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Engaging audiences on social media: Identifying relationships between message factors and user engagement on the American Cancer Society's Facebook page☆

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ABSTRACT

In this study, a content analysis was conducted with posts from American Cancer Society's (ACS) Facebook page to explore the relationship between message relevance, source characteristics, and message features with the number of likes, comments, and shares received by them. Limited Capacity Model for Motivated Mediated Message Processing (LC4MP) was used as the theoretical foundation for the study. Findings showed that cancer-related posts received more likes, comments and shares than posts that were not related to cancer. Also, posts by the American Cancer Society received more likes, comments, and shares than other source categories. Findings also indicated that though message features were related to likes, comments, and shares, the nature of relationship and the role of different features varied with each measure. Overall, findings highlight the role of motivational activation through message factors in eliciting user response in social media environments.

1. Introduction

Cancer is one of the leading causes of death worldwide, and according to statistics compiled by the World Health Organization (2017), around 14 million new cases are diagnosed each year worldwide, and around 8.8 million people die from various forms of cancer annually. Beyond the effects on patients, cancer also impacts family members, friends, colleagues, etc., many of whom use digital communication technologies to seek social support and information to help better understand the disease, its effects, and how to cope. These technologies include smartphone apps (Pandey et al., 2013), internet search engines (De Choudhury et al., 2014), and social media platforms such as Facebook (Nabi et al., 2013). The versatile nature of the internet carries great promise for platforms for information dissemination, promotion, and communication that are accessible, cost-effective, and efficient.

Social media in particular has become an important part of a growing number of individuals' daily lives (Boyd and Ellison, 2007). Applying the Uses and Gratifications perspective, Baek et al. (2011) found motivations for using Facebook include information-sharing, convenient communication and entertainment, passing time, communicating with people with similar interests and backgrounds, indicating wants and needs to others, and promoting organizations and people. Research has shown people affected by cancer utilize social media in order to satisfy differing goals in context of the disease (Cavallo et al., 2014; Bender et al., 2011). In the context of health communication environments, this implies the potential of platforms such as Facebook to create digital spaces that may bring together various stakeholders such as organizations, experts, governments, and patients. Many individual users utilize

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social media such as Facebook for interpersonal communication for health-related purposes (Moorhead et al., 2013; Grajales et al., 2014). Beyond interpersonal communication, various stakeholders including healthcare professionals, charitable and nonprofit organizations, patients, and general information-seekers, use social media for disclosure, information dissemination, and for generating involvement with organizations or causes (Waters et al., 2009). Analyzing social media users in health contexts, McLaughlin et al. (2012) found social networks fulfilled the needs of cancer survivors not being met in offline environments. Similarly, Chou et al. (2009) found younger individuals with poor subjective health and cancer experience were associated with people's use of social media for social support. However, many studies examining social media and health communication have encountered various issues such as sample size, sample quality, and methodological reliability (Moorhead et al., 2013), raising concerns and highlighting the need for more research in the area.This study examines how individuals respond to different types of messages posted to the American Cancer Society's (ACS) Facebook page. The ACS was selected for this study for a variety of reasons, including its prominence as an organization that focuses on medical aspects including cancer prevention and management, information dissemination, public education, and social support. Founded in 1913, ACS is one of the oldest organizations of its kind, (American Cancer Society, 2017; Eyre and Blount, 2006), and is one of the largest cancer-specific organizations in the world. Additionally, ACS has been active in various forms of social media since 2004 (Santicola, 2009), including unique platforms such as *Second Life*, a virtual world comprised of equal parts video game and online chatroom (Butcher, 2009).

In this study, authors propose Limited Capacity Model for Motivated Mediated Message Processing (LC4MP) as the theoretical foundation for the study and conduct a content analysis to test the relationships between source factors, message factors, message features, and user engagement on the ACS' Facebook page.

2. Literature review

2.1. Social media and user engagement: Methodological innovation and explication

Social media such as Facebook provide researchers a distinctive opportunity to unobtrusively observe user response to messages, in real-time environments, over a period of time. It allows users to send and receive messages and message feedback in the form of likes, comments, and shares (Facebook, 2017).

Facebook defines a *like* as the easiest way to indicate a user enjoys a post, whereas a *share* redistributes and publishes a post on a user's and their connections' pages, and a *comment* allows a user to create or add content to another user's posts (Facebook, 2017). Researchers argue that there may be several motivations for liking, sharing, or commenting on social media posts, including social connection and identity sharing (Joinson, 2008), social benefit and online community maintenance (Kite et al., 2016), and are influenced by attitudes, social, and subjective norms (Chin et al., 2015; Kim et al., 2015a,b). Others argue social media does not motivate, but may elicit pre-existing motivations in terms of user engagement levels (Vaccari, 2010, 2013).

Kim and Yang (2017) point out that each engagement behavior differs in value and commitment of resources. Research is consistent, however, as to the value hierarchy each behavior represents, with *like* representing the simplest and least resource-consuming behavior, followed by *comment*, which requires a user to generate content in response to a post, and *share*, which requires a user to generate content and take ownership of the post by publishing it to their own Facebook page (Kim and Yang, 2017; Kemp, 2016; Calero, 2013).

A *like* indicates an acknowledgment of a post and does not indicate how a user actually feels about that post. Users that only *like* a post or page are neither contributing to the conversation or creating/perpetuating nor publishing content to their own pages (Kim and Yang, 2017). *Liking* is positively influenced by a variety of motivations: Chin et al. (2015) found hedonic, utilitarian, compliance, conformity, and affiliation motivations all influence attitudes toward *liking* a post, and subjective norms influence the behavioral intent to *like* posts, which in turn influence actual behaviors.

Comment-level engagement is more akin to interpersonal communication and requires allocation and consumption of more cognitive resources than liking (John et al., 2017; Kim and Yang, 2017), in that a user must generate a thought – ranging from simple to complex – click the *comment* or *reply* buttons, type out that thought, consider it, then click another button to publish (John et al., 2017; Kim and Yang, 2017; Facebook, 2017). Comments have a higher digital value than likes to individual users as well as businesses and nonprofits, indicating a user has at least partially engaged with a post's content enough to formulate a response (John et al., 2017; Kim and Yang, 2017). Social media researchers point out comment-level engagement behaviors are forms of interpersonal communication (Ballantine et al., 2015; Smock et al., 2011), which may sometimes, due to the public nature of Facebook comments, be identified as *masspersonal communication* (Ballantine et al., 2015; Carr et al., 2008; O'Sullivan and Carr, 2017). As Ballantine et al. (2015) point out, while comments are posted in what is essentially a public forum for all to see, they are frequently posted with personal, interpersonal, or relational motivations and intent. Beyond interpersonal communication, comments also carry the potential to affect an audience's perception of a user, a post, or associated media content (Waddell and Sundar, 2017), and may influence a user's online communication and information-seeking behavior (Kim et al., 2016), particularly regarding health communication (Kim et al., 2015a,b), such as seeking information on potential causes, symptoms, and onsets of disease, and behavior modification for disease prevention.

Sharing-level engagement is the highest level of the three in this study and can be seen as a promotion-oriented behavior. Kim and Yang (2017) found share-level behavior may be either affective or cognitive, or a combination of the two, and may also be a user strategy for self-presentation, as shared content not only appears in other users' Facebook feeds but is published to the sharers' feeds. Share-level behaviors also allow users to introduce or comment on shared items, which requires more cognitive effort than liking or commenting alone. Herrero et al. (2017) found three primary drivers of intent to engage in share-level behaviors – performance expectancy, hedonic motivation, and habit. Chen et al. (2015) added self-expression to the list via Uses and Gratifications theory. Further, Pena and Quintanilla (2015) found, specifically concerning health-related information-sharing, that share-level behaviors may be motivated by the desire for social support, to share information related to health conditions in order to self-motivate to achieve health-related goals, and to help others seeking information on similar conditions.

2.2. Limited Capacity Model for Motivated Mediated Message Processing (LC4MP)

LC4MP is used as the foundational theoretical framework for this study. LC4MP considers the interaction between the message and the receiver as a dynamic process that takes place over time (Lang, 2006, 2009). It explains information processing on the basis of underlying cognitive mechanisms and therefore can be used to explain information processing for different communication contexts, such as mass communication or interpersonal communication. This flexibility to explain phenomena across contexts makes LC4MP a suitable framework for studying communication in social media where the nature of communication may comprise a wider range of stimuli and communication contexts than traditional, primarily one-way media such as television, radio, and newspapers.

According to LC4MP, information processing consists of three sub-processes: encoding, storage, and retrieval (Lang, 2006, 2009). Encoding refers to the creation of mental representations of messages, storage refers to storing the mental representation, and retrieval refers to the process of retrieving stored information. These sub-processes can occur sequentially or simultaneously.

Two core elements of LC4MP are the limited availability of cognitive resources and the role of motivation in the application of those resources (Lang, 2006, 2009). Humans have a finite amount of cognitive resources and information processing during task performance places demand on these cognitive resources. If the demand is more than the supply, the quality of information processing suffers. Motivational activation may increase the supply of cognitive resources to a task and may enhance the quality of information processing.

Two of the primary routes for motivational activation are activation due to perceived salience of content and motivation due to physical characteristics of the medium (Lang, 2006, 2009). The first route refers to scenarios where motivation increases because some element of the message becomes salient due to the receiver's previous experience or learning. For example, someone may find a news story more relevant and may pay more attention to read it if it covers their neighborhood. The second route refers to activation due to medium characteristics and may elicit motivational activation through a physiological route. Some examples of factors that may contribute to such activation may be physical characteristics of the message, such as variation in sound levels, colors, or the richness and intensity of the message.

In this study, we examine the association between factors that may elicit motivational activation and subsequent social media response in the form of likes, comments, and shares. More specifically, we propose to evaluate the role of message relevance and source characteristics that may influence motivational activation through the first route, and study the role of physical characteristics or message features that may influence message processing from the second route.

2.3. Message relevance

According to Petty and Cacioppo (1986), people may find communication stimuli to be personally relevant when they are connected to outcomes they consider significant to their lives. Message relevance is known to be an important factor contributing to motivational activation and influencing message reception in a wide range of contexts and across a wide range of dependent variables (Campbell and Wright, 2008; Glanz et al., 2010; Huang and Shen, 2016; Lustria et al., 2013; Petty and Cacioppo, 1979; Srivastava, 2013).

In the context of persuasive communication, Petty and Cacioppo (1979) conducted experimental studies where they manipulated issue involvement by varying message relevance and argument quality by including strong and weak arguments in the persuasive messages. Findings indicated increasing message relevance increased the persuasiveness of the strong message and reduced the persuasive effectiveness of the message with the weak argument. Evaluating these findings from the LC4MP perspective, increasing message relevance increased motivational activation and resulted in deeper processing of the message, which in turn led to people being aware of the quality of the arguments; as a result, messages with strong arguments had stronger persuasive influence than messages with weak arguments.

In an experimental study exploring the influence of relevance on message processing performance during media multitasking in online environments, Srivastava (2013) found message relevance had significant positive influence on free recall, aided recall, and recognition memories. Another study (Campbell and Wright, 2008) that examined the influence of message relevance in the context of online advertising using a survey study and a controlled laboratory experiment found that repetitive online ads that were personally relevant significantly enhanced users' attitudes toward the message.

Another application that leverages the role of message relevance toward increasing message effectiveness is message tailoring in health communication context. Tailoring health communication messages is a message relevance-oriented strategy that involves first collecting information from target groups and then communicating with the target audience with personally relevant messages based on the information collected in the first stage. For example, in a study that tested a skin cancer prevention intervention, medical history and sun sensitivity data were first collected from individuals, and then based on these data, personalized messages were created focusing on addressing risks that each individual was more likely to face (Glanz et al., 2010). The study found that enhancing message relevance through tailoring significantly improved the likelihood of behavior mitigating the skin cancer risk among the participants. A meta-analysis of 36 studies on cultural tailoring – the practice of creating messages that are culturally relevant – showed that enhancing relevance through cultural tailoring had significant influence on persuasion (Huang and Shen, 2016). The meta-analysis included studies that measured persuasion effectiveness through a range of dependent variables such as attitudes, behaviors, or behavioral intentions and also showed that deep tailoring, or tailoring which integrated cultural values and norms with message content, had a stronger persuasive influence than surface tailoring, which involved eliciting message relevance through message characteristics such as the language, ethnicity of presenters/narrators, or other elements from media or cultural environment such as food or music. Another meta-analysis (Lustria et al., 2013) that included 40 experimental or quasi-experimental studies involving web-based health interventions found conditions with tailored messages to be significantly more effective toward attaining desirable health outcomes than control conditions.

Since most users actively seek out the ACS's Facebook page, we argue that cancer-related messages in the posts will be found more relevant by users than messages that are not related to cancer. Based on the discussion about the nature of likes, comments, and shares presented earlier, we argue that though they may index different levels of user engagement comprising different contexts and attitude and behavior measures, motivational activation through message relevance may elicit increased allocation of resources to the processing of posts; this may lead to elicitation of user engagement though likes, comments, and shares. Based on the arguments presented above, we propose the following hypothesis:

H1. On American Cancer Society's Facebook page, posts with cancer-related messages will receive more likes, comments, and shares than posts with messages not related to cancer.

2.4. Source characteristics

Besides message relevance, characteristics of the source presenting the message may also elicit motivational activation (Cheung et al., 2009; Eastin, 2001; Greer, 2003; Wilson and Sherrell, 1993; Wu and Wang, 2011). In a meta-analysis involving more than 100 studies, Wilson and Sherrell (1993) found credibility, expertise, trustworthiness, physical attractiveness, and ideological similarity with the receiver to be the most typically manipulated source characteristics with expertise contributing to a stronger persuasive effect than other manipulations.

In the context of persuasive communication studies based on the Elaboration Likelihood Model (ELM), source cues often do not have independent effects, and effects are often based on interaction with other message factors, such as message involvement or argument strength. Wilson and Sherrell (1993) identified 12 such studies, and observed that in eight, source cues influenced persuasiveness in low message relevance conditions, but not in high message relevance conditions.

In the context of online environments, many studies have reported independent effects for source characteristics (Cheung et al., 2009; Eastin, 2001; Greer, 2003; Wu and Wang, 2011). In an experimental study involving processing of web-based health information, Eastin (2001) found the perception of source credibility to have significant positive influence on perceptions of message credibility. In another experimental study, source credibility was manipulated by presenting information as part of The New York Times website for high source credibility manipulation, and as part of a personal webpage for low source credibility manipulation (Greer, 2003). Findings indicated a significant relationship between source credibility and story credibility in all conditions.

Another aspect of online environments is the interaction between users of these environments and interchange or dissemination of information through electronic word of mouth (eWOM). In a survey study conducted through a Chinese online consumer discussion forum, Cheung et al. (2009) found source credibility to be a positive predictor of eWOM credibility. Another study exploring the persuasiveness of eWOM reported positive direct influence of source credibility on a range of variables indexing attitudes and behavioral intention toward product purchase (Wu and Wang, 2011).

Compared to persuasion studies exploring source credibility effectiveness in offline environments, source credibility seems to have more conclusive influence on message effectiveness in online environments. That might be rooted in fundamental differences in the nature of message processing between offline and online environments. Most studies conducted in an offline environment expose participants to just the target message, and the message effectiveness is evaluated based on the dynamics between the receiver and elements within the message. In online environments, including social media, messages compete with other messages for resource allocation. Thus, for online processing, source characteristics help not only with the processing of individual messages, but also with selection of individual messages for allocation of cognitive resources. We argue users visiting the Facebook page of ACS may find it to be a source with more credibility and expertise than other sources posting on the page. That may contribute to elicitation of higher level of user engagement for ACS posts due to a higher degree of motivational activation. Based on the discussion presented above, we propose the following hypothesis:

H2. On American Cancer Society's Facebook page, posts by ACS will receive more likes, comments, and shares than posts by other sources.

Based on the discussion presented in previous sections, we also propose the following Research question:

RQ1: On American Cancer Society's Facebook page, what is the relationship between message relevance, source characteristics and user engagement in form of number of likes, shares, and comments?

2.5. Message features

The structural elements of communication and the effects those features have on users has been widely studied in a variety of contexts (referred to by multiple descriptions, such as message features, channel features, message format, and communication modalities, as well as others), including persuasion (Worchel et al., 1975; Chaiken and Eagly, 1976, 1983; Wilson and Sherrell, 1993; Booth-Butterfield and Gutowski, 1993; Pfau et al., 2000), organizational behavior (Daft and Lengel, 1986), advertising effectiveness (Jones et al., 2005; Fortin and Dholakia, 2005), social media (Sabate et al., 2014), and health communication (Kreuter and McClure, 2004). Additional research has focused on the intersection of social media and health communication with the included variable of message features (Rus and Cameron, 2016; Kite et al., 2016; Theiss et al., 2016; Strekalova and Krieger, 2017).

Findings from studies exploring the role of message features on processing and effectiveness indicate message features' effects may often be manifested in combination with other variables. For example, the influence may vary with source factors such as source trustworthiness (Worchel et al., 1975), source likeability (Chaiken and Eagly, 1983), or message factors such as comprehensibility (Chaiken and Eagly, 1976) or argument quality (Booth-Butterfield and Gutowski, 1993). The complexity of the role of message features may also be observed at other levels of observation and analysis. Jones et al. (2005) reported that the influence of media characteristics varied across different measures of memory. Fortin and Dholakia (2005), in their study exploring the relationship of vividness and interactivity with indicators of effectiveness of web advertisements using a multi-step model, found these factors influenced advertising effectiveness through social presence and involvement.

In the context of health information processing on Facebook, studies report varying patterns of influence for message features. Kite et al. (2016), in their study of health communication-related Facebook pages targeted at Australians, found that videos received more likes, comments, and shares than photos, links, and text-only posts. The study by Theiss et al. (2016), which used engagement rate as the dependent variable and included not only likes, comments, and shares but also clicks, found that Center for Disease Control's breast cancer posts on Facebook that included a photo had the highest engagement rate, followed by status/links posts, and finally videos. Rus and Cameron (2016) reported that on diabetes-related Facebook posts, use of imagery was a significant positive predictor of user engagement through likes and shares, but not comments. This pattern may suggest visual stimulus provided by images may be more conducive for non-semantic response categories with lower levels of behavioral involvement. Strekalova and Krieger (2017) analyzed the National Cancer Institute's Facebook page and reported that posts containing photos received significantly more likes, comments, and shares than posts with links and video. That indicates the richest media (e.g. video) may not necessarily generate the highest level of user engagement, and points toward the active audience behavior on health-related social media.

From the LC4MP perspective, engagement with posts may depend on a range of features such as the nature of information processing, processing goals, and availability of cognitive resources (Lang, 2006). For example, when information processing is not driven by high degrees of motivation, adequate resources may not be available for processing of posts with videos that contain rich sensory content and needs a higher allocation of cognitive resources compared to processing of posts with photos that have a lower resource demand and may result in better processing outcomes for media with lower levels of sensory richness. Similarly, the demand for cognitive resource for different responses may also influence the nature and level of user engagement. That suggests that role of message features may involve the interplay of numerous factors situated in a message processing context. Based on the discussion presented above, we propose the following research question to explore the relationship between message features and user engagement:

RQ2: On American Cancer Society's Facebook page, what is the nature of relationship between message features of posts and user engagement?

3. Method

The hypotheses proposed in the previous sections were tested via content analysis of Facebook posts. The unit of analysis was the individual post. The number of likes, shares, and comments for individual posts were considered dependent variables. Message relevance and source characteristics were the independent variables that were operationalized through coding posts for *message content* and *message source* categories respectively.

3.1. Sample

To generate the sample, all the accessible posts on the timeline of the ACS Facebook page from October 2012 to January 2013 were archived. That was done by expanding the timeline for each month on the page in its Timeline view. For each post, a screenshot was taken and added to the archive. After completion of the archiving process, each post was assigned a serial number. Out of the total number of 5924 posts that were archived, 1992 posts were randomly selected to generate the sample for the content analysis procedure. The data were archived between February 2013 and June 2013.

3.2. Content analysis procedure

Two graduate students at a mid-sized Midwestern university served as coders to generate data for the content analysis by coding the independent variable and recording the dependent variables. A coding manual was developed to measure these variables. The coding scheme measured all the independent variables as categorical variables. Mutually exclusive coding categories were used for measurement. Number of likes, comments, and shares on each post were recorded as continuous dependent variables.

Krippendorf's alpha was used as a reliability coefficient to measure inter-coder reliability (Freelon, 2010, 2013); the values of reliability coefficient were 0.86 for message content, 0.92 for message source, and 0.97 for message features. After attaining acceptable levels of inter-coder reliability for the independent variables, the sample was distributed among the coders who coded the independent variables and recorded the dependent variables.

3.3. Content analysis coding scheme: Independent variables

As stated, the independent variables were message source, message content, and message features. A brief description of the coding scheme is provided below.

3.3.1. Message content

Message relevance was operationalized through coding for *message content,* with cancer-related content representing high message relevance and non-cancer-related content representing low message relevant. This category was used to identify the nature of content and had two subcategories: 1. Cancer-related content; 2. Non cancer-related content. Posts providing information about cancer-related issues and events were placed in the first category. Posts that provided cancer-related information about specific individuals were also placed in the first category. Posts that did not provide cancer-related information were placed in the second category. Examples of cancer-related posts included news and information about cancer, events and fundraising, questions about the disease, sharing experiences with the disease, and other posts directly related to cancer.

Non-cancer-related posts in the sample included a wide variety of content, including inspirational messages/quotes/pictures, links to external pages/videos with no mention of cancer in the post, discussions of health and healthcare in general without specifically focusing on cancer, spam messages, and others.

3.3.2. Message source

Source characteristics were operationalized through coding for *message source*, with American Cancer Society as the sub category high on source characteristics such as perceived expertise and credibility and all other sub categories relatively low on these source characteristics. The variable was measured by placing the post source in one of the four following categories: 1. American Cancer Society; 2. Nonprofits (individuals and organizations); 3. Businesses; 4. Others. A post was coded in the first category if the poster was identified as American Cancer Society or an affiliate. Posts where the poster was either a nonprofit organization or a person identified by an individual's name were placed in the second category; examples of this category included Facebook pages advocating for a specific cause/idea, accounts named after singular users of Facebook, health/wellness campaign Facebook pages, and others. Posts by commercial entities such as businesses or medical professionals were placed in the third category; examples of this category included companies across a large range of products, television shows, posts that specifically mentioned buying products, and others. All the posts that could not be placed in the first three categories were placed in the fourth category.

After coding, there were only 15 posts that were placed in the 'other' category, which constituted less than 1% of the sample. The researchers removed the posts with 'other' as source category from the dataset with the objective of reducing the number of pairwise comparisons during the analysis that may help limit type 1 error. Therefore, only three message source categories remained part of the analysis: American Cancer Society, Nonprofits, and Businesses.

3.3.3. Message features

This variable was measured by placing the post message in one of six categories: 1. Text-based information; 2. Contains embedded images; 3. Contains hyperlinks to external content; 4. Contains videos; 5. Interactive content; 6. Contains features from more than one category except the first category. After coding, there were only five posts in the 'interactive content' category which constituted less than 0.3% of the sample. With the objective of reducing the number of pairwise comparisons during the analysis that may help limit type 1 error, the interactive content category was removed. Therefore, the five categories used for the data analysis were: 1. Text-based information; 2. Contains embedded images; 3. Contains hyperlinks to external content; 4. Contains videos; 5. Contains features from more than one category except the first category.

3.4. Content analysis coding scheme: dependent variables

The number of likes, shares, and comments for individual posts were considered dependent variables. The numbers for each are displayed on each post and were recorded as dependent variables.

4. Analysis and results

After incorporating the modifications mentioned in the previous section and removing posts that could not be coded due to absence of content or because posts used a language other than English, a sample of 1938 posts was used for data analysis (See Table 1 for frequency distribution of user engagement variables across categories).

The user engagement data was skewed and reflected the inherent nature of many public social media environments where the majority of posts do not receive any user responses. Even though the means for number of likes (M = 28.31), comments (M = 2.11), and shares (M = 8.26) for the sample were more than zero, the median value for all three dependent variables was zero. To address the non-normality in data, non-parametric techniques were used for data analysis.

Table 1
Frequencies of posts, likes, comments and shares for each coding category.

	Number of Posts (%)	Number of Likes (%)	Number of Comments (%)	Number of Shares (%)
Message content				
Cancer-related	1514 (78.1%)	52,641 (96%)	3825 (94%)	15,767 (98.5%)
Non-Cancer-related	424 (21.9%)	2228 (4%)	256 (6%)	247 (1.5%)
Total	1938	54,869	4081	16,014
Message source				
American Cancer Society	121 (6.2%)	19,993 (36.4%)	1638 (40.1%)	5448 (34.0%)
Nonprofits (individuals and organizations)	1626 (83.9%)	3157 (5.8%)	1310 (32.1%)	482 (3.0%)
Businesses	191 (9.9%)	31,719 (57.8%)	1133 (27.8%)	10,084 (63.0%)
Total	1938	54,869	4081	16,014
Message features				
Text-based post	677 (34.9%)	3813 (6.9%)	1244 (30.5%)	311 (1.9%)
Post contains embedded images	244 (12.6%)	7197 (13.1%)	408 (10.0%)	2458 (15.4%)
Post contains hyperlinks to external content	845 (43.6%)	12,875 (23.5%)	1362 (33.4%)	2902 (18.1%)
Post contains videos	65 (3.4%)	536 (1.0%)	61 (1.5%)	154 (1.0%)
Post contains features from more than one category	107 (5.5%)	30,448 (55.5%)	1006 (24.7%)	10,189 (63.6%)
Total	1938	54,869	4081	16,014

4.1. Findings: message content

In order to test the first hypothesis (H1), independent samples Mann-Whitney U tests were conducted with message content as the independent variable and number of likes, comments, and shares as dependent variables respectively.

4.1.1. Message content and number of likes

A Mann-Whitney U test with message content as independent variable and number of likes as dependent variable indicated that posts coded as containing cancer-related messages (mean sample rank = 1022.69) received significantly more likes than posts coded as containing non-cancer-related messages (mean sample rank = 779.59), ($U = 240, 445.50$, $p < .001$).

4.1.2. Message content and number of comments

A Mann-Whitney U test with message content as independent variable and number of comments as dependent variable indicated that posts coded as containing cancer-related messages (mean sample rank = 1007.15) received significantly more comments than posts coded as containing non-cancer-related messages (mean sample rank = 835.07), ($U = 263, 969.00$, $p < .001$).

4.1.3. Message content and number of shares

A Mann-Whitney U test with message content as independent variable and number of shares as dependent variable indicated that posts coded as containing cancer-related messages (mean sample rank = 980.29) received significantly more shares than posts coded as containing non-cancer-related messages (mean sample rank = 930.98) ($U = 304, 634.50$, $p < .01$).

4.2. Findings: message source

To test the second hypothesis (H2), independent samples Kruskal-Wallis tests were conducted with message source as independent variable and number of likes, comments, and shares as dependent variables respectively. Each analysis was followed by pairwise comparisons with Bonferroni correction for multiple tests.

4.2.1. Message source and number of likes

A Kruskal-Wallis test with message source as independent variable and number of likes as the dependent variable indicated that there was a significant difference between different source categories [$\chi^2(2) = 354.95, p < .001$]. Pairwise comparison of categories showed that posts with ACS as the source (mean sample rank = 1813.81) received significantly more likes than posts with both nonprofits (mean sample rank = 911.50) and businesses (mean sample rank = 928.41) as the source ($p < .001$). The difference in number of likes between posts with nonprofits and businesses as source was not significant.

4.2.2. Message source and number of comments

A Kruskal-Wallis test with message source as the independent variable and number of comments as the dependent variable indicated a significant difference between different source categories [$\chi^2(2) = 358.67, p < .001$]. Pairwise comparison of categories showed that posts by ACS as the source (mean sample rank = 1733.74) received significantly more comments than posts with both nonprofits (mean sample rank = 926.34) and businesses (mean sample rank = 852.79) as source ($p < .001$). The difference in the number of comments between posts with nonprofits and businesses as source was not significant.

4.2.3. Message source and number of shares

A Kruskal-Wallis test with message source as the independent variable and the number of shares as the dependent variable indicated a significant difference between different source categories [$\chi^2(2) = 535.91, p < .001$]. Pairwise comparison of categories showed that posts by ACS as the source (mean sample rank = 1495.50) received significantly more shares than posts with both nonprofits (mean sample rank = 920.65) and businesses (mean sample rank = 1052.15) as source ($p < .001$). The difference in the number of shares between posts coded as nonprofits and businesses was also significant at the $p < .001$ level; posts with a business as source received more shares than posts from nonprofits.

4.3. Findings: relationships between message source, message relevance and user engagement

To investigate RQ1, all source categories except American Cancer Society were merged to create an "all others" category. After that posts were recoded into four categories based on the combination of message relevance category (Cancer-related, Non-cancer-related) and message source category (American Cancer Society, All others). Out of the total 1938 posts used for the analysis, the first category with cancer-related posts by American Cancer Society had 108 (5.5%) posts. The second category with Non-cancer-related posts by American Cancer Society had 13 (0.7%) posts. The third category with cancer-related posts by all others had 1406 (71%) posts, and the fourth category with non-cancer-related posts by all others had 411 (20.8%) posts. The second category had less than 1% of overall posts and indicates that it is very rare for American Cancer Society to post content that is not related to cancer. The researchers removed non-cancer-related posts by American Cancer Society from the dataset with the objective of reducing the number of pairwise comparisons during the analysis that may help limit type 1 error.

Independent samples Kruskal-Wallis tests were conducted with the combination of message source and message relevance as the independent variable where each category form a different level, and number of likes, comments, and shares as dependent variables respectively. Each analysis was followed by pairwise comparisons with Bonferroni correction for multiple tests.

4.3.1. Message source, message relevance and number of likes

A Kruskal-Wallis test with the above-mentioned combination variable as the independent variable and number of likes as the dependent variable indicated that there was a significant difference between different combinations of source and relevance categories [$\chi^2(2) = 374.322$, $p < .001$]. Pairwise comparison of categories showed that cancer-related posts with ACS as the source (mean sample rank = 1801.5) received significantly more likes than both cancer-related (mean sample rank = 962.16) and non-cancer-related (mean sample rank = 745.55) posts by all others. Among posts by all others, cancer-related posts received significantly more likes than non-cancer-related posts.

4.3.2. Message source, message relevance and number of comments

A Kruskal-Wallis test with the above-mentioned combination variable as independent variable and number of comments as the dependent variable indicated that there was a significant difference between different combinations of source and relevance categories [$\chi^2(2) = 349.005$, $p < .001$]. Pairwise comparison of categories showed that cancer-related posts with ACS as the source (mean sample rank = 1721.28) received significantly more comments than both cancer-related (mean sample rank = 950.92) and non-cancer-related (mean sample rank = 805.08) posts by all others. Among posts by all others, cancer-related posts received significantly more comments than non-cancer-related posts.

4.3.3. Message source, message relevance and number of shares

A Kruskal-Wallis test with the above-mentioned combination variable as independent variable and number of shares as the dependent variable indicated that there was a significant difference between different combinations of source and relevance categories [$\chi^2(2) = 465.817$, $p < .001$]. Pairwise comparison of categories showed that cancer-related posts with ACS as the source (mean sample rank = 1488.62) received significantly more shares than both cancer-related (mean sample rank = 937.95) and non-cancer-related (mean sample rank = 910.57) posts by all others. Among posts by all others, the difference in number of shares between cancer-related and non-cancer-related posts was not significant.

4.4. Findings: message features

To investigate RQ2, independent samples Kruskal-Wallis tests were conducted with message features as independent variable and number of likes, comments, and shares as dependent variables respectively. Post hoc analysis was conducted using stepwise stepdown multiple comparison tests to explore the differences between individual coding categories. Findings from the post hoc analyses were presented as homogeneous subsets. Categories for which the mean sample rank of dependent variables was not significantly different were placed in the same subset. Categories with significant differences in mean sample rank of dependent variables were placed in different subsets.

4.4.1. Message features and number of likes

A Kruskal-Wallis test with message features as the independent variable and the number of likes as the dependent variable indicated a significant difference between different message feature categories [$\chi^2(4) = 82.26$, $p < .001$]. Post hoc homogeneous subset analysis identified three homogeneous subsets (See Table 2).

Posts containing features from multiple categories and posts containing embedded images formed the third subset with the

Table 2
Message feature categories: homogeneous subsets based on number of likes.

	Subset*		
	1	2	3
Post contains video	766.54		
Post contains hyperlinks to external content	888.63		
Text based post		990.96	
Post contains embedded images			1154.63
Post contains features from more than one category			1173.46
Adjusted sig. (2-sided test)	.121	.**	.856

Each cell shows the mean sample rank of number of likes.
* Homogeneous subsets are based on asymptotic significances (p < .05).
** Statistic not available. Subset contains only one sample.

highest mean sample ranks of number of likes, followed by a second subset that contained only text-based posts. The first subset with the lowest mean sample ranks for number of likes included posts containing videos and hyperlinks to external content.

4.4.2. Message features and number of comments

A Kruskal-Wallis test with message features as the independent variable and number of comments as the dependent variable indicated a significant difference between different message feature categories [$\chi^2(4) = 80.59$, $p < .001$]. Post hoc homogeneous subset analysis identified two homogeneous subsets (See Table 3).

Text-based posts and posts containing features from multiple categories formed the second subset with the highest mean sample ranks of number of comments. Posts containing embedded images, posts containing videos, and posts containing hyperlinks to external content formed the first subset.

4.4.3. Message features and number of shares

A Kruskal-Wallis test with message features as the independent variable and number of shares as the dependent variable indicated a significant difference between different message feature categories [$\chi^2(4) = 144.50$, $p < .001$]. Post hoc homogeneous subset analysis identified four homogeneous subsets (See Table 4).

Posts with features from multiple categories formed the fourth subset with the highest mean sample rank for number of shares. The third subset contained posts with videos and posts with embedded images. The second subset contained posts containing video and hyperlinks to external content. Posts containing videos featured in both the second and third subsets because though there was no significant difference between posts containing videos, posts containing embedded images, posts containing videos, and posts containing hyperlinks, there was a significant difference between posts containing embedded images and posts containing hyperlinks to external content. The first subset with lowest mean sample rank for number of shares contained only text-based posts.

5. Discussion

This study proposed to investigate the relationship between message relevance, source characteristics, and message features of Facebook posts with number of likes, number of comments, and number of shares as social media user engagement variables. The first hypothesis proposed that cancer related posts will receive higher number of likes, comments, and shares than post that are not related to cancer and the second hypothesis proposed that posts with ACS as the source will receive more likes, comments, and shares than posts from other sources. Both the hypotheses were supported. Two research questions were proposed; first to explore the relationship between message relevance, source characteristics, and user engagement, and second to explore the relationship between message features and user engagement variables. In context of the first question, primary findings indicated that cancer-related posts

Table 3
Message feature categories: homogeneous subsets based on number of comments.

	Subset*	
	1	2
Post contains video	797.72	
Post contains hyperlinks to external content	898.57	
Post contains embedded images	904.19	
Post contains features from more than one category		1033.80
Text based post		1087.90
Adjusted sig. (2-sided test)	.259	.76

Each cell shows the mean sample rank of number of comments.
* Homogeneous subsets are based on asymptotic significances (p < .05).

Table 4
Message feature categories: homogeneous subsets based on number of shares.

	Subset*			
	1	2	3	4
Text based post	899.99			
Post contains hyperlinks to external content		968.23		
Post contains video		978.19	978.19	
Post contains embedded images			1075.38	
Post contains features from more than one category				1172.58
Adjusted sig. (2-sided test)	.**	.976	.151	.**

Each cell shows the mean sample rank of number of shares.

* Homogeneous subsets are based on asymptotic significances ($p < .05$).

** Statistic not available. Subset contains only one sample.

by ACS received the highest level of user engagement compared to both cancer-related and non-cancer-related posts by all others, and for all other sources except ACS, cancer-related posts generated higher level of user engagement in form of likes and comments than non-cancer-related posts. For the second research question, findings indicated that source categories had significant relationship with user engagement but the nature of these relationships was different for number of likes, comments, and shares. That indicates toward the difference in underlying motivations contributing to the three user engagement variables.

5.1. Message and source characteristics and user engagement

Cancer related posts received more likes, comments, and shares than posts not related to cancer. From the LC4MP perspective (Lang, 2006, 2009), this suggests that in the social media environment, since visiting a webpage is often an active behavior, the fit between the nature of webpage and content may act as a relevance cue and trigger motivational activation. In other words, if a user decides to visit the social media page of the ACS, it is likely that the user will find posts related to cancer more relevant than posts that are not cancer related.

Posts by ACS received more likes, comments, and shares than posts by business and nonprofit entities. From the LC4MP perspective (Lang, 2006, 2009), that suggests that in social media environments where the owner of the webpage might not be the only one presenting content, content posted by the owner may benefit potentially from a match between the users' motivation to visit a webpage and the perceived expertise of the owner in catering to these motivations. Also, source relevance may help in filtering out messages that are relevant and may help with navigating through the page.

Post hoc analysis showed that businesses received more shares than nonprofits but there was no significant difference between the two categories for number of likes and comments. Since sharing is driven to a large extent by promotion and self-presentation (Kim and Yang, 2017), that may indicate toward the difference in the persuasive effectiveness of posts by nonprofit and businesses. Businesses might be able to invest more resources in promoting themselves compared to nonprofit organizations and individuals, which may reflect in the number of shares.

For both message relevance and source characteristics, the direction of results was the same for all number of likes, comments, and shares. That indicates that the motivational activation created by these factors contributed toward preferential evaluation of relevant posts for different levels of behavioral involvement and communication (Kim and Yang, 2017; Kemp, 2016; Calero, 2013).

Findings from analysis exploring the relationship between message relevance and source type indicated that most content posted by ACS is cancer-related and ACS rarely posts non-cancer-related content. Cancer-related posts by ACS received higher user engagement across likes, comments and shares than both cancer-related and non-cancer-related posts by all others posting on the page.

For all sources others than the ACS, cancer-related posts received more likes and comments than non-cancer-related posts. However, there was no difference between cancer-related and non-cancer-related posts by all others in terms of shares received by the post. It suggests that though users may engage more with cancer-related posts than non-cancer-related posts in terms of likes and comments due to increased motivation for cancer-related posts driven by message relevance, the motivation may not be strong enough to create the difference in sharing behavior that is seen as the most complex and resource consuming behavior compared to likes and comments because it requires generation of content as well as taking ownership of post by publishing on the users' page (Kim and Yang, 2017; Kemp, 2016; Calero, 2013).

5.2. Message features and user engagement

Message features had a significant relationship with number of likes, comments, and shares. However, the nature of relationship and the role of different message features varied with each measure.

With likes as the user engagement measure, posts with features from multiple categories and those containing embedded images were most effective whereas posts with videos and posts with hyperlinks to external content were the least effective. For comments as the dependent measure, posts with features from multiple categories and text-based posts were the most effective compared to posts containing videos, posts containing hyperlinks, and posts containing embedded images. For shares as the dependent measure, posts with features from multiple categories were the most effective and text-based posts were the least effective.

Overall, those findings suggest that posts containing visual or multimedia content were most effective for likes and shares. However, for comments, text-based posts were more effective than posts containing images, hyperlinks, and videos. That pattern is similar to the pattern reported by Rus and Cameron (2016), who argued that the visual stimulus might be more conducive for non-semantic response categories, such as likes and shares. Similarly, text-based content may be effective eliciting comment responses.

Also, for all three measures, posts with more features from more than one category were the most effective. Though we did not identify individual feature categories while coding for the category with more than one feature, a post hoc analysis of posts coded as having features from more than one category showed that more than 95% of these posts consisted of text, imagery (video or image), and links to content inside or outside Facebook. That suggests that the visual component of the posts could have contributed to higher user engagement through likes and shares and the text component could have provided the semantic content that could have simulated user engagement through comments. Interactivity provided through links, especially to other pages on Facebook, could have exposed the posts to a user base which might find the post relevant, thus enhancing user engagement.

5.3. Limitations and future studies

One of the strengths of this and other similar studies is data that are based on user behavior in real message processing environments over a period of time. Findings from the study can be generalized to public Facebook pages of a wide range of organizations and entities that can be associated with a central theme and which attract organizations and individuals that may attempt to post messages to communicate with the audience for such sites. Some examples of such pages are Facebook pages of different chapters of American Cancer association, American Breast Cancer Associations, American Diabetes Association, St. Jude children's research hospital, Center for disease control etc.

However, as Strekalova and Krieger (2017) observe, there are also inherent limitations such as lack of ways to explicitly identify motivations underlying user behavior and inability to account for lurkers – users who are exposed to posts but do not respond. This study uses posts from 2012 to 2013 when Facebook provided only like, comments, and shares as modes of user response. In 2016, four new reactions were introduced with functionality similar to the 'like' button but providing a wider range of emotional responses (Gottke, 2016). Gottke (2016) reported that based on an analysis including posts from May and June 2016, of all the reactions (likes, love, haha, sad, angry, and wow) used on Facebook, likes still constituted more than 90% of the total reactions. It is also important to note Facebook relies on an ever-evolving algorithm that it vehemently protects (Oremus, 2016, Jan. 3) and is largely a mystery to those outside the company. It controls which posts are seen by a user based on indicated preferences, liked pages, posts with which a user interacts, and other online behaviors (Facebook, 2017). While this does present a small issue in terms of generalizability, in that its algorithm has changed many times since the data for this study was collected, it is likely that Facebook users seeking cancer-related information and social support now may see similar content at similar frequency intervals. In light of those developments, more studies need to be conducted to understand the nature of relationship between variable connected to relevance and message features and user engagement in the current social media environments. Future studies could also explore similar relationships on other social media such as Twitter or Instagram.

Conflict of interest

None.

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