Introduction

People are exposed to food safety risks daily (World Health Organization, 2016). The Centers for Disease Control and Prevention (CDC, 2018) estimates that each year one in six Americans, approximately 48 million people, get sick, 128,000 people are hospitalized, and 3,000 die of foodborne diseases. Despite the high impact of foodborne illnesses, engaging the public when reporting foodborne illness outbreaks and food recalls is challenging. Americans, particularly young people, have low awareness and knowledge of foodborne pathogens (e.g., E. coli, salmonella, norovirus) (Ferk et al., 2016; Green & Knechtges, 2015). Even among high-risk populations, such as pregnant women, consumption of unsafe foods is high (Xu et al., 2017).

The World Health Organization (2016) stressed the need to effectively communicate food risks to the public in order to inform and improve risk assessment, risk management, and food safety decisions. Effective communication requires understanding and addressing the target audience's information needs and concerns (Rutsaert et al., 2013). Traditionally, however, food safety risk information has not been communicated in ways that allow for understanding of the target audiences' concerns or interests. Instead, food safety risk messages are communicated in a top-down process where food safety risks are announced by government agencies (e.g., FDA) ostensibly to the public with limited opportunity for the message sender to assess the target audiences' response to the message (Vijaykumar et al., 2015). Griffin et al. (1999) indicated that "This top-down approach, no matter how well intentioned, runs counter to suggestions by many risk perception researchers that risk communication be used to facilitate a bottom-up process" (p. 230) , which means effective food safety risk communication must engage the public.

This study examines how risk communication messages might gain traction with the public during a food safety crisis. In particular, the current study investigates characteristics of food safety risk communication messages that enable the messages to go viral or spread on social media. According to the model of risk information seeking and processing, emotion influences the formation of risk judgments and information seeking and processing (Griffin et al., 1999). However, few studies have applied emotion analysis to investigate food safety risk communication. Guided by leading theories of emotions (Bradley & Lang, 1999, 2007; Plutchik, 1994), this study examines how the emotional content of food safety risk communication messages might predict the virality of the messages on popular social media platforms (e.g., Facebook, Twitter, Reddit, and Pinterest).

Crisis and Risk Communication

Crisis communication refers to communication to prevent or reduce the negative consequences of an unpredictable event that threatens stakeholder expectations (Coombs, 2015). This study is concerned with communication about a food safety crisis, specifically, the 2018 romaine lettuce recall, an unpredictable event that threatened consumers' expectations that the food they purchase is safe for consumption. While food recalls may certainly be considered crises (e.g., Charlebois et al., 2010; Liao et al., 2020), food recall communication also focuses on the warning the public of risks in consuming the contaminated product. Risk communication on the other hand refers to communication warning the public about the potential negative outcomes of engaging in certain behaviors. Thus, food recalls can be considered crises, but they also require risk communication to prevent further harm to consumers. Indeed, providing specific information about what people can do to reduce their risk and in turn boost their self-efficacy is a best practice in crisis communication (Seeger, 2006). Recognizing that risks and crises develop over time and effective communication is an "integrated and ongoing process," researchers have worked to merge the risk and crisis communication traditions into more comprehensive approaches (Seeger, 2006, p. 234). We approach this research from a risk communication perspective focused on reducing health harms while recognizing that this communication is taking place within a crisis context. Examining the risk communication that emerged from the media and consumers' responses during this specific crisis may allow risk communicators to better create messages that engage the media and consumers when the next food safety crisis occurs.

Food Recall and Media Messages

Media messages affect people's risk perceptions about food safety issues (Mou & Lin, 2014). A survey of 143 food safety experts in Ireland showed that 96% of them agreed that the public's awareness of food safety issues is driven by the media (De Boer et al., 2005). Indeed, exposure to food safety news in newspapers and television significantly increased participants' concerns about food safety (Fleming et al., 2006). Social media use by members of the public also significantly predicted their awareness and preventive actions regarding a series of food safety risks (Mou & Lin, 2014). Social media increases the public's ability to interact with food safety messages, thus changing the role of the public "from passive recipients of information, to more active players in the process" (Rutsaert et al., 2013, p. 87). Social media is therefore a particularly useful tool not only to distribute food safety messages but also to assess public response to specific message features. For example, Cui et al.'s (2019) study investigated how the diffusion of food safety messages affect audience's purchase intentions on social media. Chung et al. (2019) analyzed over 2.6 million tweets regarding a food poisoning case and how it affects audience's concerns about food safety.

Messages about food recalls as a result of foodborne illnesses are among the most common and important food safety risk communication messages. Seeger and Novak's (2010) integrated model of food recall describes four stages of food recall. Recognition, the first stage, occurs within organizations, institutions, or regulatory agencies such as the Food and Drug Administration and requires recognition and consensus regarding potential harm and identification of a specific product. Messaging, the second stage, describes the creation and distribution of recall messages by regulatory agencies, producers, and distributors to other companies along the supply chain in an attempt to recover affected products and to communicate to the consumer. The third stage, message processing/integration describes the audience's reception and understanding of recall messages. The model ends with the response stage when the audience takes action or fails to take action in response to the recall message, which is influenced by multiple factors, including the ease of the recommended action. This study is concerned with the transition between the second stage, messaging, and the third stage, message processing/integration. Specifically, this study investigates how message characteristics are linked with audience engagement metrics and suggests that the emotional tone of messages plays an important role in message virality.

Emotion and Virality

Emotional aspects of content affect information sharing behaviors (Hasell & Weeks, 2016; Stieglitz & Dang-Xuan, 2013; Wang et al., 2019). Emotions conveyed through text-based messages in social media, such as the text-based content analyzed for this study, may affect information sharing behavior (Stieglitz & Dang-Xuan, 2013). However, study findings have been inconsistent with regard to the relationship between emotion and virality. Stieglitz and Dang-Xuan (2013) found that messages conveying negative emotions are shared more than messages containing positive emotions but Ferrara and Yang (2015) found that messages conveying positive emotions received more "favorites." These conflicting findings may be due to a number of differences, including in the outcomes measured (e.g., number of retweets on Twitter v. number of favorites on Twitter) and context of the communication, including the topic of conversation (e.g., political communication v. unspecified content) and location of tweets (e.g., Germany v. all public tweets in English). Virality on social media has been defined as "computer-generated descriptive statistics displayed on a website to represent aggregated user interactions with content available online" (Kim, 2018, p. 154). For example, the "like", "share", and "comments" functions, are widely utilized on social media platforms by demonstrating the aggregate number of users' interactions with social media content (Alhabash & McAlister, 2015). These indicators demonstrate the extent to which consumers are responding to media messages.

Research on emotions has generally been guided by two theoretical perspectives (Nabi & Wirth, 2008). One perspective does not distinguish among specific emotions, instead categorizing all emotions along the dimensions of valence (positive to negative), arousal (high to low), and dominance (high to low) (Bradley & Lang, 1999, 2007). The other perspective categorizes emotions as discrete (e.g., fear, anger, happiness) and attempts to identify their antecedents and consequences (Mohammad & Turney, 2013). Barrett (1998) suggested that taking only one approach "may not accurately describe the subjective affective experience of all individuals" (p. 579). Supporting this contention, Barrett (1998) found that individuals in a high-arousal state were likely to report multiple discrete emotions at the same time. Hinojosa (2016) similarly proposed taking a combined approach in order to provide "a more comprehensive view of emotional effects on word processing" (p. 273). Thus, the current study examines the content of food recall messages using both the general and discrete emotion perspectives.

Valence, Arousal, and Dominance

In examining the relationships between emotion and online message virality, many studies have adopted an emotional valence framework (Berger & Milkman, 2013; Guerini & Staiano, 2015; Stieglitz & Dang-Xuan, 2013). Emotional valence is said to vary along a positive to negative continuum. Positive emotion is "the extent to which a person feels enthusiastic, excited, and inspired," while negative emotion, refers to "a variety of aversive mood states" (Watson et al., 1988, p. 1093). In general, online content that conveys positive or negative emotions is more viral than content that does not evoke emotion (Berger & Milkman, 2013; Stieglitz & Dang-Xuan, 2013). Furthermore, emotional valence drives content sharing. Eckler and Bolls (2011) found that positive emotional tone conveyed in commercial videos resulted in participants' greater intentions to forward the videos. Similarly, city government tweets that adopted a positive sentiment overall resulted in more citizen participation on social media

(Zavattaro et al., 2015). On the other hand, Ferrara and Yang (2015) found that messages with negative emotions were shared more than messages with positive emotions, though messages with positive emotions reached larger audiences and received more “favorites.” Again, there are several factors that may contribute to these conflicting findings, including differences in the outcomes measured, the communication context, and operationalization of emotion within each study. Further, these studies only provided evidence about the relationship between valence and information sharing in commercial or political contexts. In regard to health risks, Griffin et al. (1999) indicated that risk communication messages about a hazard designed to elicit negative valence motivate information seeking and processing about a risk and affect the public’s risk perception and preventive actions.

In addition to valence, emotions can be differentiated along arousal and dominance dimensions (Bradley & Lang, 1999, 2007). Barrett (1998) defines arousal as “a subjective state of feeling activated or deactivated” (p. 580). High arousal is triggered by activity, while low arousal is demonstrated by deactivation (Berger & Milkman, 2012). Past studies indicated that content that evokes high-arousal emotions is more likely to go viral (Nelson-Field et al., 2013; Stieglitz & Dang-Xuan, 2013). For example, when New York Times articles evoked high-arousal, people were more likely to share the article by email (Berger & Milkman, 2012). In another experimental study, Berger (2011) found that participants shown an article and a video that induced high arousal were more willing to share the content with other people compared to those participants who were induced to feel low arousal.

In practice, “many researchers do not pay attention to the influence of the dominance dimension” (Bakker et al., 2014, p. 412). However, Shaver et al. (1987) compared the valence-arousal-dominance model with the valence-arousal model by rating 135 different emotion terms and found that “the three-dimensional solution helps to differentiate between what the cluster analysis suggests are separate basic-emotion categories, and it is clearly more informative as a representation of emotion knowledge than the two-dimensional solution” (p. 1071). Dominance ranges from “control” to “in control” (Bradley & Lang, 1999, 2007). Dominance affects people’ perceptions and action taking tendency. Demaree et al. (2005) indicated that high dominance is associated with triggering people’s behavioral activation system (motivated to take action), but low dominance activates a person’s behavioral inhibition system (tend to avoid the situation). For example, people who see the word “confident” in a behavior change message may be more motivated to act based on the message compared with people who see the word “depressed” in a message. “Confidence” has high dominance and “depressed” has low dominance in Bradley and Lang’s Affective Norms for English Words (ANEW). High dominance is an essential factor that activates content sharing on social media (Jones et al., 2016). Similarly, Guerini and Staiano (2015) found that when news article content conveyed high dominance, people provided more comments and shared the articles more frequently on social media.

Discrete Emotions

Beyond the general emotional dimensions of valence, arousal, and dominance, emotions can be further distinguished based on their distinct antecedents and consequences. Eckman’s (1992) six basic emotions are frequently cited: happiness, sadness, disgust, fear, surprise, and anger (Mohammad & Turney, 2013). Plutchik’s (1980) the wheel of emotions model has two more basic emotions: anticipation and trust. Each emotion in this model acts as a discrete category instead of an individual emotional state. This study uses the wheel of emotions model because it includes trust, which has been widely investigated as it relates to food safety issues in media and information related studies (Lobb, 2005, p. 5). While trust in the context of food safety has been widely studied, most studies predominantly focus on how the public's perceived trust (Mou & Lin, 2014) or the use of a trusted information source (Liu et al., 2014) influences their response to food safety communication. This study aims to fill the gap of how the basic emotion trust plays a role in food safety risk communication messages on social media.

Other discrete emotions have also been linked with information sharing (see Table 1). Different discrete emotions may affect how people react to risk messages. Griffin et al. (1999) state that anger is associated with "an attempt by the person to reassert control over the risk" (p. 236) and fear is related to "the unknowability of outcome or consequences and a perceived loss of control" (p. 236). Thus, these emotions rouse the public to assess the health risk and take actions to prevent the risk (Griffin et al., 1999).

Table 1

The Names, Definitions, and Relevant Research Findings of Discrete Emotions

Discrete Emotions	Definitions	Relevant Research Findings
Anger	A feeling of annoyance, displeasure, or hostility	Messages conveying anger on social media spread more quickly and broadly than those conveying positive emotions (e.g., joy) (Fan et al., 2013)
Fear	An unpleasant feeling caused by the threat of danger, pain, or harm.	The doctors' blog post promoting colonoscopy that conveyed fear was positively associated with the number of times the post was shared through Facebook and Twitter (Lee-Won et al., 2017).
Anticipation	A feeling of excitement that something is going to happen	When the movie reviews conveyed anticipation, they were more likely to be shared on Twitter than those reviews that contained sadness, fear, surprise, anger, and disgust (Dilip et al., 2018).
Trust	A feeling of belief in the honesty or integrity of a person or thing.	When the movie reviews conveyed trust, they were more likely to be shared on Twitter than those that contained anticipation (Dilip et al., 2018).
Surprise	A feeling of mild astonishment or shock caused by something unexpected	When video ads that conveyed high levels of surprise increased a participant's motivation to share them (Knossenburg et al., 2016).
Sadness	A feeling of sorrow or unhappiness	The participants were less likely to share an advertising campaign when the news articles induced more sadness (Berger & Milkman, 2012).
Joy	A feeling of great pleasure and happiness	Participants were more likely to forward the video when it conveyed joy than when the videos contained anger, disgust, or a neutral emotion (Guadagno et al., 2013).
Disgust	A feeling of revulsion or strong disapproval aroused by something unpleasant or offensive	The videos that contained disgust were more likely to be shared than videos that conveyed anger or a neutral emotion (Guadagno et al., 2013).

Social Media Platforms

It is important to recognize that differences in communicative affordances among social media platforms, defined as “possibilities for action that emerge from […] given technological forms” likely influenced information sharing and interaction (Hutchby, 2001, p. 30). Such affordances include low-level affordances such as the technical features of social media platforms (e.g., “like” buttons, retweet function, upvotes), and high-level affordances that “reflect the complex co-evolution of users and environment” (Bucher & Helmond, 2017, p. 240). Hall and Zarro (2013) conducted a 2012 content analysis of Pinterest.com and found that repinning, where a user can “categorize an image onto one of their own boards,” was the most frequently observed user behavior (p. 1). Other Pinterest affordances include liking and commenting on others’ pins. They further described comments on pins as “plentiful” with comments generally of the following type: sharing opinion and judgment, engaging in dialog, sharing a personal history with the image, and providing additional narrative details (Hall & Zarro, 2013). Reddit users can similarly post links to content hosted on other websites but can also upload their own textual and visual content directly to Reddit (Singer et al., 2014). Other Reddit users, called “Redditors” can up- or down-vote content, creating an ever-changing user-generated list of most popular content (Singer et al., 2014). Users can also comment on submissions and create their own communities within Reddit called subreddits dedicated to specific topics and moderated by volunteers (Singer et al., 2014). Twitter is a micro-blogging platform that consists of many types of users: individuals, typically celebrities, with millions of followers; “semi-public” individuals (e.g., authors, bloggers, journalists); governments, corporations, and traditional media sources; and ordinary individuals who communicate primarily with their friends and acquaintances through Twitter (Kwak et al., 2010). Tweets (i.e., messages) are limited to 140 characters and can be organized via the use of hashtags (Pai & Alathur, 2018). Users receive the tweets of those they follow and can share those messages via retweeting (Liang et al., 2019). Most trending topics are “headline or persistent news” (Kwak et al., 2010, p. 600). Facebook is a social networking site where individuals who create accounts can create a profile page where they present themselves to others with a profile picture, basic information about themselves, and status updates that friends can like or comment on (Caers et al., 2013). On the Facebook homepage, users see a news feed consisting of status updates and other activities from their friends (Caers et al., 2013). Users must reach out and request to be “friends” with other users (Caers et al., 2013).

Emotions communicated in messages may predict virality differently depending upon the social media platform through which messages are shared. For example, when a political Twitter message exhibits stronger emotion, the message will be retweeted more often (Stieglitz & Dang-Xuan, 2013). However, it is unclear whether this result would occur on different social media platforms (e.g., Facebook, Reddit, Pinterest). Thus, we examine potential differences in the relationship between emotion conveyed in a message and virality across social media platforms (i.e., Facebook, Twitter, Reddit, and Pinterest). The current study examines these platforms because they are the most popular social media applications (Pew Research Center, 2019) in the U.S. with more than 365.98 million users in total using the four applications (Statista, 2019).

Purpose and Research Objectives

In the event of a food safety crisis, communicators must have evidence demonstrating how to effectively utilize social media to engage the rhetorical arena, including consumers and the media in information sharing. Research on emotions suggested that emotions conveyed through messages could influence people's information sharing behaviors (Stieglitz & Dang-Xuan, 2013). Characteristics that enhance responses and dissemination to media messages about crises may help the risk communicators more effectively formulate messages that will reach and engage their audience. Based on the information reviewed on emotion and virality, we put forth the following hypotheses and research questions.

H1: Arousal conveyed in a food safety message is positively associated with virality on social media.

H2: Dominance conveyed in a food safety message is positively associated with virality on social media.

RQ1: How does emotional valence conveyed in a food safety message predict message virality on social media?

RQ2: How do discrete emotions conveyed in a food safety message predict message virality on social media?

RQ3: How does the relationship between a message's emotional tone (e.g., emotional valence, arousal, dominance, and discrete emotions) and virality vary across social media platforms?

Methods

Emergency Food Safety Event

This study focuses on the 2018 romaine lettuce recall. On November 1, 2018, the FDA, CDC, state partners, and Canadian Officials began investigating an outbreak of E. coli O157:H7 infections in multiple U.S. states and Canadian provinces (FDA, 2019a). On November 20, 2018, the FDA issued a public health advisory informing the public that they were conducting a traceback investigation to identify the source of the romaine lettuce eaten by those who became sick with E. coli O157:H7, asking the industry to voluntarily withdraw products from the market and withhold distribution of romaine, and advising consumers to discard romaine (FDA, 2019b). On November 26, 2018, FDA tracebacks identified a California growing region where romaine lettuce contaminated with the outbreak strain likely originated and on December 13, 2018, the traceback narrowed in on three specific California counties (FDA, 2019b). On January 29, 2019, the CDC reported that the outbreak appeared to be over and that contaminated lettuce should no longer be available (CDC, 2019). The outbreak of E. coli O157:H7 linked to romaine lettuce grown in California in Fall 2018 caused a reported 62 illnesses and 25 hospitalizations across 17 states with the last illness onset on December 4, 2018.

Sample

The BuzzSumo was used to construct the sample on November 29, 2018. BuzzSumo is a social media analytic tool available through subscription that allows researchers to monitor topics of interest by pulling content related to the topic over a set period of time and engagement metrics for the content, including the number of shares, likes, and comments. BuzzSumo has been used for data collection in the field of public health and social media (Alsyouf et al., 2019; Obiała et al., 2020; Waszak et al., 2018). Searching the term "romaine lettuce" on BuzzSumo for the dates of October 30 to November 29, 2018 resulted in an initial sampling frame of 3,764 articles. The data were collected for 30 days following the initial warning because food recalls receive most media attention following the initial recall. Food recalls also typically do not remain in place for more than a few weeks (United States Department of Agriculture, 2021). The sample size was first determined using a "The 10% Condition" which suggests that a maximum sample size is usually around ten percent of the population if this sample is smaller than 1000 (Berry & Lindgren, 1990). Second, a power analysis was conducted to ensure that this sample size is suitable to detect an effect. Guadagno et al. conducted a similar study in 2013 and resulted in a large effect size in their study. The G-power 3.1 was used to estimate the sample size needed for linear multiple regression test. When the effect sized was estimated as (effect size $f^2 = 0.15$), power = 0.8, $\alpha = 0.05$ level), 98 articles would be needed to test R1 and H1-2 and 123 articles would be needed to test R2. Based on this, ten percent of the total articles (n = 377) were randomly selected from the sampling frame using a random number table. In total, 3% (n = 13) of articles were replaced by substituting another randomly selected article that met the criterion because these articles did not relate to the 2018 romaine lettuce recall or contained no text (e.g., video or pictures only).

In this study, virality was measured using the following indicators collected by BuzzSumo: Twitter shares[1], Pinterest shares[2], Reddit engagement (sum of upvotes and comments), Facebook engagements (sum of likes, shares, and comments), and total number of shares across the four social media platforms (Twitter, Pinterest, Reddit, and Facebook). The title and content of each article were machine coded. Several factors were statistically controlled in the current study, including the date each article was published, word count for each article, and the publishing source for each article.

Computerized Coding

Computerized coding for emotional valence was undertaken using ANEW, which was developed to "provide a set of normative emotional ratings for a large number of words in the English language" (Orăștean et al., 2021, p. 94). ANEW is founded on the premise that emotion is multidimensional and that variance in emotional assessments is largely accounted for by 1) affective valence, 2) arousal, and 3) dominance. ANEW contains words that were rated by people in terms of affective valence (ranging from positive to negative), arousal (ranging from excited to calm), and dominance (ranging from controlled to in-control). Each article received a score on affective valence, arousal, and dominance calculated by the cumulative scores of all words in the article based on the ANEW standardized list (Bradley & Lang, 1999, 2007) (See Table 2). Each word was scored on a 9-point range for valence, arousal, and dominance. Valence was scored on a scale of 0, very negative, to 9, very positive. Words that scored below 4.5 were coded as negative valence, all words scored 4.5 and above were coded as positive valence. For example, the word "infection" is scored 1.66, indicating negative valence whereas the word

[1] According to BuzzSumo, Twitter no longer provides data of numbers of comments and likes to a third party through its application programming interface (API).
https://blog.twitter.com/official/en_us/topics/product/2018/investing-in-the-best-twitter-experience-for-you.html

[2] According to BuzzSumo, Pinterest no longer provides data of numbers of comments and likes to a third party through its application programming interface (API).https://newsroom.pinterest.com/en/post/goodbye-like-button

"pleasure" scored 8.28, indicating positive valence. Arousal was scored on a scale of 0, not arousing, to 9, very arousing. For example, the word "relaxed" was scored 2.39, indicating low arousal whereas the word "danger" scored 7.31, indicating high arousal. Dominance was scored on a scale of 0, controlled, to 9, in control. For example, the word "failure" is scored 2.40, indicating low dominance whereas the word "confident" scored 7.20, indicating high dominance.

Table 2

Descriptive Statistics of Valence, Arousal, Dominance Using ANEW Across the Sampled Articles

Predictors	Range	M	SD	Skewness
Valence	542.64	102.96	75.29	1.67
Arousal	490.43	91.91	67.82	1.75
Dominance	496.28	92.08	67.78	1.74

Note. N = 377

Computerized coding for discrete emotions was undertaken using NRC Word-Emotion Association Lexicon, also called EmoLex (Mohammad & Turney, 2013) [3]. EmoLex is an English term-emotion association lexicon with a large lexicon size and richness in terms of the emotional dimensions used (Giatsoglou, 2017). EmoLex includes 14,182 words tagged via crowd-sourcing in a binary manner (0 = emotion not present; 1 = emotion present) with respect to the eight basic discrete emotions based on Plutchik' (1994) wheel of emotions model, such as happiness, sadness, disgust, fear, surprise, and anger, anticipation, and trust. First, all the words in each articles were imported to NRC emotion lexicon. Then NRC emotion lexicon calculated the scores of the word. For example, the word "infection" with scored 1 fear, "tension" with score 1 anger, "address" with score 1 anticipation, "contaminate" with score 1 disgust, "accomplish" with score 1 joy, "isolate" with score 1 sadness, "rapid" with score 1 surprise, and "real" with score 1 trust. Some words are associated with multiple emotions. For example, "dislike" is associated with anger and disgust. Thus, a sentence: "So we're able to actually get real-time information and conduct effective trace back and isolate what the source is" would score 2 in trust and 1 in sadness in the article[4]. In the analysis, the scores of discrete emotion for each article are based on the scores of words analyzed by EmoLex.

Table 3

Descriptive Statistics of Discrete Emotions Using EmoLex across the Sampled Articles

Predictors	Range	M	SD	Skewness
Anger	23	1.67	2.49	3.65
Fear	56	8.12	8.04	2.74
Anticipation	38	4.28	4.38	2.59
Trust	31	6.00	5.39	1.50
Surprise	6	0.67	0.97	1.80
Sadness	47	6.09	6.40	2.68
Joy	13	2.99	2.89	1.38
Disgust	42	5.45	5.28	2.69

[3] The NRC Emotion Intensity Lexicon. http://saifmohammad.com/WebPages/AffectIntensity.htm

[4] *Don't eat romaine lettuce, CDC urges amid E. coli concerns* (2018, November 21). CNN. Retrieved from https://www.cnn.com/2018/11/20/health/romaine-lettuce-e-coli-cdc/index.html

Note. N = 377

Data Analysis

To address research question 1 and hypotheses 1 and 2 concerning the association between emotional valence, arousal, and dominance conveyed in a food safety message and social media virality, five hierarchical multiple regression analyses were conducted. All five regression models had the same 2-block structure. The first block contained control variables as the predictors, including the publication date[5], the number of words, and the source for each article[6]. The second block included valence, arousal, and dominance. Total number of shares, Twitter shares, Pinterest shares, Facebook engagement, and Reddit engagement were the dependent variables (See Table 4).

Table 4

Descriptive Statistics of Engagement Metrics across the Sampled articles

Predictors	Range	M	SD	Skewness
Total shares	213,033	2,023.89	16,013.07	11.98
Facebook engagement	202,378	1,863.46	14,209.27	11.84
Twitter shares	27,662	95.32	1,432.85	19.06
Pinterest shares	12	0.10	0.84	12.24
Reddit engagement	22,899	65.01	1,180.36	19.36

Note. N = 377

Research question 2, concerning how discrete emotions in a food safety risk communication message are associated with virality on social media, was tested in the same way using five hierarchical multiple regression analyses. All five regression models had the same 2-block structure. The first block contained control variables as the predictors, including the publication date, the number of words, and the source for each article. The second block included anger, fear, sadness, joy, disgust, surprise, anticipation, and trust. Total number of shares, Twitter shares, Pinterest shares, Facebook engagement, and Reddit engagement were the dependent variables.

Results and Discussion

Valence, Arousal, and Dominance

RQ1 and hypotheses 1-2 examined the association between valence, arousal, and dominance in message content and message virality on social media. Results of the regression analyses are summarized in Table 5.

[5] Publication date is coded in terms of proximity to the first article published in the sample.

[6] The source for each article was manually code as 0 = non-national sources, 1 = national sources. National sources refer to the article source has a wide circulation and are most likely to cover stories and issues from across the U.S., and around the world (e.g., CDC, CNN).

Table 5

Valence, Arousal, and Dominance Predicting Virality on Social Media

	Total Shares			Facebook Engagement			Twitter Shares			Reddit Engagement			Pinterest Shares		
Predictors	*β*	*B*	*SE (B)*	*β*	*B*	*SE (B)*	*β*	*B*	*SE (B)*	*β*	*B*	*SE (B)*	*β*	*B*	*SE (B)*
Valence	-1.83	-392.41	240.49	-1.30	-247.33	214.05	-4.10**	-78.55**	22.42	-3.57***	-66.51***	18.62	-1.69	-0.02	.01
Arousal	0.05	12.73	1208.99	0.59	124.93	186.02	-2.83*	-60.08*	19.49	-3.22**	-52.13**	16.18	0.17	0.00	.01
Dominance	2.05	486.96	450.82	0.95	199.98	401.36	7.28***	154.79***	42.04	3.79***	132.17***	34.91	1.79***	0.02***	.02
Date	0.01	31.28	280.85	0.00	14.00	249.98	0.02	1557.23	328.19	0.02	8.24	21.74	0.01	0.00	.02
Words	-0.07	-4.12	3.06	-0.06	-2.73	2.73	-0.15**	9.04**	26.19	-0.16**	-0.65**	.24	-0.06	0.00	.00
Source	0.40***	30990.11***	6194.34	0.41***	28309.97***	3133.05	0.23***	-555.36***	577.54	0.20***	1121.49***	272.48	0.35	1.42	.19
R^2	0.256			0.251			0.192			0.179			0.213		

Note: $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$

Control Variables

Article source had a significant positive relationship with total shares (β = .40, $p < .001$), Facebook engagement (β = .41, $p < .001$), Twitter shares (β = .23, $p < .001$), Reddit engagement (β = .20, $p < .001$), and Pinterest shares (β = .35, $p < .001$), after controlling for other variables. In other words, articles published by national sources were more frequently shared and engaged with across all platforms than those published by non-national sources. The number of words in each article was significantly negatively associated with Twitter shares (β = -.15, $p = .01$) and Reddit engagement (β = -.16, $p = .007$), after controlling for other variables. Number of words in the article was not significantly associated with Facebook engagement, Pinterest shares, or total shares. Date of article publication was not significantly associated with Twitter shares, Pinterest shares, Facebook engagement, Reddit engagement, or total shares.

Valence

Articles were first examined for emotional valence ranging from negative to positive. Valence was significantly negatively associated with Twitter shares (β = -4.10, $p = .001$) and Reddit engagement (β = -4.21, $p < .001$), after controlling for other variables. Valence was not significantly associated with Pinterest shares, Facebook engagement, or total shares. The findings are consistent with previous studies where messages containing negative emotional tone were shared more compared with messages containing positive emotional tone on Twitter (Ferrara & Yang, 2015; Guerini & Staiano, 2015). The two articles[7] that conveyed the most negative emotional tone discussed E. coli infection linked to romaine lettuce and people's illness. Multiple health risk-related words repeatedly appeared in the two articles, such as "infection," "sick," and "contamination."

Emotions provoked by food safety messages could drive individuals to assess risks and subsequently influence their action tendencies (Watson & Spence, 2007). Specifically, negative emotions could motivate people to take preventive actions (Mou & Lin, 2014). The two articles conveying the most negative valence also provided advice about how to prevent E. coli infection and the symptoms of E. coli infection. On the other hand, the most positively valenced article[8] focused on government agencies (e.g., FDA) and retailers (e.g., Walmart) planning to design programs (e.g., a new food safety program) to deal with the romaine lettuce crisis. One possible explanation linking negative valence and virality is that negative emotions are associated with anxiety, which is related to perceived issue importance (Stieglitz & Dang-Xuan, 2013). Thus, articles with a negative valence may increase perceived issue importance among readers, ultimately motivating readers to assess the risk and share the article as a form of preventive action. These findings continue previous literature (e.g., Ferrara & Yang, 2015) by suggesting that negative emotions conveyed in messages are likely to trigger virality.

Arousal

Arousal was significantly negatively associated with Twitter shares (β = -2.83, $p = .002$) and Reddit engagements (β = -3.0, p . < 001), after controlling for other variables. Arousal was not significantly associated with Pinterest shares, Facebook engagement, or total shares. This finding contrasts with prior work that found content that evokes high arousal emotions induced

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[7] *Public Health Notice: Outbreak of E. coli infections linked to romaine lettuce.* (2018, November 20). Restobiz. Retrieved from https://www.restobiz.ca/public-health-notice-outbreak-e-coli-infections-linked-romaine-lettuce
Centers for Disease Control and Prevention. (2018, November 20). *Outbreak of E. coli infections linked to romaine lettuce.* Retrieved from https://www.cdc.gov/ecoli/2018/o157h7-11-18/index.html

[8] *Consumers warned not to eat romaine lettuce.* (2018, November 21). Supermarket News. Retrieved from https://www.supermarketnews.com/food-safety/consumers-warned-not-eat-romaine-lettuce

greater virality (Berger & Milkman, 2012). However, their study tested specific emotions representative of high/low arousal emotions rather than arousal as a dimension (Berger & Milkman, 2012). Additionally, other research points to the possibility that low arousal articles induce feelings of calm and perceived utility of the article, ultimately influencing audience engagement with the message (Rodas & Ahluwalia, 2017). Rodas and Ahluwalia (2017) found that low arousal emotions are likely to slow down the speed of people's thoughts and broaden their focus of attention. Indeed, previous research suggests that too much arousal in a review decreased perceived review helpfulness (Yin et al., 2017). Hypothesis 1 is not supported.

Dominance

Dominance had a significant positive relationship with Twitter shares ($\beta = 7.28$, $p < .001$) and Reddit engagements ($\beta = 7.54$, $p < .001$), after controlling for other variables. Dominance was not significantly associated with Facebook engagement, Pinterest shares, or total shares. In linguistic studies, messages that convey high dominance typically include lower uncertainty language (Zhou et al., 2014). Thus, articles that convey high dominance may reduce audience uncertainty. According to uncertainty reduction theory, people are not comfortable with uncertain feelings, thus they have a tendency to avoid or reduce uncertainty (Berger & Calabrese, 1974). The desire to avoid uncertainty may influence sharing behaviors. Indeed, a disaster tweet containing more uncertain information resulted in a lower retweet count (Son et al., 2019). This may result in risk message virality on Twitter, Reddit, and Pinterest when low arousal and high dominance contents are presented in the messages.

Discrete Emotions

RQ2 examined the association between the presence of discrete emotions in message content and message virality on social media. Results of the regression analyses are summarized in Table 6.

Table 6

Discrete Emotions Predicting Virality on Social Media

	Total Shares			Facebook Engagement			Twitter Shares			Reddit Engagement			Pinterest Shares		
Predictors	*β*	*B*	*SE (B)*	*β*	*B*	*SE (B)*	*β*	*B*	*SE (B)*	*β*	*B*	*SE (B)*	*β*	*B*	*SE (B)*
Anger	0.17*	1,115.73*	555.10	0.10	573.49	495.92	0.51***	292.15***	49.83	0.53***	250.06***	41.22	0.10	0.04	.03
Fear	-0.48**	-959.82**	348.67	-0.46**	-808.98**	311.50	-0.47**	-84.02**	31.30	-0.46**	-66.78**	25.89	-0.45*	-0.05*	.02
Anticipation	0.02	58.38	328.99	-0.01	-15.83	293.92	0.12	39.25	29.53	0.13	34.97	24.43	-0.01	0.00	.02
Trust	0.02	43.98	258.90	0.02	58.33	231.30	-0.03	-7.58	23.24	-0.03	-6.78	19.23	0.02	0.00	.01
Surprise	-0.01	-232.28	856.97	0.00	-33.26	765.62	-0.07	-107.39	76.932	-0.07	-91.63	63.64	0.00	0.00	.05
Sadness	0.77***	1,931.75***	466.84	0.82***	1,836.42***	417.07	0.26	58.46	41.91	0.20	36.76	34.67	0.88***	0.12***	.03
Joy	0.02	113.84	458.70	0.02	114.97	409.80	0.00	0.30	41.18	0.00	-1.45	34.06	0.03	0.01	.03
Disgust	-0.15	-449.38	393.30	-0.20	-539.47	351.38	0.17	45.70	35.31	0.20	44.43	29.21	-0.23	-0.04	.02
Date	-0.05	-261.65	294.37	-0.04	-197.62	262.99	-0.07	-34.90	26.43	-0.07	-29.13	21.86	-0.03	-0.01	.02
Words	-0.09	-5.11	3.09	-0.07	-3.35	2.760	-0.19**	-0.95**	0.28	-0.07***	-0.82***	21.86	-0.07	0.00	.00
Source	0.38***	29,341.87***	3,491.91	0.39***	26,818.21***	3,119.66	0.21***	1,468.47***	313.48	0.19***	1,053.85***	259.3	0.33***	1.33***	.19
R^2	0.283			0.273			0.278			0.272			0.242		

Note: $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$

Control Variables

Article source had a significant positive relationship with total shares (β = .38, $p < .001$), Facebook engagement (β = .39, $p < .001$), Twitter shares (β = .21, $p < .001$), Reddit engagement (β = .19, $p < .001$), and Pinterest shares (β = .33, $p < .001$), after controlling for other variables. The number of words in each article had a significant negative relationship with Twitter (β = -.19, $p = .001$) and Reddit engagement (β = -.20, $p < .001$), while it was not significantly associated with Facebook engagement, Pinterest shares, or total shares, after controlling for other variables. Date of article publication was not significantly associated with Twitter shares, Pinterest shares, Facebook engagement, Reddit engagement, or total shares.

Anger

Anger was significantly positively associated with total shares (β = .17, $p = .04$), Twitter shares (β = .51, $p < .001$), and Reddit engagement (β = .53, $p < .001$). However, anger was not significantly associated with Facebook engagement or Pinterest shares, after controlling for other variables. Anger has significantly predicted the virality of content on Twitter (Hansen, et al., 2011; Heimbach et al., 2015). Twitter is a microblogging site where is no need for approval to follow others or require any identity information. Jaidka et al. (2018) found that compared with Facebook, the social connections on Twitter have been found to comprise more strangers and people are more open to discussing negative emotions on Twitter. Leopold (2013) proffered that Twitter has become a place filled with online anger because Twitter users are anonymous and thus perceive fewer consequences. Similar to Twitter, Reddit is also anonymous. According to the social identity model of deindividuation effects (Lea & Spears, 1991), anonymity results in people identifying as group members rather than individuals and thus rely on group norms to guide their behavior. Thus, "If the aggression is met with approval by other users, it can escalate and elicit an 'online firestorm,' which is described as a wave of negative and angry online comments in social media" (Pfeffer, et al., 2013, as cited in p.1, Rösner & KrämerIf, 2016). Conveying anger in content may make an article more likely to be shared on relatively anonymous platforms because of deindividuation effects. However, the studies indicated that users' "overly emotional" expressions (e.g., anger and aggression) on Facebook are considered norms and positive self-image violations (Waterloo et al. 2018).

Fear

Fear was significantly negatively associated with total shares (β = -.48, $p = .006$), Facebook engagement (β = -.46, $p = .01$), Twitter shares (β = -.47, $p = .008$), Reddit engagement (β = -.46, $p = .01$), and Pinterest shares (β = -.45, $p = .01$), after controlling for other variables. Fear is characterized as "a motivational state aroused by specific stimuli that give rise to defensive behavior or escape" (Steimer, 2002, p. 233). Fear is an avoidance emotion, thus fearful individuals tend to avoid risks (Lerner & Keltner, 2001). Articles about the romaine lettuce risk that conveyed fear may activate the avoidance mechanism associated with fear and reduce article sharing behavior on social media. This finding is consistent with Jin et al.'s study (2007). They also explained this effect may be due to audience's coping strategy when they feel uncertain, so they would choose avoidance in order to "escape" from the crisis.

Sadness

Sadness was significantly positively associated with total shares (β = .77, p < .001), Facebook engagement (β = .82, p < .001), and Pinterest shares (β = .88, p < .001). Sadness was not significantly associated with Twitter shares or Reddit engagement, after controlling for other variables. This finding is contrary to Berger and Milkman's (2012) study where people were less likely to share an advertising campaign when it induced more sadness.

These discrepant findings may be explained by the context of the messages. Nabi (1999) stated that sadness can “motivate problem-solving activity by forcing people to focus inward, looking for possible solutions, and/or help from others” (p. 298). When individuals experience sadness, they want to comfort themselves or recover from this negative feeling (Roseman et al., 1994). This desire to look for possible solutions to recover from sadness may motivate people to take action to change their situation. Facebook friends are usually existing friends, family, and acquaintances from users’ real lives, so the users tend to have a high need for belonging and social support for their emotions (Jaidka et al., 2018). Thus, sharing contents conveying sadness may help with Facebook users to recover from their negative feeling by receiving support and belonging from their existing social network. Liking and sharing sad messages that communicate a risk may also stem from people’s attempts to be socially responsible. Liking and sharing sad messages (e.g., earthquakes, war, and famine) on Facebook is based on people’s social responsibility motivations and a desire to “use the like button to express sympathy or solidarity with the cause” (Brandtzaeg & Haugstveit, 2014, p. 274). Several articles[9] with high level of sadness mentioned the symptoms of E. coli infection and the number of people being hospitalized. People might share these messages to perform social responsibility. Whether to recover from sadness or be socially responsible, articles about a food recall risk conveying sadness went viral on Facebook and Pinterest.

Positive discrete emotions (joy, surprise, anticipation, trust) and disgust were not significantly associated with total shares, Twitter shares, Pinterest shares, Reddit engagement, or Facebook engagement, after controlling for other variables. This may be due to a desire to see one’s feelings about a risk mirrored in messages conveying information about the risk. Individuals’ anger, fear, and sadness emotions can be triggered during a crisis (Jin et al., 2007). Compared with positive discrete emotions, negative discrete emotions, such as anger, fear, and sadness are highly relevant to the food crisis context (Mou & Lin, 2014). Although anger, fear and sadness are all negative emotions, they showed different associations with message virality. Anger and sadness resulted in greater social media engagements, whereas fear resulted in fewer social media engagements. These findings suggested that a combined perspective of the emotional dimension approach and the discrete emotion approach is needed to fully understand impact of emotional tones on message virality.

The four platforms differ in terms of user demographics, which might explain why valence, arousal, and dominance predict virality on Twitter and Reddit but not on Facebook. According to a report by the Pew Research Center (Shearer & Matsa, 2018), Facebook is dominated by female users (61% female; 39% male), yet Reddit (28% female; 72% male) and Twitter (49% female; 51% male) have more male users than female users. Previous studies found that males were more active in sharing news (Reis et al., 2017) and their sharing behaviors are more influenced by emotions compared to females (Wang et al., 2017). Moreover, Reddit users and Twitter users report a higher educational level than Facebook users: on Reddit, 46% users had a college degree, 17% users had a high school or less degree; on Twitter, 41% users had a college degree, 24% users had a high school or less degree; on Facebook, 31% users had a college degree; on Facebook, 35% users had a high school or less degree (Shearer & Matsa, 2018). People with higher education were found to have more perceived news literacy skills (Ameen & Naeem, 2020) and food safety knowledge (Albrecht, 1995). In the political context,

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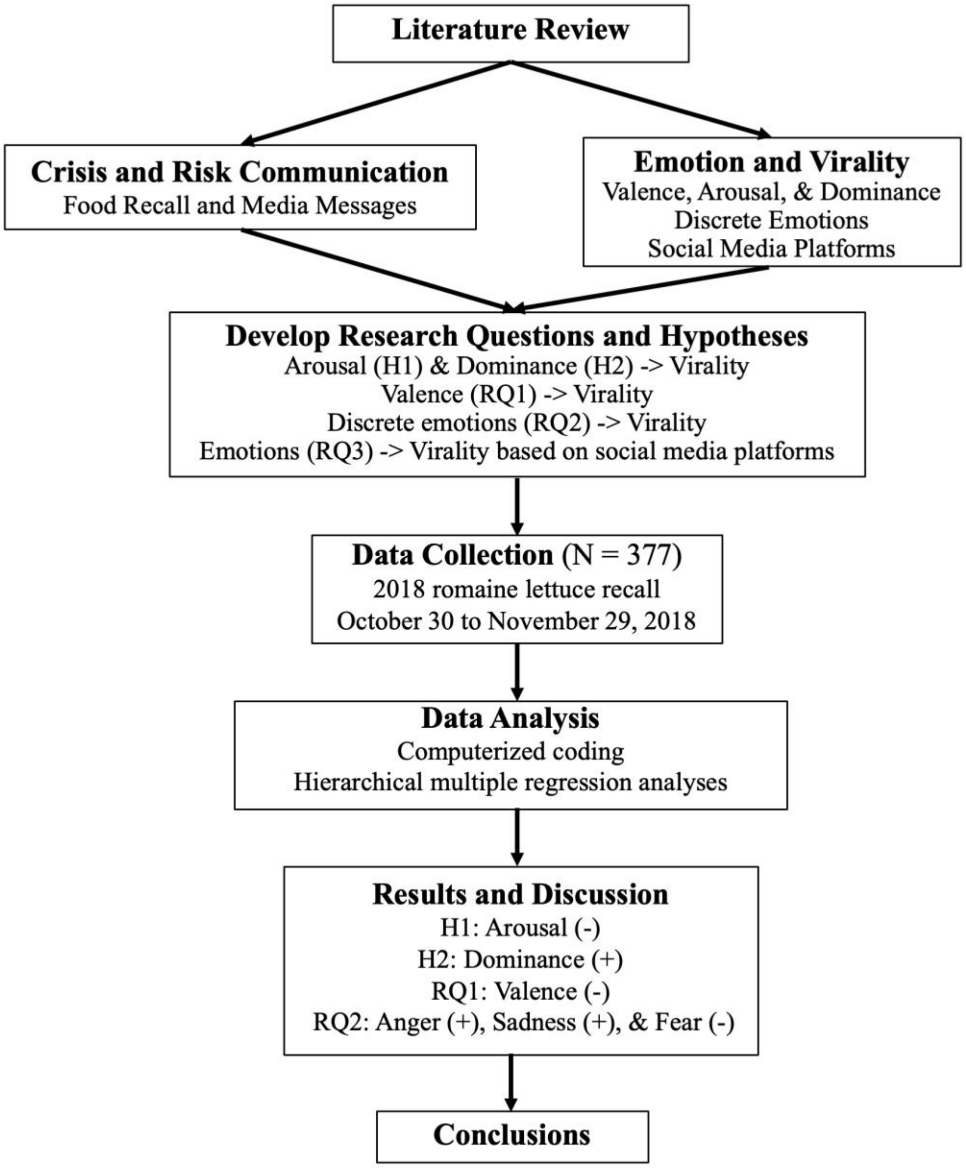
[9] *Don't eat romaine lettuce, CDC urges amid E. coli concerns. (2018, November 20).* Island News. Retrieved from https://www.kitv.com/story/39516325/dont-eat-romaine-lettuce-cdc-urges-amid-e-coli-concerns

studies found that people with more political knowledge are more likely to share online news (Beam et al., 2016). Therefore, the impact of emotional tones on virality might be stronger for platforms such as Twitter and Reddit, which have more male users and well-educated users. The association of word count with virality also varied by social media platform: word count was significantly negatively associated with shares on Twitter and Reddit engagement but not significantly associated with Facebook engagement or Pinterest shares. This may be due to differences in the word limit imposed by Twitter (140 characters) though why word count is negatively associated with Reddit engagement is less clear.

Conclusions

Foodborne safety risks impact millions every year (CDC, 2018) yet engaging the public about food safety risks is challenging. Food safety risks are communicated by government agencies in a top down approach that provides little opportunity for audience response to messages (Vijaykumar et al., 2015). To provide insight into audience response to risk message characteristics, this study examined articles covering the 2018 romaine lettuce E. coli outbreak for emotional valence, dominance, arousal, and the presence of discrete emotions using machine coding (see *Figure 1* Research Process Diagram). These message characteristics were connected with sharing, commenting, and liking on social media platforms Facebook, Twitter, Pinterest, and Reddit. This approach allowed us to link messaging about food safety risks with audience response in order to determine what message characteristics are associated with risk message virality. Based on the findings, there are several recommendations. The results from RQ1, H1, and H2 indicate that content be negatively valenced to increase message virality on Twitter and Reddit. Less arousal may be helpful to increase article shares on Twitter and engagement (i.e., comments and upvotes) on Reddit. On the basis of evidence presented, in order to support risk message virality on Twitter, Reddit, and Pinterest, communicators create low arousal and high dominance content. The RQ2 findings show that conveying anger in the message may increase shares on Twitter and engagement on Reddit. Moreover, articles that contained more words associated with fear were less frequently shared and engaged with on all social media platforms than content that conveyed less fear. Creating sad messages about a risk is a useful message strategy to increase virality on Facebook and Pinterest. Articles about food safety risk should convey less fear in order to avoid decreasing message virality. The findings also indicate that the associations between message content and message virality could differ across different platforms (e.g., Stieglitz & Dang-Xuan, 2013). These differences should be explored in future research by examining user demographics, social media preferences, media affordances, emotional responses and the effectiveness of various risk communication and safety messages.

Figure 1
A Research Process Diagram



Note. The symbol "-" indicates a negative relationship with virality. The symbol "+" indicates a positive relationship with virality.

Theoretically, this study is among the first to integrate different approaches of emotion analysis in the context of risk communication via four social media platforms. Specifically, the general and discrete emotion frameworks analyzed in this paper extends current theorizing in the area of food safety by recognizing the importance of a range of emotions (valence, arousal, dominance, anger, sadness, and fear) that conveyed in the messages, linking the effects of emotion to message virality, and considering how this process may apply to understanding how message characteristics are linked with audience engagement metrics on four popular social media platforms (Twitter, Facebook, Pinterest, and Reddit). In sum, it attempts to build the bridge between different approaches of emotion analysis and food safety risk communication, providing a way of understanding how to use emotion in a risk communication message can aid in creating content that increases the likelihood of viral success on social media.

There are also some practical implications. Recent research found that social media carries more weight in managing food recall than was originally believed (Jinho et al., 2021).

This is a call for government officials, businesses, and product producers to pay closely attention on how food recall messages delivered through social media to engage the public. There is also a need for health official, government, and public health organizations to develop guidelines for using social media to communicate risk and food safety effectively. This study suggests that the emotional tone of risk communication messages may be altered to engage members of the public via liking, sharing, and commenting on social media when reporting foodborne illness outbreaks. The findings contribute to provide an understanding for health officials, government, and business agencies to better construct food recall messages to engage the public through social media. A better understanding of these relationships also sheds a light on designing relevant risk communication messages that increase safety awareness and convey consequences to increase public safety.

Limitations and Future Research

Limitations of this study should be acknowledged. First, this research design was correlational, not experimental, and so claims of causality cannot be made. Second, valence, dominance, arousal, and discrete emotions were assessed as characteristics of article content using machine learning programs. The presence of these predictors was not based on the emotions of message recipients, there are likely differences between the emotion expressed in the content and the emotion experienced by a person reading the content, especially because terms were rated in isolation without context (Mohammad & Turney, 2013). Next, this study assessed articles written about one food safety risk (i.e., E. coli linked to romaine lettuce) in a relatively short period of time. Most people do receive information about food risks and recalls from the media (de Boer et al., 2005; Fleming et al., 2006), but relying on the media to disseminate information about food safety risks is problematic because the media do not report on every food safety risk or recall. Future research should examine characteristics of food safety risk messages created by government agencies and connect those message characteristics to measures of virality. The results may be affected by the different characteristics of social media platforms. For example, Pinterest has less shares compared to other social media platforms in this study. It may be because users may be less likely to share real-time news on Pinterest than other social media platforms. Researchers should be cautious when investigate cross social media platform effects on users' information sharing behavior. Future research should also examine different foods recalled (e.g., processed foods) and causes of recall (e.g., mislabeling, contamination, causing a foodborne illness outbreak), as well as different recall time periods. The recall examined in this study occurred over the Thanksgiving holiday in the US, a fact that was often noted in the articles assessed and that may have contributed to the extensive media coverage of the recall and engagement with messages about the recall. Also, there are many factors in a food recall message could potentially affect people's information sharing behavior. The current study only focuses on analyzing text-based message, future study could also consider the effects of images on virality on social media. Finally, message sharing, liking, and commenting do not necessarily translate into protective action taking (NRC, 2013). Nor are emotions the sole factors that influence virality. Future research should examine not only audience engagement with food safety risk messages but also whether engagement results in behavior change such as reduced consumption of the recalled food product.

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