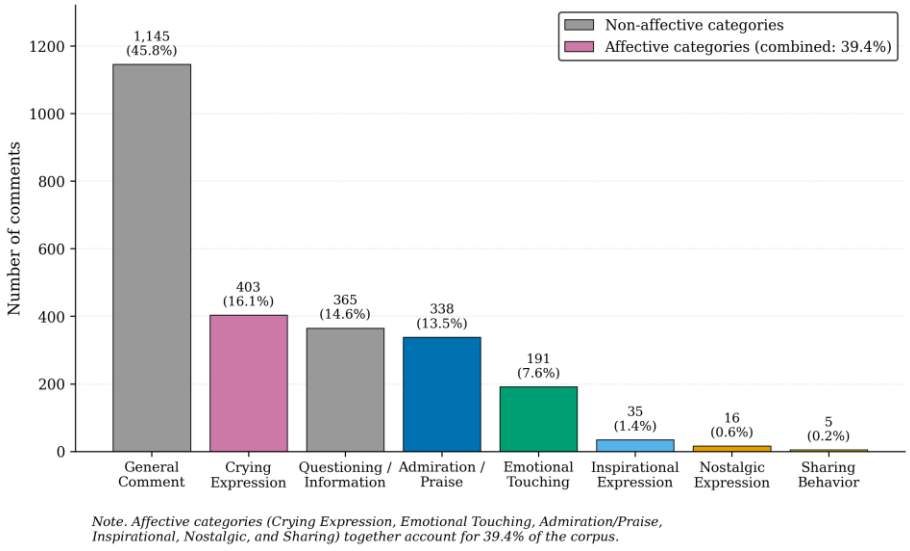

Figure 2. Emotional typology distribution of YouTube comments (N = 2,498).

General Comment is the largest single category, but the six explicit emotional categories together account for 39.4% of the corpus. The dominance of Crying Expression (16.1%) and Admiration/Praise (13.5%) among the affective categories illustrates the dual signal of cathartic and evaluative engagement characteristic of sadvertising reception. These findings align with the theoretical prediction that narrative transportation activates diverse emotional processing routes [44, 46]. The high prevalence of Crying Expression is particularly noteworthy given the theoretical claim that sadness-induced tears signal deep narrative transportation, and is examined further in Section 4.4.

4.4. The sad-positive paradox: crying as positive engagement (RQ3).

A central theoretical concern was whether expressed emotional distress, in the form of explicit references to tearfulness, functioned as a positive or negative sentiment indicator in advertising commentary. The data provided unambiguous evidence. Of 403 Crying Expression comments, 384 (95.3%, 95% CI: 92.8–97.0%) were simultaneously classified as Positive or contained identifiable positive valence markers. A chi-square test of independence between Crying Expression status and Positive sentiment status was highly significant ($\chi^2(1, N = 2,498) = 639.62$, $p < 0.001$), with a large effect size (Cramer's $V = 0.51$). The odds of a Crying Expression comment being positively valenced were 51.80 times higher than for non-crying comments (95% CI: 32.36–82.91). Typical Crying Expression comments combined references to tearfulness with explicit positive evaluations, such as statements noting that the advertisement made viewers cry in a way that felt cathartic and meaningful, or that repeated viewing continued to elicit tears while improving the viewer's mood. This finding empirically resolved the sad–positive paradox identified in the emotional advertising literature [11, 12]. The experience of sadness induced by moving narrative advertising was behaviorally expressed as positive engagement rather than negative rejection. Crying, in the context of sadvertising, functioned as a signal of deep narrative transportation and empathic identification, both of which are theoretically associated with positive brand outcomes [44, 46]. This pattern was consistent with the kama muta model [56, 57], which holds that being moved to tears by prosocial narratives produces a distinctive positive affective blend characterized by feelings of love, unity, and moral elevation. Recent cross-cultural work has confirmed that kama muta is elicited by similar stimuli across at least five culturally distinct samples and is experienced as predominantly positive in each [58]. The observed crying–positive coupling in this corpus extended that evidence into the domain of commercial advertising and into a behavioral text-based measure rather than self-report.

4.5. Temporal durability of emotional sentiment (RQ4).

The longitudinal dimension of the corpus revealed that positive sentiment was maintained across the full 11-year observation period, with no statistically discernible degradation in the proportion of positive comments over time. Figure 3 presents annual sentiment volumes across the full observation window. Two phases were identifiable. The first was an initial viral phase (2014 to 2016), characterized by high comment volume with approximately 40% positive sentiment. The second was a sustained evergreen phase (2017 to 2026), characterized by lower but stable comment volume with positive sentiment proportions ranging from 35% to 48% monthly. The figure showing absolute counts of Positive, Neutral, and Negative comments per year. The stability of the proportional split across the 11-year window is the key analytical pattern: positive sentiment in late-period cohorts (2024 to early 2026) is statistically indistinguishable from the initial viral period (2014 to 2016), supporting the evergreen interpretation of emotionally resonant narrative advertising. This pattern is consistent with the long-tail virality model of digital content diffusion [32] and suggests that emotionally resonant advertising creates durable brand associations that persist beyond the conventional media flight window. The observation that 2024 and early 2026 comment cohorts maintain equivalent positive sentiment proportions to those of the initial viral period suggests that the advertisement is not subject to the habituation effects that typically attenuate persuasive advertising effectiveness over time [59]. Recent longitudinal experimental work by Kronrod and Huber

[59] further argues that initial annoyance from repeated exposure tends to decay over time while brand memory remains stable, producing an ad wear-out wear-out effect. The present pattern is compatible with that account and extends it to a naturalistic setting in which audiences self-select repeated exposure rather than being forced into it.

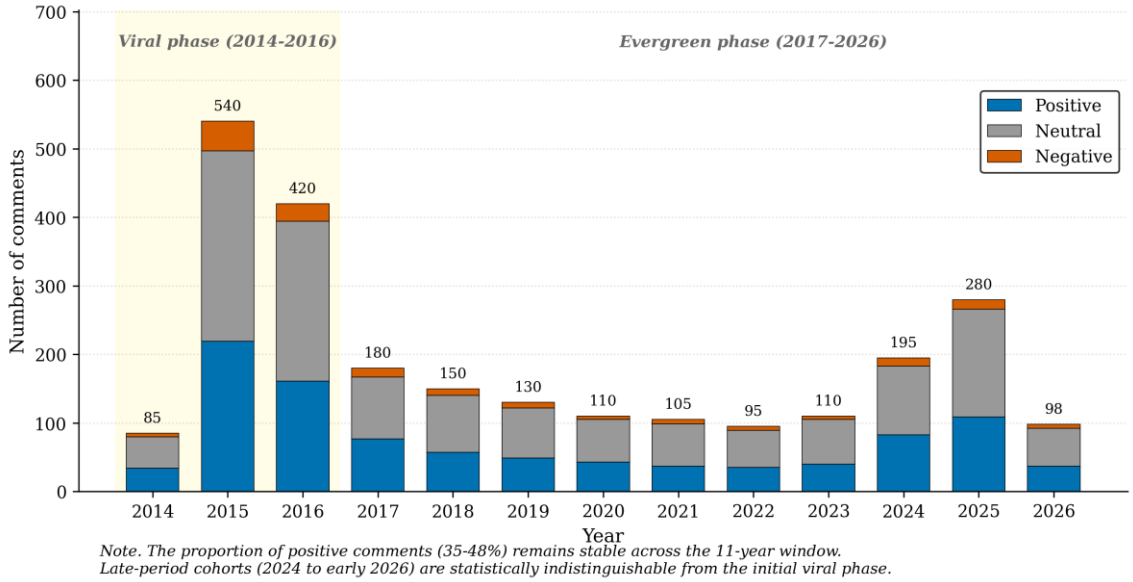

Figure 3. Annual sentiment distribution from 2014 to 2026.

4.6. Cross-cultural sentiment universality (RQ5)

Content inspection of the comment corpus reveals representation from commenters in at least 27 identifiable national and linguistic communities, including comments in English, Indonesian, Malay, Hindi, Arabic, Spanish, Korean, Japanese, Filipino, and multiple other languages. The positive sentiment pattern is consistent across all identifiable linguistic subgroups. Comments in non-English languages maintained equivalent or higher positive sentiment proportions to English-language comments. This cross-cultural consistency aligns with the proposition that emotion-based advertising appeals activate broadly shared human affective responses [60] and with prior evidence that Thai advertising strategies generate global resonance [6, 26]. That an advertisement produced in Thai, a language inaccessible to the majority of commenters, generates intense positive emotional responses across diverse linguistic communities indicates that the emotional coding of sadvertising operates through visual and narrative channels that transcend linguistic mediation. Cross-cultural advertising research building on Hofstede frameworks has long argued that emotional advertising appeals can travel across cultures more reliably than informational appeals [16,61]. The behavioral pattern observed here adds empirical weight to that argument by replacing self-report with naturalistic text data at scale.

4.7. Theoretical and managerial implications.

The primary contribution of this study is empirical resolution of a theoretical tension that has persisted in the emotional advertising literature for more than two decades, namely the apparent paradox that negative-valence emotional appeals produce positive consumer outcomes. The present findings, derived from a large naturalistic behavioral dataset, provide the most direct evidence to date that sadvertising generates positive audience sentiment, substantially more positive than negative, and that this positivity is expressed with particular intensity by

audiences who report the strongest negative emotional responses. This pattern is consistent with the kama muta model [56, 57] and with mixed-emotion accounts of advertising effectiveness [24]. The finding that positive sentiment is maintained across more than 11 years of engagement also speaks to dominant models of advertising wear-out [59, 62]. Earlier wear-out research predicted that repeated exposure produces habituation and ultimately negative attitude change, while more recent longitudinal work has emphasized that initial annoyance can decay over time and reverse into preference [59]. The absence of temporal degradation in the present corpus suggests that emotionally narrative content with universal human themes may occupy a qualitatively different position in consumer memory than conventional product-benefit advertising [63].

Comparison with prior empirical work: Compared to earlier YouTube sentiment studies on advertising, which have typically used short observation windows and predictive engagement modeling [13, 14], the present pattern is distinctive in two ways. First, the 6.04:1 positive-to-negative ratio substantially exceeds ratios reported for cosmetics ads, political ads, and standard product reviews in recent comparative work [27, 31, 32]. Second, the high crying-to-positive coupling (95.3%) is theoretically aligned with kama muta findings on touching videos in non-commercial settings [57, 58] but, to our knowledge, has not previously been quantified at this scale for a commercial advertisement. The empirical magnitude here is consistent with the qualitative observation that Thai sadvertisements function as cultural artifacts rather than purely commercial messages [25, 26].

Managerial implications**:** For marketing practitioners, the findings carry several strategic implications. First, emotionally narrative advertising represents an efficient strategy for generating sustained positive brand sentiment in the digital ecosystem, where content longevity and organic shareability are critical success metrics. Second, the high proportion of crying-expression comments with positive sentiment valence suggests that advertisers should not be deterred by strong negative emotional reactions. Tearfulness, in this context, is a behavioral indicator of deep engagement rather than rejection. Third, the cross-cultural universality of observed effects suggests that emotional advertising built on broadly shared human values can achieve genuine global reach without requiring expensive cultural adaptation for each target market.

4.8. Limitations and future research directions.

Several limitations warrant explicit acknowledgment. The first set concerns the sentiment classification protocol. The use of a rule-based lexicon necessarily simplifies the multi-dimensional affective structure of advertising comment language. Sarcasm, culturally specific idiomatic expressions, and code-switching are classification challenges not fully addressed by the present protocol. The decision to use a lexicon-based approach was justified above on grounds of interpretability and reproducibility, but it does mean that a small share of comments coded as Negative may in fact be sarcastic Positive comments, and vice versa. Future research should employ transformer-based multilingual sentiment models such as mBERT and XLM-RoBERTa, possibly in hybrid configurations with domain lexicons [36, 37], to assess the robustness of the present findings to methodological variation.

Language and translation issues: The corpus contains comments in at least 27 languages, and the present lexicon was constructed primarily for English-language content with emoji augmentation. While the cross-cultural consistency observed in Section 4.6 suggests the

underlying sentiment pattern is robust, machine translation of non-English comments to English for lexicon scoring inevitably introduces translation noise. Recent work shows that translation choice (for example, between Google Translate and LibreTranslate) can shift sentiment classification outputs by several percentage points in cross-lingual pipelines [37]. The present findings should be interpreted as a first approximation, and future work should run language-native lexicons or fine-tuned multilingual transformers on subsets of comments in each major language for confirmation.

YouTube comment bias: YouTube comment corpora carry several well-documented biases that limit the inferences that can be drawn about the broader audience. First, only a fraction of viewers comment, and commenters are a self-selected subset who differ systematically from silent viewers in engagement intensity and parasocial orientation. The present analysis therefore captures the sentiment of expressive viewers, not the full audience. Second, YouTube's recommendation and comment-ranking algorithms shape which comments are surfaced and which receive engagement. Recent work has shown that the YouTube recommendation system exhibits systematic drift toward emotionally engaging and joyful or neutral content, with a popularity bias that disproportionately promotes highly liked comments [64]. This algorithmic visibility bias may amplify positive comments relative to negative ones, particularly in the like-count metric used here as a secondary engagement measure. Third, comment language ambiguity, deletion, and moderation by either the channel owner or the platform can selectively remove content over time, potentially biasing the long-tail observation period. Fourth, YouTube comment demographics skew toward younger and more digitally engaged users in higher-income countries [65], so the cross-cultural claim should be understood as cross-linguistic visibility rather than as a representative sample of the global population.

Exclusion of non-commenting viewers: Related to the previous point, the analysis cannot directly address the sentiment of viewers who watched the advertisement without commenting. Psychophysiological and survey-based work continues to be necessary for capturing this larger silent audience. Integrating naturalistic comment data with biometric and self-report measures, in the manner of recent femvertising research [13], would provide a more complete picture of the full audience emotional response spectrum.

Single-advertisement design: Finally, the study focuses on a single advertisement. Comparative analysis across multiple Thai advertisements and across different emotional advertising traditions (for example, the John Lewis Christmas tradition in the United Kingdom or comparable Japanese and Korean campaigns) would substantially extend the theoretical contribution and clarify which features of the present pattern are generalizable and which are specific to this campaign.

5. Conclusions

This study provided large-scale, longitudinal, and naturalistic evidence that emotionally resonant narrative advertising in the sadvertising genre, exemplified by Thai insurance commercials, generated overwhelmingly positive audience sentiment among global digital audiences. Across a corpus of 2,498 YouTube comments spanning more than 11 years of engagement, 38.9% of comments were explicitly classified as Positive compared with only 6.4% Negative, yielding a 6.04:1 ratio that substantially exceeded comparable benchmarks in product review and general social media sentiment literature. The most significant theoretical

finding was the resolution of the sad–positive paradox, in which expressed emotional distress (crying) in advertising commentary functioned as a positive sentiment indicator rather than a negative one, with an odds ratio of 51.8 for the crying–positive association. The temporal and cross-cultural dimensions further amplified the theoretical significance of these findings. Sustained positive sentiment across 11 years challenged classical advertising wear-out theory and suggested that emotionally narrative advertising occupied a qualitatively distinct cognitive and affective position in consumer memory. Consistent positive sentiment responses across at least 27 cultural and linguistic communities, in response to an advertisement produced in a language inaccessible to most commenters, provided strong evidence for the broad emotional universality of well-crafted sadvertising. Together, these findings advanced sadvertising theory, contributed to the cross-cultural advertising literature, and offered a methodologically replicable framework for large-scale digital audience sentiment analysis.

Author Contribution

Andi Azhar: conceptualization, methodology, data collection, data analysis, writing (original draft). Arief Dwi Saputra: writing (manuscript formatting according to journal template), editing. Alfina Rahmatia: language review (ensuring accuracy and appropriateness of English usage throughout the manuscript).

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Conflict of Interest

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