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Exploring the Association Between Suicide Prevention Public Service Announcements and User Comments on YouTube: A Computational Text Analysis Approach

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In the United States, suicide rates have increased by 30% over the past few decades. Public service announcements (PSAs) are effective health promotion vehicles and social media can help spread PSAs to hard-to-engage individuals who may benefit from intervention efforts, yet the most meaningful characteristics of PSAs for influencing health promotion attitudes and behaviors are inconclusive. This study applied content and quantitative text analyses to suicide prevention PSAs and comments on YouTube to assess the relationships between message frame, message format, and the level of sentiment and help-seeking language within them. Seventy-two PSAs were analyzed for gain/loss-framing and narrative/argument-format, and 4,335 related comments were analyzed for positive/negative sentiment and frequency of help-seeking language use. Results indicate that a higher ratio of positive comments was more likely to be found on gain-framed and narrative-formatted PSAs, and a higher ratio of comments with help-seeking language was more likely to be found on narrative-formatted PSAs. Implications and future research are discussed.

Suicide is a significant public health concern in the United States, with a 30% increase since 2000, making it a leading cause of death across all demographics (Garnett, Curtin, & Stone, 2022). Existing research on suicide and suicidal behavior suggests that it is a pervasive issue requiring wide-reaching interventions for effective prevention (Ftanou et al., 2017). Social media platforms have become increasingly popular and widely used, making them an ideal medium for disseminating information about mental health and suicide risk to large populations, including hard-to-reach audiences (Du et al., 2018). YouTube is one of the most widely used social media platforms, with over 81% of U.S. adults users (Pew Research Center, 2021). YouTube has a higher engagement rate at 18% compared to other media sharing platforms such as Instagram or TikTok (Aspire, 2021). Studies that have examined the relationship between social media use and suicide-related behaviors have noted a relationship between the two (Luxton, June, & Fairall, 2012; Nesi et al., 2021; Sedgwick, Epstein, Dutta, & Ougrin, 2019).

YouTube is an especially useful platform for suicide prevention efforts due to its ability to reach hard-to-engage individuals (Robinson et al., 2016). The platform's emphasis on broadcasting multimedia messages to large audiences allows for anonymous, bi-directional information sharing, including disseminating public service announcements (PSAs) (Robinson et al., 2016). The current study aims to explore the relationship between two important attributes of suicide prevention PSAs (SP-PSAs) on YouTube - message framing and format - and their relationship with positive and negative sentiment and the degree of help-seeking language in user comments. To date, no prior research has investigated these relationships in tandem. Understanding the relationships between these variables has implications for the success of future suicide prevention messaging campaigns published on YouTube.

Technological advances offer new opportunities to develop and expand suicide prevention approaches relevant to wider audiences and applicable to new platforms. Larsen et al. (2015) overview of technology advances supporting suicide prevention research describes developments in acoustic detection of mental health crises in speech patterns, suicide risk screening through mobile phones, the use of mHealth applications for Indigenous populations, and the automatic detection of suicidality in social media content. Unlike other suicide prevention interventions such as gatekeeper programs and psychoeducational training, there are few studies investigating the attributes and influence of public service messaging on suicidality (Klimes-Dougan, Klingbeil, & Meller, 2013).

Public service announcements (PSAs) are widely used intervention tools whose reach and influence have magnified through social media. PSAs are persuasive communication used to

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promote programs, activities, or services of nonprofit organizations or of federal, state, or local governments, or any other announcements regarded as serving community interests (Federal Communications Commission, 1978). Evidence suggests that PSAs are effective in influencing attitude and behavior change across a variety of health-related issues from hearing loss to poor sleep habits, smoking cessation, vaccination, and drunk driving (Binder, Naderer, & Matthes, 2020; Robbins & Niederdeppe, 2019). The use of PSAs to address suicidality and mental distress among social media users has increased over the past few decades; however, few studies have investigated the various message attributes and how they might influence different audiences (Pirkis, Mok, Robinson, & Nordentoft, 2016).

PSA Audience Sentiment

There are various methods to measure advertising effectiveness, including audience self-report on sentiment and biometric measurement for emotional response, with the goal of understanding user engagement (Syrdal & Briggs, 2018). Sentiment analysis, a natural language processing (NLP) approach to interpret and classify opinion from text (Drus & Khalid, 2019), provides a useful feedback loop for advertising and helps predict results (Sánchez-Núñez, Cobo, De Las Heras-Pedrosa, Peláez, & Herrera-Viedma, 2020). Stout and Leckenby (1986) identified emotion-related continua associated with sentiment response to advertisements; additionally, multiple others have found that sentiment and emotions toward advertisers are associated with attitudes toward advertisements and serve as antecedents to attitude change (MacKenzie & Lutz, 1989; Spears & Singh, 2004). More recent research has leveraged sentiment analysis to better understand engagement and audience sentiment and advertisements (Berkovic, Ackerman, Briggs, & Ayton, 2020; Dacres, Haddadi, & Purver, 2013; Ford, Curlewis, Wongkoblap, & Curcin, 2019). Viewers' sentiment about advertising influences subsequent actions, and user self-report is a common measure of advertising effectiveness. Considering the scarcity of research on sentiment response to suicide prevention-specific messaging, it is important to empirically investigate the influence of suicide prevention messaging on user sentiment, opinions, and attitudes, which can be effectively done through computational text analysis.

Help-Seeking Attitudes

Previous research has established a positive relationship between suicide prevention public service announcements (PSAs) and help-seeking intentions and behaviors related to suicide (Klimes-Dougan, Wright, & Klingbeil, 2016; Robinson, Braybrook, & Robertson, 2014). Help-seeking, the act of seeking assistance from both informal and professional sources (Klimes-Dougan, Wright, & Klingbeil, 2016), serves as an essential link between identifying a problem and receiving the necessary assistance to resolve it. Given the evidence in studies using advertising frameworks, such as the attention, interest, desire and action model (AIDA) (Polk, 2018), most public messaging campaigns are designed to persuade viewers toward a desired action. The goal of many suicide prevention campaigns is to increase help-seeking intentions (Carlton & Deane, 2000; Gould, Greenberg, Velting, & Shaffer, 2003; Klimes-Dougan, Wright, & Klingbeil, 2016). While previous studies indicate a positive relationship between help-seeking and improvement in certain mental health conditions (Feehan, McGee, & Stanton, 1993; Vidourek, King, Nabors, & Merianos, 2014), there remains a gap in the literature regarding the relationship between social media-based messaging, help-seeking and reduced suicidal behavior.

Message Framing in PSAs

There is a wealth of research on message framing as a construct across health communication, with studies supporting the effectiveness of gain or loss-framing in different contexts. Research on message framing in health communication shows that framing can influence individual decisions (Shamaskin, Mikels, & Reed, 2010), and some of the most studied types of frames are gain and loss framing (Rothman & Salovey, 1997; Tversky & Kahneman, 1989). Evidence from previous research indicates that viewer responses to health-focused messages are a function of a message's frame (Rothman, Bartels, Wlaschin, & Salovey, 2006; Zimmerman et al., 2014) Gain-framed messages emphasize positive consequences, while loss-framed messages emphasize negative consequences of a behavior. While there is evidence that both types of frames can be effective in different contexts, some studies suggest that negative and loss-framed messages have a greater influence on viewer perceptions of certain health behaviors (Abhyankar, O'Connor, & Lawton, 2008; Cho & Boster, 2008; Zhao & Nan, 2010), while others suggest that gain-framed messages are more persuasive in other contexts (Alhabash & Ma, 2017; Gerend & Cullen, 2008; Van't Riet, Ruiter, Werrij, & De Vries, 2010; Wyllie, Baxter, & Kulczynski, 2015). In a suicide help-seeking context, a positive-framed message might accentuate the life-saving benefits of seeking mental health support, while a negative-framed message might emphasize either the failure to prevent suicidal behavior as a result of not seeking mental health support or the loss of life because of bullying or mistreatment of others. While the influence of message framing is well supported across a variety of health-related contexts, the influence of framing on viewer sentiment with respect to suicide prevention messaging is understudied. Based on the extensive literature on message framing, the following hypotheses can be posited:

H_1: The framing of SP-PSAs on YouTube will be significantly associated with the polarity of sentiment in user comments.

H_2:The framing of SP-PSAs on YouTube will be significantly associated with the degree of help-seeking language in user comments.

Message Format in PSAs

In addition to message framing, message formatting is an attribute of PSAs that has been found to influence viewers' attitudes, intentions, and actions. PSA messages may be formatted in either narrative or argument forms. Narrative advertising format portrays a series of experiences and consequences organized temporally, involving a plot and protagonist, providing a basis for causal inference by the message audience (Escalas, 2004; Zheng & Phelps, 2019). Conversely, the argument-format involves no plot, protagonist, or temporal elements, but rather a lecture approach, delivering information directly to audiences (Chang, 2008). Research suggests that a higher degree of dramatization, as is found in narrative advertising, induces greater immersion, fewer counterarguments, and more positive attitudes toward advertisement messages (Deighton, Romer, & McQueen, 1989). Some studies have found the narrative advertising format to be less effective in health-related behaviors such as limiting sugar intake (Li, 2021), and decreasing the use of tanning beds (Greene & Brinn, 2003), while others have found it to be more effective, for instance, in increasing literacy about depression (Chang, 2008), promoting students' sleep hygiene (Robbins & Niederdeppe, 2019), or triggering emotional responses about depression (Tseng & Huang, 2016). Like message framing, findings differ in the degree of influence between different message formats; however, the literature supports the notion that format is a significant factor in the influence on viewers' responses; therefore, the following hypotheses are posited:

H_3: The format of SP-PSAs on YouTube will be significantly associated with the polarity of sentiment in user comments.

H_4: The format of SP-PSAs on YouTube will be significantly associated with the degree of help-seeking language in user comments.

The literature suggests a strong influence of both message frame and format on sentiment and help-seeking behaviors related to other health-related PSAs, yet little is known about how they influence sentiment polarity and help-seeking behavior in a suicide prevention context. The consensus in the suicide-related public health messaging field is that more research is needed to understand the most effective aspects of prevention messaging in influencing attitudes, knowledge and intentions (Klimes-Dougan & Lee, 2010; Pirkis et al., 2019). This study aims to understand the association of message framing and format on sentiment and help-seeking language in comments about SP-PSAs on YouTube, as there is a knowledge gap on their effect on suicide prevention-focused PSAs. By addressing this gap, practitioners can improve the design of SP-PSAs, thereby increasing their effectiveness in preventing suicide.

Methods

Research Design

The current study adopted a two-step methodology−1) content analysis of YouTube SP-PSAs to assess frame and format, and 2) computational text analysis involving sentiment analysis and latent semantic scaling design to identify associations between PSA video frame and format and characteristics across viewers' comments. As suggested by Roberts (2000), computational text analysis involves mapping words onto a two-dimensional matrix for further statistical analysis; therefore, it is an appropriate approach to test the current study's hypotheses. Four variables were tested for independence in this study – PSA message frame, PSA message format, comment sentiment polarity, and comment help-seeking language.

To explore the associations between suicide prevention PSA message framing, format, sentiment polarity, and degree of help-seeking, statistical association tests were used. The chi-square test statistic is used when all variables are at the nominal or ordinal level, levels of each variable are mutually exclusive, and variable groups are independent (McHugh, 2013). Since the data collected in the current study met each of these assumptions, the chi-square test statistic was deemed appropriate. This section describes the results of statistical tests conducted on the PSA video comment data collected.

Data Collection

The unit of analysis of the current study was YouTube user comment on suicide PSA videos. While the current study did not involve interaction or intervention with human subjects and therefore lies beyond the scope of ethics board review, approval for this research was received through YouTube's Research Program. To obtain relevant comments, videos were identified in June of 2022, on YouTube using the keyword search terms intitle:suicide PSA OR "public service a*." This keyword selection ensured retrieval of PSA videos that include the word "suicide" along with PSA or other variants such as public service announcement, public service ad, or public service advertisement in its title. The search results were sorted by relevance. Exclusion criteria for the videos included those that were not PSAs, videos not topically focused on suicide, videos speaking a language other than English, videos with zero comments, and videos with disabled comments. As described in previous studies (Ache & Wallace, 2008; Briones, Nan, Madden, & Waks, 2012; Keelan, Pavri-Garcia, Tomlinson, & Wilson, 2007), videos with the highest relevance were retained for the current study. The search generated a total of 94 videos, with 22 videos subsequently removed after meeting the previously described exclusion criteria. The comment data and metadata for each of the videos were downloaded through YouTube's API, R version 4.1.2, and the vosonSML package version 0.29.13. The final sample included 72 videos and 4,335 comments.

Content Analysis of YouTube Videos

To determine the frame and format of the sampled PSA videos, a content analysis was conducted by two independent coders. Among the 72 videos, 20% ($n = 15$) of the videos were targeted to be rated by both coders, requiring Coder 1 to review 43 videos and Coder 2 to review 44 videos. The coders rated each video on a series of nine questions relating to observed behaviors identified in the PSAs, observed positive or negative outcomes, the method for delivery of suicide-related information, the number of likes, and the number of views. Additional information captured during the retrieval of the videos included the video title, date of posting, text and posting dates for each comment, and the number of subscribers. Before rating the videos, the coders were advised on the operationalization for each coding variable. The frame of the video was classified into two categories: gain-frame and loss-frame, as derived from Carling et al. (2010). Gain-framed videos were operationally defined as PSAs that portray positive outcomes because of behavior displayed during the PSA. Conversely, loss-framed videos were defined as PSAs depicting negative outcomes resulting from behavior displayed throughout the PSA. Format was categorized as either argument or narrative-format. As derived from Boller and Olson (1991), Deighton, Romer, and McQueen (1989), and Zheng and Phelps (2019), argument and narrative-formatted videos were operationally defined as PSAs that attempt to persuade the viewer through logical arguments, facts, statistics, appeals, or reasoning, or as those containing a story with a beginning, middle, and end timeline with linked experiences across the video.

Cohen's kappa statistics were calculated to assess interrater agreement between coders. Cohen's kappa represents the degree of reliability and interrater accuracy between two raters on a classification task controlling for chance agreement; therefore, this statistic was appropriate for this study (Cohen, 1960). In the current study, the kappa statistic between the two raters was 0.70 on frame rating, and 0.73 on format rating. According to Cohen (1960), a kappa statistic between 0.61 and 0.80 indicates substantial agreement, suggesting substantial and adequate agreement between the coders for this study.

Computational Text Analysis of User Comments

Sentiment Analysis

After coding PSA videos for frame and format, user comments associated with each of the videos were evaluated for sentiment. Sentiment analysis is an automated classification task that quantifies text based on a predetermined sentiment dictionary of words with associated scores, then assigns that text to specific classes. The comment data were analyzed for positive and negative sentiment using R version 4.1.2 and the Quantitative Analysis of Text Data (Quanteda) package 3.1.0, along with the Valence Aware Dictionary and Sentiment Reasoner (VADER) package version 0.2.1 (Hutto & Gilbert, 2014). The VADER package is ideal for sentiment analysis in the current study because its design is specifically adapted to sentiments communicated through social media. After data collection through the YouTube API, the comment data were prepared for VADER sentiment analysis through preprocessing which involved transforming the data to a corpus of comments in a table represented as individual documents, then analyzing the documents against the VADER dictionary. After analysis, the sentiment analysis was exported to a table with rows representing distinct comments, and six columns containing a vector of scores for each word in the comment, a compound sentiment score for the entire comment, the positive, negative, and neutral scores for each comment, and a count for the number of uses of the word "but" in each comment. Sentiment polarity scores were determined based on the compound scores for each comment. By default, VADER scores comments between 0 and 1 as positive, and comments between 0 and−1 as negative. To improve analytical accuracy against potentially neutral or ambiguous sentiment in the current study, comments scored between 0.25 and 1.0 were classified as positive, while comments between−0.25 and−1.0 were labeled negative. Comments between−0.25 and 0.25 were labeled as NA and excluded from the analysis.

Latent Semantic Scaling

To classify user comments across the help-seeking dimension, latent semantic scaling was used. Latent semantic scaling (LSS) is a semisupervised machine learning model that uses a small set of polarity words to assign scores to all other words in a corpus along a single dimension (Watanabe, 2021). LSS has been applied in previous research to identify Iraqi politics on the reconciliation-sectarianism continuum in news articles (Yamao, 2020), to identify street protests in Russia on the disorder-freedom dimension (Lankina, Watanabe, & Netesova, 2020), and to classify UN speech transcripts on the diplomatic politeness continuum (Baturo & Watanabe, 2019).

The first stage in LSS analysis was the preprocessing of text data which entailed tokenizing the previously described corpus of comment documents into individual words, removing punctuation, symbols, and stopwords from the tokenized data, converting all text to lowercase, then converting the tokens to a document-feature matrix for analysis. After preprocessing the data, seed words were determined to establish the polarity of the help-seeking dimension. To identify appropriate seed words for the help-seeking dimension, Fischer and Turner's Attitudes Toward Seeking Professional Help scale was referenced (Fischer & Turner, 1970). The 10-item scale includes statements measuring a respondent's degree of positivity toward help-seeking. Keywords were extracted from the five straight-scored items and the five reverse-scored items to develop the seed word dictionary for latent semantic analysis. The five help seeking seed words used in the analysis were - "seek," "willing," "believe," "solve," and "together," while the five help avoidance terms were - "avoid," "doubt," "reluctant," "unlikely," "alone." As stated by Watanabe (2021), the LSS algorithm produces polarity scores for each word based on its relative proximity to the polar seed words. LSS analysis produces numeric scores for each word that may be negative or positive with zero indicating a neutral word. Comment-level scores were composites of the sum of word-level scores from the analysis.

Results

Data collected through sentiment analysis and latent semantic scaling to identify associations between PSA video frame and format and characteristics across viewers' comments were analyzed using chi-square tests. PSA message frame and format along with comment sentiment polarity and help-seeking language were compared to determine statistically significant relationships.

H1 proposed that the framing of SP-PSAs would be significantly associated with the sentiment polarity of user comments. Figure 1 compares the frequency of comments classified by the VADER automated text analysis model with positive and negative sentiment between gain and loss-framed PSA videos. Among the gain-framed PSA videos, 1,351 comments were classified as positive, while 574 were classified as negative. Across the loss-framed PSA videos, 682 comments were classified as positive and 506 were identified as negative. A chi-square test revealed that there was a significant association between PSA framing and comment sentiment polarity, X^2 (1, $N = 3{,}113$) = 52.911, $p < .001$); therefore, H1 was supported.

H2 proposed that the gain or loss-framing of SP-PSAs would be significantly associated with the degree of help-seeking language identified in user comments to those SP-PSAs. Figure 2 compares the frequency of comments classified by the LSS model with either a help-seeking or help-avoidant polarity score, between gain and loss-framed PSA videos. Among the gain-framed PSA videos, 577 comments were classified as help-seeking, while 561 were classified as help-avoidant. Across the loss-framed PSA videos, 333 comments were identified as help-seeking and 306 were labeled as help avoidant. A chi-square test showed that there was no significant association between PSA framing and help-seeking language used in comments at X^2 (1, $N = 1{,}777$) = 0.325, $p = .568$; H2 was thus not supported.

The third hypothesis proposed that the format of SP-PSAs would be significantly associated with the sentiment polarity of comments to those PSAs. Figure 3 illustrates the frequency of comments classified by the VADER automated text analysis model with positive and negative sentiment between narrative and argument-formatted PSA videos. Among the narrative PSA videos, 1,511 comments were classified as positive, while 744 were classified as negative. Across the argumentative PSA videos, 522 comments were

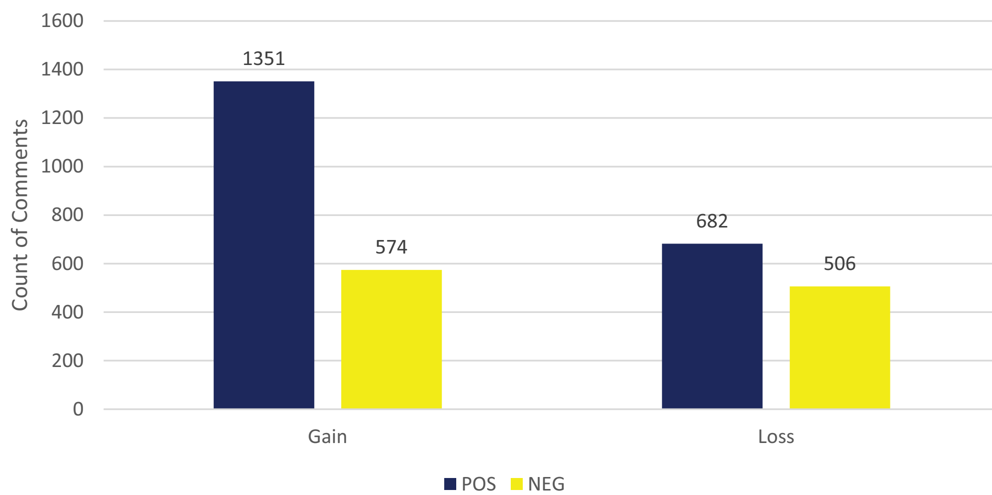

Figure 1. H1. Frequency of sentiment-related comments by PSA frame type.

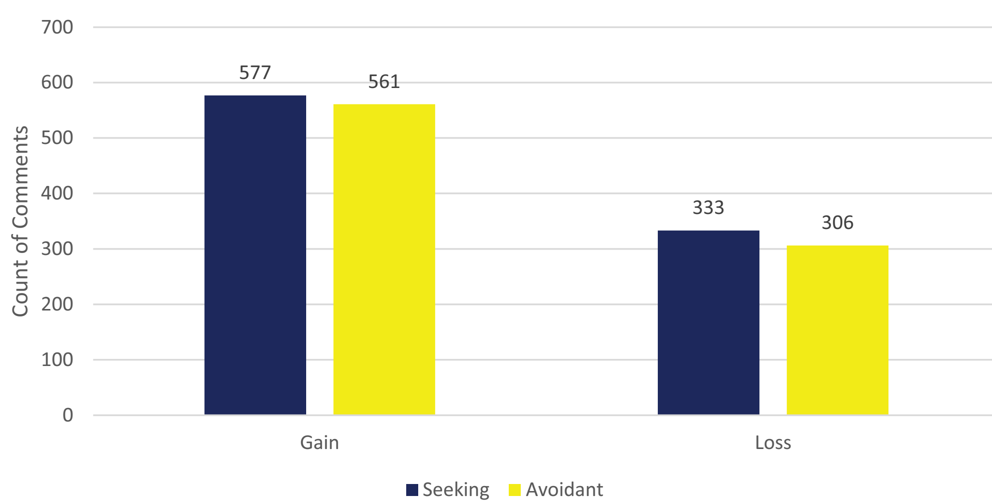

Figure 2. H2. Frequency of help seeking-related comments by PSA frame type.

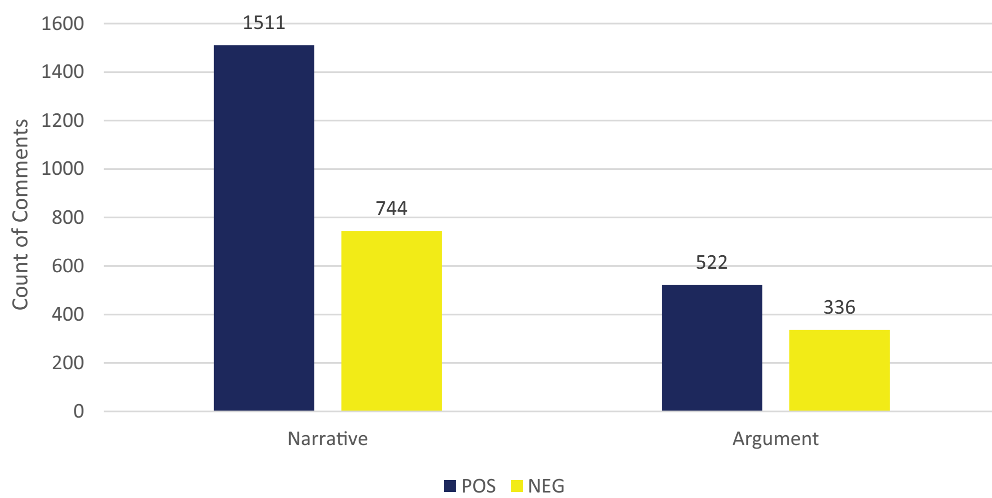

Figure 3. H3. Frequency of sentiment-related comments by PSA format type.

classified as positive and 336 were identified as negative. There was a significant association between PSA format and comment sentiment polarity at X^2 (1, $N = 3{,}113$) = 10.434, $p < .001$; H3 was thus supported.

H4 posited that the format of SP-PSAs would be significantly associated with the degree of help-seeking language used in comments to those PSAs. Figure 4 compares the frequency of comments classified by the LSS model with either a help-seeking or help-avoidant polarity score, between narrative and argumentative formatted PSA videos. Among the narrative PSA videos, 664 comments were classified as help-seeking, while 591 were labeled as help-avoidant. Across the argument-formatted PSA videos, 246 comments were identified as help-seeking and 276 were classified as help-avoidant. There was a significant association between PSA format and help-seeking language used in comments at X^2 (1, $N = 1{,}777$) = 4.9327, $p < .05$; the hypothesis supports that narrative-formatted videos were more likely to contain help-seeking comments than argument-formatted videos.

In a post-hoc assessment to determine cell count significance in H1, H3, and H4, standardized residuals (SR) were calculated using the statistical method suggested by Sharpe (2015). The results of these analyses confirm that in H1, gain-framed videos were more likely to contain positive comments (SR = 35.4) than loss-framed videos (SR = 27.8). Likewise, in in H3, narrative-formatted videos were more likely to contain positive comments (SR = 38.3) than argument-formatted videos (SR = 23.6), and finally in H4, narrative-formatted videos were more likely to contain help-seeking comments (SR = 25.3) than argument-formatted videos (SR = 16.3).

Discussion

Using a two-step methodology, the current study tested hypotheses predicting significant associations between the frames and formats of PSAs and the sentiment polarity and help-seeking language used in user comments on YouTube. YouTube videos

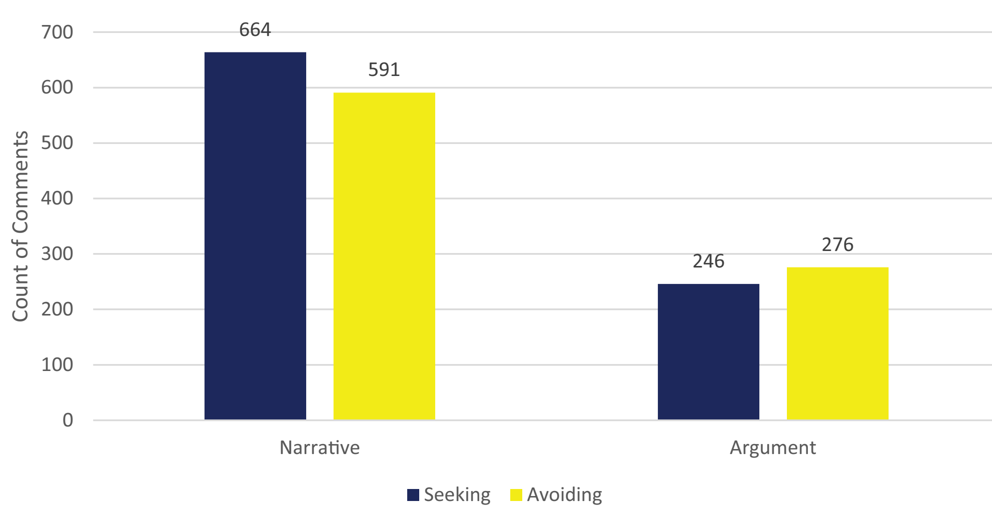

Figure 4. Frequency of help seeking related comments by PSA format type.

have become one of the most popular methods for concerned entities to share important suicide prevention information. While previous research had investigated the connection between characteristics of health-related PSAs and the attitudes and actions of viewers (Klimes-Dougan & Lee, 2010; Pirkis et al., 2019), these phenomena had not been investigated within the context of social media. Among the four hypotheses, three statistically significant associations were found between PSA framing and sentiment polarity, PSA format and sentiment polarity, and PSA format and help-seeking language in comments. Across the comments analyzed, those with either a gain-frame or narrative-format tended to have greater than expected frequencies of positive comments; also, videos with a narrative-format tended to have greater than expected frequencies of help-seeking comments on the SP-PSAs.

Interesting distinctions exist between these findings and those of previous studies on message framing. Contrary to our results, previous studies have found that loss-framing is associated with increased receptivity and more positive attitudes regarding such health issues as alcohol use prevention and cancer screening (De Graaf, Van den Putte, & De Bruijn, 2015; Lucas, Hayman, Blessman, Asabigi, & Novak, 2016; Umphrey, 2003). Differing methodological approaches between the current study and prior studies may explain these differences. Prior studies tested gain and loss-framing by providing participants with *text-based* messages outlining guidelines, definitions, statistics, and consequences that were read through, then subsequently measured for sentiment. While not explicitly measuring message format, their reliance on text-based messages formatted as factual arguments may have influenced the level of immersion that narrative videos afford.

Narrative SP-PSAs contained a significantly higher frequency of positive sentiment comments than argument-formatted SP-PSAs, aligning with prevailing evidence in the literature on messaging. The predominant perspective suggests greater engagement and more positive feelings are evoked through narrative messaging (Chang, 2008; Deighton, Romer, & McQueen, 1989; Robbins & Niederdeppe, 2019). Narrative advertisements cause viewers to become "lost in the story and experience the concerns and feelings of the characters" (Deighton, Romer, & McQueen, 1989). Escalas (2004) examination of the effect of narrative transportation on attitudes about advertisements demonstrated that [cognitive] transportation affects attitudes by evoking positive feelings. The current results provide a directional continuation of this line of evidence into SP-PSAs on YouTube. Narrative SP-PSAs also contained a higher frequency of help-seeking language in comments than argument-formatted SP-PSAs, which is consistent with prior studies providing evidence for higher engagement and positive feelings toward narrative messaging, a prerequisite for action (Deighton, Romer, & McQueen, 1989). As indicated by Ftanou et al. (2017), most SP-PSAs advise at-risk individuals to seek help, yet there is limited evidence on the impact of PSAs to influence help-seeking action. While no causal link can be established, the results of this study extend our understanding of the relationship between the format of SP-PSAs and help-seeking responses from those who view them.

No relationship was identified between the gain/loss-framing of SP-PSAs and the help-seeking language used by viewers within their comments. This relationship between framing and help-related comments is complex due to the nature of suicide-related discussions. Responses to gain/loss frames may be difficult to differentiate on the help-seeking dimension; for instance, the help-*seeking* comments "Hope that your message will reach out and help people all across the world!" and "Please stay alive to find that person that will love u, care for u, and be with u." both come from gain/loss-framed SP-PSAs, respectively. Comments classified as help-*avoidant*, such as "it's better to suicide than living here" and "it feels like it will never get better" also originate from gain and loss-framed PSAs. A significant limitation of text analysis is the inability to engage comment creators to discern their mental state. Future studies may address this limitation by pairing survey and text analysis methods.

Limitations & Recommendations for Future Research

Limitations should be addressed to put the findings of this study into perspective and some of these limitations represent future research opportunities across different research designs, methodologies, time frames, and populations. The methodological, temporal, and population decisions for the current study were sufficient to address the research problem and test the four relevant hypotheses; however, they also present opportunities for future research to extend the current findings. The keywords used to collect video data were identified to yield the widest selection of relevant suicide-related PSA videos on YouTube. While several duplicate videos were removed from initial data collection, indicating saturation in data collection, it is possible that different search terms could yield a different PSA data set. Future research could identify videos using different search terms that are either more abstract or more descriptive using a video file-sharing platform other than YouTube. Video coding guidance for PSA videos was derived from several sources across the framing and format literature and the operationalization of the framing and formatting constructs was integral to the hypothesis testing for the study. Future research may operationalize gain/loss-framing or message formatting differently to address different research problems.

The use of automated text analysis software is essential for the evaluation of a large volume of unstructured data, such as social media comments. There are several options for automated text analysis software available to researchers for this task and the decisions made for the current study were based on the most sufficient and applicable to the evaluation of sentiment and latent semantics across social media. Other researchers may yield different results by conducting similar studies that use different text analysis lexicons or sentiment dictionaries. A key limitation was the exclusion of non-English PSAs and non-English comments. While help-seeking is a widely studied and important topic in health communication research, the study of social media comments is inherently limited to the characteristics of the text; therefore, future research should explore the relationships between user comments and help-seeking behavior. By extending this study to other languages, a broader data set can be collected, potentially yielding alternative results.

Conclusion

The results of this study demonstrate associations between PSA framing, format, sentiment, and the frequency of help-seeking language found in comments. This study extends our knowledge of health messaging across social media and its relationship with viewer responses. While causality cannot be inferred from the study design, it benefits practitioners producing SP-PSAs to understand the potential emotional relationship that viewers may have with messages using different types of framing and formatting. The implications of this study indicate that message framing and format are specific characteristics that are important to consider when crafting suicide prevention campaigns for social media. Gain-framing and narrative-format are more closely associated with positive textual responses and a higher frequency of help-seeking language. These results provide evidence to support public health practitioners in the development of effective suicide prevention public service announcements.

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