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# Rethinking Social Amplification of Risk: Social Media and Zika in Three Languages

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Using the Zika outbreak as a context of inquiry, this study examines how assigning blame on social media relates to the social amplification of risk framework (SARF). Past research has discussed the relationship between the SARF and traditional mass media, but the role of social media platforms in amplification or attenuation of risk perceptions remains understudied. Moreover, the communication and perceptions of Zika-related risk are not limited to discussions in English. To capture conversations in languages spoken by affected countries, this study combines data in English, Spanish, and Portuguese. To better understand the assignment of blame and perceptions of risk in new media environments, we looked at three different facets of conversations surrounding Zika on Facebook and Twitter: the prominence of blame in each language, how specific groups were discussed throughout the Zika outbreak, and the sentiment expressed about genetically engineered (GE) mosquitoes. We combined machine learning with human coding to analyze public discourse in all three languages. We found differences between languages and platforms in the amount of blame assigned to different groups. We also found more negative sentiments expressed about GE mosquitoes on Facebook than on Twitter. These meaningful differences only emerge from analyses across the three different languages and platforms, pointing to the importance of multilingual approaches for risk communication research. Specific recommendations for outbreak and risk communication practitioners are also discussed.

**KEY WORDS:** Blame; GE mosquitoes; SARF

## 1. INTRODUCTION

The first Brazilian cases of the Zika virus were confirmed in the spring of 2015, but did not generate concern until the number of Zika infections dramatically increased early in 2016 (World Health Organization, 2016). The growing number of cases in Brazil was soon coupled with an unusual increase of microcephaly and central nervous system (CNS) malformation among the newborns of Zika-infected mothers. By February 2016, the World Health Organization (WHO) reported the link between neurological problems, like microcephaly, and the Zika virus was "strongly suspected, though not yet scientifically proven" (Chan, 2016), but the link was not officially confirmed until April 2016 (Centers for Disease Control and Prevention, 2016). The speculations and eventual confirmation caused concern for travelers and those living in regions with Zika infections, especially in Brazil where over 11,000 pregnant

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women had confirmed cases of the Zika virus from January 2016 to January 2017 (World Health Organization, 2016). Since the initial outbreak, 84 countries and territories, including almost every country in the Americas, have reported mosquito-borne transmissions of the Zika virus (World Health Organization, 2017b). In the Americas alone, there were 211,500 confirmed cases and 563,168 suspected cases of the Zika virus between 2015 and 2017 (Pan American Health Organization, 2017).

To better understand public health emergencies like the Zika virus, past research has applied the social amplification of risk framework (SARF) (R. E. Kasperson & J. X. Kasperson, 1996; R. E. Kasperson et al., 1988; Renn, Burns, Kasperson, Kasperson, & Slovic, 1992) to various outbreaks (e.g., Busby & Duckett, 2012; Raupp, 2014; Rossmann, Meyer, & Schulz, 2017), diseases (e.g., Rickard, McComas, Clarke, Stedman, & Decker, 2013; Strekalova, 2016; Strekalova & Krieger, 2017), and health-related topics (e.g., Barnett & Breakwell, 2003; Chong & Choy, 2018; Petts & Niemeyer, 2004). The SARF was developed to explain why certain risks experts characterize as small "produce massive public reactions" (R. E. Kasperson et al., 1988, p. 178). The initial conceptualization positioned that several psychological, social, and cultural factors amplify, or attenuate, public risk perceptions, and these impacts can go beyond the initial risk or event of concern (R. E. Kasperson et al., 1988). The spreading of amplified risk perceptions can then have secondary and tertiary impacts, especially when public contention and concern are high (R. E. Kasperson & J. X. Kasperson, 1996).

The SARF has been especially helpful in examining different aspects of risk-related mass media environments (Binder, Cacciatore, Scheufele, & Brossard, 2014), such as volumes of coverage over time (Frewer, Miles, & Marsh, 2002; Petts et al., 2000), differences between publication types (Rossmann et al., 2017), and audience perceptions (Frewer et al., 2002). However, the SARF was formulated 30 years ago, long before the advent of the online media environment we know today, and, as a result, has been largely studied within traditional mass media. More recently, scholars have begun to consider online media (e.g., Chung, 2011; Guo & Li, 2018) and social media (e.g., Fellenor et al., 2017; Strekalova & Krieger, 2017) within the framework. This study uses the recent outbreak of the Zika virus as a case study to expand our understanding of the SARF within online social media environments. These communication platforms are changing the way people around the world get information, but are only beginning to be considered and studied within the SARF. We specifically analyze the discourse about Zika and genetically engineered (GE) mosquitoes on two prominent social media platforms, Facebook and Twitter, to examine how the SARF functions in modern media environments.

While the SARF has been applied to many different types of risk, most of this research was conducted in Western, English-speaking countries. We reviewed 44 peer-reviewed articles and book chapters that applied the SARF to specific case studies (see Table I). Within this body of research, a majority (29) were conducted in English-speaking countries (United States, United Kingdom, and Canada), nine studies were conducted in Asian countries (China, South Korea, India, Singapore, and the Maldives), and five studies were conducted in non-English-speaking European countries (France and Germany). We did not find any articles that applied the SARF to countries or territories within Latin America, the region most affected by the Zika virus. Additionally, we only found one article that studied the SARF using a comparative approach (Rossmann et al., 2017). To address this gap in how the SARF has been applied, we studied Zika-related conversations on social media in English, Portuguese, and Spanish. We use a comparative approach to better understand variations between languages, as well as to apply the SARF to regions and populations in Latin America that have not previously been empirically studied within the framework.

## 2. THE SOCIAL AMPLIFICATION OF RISK FRAMEWORK

The social amplification of risk refers to how "information processes, institutional structures, social group behavior, and individual responses shape the social experience of risk, thereby contributing to risk consequences" (Renn, 1991, p. 289). To better explain this process and synthesize the work being done across many different areas of research, scholars developed the SARF (R. E. Kasperson et al., 1988). R. E. Kasperson et al. (1988) used the amplification metaphor from communication theory as a basis for the framework to better understand how risk information is disseminated and changed through different actions and interactions.

The initial SARF framework proposed two amplification stages: the transfer of information

**Table I.** List of Reviewed Applications of the SARF and Their Locations

| Location | Study |
|---|---|
| United States | • Binder et al. (2011)<br>• Brenkert-Smith, Dickinson, Champ, and Flores (2013), Burns et al. (1993), Hart et al. (2011)<br>• Heberlein and Stedman (2009)<br>• Ibitayo, Mushkatel, and Pijawka (2004)<br>• Kandiah, Binder, and Berglund (2017)<br>• MacGregor (2003)<br>• Machlis and Rosa (1990)<br>• Mase, Cho, and Prokopy (2015)<br>• McComas (2003)<br>• Metz (1996), Rickard et al. (2013)<br>• Strekalova (2016)<br>• Strekalova and Krieger (2017) |
| United Kingdom | • Bakir (2005)<br>• Barnett and Breakwell (2003)<br>• Busby, Alcock, and MacGillivray (2009)<br>• Busby and Duckett (2012)<br>• Busby and Onggo (2013)<br>• Eldridge and Reilly (2003), Fellenor et al. (2017), Frewer et al. (2002)<br>• Hill (2001), Petts et al. (2000)<br>• Petts and Niemeyer (2004)<br>• Urquhart et al. (2017) |
| Canada | • Lewis and Tyshenko (2009)<br>• Masuda and Garvin (2006) |
| China | • Guo and Li (2018)<br>• Zhang et al. (2017)<br>• Zhou et al. (2017) |
| South Korea | • Chung (2011)<br>• Chung and Yun (2013)<br>• Kim et al. (2015) |
| India | • Susarla (2003) |
| Singapore | • Chong and Choy (2018) |
| Maldives | • Shakeela and Becken (2015) |
| France | • Poumadère and Mays (2003)<br>• Raude, Fischler, Lukasiewicz, Setbon, and Flahault (2004) |
| Germany | • Moussaïd et al. (2015)<br>• Raupp (2014)<br>• Renn (2003) |
| Comparative | • Rossmann et al. (2018) |

and response mechanisms (R. E. Kasperson et al., 1988). The first is composed of a series of interconnected chambers for processing a risk event, and considers factors such as information sources and channels, "social stations" (referring to sources such as opinion leaders and news media), "individual stations" (referring to processes considered within the psychometric tradition such as risk heuristics and prior attitudes), and individual and different behavioral components (J. X. Kasperson, R. E. Kasperson, Pidgeon, & Slovic, 2003). Renn (1991) has elaborated several mechanisms by which risk amplification and attenuation can occur: volume effects (intensifying or attenuating messages), filtering effects (intensifying or attenuating information), muting and adding effect (adding or deleting information), mixing effect (changing the order of presentation), equalizing effect (embedding the message in different contexts), and stereo effects (receiving similar messages through different channels).

We focus primarily on the transfer of information stage as a first step in rethinking the framework in the times of social media and Web 2.0 information environments. Within the transfer of information, there are several mechanisms that may contribute to social amplification of risk: the volume of media coverage, amount of attention by information consumers, how controversial or disputed the information is, how dramatized the information is, and the channels of information involved (R. E. Kasperson et al., 1988).

Some scholars have criticized the SARF for issues such as the terminology used, reifying risks, and not sufficiently explaining the role of the media (Murdock, Petts, & Horlick-Jones, 2003; Rayner, 1988; Rip, 1988). See Duckett and Busby (2013) for a review of SARF criticisms. Despite these criticisms, the SARF has been applied in many different contexts and used to understand individual responses as well as information transfer related to a variety of risks and risk-related events. The SARF has proven useful because it was designed to be flexible and allowed researchers to "deduct empirically testable theories and to offer a perspective to interpret and classify risk communication data" (Renn, 1991, p. 320). However, it is important to note that the SARF is a conceptual framework, not a theory. Instead of a falsifiable theory, the authors intended the framework to be a "guideline for initiating research that can yield results beyond the scope of the traditional frameworks" (Renn, 1991, p. 321)

### 2.1. Ripple Effects

Within the SARF, secondary and tertiary impacts of the initial risk event can spread, or "ripple," beyond those directly affected to other individuals and groups—regardless of proximity to the risk issue (R. E. Kasperson et al., 1988). The ripple effects also extend the effect of the risk event beyond direct physical harm to indirect social and economic impacts (R. E. Kasperson & J. X. Kasperson, 1996). These secondary and tertiary impacts often focus more on the evaluation of institutions' responses, fairness of risk management, placing blame, and social and community conflict (R. E. Kasperson & J. X. Kasperson, 1996; R. E. Kasperson et al., 1988). These effects may have social and political implications for future risk reduction (Renn et al., 1992). These effects can lead to lower levels of social trust in institutions and impact public acceptance of technologies related to the risk event (R. E. Kasperson & J. X. Kasperson, 1996; R. E. Kasperson et al., 1988; Renn et al., 1992). If individuals feel that the risks were not managed appropriately or competently, public reactions may, in turn, affect an industry, a specific company, or the government (Burns et al., 1993). Beyond industry and government, specific technologies can also become stigmatized and have decreased levels of perceived acceptability (R. E. Kasperson & J. X. Kasperson, 1996; Renn et al., 1992). As a result, blame attribution for the risk and perception of technology are key factors for understanding the SARF.

### *2.1.1. Blame*

One of the potential ripple effects from the social amplification of risk can take place through blame attribution and lead to lower levels of social trust in institutions (R. E. Kasperson & J. X. Kasperson, 1996; R. E. Kasperson et al., 1988; Renn et al., 1992). Indeed, Renn et al. (1992, p. 156) found that "dread and blame were good predictors for behavioral intentions of individuals" when responding to risk events within the SARF. In terms of media coverage in the context of risk events, blame is also a relevant concept for understanding risk communication. While analyzing news media coverage of arsenic and plague in India, Susarla (2003) found that the government was the target of collective blaming. However, blaming private and lesser involved institutions or groups was less common (Frewer et al., 2002). The lack of blame placed on these groups could also be dependent on the specific risk events and the groups involved. For instance, risk events may not "develop as a journalistic focus" if there are no clear targets for directing blame (Burgess, 2012, p. 1700), which suggests that the blame-related ripple effects are at least somewhat contingent on the target groups related to the risk or risk event.

A more recent example of blame attribution in the context of a public health crisis is the 2003 SARS outbreak in New York City. Chinese immigrants were stigmatized and blamed by other residents and people working in their community in the response to uncertainty surrounding the epidemic (Eichelberger, 2007). Douglas (1992) also stated that uncertain risk can lead to a conspiracy-minded, self-destructive ambiance, which may explain the conspiracies and blaming nature that followed the initial uncertainty surrounding the Zika outbreak. These conspiracies blamed the Zika outbreak on GE mosquitoes, larvicides, and vaccinations, and on groups such as Monsanto, the Bill & Melinda Gates Foundation, and the Rockefeller Foundation (Specter, 2016).

In sum, blame is an important indicator of risk amplification beyond the initial risk or risk events. This concept illustrates the way related groups or organizations may be implicated in risk discussions and subsequent public perceptions. Based on these theoretical foundations, we use blame as one of the concepts of interest for this study.

### *2.1.2. Stigmatization of Technology*

According to the SARF, ripple effects can include effects on public acceptance of technologies related to the considered risk (R. E. Kasperson & J. X. Kasperson, 1996; R. E. Kasperson et al., 1988; Renn et al., 1992), with the technologies ending up being stigmatized. In this case, stigma generally refers to an unwarranted negative, averse, or skeptical perception of a technology (R. E. Kasperson, Jhaveri, & Kasperson, 2001). Stigma has been a well-studied phenomenon within risk research (e.g., Gregory & Satterfield, 2002; R. E. Kasperson et al., 2001; Link & Phelan, 2001). Early research in the area documented the amplification of risk perceptions and stigmatization of different energy-related facilities and technologies (Flynn, Peters, Mertz, & Slovic, 1998; Slovic et al., 1991). More recently, research has focused on technology (e.g., genetically modified foods; Ellen & Bone, 2008) and health (e.g., stigma surrounding HIV/AIDS; Herek, Capitanio, & Widaman, 2003 and H1N1; Williams, Gonzalez-Medina, & Le, 2011). In the present study, we are interested in how GE mosquitoes, one technological solution proposed to combat the spread of the Zika virus, were discussed on social media. Considering the controversial nature of the technology (see Bawa & Anilakumar, 2013 for a review), this is particularly interesting when thinking of potential amplification of risk perceptions.

### 2.2. Traditional Media

The initial framework and conceptualizations of the SARF focused on the strong role of professionals and mass media, rather than on the individual. For example, R. E. Kasperson and J. X. Kasperson (1996) emphasized how "risk communicators, and especially the mass media, are major agents, or what we term social stations, of risk amplification and attenuation" (p. 97). In another early piece by Renn (1991), secondary sources (such as media channels) were considered the main amplification stations that interpreted and represented signals, or risk information, to wider audiences (Renn, 1991). Burns et al. (1993) also determined "the behavior of the media and the public play crucial roles in determining the impact of a hazardous event" (p. 621).

Past research has explored the impact of mass media coverage and attention to risk events on public risk perceptions. For example, risk perceptions of genetically modified foods were higher, regardless of demographics, at times of high media coverage in the United Kingdom (Frewer et al., 2002). However, there are several factors that impact the attention and coverage of risk events (Mazur, 1984, p. 46), and high levels of media coverage do not guarantee that risks will be amplified (Petts et al., 2000). More recently, Rossmann et al. (2017) applied the SARF to determine that newspapers and tabloids were more likely to amplify risks related to A/H1N1, when compared to press releases. Many additional studies have examined different aspects of the SARF and mass media (e.g., Hart, Nisbet, & Shanahan, 2011; Kim, Choi, Lee, Cho, & Ahn, 2015; Raupp, 2014). For a detailed review of the role mass media plays in the social amplification of risk, see Binder et al. (2014).

By contrast, the SARF has traditionally considered individuals as mostly influencing, or contributing to, these secondary sources and amplification stations (Renn, 1991, p. 312). This is likely because the initial conceptualization of SARF reported "individual sources are rare in risk communication, unless they are eyewitnesses of risk events or directly affected by a cause of a risk" (Renn, 1991, p. 302). Individuals were credited with the ability to initiate secondary effects, while groups and agencies were generally the ones that determined the public agenda (Renn, 1991). However, other scholars have critiqued this aspect of the SARF and called for a more "interactionist framework" that places more emphasis on audiences' ability to process risk information more dynamically "depending on their prior experience and stocks of cultural knowledge" (Murdock et al., 2003, p. 171). Additionally, scholars have argued that the model places more importance on individual factors despite the fact that it is called the *social* amplification of risk (Rip, 1988).

These concerns are beginning to be addressed by more recent applications of the SARF that have explored the roles of individuals. Different types of individual-level communication processes taking place through social networks (Moussaïd, Brighton, & Gaissmaier, 2015; Petts & Niemeyer, 2004), network ties (Scherer & Cho, 2003), and interpersonal communication (Binder, Scheufele, Brossard, & Gunther, 2011) have been shown to impact understanding and perceptions of risks. The growing body of research on the influence of individuals and social networks raises questions about the role new media platforms might play within the SARF.

### 2.3. New Media

The SARF was conceptualized 30 years ago and much has changed since the authors first presented their framework. These scholars could not have foreseen how communication would change from advances such as widespread Internet access, mobile communication, and social media. However, as media and communication technologies have evolved, so too have the way we study and understand media effects (Bennett & Iyengar, 2008; Cacciatore, Scheufele, & Iyengar, 2016). Digital communication has provided researchers with new opportunities to study concepts and frameworks, like the SARF, in ways that were not previously possible (González-Bailón, 2017). Online exchanges, through avenues like comment sections on news sites and social media sites, allow researchers to collect data and analyze how individuals and groups communicate on these platforms.

Researchers have begun to take advantage of these opportunities by examining how the SARF can be applied to online environments (e.g., Chung, 2011; Guo & Li, 2018), even though it was conceptualized and initially applied during a different media era. In contrast to traditional news media, the Internet establishes an "efficient means for interactive communication and an open space for active information sharing and public participation" (Chung, 2011, p. 1893). In one example of the SARF being applied to online environments, Chung (2011) found that the amount of online engagement, through actions like commenting, does not always mirror the amount of media coverage the topic received over time. The differences between online engagement and media coverage suggest that the sheer volume of news media does not represent public concern or interest in an issue (Chung, 2011, p. 1893). The successful application of SARF in this case study demonstrates how as times change, researchers can still use the foundations of the framework to better understand risk amplification and attenuation processes.

Social media platforms, such as Facebook and Twitter, are another especially important area to consider within the SARF because of their widespread adoption across the world and increasing role as an information source. As of 2016, 21% of adults in the United States use Twitter and 68% use Facebook (Greenwood, Perrin, & Duggan, 2016). The high adoption rates for Facebook extend past the United States to the regions most affected by the Zika virus. More specifically, 62% of the entire population in North America and 52% of the entire population in Latin America and the Caribbean used Facebook in 2016 (Internet World Stats, 2016). There are differences in the overall adoption across these regions at the country level, i.e., Brazil (54%), Argentina (66%), and Chile (68%), while others are much lower, i.e., Guatemala (35%), Nicaragua (32%), and Honduras (30%) (Internet World Stats, 2016).

Social media users worldwide are increasingly getting news from these platforms. A survey of news consumers from 26 different countries in 2016 found that half of the respondents reported weekly use of social media for news, and 12% stated social media as their *main* news source (Newman, Fletcher, Levy, & Nielsen, 2016). When looking at differences by age, the role of social media as a news source is even greater, with 28% of people ages 18–24 reporting social media as their main source of news (Newman et al., 2016). These rates have been growing, especially in countries like Brazil, with urban populations reporting 18% using social media as their main news source in 2016, up from just 10% in 2015 (Newman et al., 2016). The prominence and uses of social media demonstrate the need to look beyond the individual level and consider social networks to explain differences in how individuals engage and discuss information about risk in communities, both online and offline.

Only over the past few years has research begun applying SARF to social media (Chong & Choy, 2018; Chung & Yun, 2013; Fellenor et al., 2017; Strekalova, 2016; Strekalova & Krieger, 2017; Zhou, Wang, & Zhang, 2017). In fact, the integration of social media into the framework is unfolding so quickly that none of these initial studies on the topic cite another and were all submitted and published on similar timelines. In this section, we synthesize the early findings from this small body of research. Many of these scholars build on work by Chung (2011) that initially considered online communication as allowing users to be more active and influential stations within the SARF. Researchers have used this and the emerging role of social media as an information source to argue for the importance of applying the framework to social media (Fellenor et al., 2017). To synthesize this research, perhaps for the first time, we have outlined four main findings. First, there is evidence to suggest the type of media source matters with the SARF (Chong & Choy, 2018). In an analysis of several different media types that included a mainstream newspaper, online forum, and the social media platform Facebook, the authors found Facebook to have an amplifying effect on emotions that the other mediums did not have (Chong & Choy, 2018).

Second, social media platforms "provide a lens to more directly view the perspectives of a range of publics and stakeholders" (Fellenor et al., 2017, p. 14). These platforms allow a variety of different actors to engage and share information about an issue because social media, like Twitter, for example, is composed of many different voices ranging from individual (users who compromise the majority of users) (Lotan, Graeff, Ananny, Gaffney, & Pearce, 2011), to activist organizations, government agencies, news outlets, and private companies (Fellenor et al., 2017; Lotan et al., 2011). These different actors impact how risk information is circulated, with content produced or forwarded by official and professional accounts circulating information faster (Zhang, Xu, & Zhang, 2017).

Third, social media reconfigure the classification of direct and indirect information sources and social stations (Fellenor et al., 2017; Zhang et al., 2017; Zhou, Wang, & Zhang, 2017). Individuals and witnesses to events can directly produce and circulate information to large, online audiences without having to rely on the translation by another actor, like a traditional media source. However, this freedom also facilitates the propagation and dispersal of false/misinformation (Zhou et al., 2017).

Finally, in addition to allowing individuals (and other groups, as discussed above) to directly produce risk signals and information, social media also enable individuals to amplify/attenuate signals/information from official sources/stations (Strekalova & Krieger, 2017). User engagement is generally uncontrolled and can impact/complicate dispersal of official communications (Strekalova & Krieger, 2017). This message amplification can be done by a variety of actors through behaviors such as commenting, sharing, and liking content posted on social media (Strekalova & Krieger, 2017). However, this engagement differs depending on the topic being discussed (Strekalova, 2016).

### 2.4. Regions Studied and the Need for Comparative Approaches

Most of the research discussed above does not consider comparisons of risk topics between countries, cultures, or languages. Our review of the literature demonstrated how the SARF has been applied to predominantly Western, developed countries, but has not been applied to many developing countries and territories, like those most impacted by the Zika virus (Puerto Rico, Columbia, Mexico, and Brazil) (Pan American Health Organization, 2017).

To the best of our knowledge, only Rossmann et al. (2017) have taken a comparative, multilingual approach to understanding the social amplification of risk, but no studies have done so for social media. Analyzing and comparing risk discourse in multiple languages can enhance our understanding of risk because these discussions happen within a variety of media systems, such as the liberal model, the democratic corporatist model, and the polarized pluralist model (Hallin & Mancini, 2004). These systems are categorized by different factors, such as political parallelism, journalistic professionalism, and the development of media markets (Hallin & Mancini, 2004). For an in-depth analysis of the different media systems, see Hallin and Mancini (2004).

Several of the predominately Portuguese and Spanish-speaking countries most affected by Zika (i.e., Brazil, Colombia, and Mexico) are not represented in these categorizations. However, their media systems have many similarities with the media systems of the southern European countries of Greece, Italy, Portugal, and Spain (Hallin & Papathanassopoulos, 2002), and therefore could be consider operating under the polarized pluralist model. These categorizations of media systems have relevant implications for understanding how Zika is discussed in the media. With the United States operating under the liberal model, differences in media systems ultimately have the potential to impact the way individuals perceive and utilize the media in a given country or region.

Additionally, the lack of comparative research across cultures is especially problematic for the SARF because social and cultural differences were conceptualized as playing key roles in the framework (Renn et al., 1992). In fact, in a simplified representation of the SARF by Renn et al. (1992), culture was represented as having a large influence on information flow, interpretation, and behavioral response, as well as on the spread of impacts, and the types of societal impacts. However, while research has examined how culture and place integrate into the framework (Masuda & Garvin, 2006), our review shows that the SARF remains largely understudied in comparative and non-English, Western contexts.

## 3. THIS STUDY

This study expands current applications of the SARF by examining the secondary effects of amplification on two prominent social media platforms (Facebook and Twitter) and studying the framework within cultural contexts in which it has not previously been applied.

First, to explore the impact of social media discourse imbedded in differential media systems on SARF and risk perceptions, we need a better understanding of what the conversations look like on different social media platforms. We analyze two key indicators of risk amplification, blame attribution and perception of a specific technology, GE mosquitoes, in Zika-related discussions on Facebook and Twitter. Facebook (and Twitter) are commonly used by media outlets to post news items, and discussions about this news through comments (on Facebook) and tweets can give a good snapshot of the sentiments, or attitudes and opinions, expressed online. Specifically, we pose the following research questions:

> **RQ1a**: How does the amount of blame expressed for Zika differ by the social media platform in which Zika sentiments are expressed?
>
> **RQ1b**: How do the targets of blame expressed for Zika relate to the social media platform in which Zika sentiments are expressed?
>
> **RQ1c**: How do the sentiments expressed toward GE mosquitoes differ by the social media platform in which Zika sentiments are expressed?

Second, our study builds the components of comparative risk research by analyzing social media discourse about Zika and GE mosquitoes in English, Portuguese, and Spanish on Facebook and Twitter.

Including different languages will capture online conversations initiated in many different countries and will allow us to begin forming a clearer picture of how “global” social media platforms are for users, or if differences exist in how people communicate about Zika risks. We can also test the generalizability of SARF by examining how the different factors outlined in SARF are apparent on social media platforms. Specifically, this study will give insight into how generalizable the framework is by tracking how the secondary and tertiary impacts of risk amplification vary from language to language.

In addition to differences in how risk is perceived or discussed, we also consider the differences between media systems. As discussed earlier, the United States operates under the liberal model while Latin American countries tend to operate under the polarized pluralist model. Because social media platforms are imbedded in distinct media systems, we examine how Zika and GE mosquitoes are discussed within the SARF in each media system.

**RQ2a**: Are there differences in the amount of blame expressed for Zika that relate to the language in which Zika sentiments are expressed?

**RQ2b**: How do the targets of blame expressed for Zika relate to the language in which Zika sentiments are expressed?

**RQ2c**: How do the sentiments toward GE mosquitoes relate to the language in which Zika sentiments are expressed?

**Table II.** Sources and Country of Origin for the News Source Facebook Page Data; The Overall (Not Zika-Related) Average Volume of Activity on Each Page Is Also Listed

| Avg. Daily Volume | Source | Country |
|---|---|---|
| Spanish | | |
| 42,187 | LA NACION | Argentina |
| 26,643 | Diario El Comercio | Peru |
| 24,642 | Diario Clarín | Argentina |
| 22,272 | El Universal Online | Mexico |
| 21,138 | El Espectador | Colombia |
| 6,975 | El Tiempo | Colombia |
| 4,862 | El Universo | Ecuador |
| 2,121 | El Nacional | Venezuela |
| 1,901 | nacion.com | Costa Rica |
| 267 | Página/12 | Argentina |
| English | | |
| 71,622 | Fox News | United States |
| 37,591 | NBC News | United States |
| 35,269 | CNN | United States |
| 27,876 | The New York Times | United States |
| 25,184 | ABC News | United States |
| 22,136 | TIME | United States |
| 21,179 | BBC News | United Kingdom |
| 18,352 | MSNBC | United States |
| 15,312 | Washington Post | United States |
| 13,353 | USA TODAY | United States |
| Portuguese | | |
| 74,473 | Estadão | Brazil |
| 37,845 | O Globo | Brazil |
| 17,609 | Jornal Extra | Brazil |

## 4. METHODS

To answer our research questions, we rely on sentiment analysis software from the social media monitoring company, Crimson Hexagon. The software, ForSight, uses an algorithm described in Hopkins and King (2010) to analyze all publicly available tweets and a subset of Facebook posts and comments. Specifically, ForSight’s algorithm uses nonparametric statistical modeling and directly estimates the proportions of the sentiments of interest (Hopkins & King, 2010, p. 237). Human coders train the algorithm to recognize patterns of words representative of specific concepts using posts they have identified as exemplars after classifying random samples of the posts manually, as we will discuss in greater detail below.

For Twitter, we had access to all posts via the Twitter Firehose. To capture a census of these tweets mentioning the Zika virus, we designed a Boolean search string for each language (Appendix A). We integrated potential misspellings, abbreviations, and the use of key terms and wording from hashtags to be as comprehensive as possible. Specifically, we included “sika” and “sica” in our Portuguese and Spanish search strings because our collaborators and the coding teams informed us that substituting an “s” for a “z” was relatively common in these contexts. These search strings were then used to capture all potentially relevant tweets.

However, for Facebook, we did not have access to all publicly available posts and comments. As a result, we collected and analyzed the content from the Facebook pages of major news outlets. We selected news outlets because they are widely followed, post Zika-related information, and generate large amounts of content and discussions. These data came from 10 English-language Facebook pages, 10 Spanish-language Facebook pages, and three Portuguese-language Facebook pages. The news sources and the average daily volume of content they produce are listed in Table II. We selected these specific outlets because they were among the most widely used news sources in the respective countries ("All You Can Read: World News," 2018; Newman, Fletcher, Kalogeropoulos, Levy, & Nielsen, 2017), but were also limited in some cases to sources that we could access archival data for the entirety of our study. The data for Facebook were also collected using the same Boolean search string to capture posts and comments from the walls of major news outlets in each language.

We collected the data from Facebook and Twitter in each language from November 1, 2015 to February 1, 2017. Strategies for establishing date frames for content analyses of risk events are widely varied. Some studies look at very focused ranges of a few hours or days (Sutton et al., 2015), while others cover several months (Shan et al., 2014; Strekalova, 2016). These date ranges are usually bound by specific events (Strekalova, 2016) or restricted by the ability to analyze larger volumes of data (Sutton et al., 2015). These restrictions did not limit our study because we used machine learning to analyze our data. This approach lets us efficiently process large amounts of content that would not be feasible by human coding alone. As a result, we could set a much wider date range and get a better sense of the conversation around the Zika virus. We started our analysis in November 2015, when several countries started reporting locally transmitted cases of Zika and Brazil declared a national public health emergency (World Health Organization, 2017a). We stopped our analysis several months after the WHO determined Zika was "no longer a global emergency" (McNeil Jr., 2016).

After collecting all data from Facebook and Twitter for the given period of analysis, we used random samples of posts for reliability training. We conducted separate intercoder reliability trainings for the codebooks on both Facebook and Twitter and for each language. In other words, there were six separate intercoder reliability trials for blame related to Zika: (1) blame on Twitter in English, (2) blame on Facebook in English, (3) blame on Twitter in Portuguese, (4) blame on Facebook in Portuguese, (5) blame on Twitter in Spanish, and (6) blame on Facebook in Spanish. There were an additional six trials for GE mosquitoes, also for each language and platform, as described above for the Zika virus. Each of the 12 trials consisted of several rounds of reliability coding between a pair of human coders.

This method generally relies on consensus coding, where all coders collectively come to an agreement on categorizations, rather than reliability trials (e.g., Runge et al., 2013; Simis-Wilkinson et al., 2018; Su et al., 2018; Su, Scheufele, Bell, Brossard, & Xenos, 2017b; Yeo et al., 2017a, 2017b). Consensus coding is effective in these cases because coders are picking posts to be used as exemplars for each coding category, rather than independently coding all the data "by hand." However, for this study, we added the series of reliability trials for each language and platform to make sure we were operating consistently across the many different content types. For each trial, the pair of coders used a codebook to independently code a random sample, which is essential for effectively training the algorithm (Ceron, Curini, Iacus, & Porro, 2014), of between 100 and 125 posts.

After each trial, we calculated percent agreement between the coders. The codebook was updated to address any ambiguities or areas of disagreement. This process was repeated on new random samples of posts until the coders reached a minimum of 80% agreement for each of the six reliability trials. After the coders reached this threshold, we trained the intelligent algorithm using a subset of posts for each category (Hopkins & King, 2010). The ForSight platform then uses these exemplars to assess sentiment patterns. These training sets were selected posts that coders agreed fit the respective categories. This is the form of consensus coding commonly used for this approach (Runge et al., 2013; Simis-Wilkinson et al., 2018; Su et al., 2017b, 2018; Yeo et al., 2017a, 2017b).

After the intelligent algorithm runs its analysis across the entire census of posts, it then provides categorizations and estimates for each category across the specified timeline. This combination of human-coding and computer-based techniques, also known as supervised machine learning, combines the strengths of both human coding (validity) and computer-based (efficiency) content analysis (Su et al., 2017a). In other words, platforms like ForSight can efficiently analyze substantial amounts of detail, while retaining more accuracy than systems that do not also use traditional content analysis methods. See Hopkins and King (2010) and Su et al. (2017a) for a more detailed review. Our analyses are census estimates for the entire population, rather than a sample, of posts (Zika-related tweets on Twitter and posts/comments on Facebook), and, as a result, we did not perform any further statistical analyses.

We later calculated the Krippendorff's alphas, in addition to the percent agreement, for each reliability trial. Several of the trials, while meeting the accepted standard for percent agreement, fell below the standard for Krippendorff's alpha. However, it is important to keep in mind that these standards are for establishing intercoder reliability so that coders can then independently code content. This is not the goal for the hybrid approach we used. Instead, the reliability trials were an additional measure to ensure consistency among languages and platforms before selecting posts using the standard consensus approach mentioned above. The Krippendorff's alphas and percent of agreement are listed in Appendix E.

### 4.1. Coding Schema

To analyze blame, we divided posts into three categories: blame, no blame, and off-topic. Blame was operationalized by looking at how posts attributed responsibility for the Zika virus or the problems associated with it. This included posts that implied an individual, group, action, or technology was connected or responsible for the difficulties, losses, harm, damages, or complications that came from the Zika virus or its side effects. Our measurement captures a broad conceptualization of blame. For example, we consider both blame placed at the individual and group level to be consistent with how blame was conceptualized by Renn et al. (1992). For the sentiment related to GE mosquitoes, we used three coding categories: positive, negative, and neutral. These are the categories the human coders used during the reliability trials, and the categories that were trained into the ForSight platform (for more details about the coding categories, see Appendix 2B). Specific examples of posts from each of the categories are listed in Tables III and IV.

### 4.2. Filters

We created a series of search strings to determine how often certain groups were being discussed and how often they were discussed in a way that attributed blame for the Zika virus. These search strings were used to filter the final data from the ForSight platform. Using these filters, we can further analyze relevant sentiments about the Zika virus, and determine the volume and proportion of these sentiments referencing each group of interest. We selected groups representing corporations and government groups that have been outlined as targets of ripple effects within the SARF (R. E. Kasperson & J. X. Kasperson, 1996; R. E. Kasperson et al., 1988; Renn et al., 1992). These included the private-sector groups Monsanto, the Bill & Melinda Gates Foundation, and the Rockefeller Foundation because they were all associated with Zika-related conspiracies (Specter, 2016), as well as U.S. and Brazilian executive and legislative groups, specifically the different parties and the presidents of each country included in our study. A list of these group-level filters can be found in Appendices C and D.

## 5. RESULTS

Over the time of our study (November 1, 2015–February 1, 2017), we identified 7,975,602 relevant English-language tweets, 2,223,460 relevant Portuguese-language tweets, and 4,627,961 relevant Spanish-language tweets referencing the Zika virus. For Facebook, we collected 26,858 relevant English-language posts and comments, 10,478 Portuguese-language posts and comments, and 3,346 Spanish-language posts and comments referencing the Zika virus on the pages of the selected news sources. These trends are represented in Fig. 1. The fluctuations coincide with key events and media coverage of the Zika virus. The largest peak of volume for both Twitter and Facebook content was late January to early February 2016. This was also one of the highest points for news coverage and Internet searches (Southwell, Dolina, Jimenez-Magdaleno, Squiers, & Kelly, 2016). Many key events happened during this short amount of time: the reports of Zika and microcephaly cases continued to grow and the WHO declared the association between neurological disorders and the Zika virus a "public health emergency of international concern" (Chan, 2016). Several other key events highlighted in Fig. 1 are described below:

- **A:** The concerns about an association between cases of Zika virus and birth defects grow in Brazil. Several countries in Latin America also report locally acquired cases of Zika (World Health Organization, 2017a).
- **B:** Sexual transmission of the Zika virus is confirmed in Texas (Wagner, 2016). Cases of Zika and Guillain-Barre continued to increase in Latin America (Nebehay, 2016).
- **C:** The CDC confirms the link between Zika infections and birth defects (Berkrot, 2016).
- **D:** The WHO published guidelines about Zika and the 2016 Olympics (Belluck, 2016). The Zika virus continued to spread to new countries and throughout the United States (Dennis, 2016).

**Table III.** Example Posts for Each Category of the Blame Codebook for Twitter and Facebook

| | Facebook | Twitter |
|---|---|---|
| Blame | • Yes, You Can Blame The DDT Ban For Zika<br>• Zika epidemic and resulting birth defects are fault of governments that abandoned antimosquito programs | • There are nearly 300 pregnant women with confirmed cases of #Zika in United States, but @HouseGOP has yet to take action. #DoYourJob<br>• #Zica #Pyroproxifen Report says #Monsanto-linked pesticide is to blame for microcephaly outbreak |
| No blame | • Colombia reports more than 2,000 Zika cases in pregnant women<br>• RT @ajplus There's a new therapy to comfort extra-fussy babies with Zika-linked microcephaly | • US CDC says six confirmed and probable cases of Zika sexual transmission<br>• RT @MoreScienceNews RTI International Launching Initiatives in Latin America to Combat Zika |
| Off-topic | • The Vancouver Sun vancouversun.com http://vancouversun.com/health/sexual-health/zika-virus<br>• Mas que leer sobre el zica | • RT @bertrandOD A starter pack to the new @TataMotors #Zica<br>• http://thefreethoughtproject.com/experience-purchase-zika-virus/ |

**Table IV.** Example Posts for Each Category of the GE Mosquitoes Codebook for Twitter and Facebook

| | Facebook | Twitter |
|---|---|---|
| Positive | • The GM mosquitoes are actually helping to control the Aedes mosquito in areas where there were released, which incidentally is far away from areas where people are suffering | • RT @emboreports >90% reduction in mosquitos using @Oxitec gene technology and GM insect release Warner says. Better than any other approach #scisoc2015 |
| Negative | • blah blah every year. GMO Mosquitoes released in Brazil are to blame for this. Now who is going to prison? | • OX513A mosquitos began release in Brazil (Itaberaba) in 2011 April 2015, release 6 million elsewhr #Zika #zikavirus |
| Neutral | • I'm fairly certain the genetically modified mosquitos are the males, they are made sterile | • OX513A mosquitos began release in Brazil (Itaberaba) in 2011 April 2015, release 6 million elsewhr #Zika #zikavirus |
| Off-topic | • http://thefreethoughtproject.com/experience-purchase-zika-virus/genetically-modified-mosquito | • Field study shows how a GM crop can have diminishing success at fighting off insect pest http://t.co/MDxjiRtRgU |

- **E:** Local transmissions of Zika are confirmed in Florida (Belluck, Alvarez, & McNeil, 2016).
- **F:** The U.S. Congress fails to pass Zika funding (Newton-Small, 2016).

These events highlight major developments that were unfolding when social media discussions about Zika were at their highest. These trends reflect the findings of past research. For example, social media coverage of public health events peaks at a similar, if not slightly later, point as traditional media, but social media coverage tends to dissipate faster than traditional media coverage (Shan et al., 2014). Additionally, the communication strategies official agencies, like the CDC, use on social media impact the circulation and engagement of information about risks online (Panagiotopoulos, Barnett, Bigdeli, & Sams, 2016; Strekalova, 2016; Sutton et al., 2015). As Fig. 1 illustrates, the conversation about Zika does not reach another peak for several months.

In our results, we include the overall volumes of sentiments to demonstrate the different levels of discussion across languages. These volumes demonstrate what the conversations on social media are like overall. However, we also include the proportions of each category we analyzed for each language to provide insights into differences when controlling for the volume of content. However, before we discuss the rest of our results, it is important to review the geographic origins of our data to provide context on what countries and areas are represented by each language. The ForSight platform collects geotags and location estimates for posts with the data available. For the conversations about Zika on Twitter, 68.6% (5,475,107) of the posts in English, 72.3% (1,617,919)

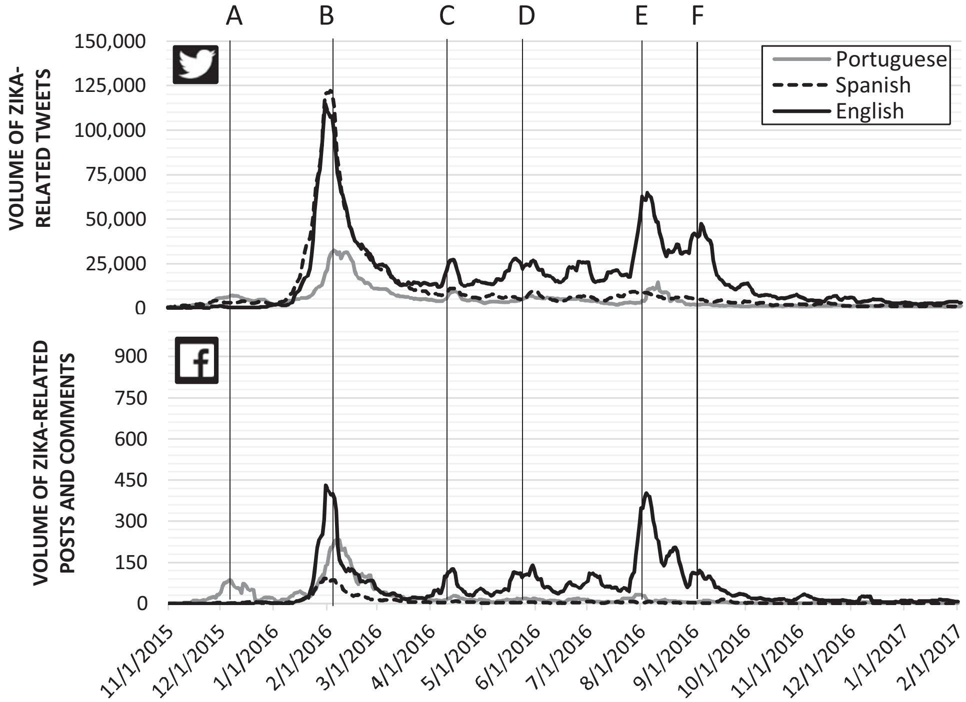


**Fig. 1.** Volume of content about Zika on Twitter and Facebook in English, Portuguese, and Spanish.
*Note*: Graph uses a seven-day average for data smoothing—the value for each day is the average for that value and the three days before and after.

of the posts in Portuguese, and 65.3% (3,021,420) of the posts in Spanish had geographic information available. Of the English Twitter data with available geographic information, the United States accounts for 62% (3,783,386 posts) of posts about the Zika virus. The next largest contributor is the United Kingdom with 6% (379,694). The remaining 32% of the posts with location information are fractured, in small percentages, to other countries around the world. For the purpose of this article, English-language data generally reflect the conversations in the United States and to a lesser extent in the United Kingdom. By contrast, most of the Twitter discussions about Zika in Portuguese are attributed to Brazil with 92% (2,569,776 posts) of the posts in Portuguese with available location data located in the country. Therefore, discussions about data and content in Portuguese can generally be assumed to represent discussions in Brazil.

However, Spanish discussions are more complex, as the language is spoken in many different countries. Of the Spanish Twitter data with available geographic information, the countries with the largest percentages of the conversation are Venezuela (1,215,519 posts; 26.03%), Mexico (703,010 posts; 15.06%), United States (484,146 posts; 10.37%), Argentina (409,702 posts; 8.78%), Spain (378,143 posts; 8.1%), and Colombia (326,963 posts; 7%). Of the top 15 countries, Latin American countries make up 75% (3,491,845 posts) of the Zika conversations in Spanish. While not very specific, the best approximation for the Spanish data discussed below is that they largely reflect the conversation within Latin American countries, with contributions from people in Spain and the United States.

Conversely, location data for Facebook content were not available. Instead, we use the country of origin for the Facebook pages as an approximation for the countries that are represented by each of the languages. The English data come from nine U.S.-based sources and one source based in the United Kingdom (Table II, English). As with Twitter, English content on Facebook generally represents conversations in the United States. For Portuguese, all the Facebook sources are from Brazil (Table II, Portuguese), and, as a result, Portuguese content can be assumed to reflect conversations in Brazil. Similar to Twitter, the content in Spanish comes from a variety of different countries (Table II, Spanish). As a result, the Facebook results discussed below loosely reflect conversations from the Latin American countries we identified.

## 5.1 Blame

In English, 30% of the sentiments on Twitter and 71% of sentiments on Facebook attributed some blame for the Zika virus or problems related to the outbreak. For Portuguese, there was much less blame for Zika on both platforms, with 18% of sentiments on Twitter and 34% of sentiments on Facebook expressing blame for Zika. Finally, in Spanish, the platforms were more similar, with 39% of sentiments on Twitter and 36% of sentiments on Facebook placing blame for Zika. In English and Portuguese, there was more blame on the major news sources' Facebook pages than on Twitter. However, there was more blame overall in English and Spanish than in Portuguese. The amount of blame fluctuated over time for both Facebook and Twitter in each language. The trends for volume of blame over time on Facebook and Twitter are shown in Fig. 2.

### *5.1.1. Private Sector*

On Twitter, there were 43,974 English, 3,783 Portuguese, and 20,778 Spanish Zika-related posts that mentioned the private sector. Of these posts, 70% of the English, 32% of the Portuguese, and 93% of the Spanish posts also expressed blame for the Zika outbreak. On Facebook, there was much less content mentioning the private sector, with 775 English, 37 Portuguese, and 68 Spanish Zika-related posts. Of these posts, 87% of the English, 37% of the Portuguese, and 38% of the Spanish posts also expressed blame for the Zika outbreak

When looking at the group-level data, the relative amount of sentiments expressing blame and mentioning private-sector groups varied over time in similar patterns on Twitter and Facebook for each language (Fig. 3). The private sector is mentioned in blaming sentiments primarily during the initial peak in conversation. These spikes relate largely to the blaming of different private-sector groups for the creation of the Zika virus or being the "real" cause of its side effects. There is a wide range in the prominence of blame associated with the private sector and Zika between languages and platforms (Tables V and VI). The largest volumes are seen in English on Twitter, followed by Spanish. However, hardly, any posts in Spanish mention the private sector and express blame on Facebook. Portuguese expresses hardly any blame while mentioning the private sector on Facebook or Twitter.

When the private-sector groups are separated out even further, we get a better picture of what groups are being blamed on Twitter (Table V). The blame of the Rockefeller Foundation largely comes from misrepresentations of the foundation's patent for the Zika virus. The foundation has held a patent for a strain of the virus that can be purchased for research. However, on both Twitter and Facebook, this was turned into accusations of the foundation creating and selling the virus as a population control method (Griffin, 2016).

Overall, Monsanto received the highest amounts of blame in the private-sector category on Twitter and Facebook (Tables V and VI). The attribution of responsibility largely comes from conspiracy theories such as those claiming Monsanto's larvicides and/or pesticides were the true cause of microcephaly—not the Zika virus (Mitchell, 2016). Less common, but still discussed as a potential culprit, was the Bill & Melinda Gates Foundation, which was blamed as often as the Rockefeller Foundation and accused of providing funding to the company that released the GE mosquitoes the conspiracies state caused the Zika virus to spread (Jacobs, 2016).

### *5.1.2. Executive and Legislative Groups*

Blame was more often expressed in sentiments that mentioned executive and legislative groups than those mentioning the private sector. On Twitter, there were 765,522 English and 90,247 Portuguese Zika-related posts that mentioned government executive and legislative groups in the United States and Brazil. Of these posts, 47% of the English posts and 15% of the Portuguese posts also expressed blame for the Zika outbreak. On Facebook, there were 3,237 English and 1,649 Portuguese Zika-related posts that mentioned the groups. However, these posts expressed higher proportions of blame than those on Twitter, with 84% of the English posts and 37% of the Portuguese posts expressing blame.

In English, U.S. executive and legislative groups appear much more prominently in the second major spike in Zika-related sentiments on Twitter (Fig. 4). These spikes coincide with the larger conversation

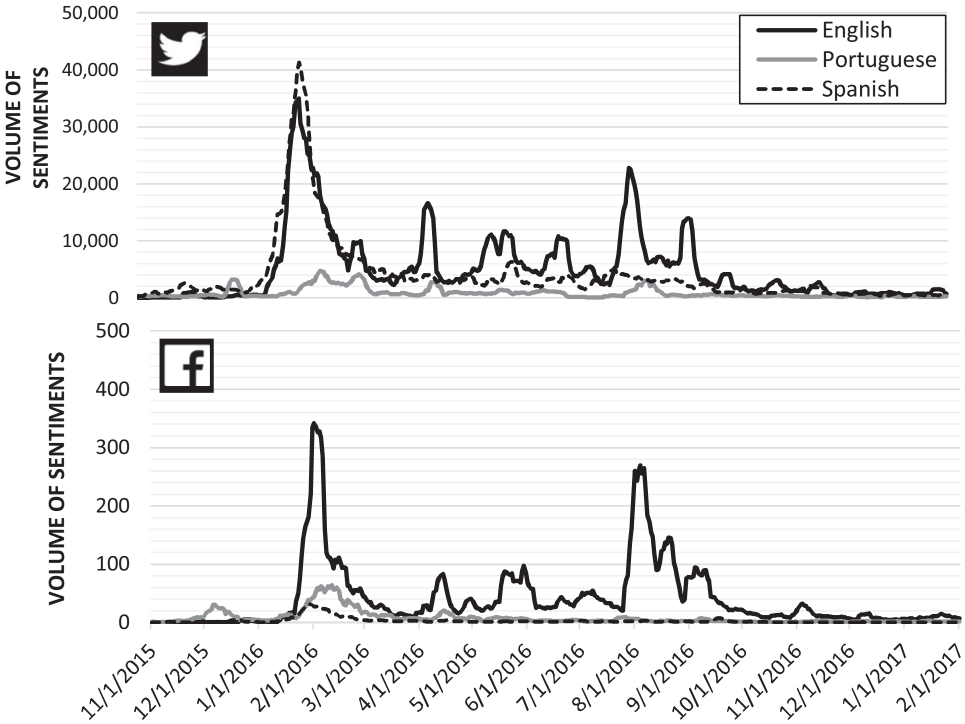


**Fig. 2.** Sentiments placing blame for Zika on Twitter and Facebook in English, Portuguese, and Spanish.
*Note*: Graph uses a seven-day average for data smoothing—the value for each day is the average for that value and the three days.

**Table V.** Volume of Zika-Related Content Mentioning Private-Sector Groups and the Proportion of the Posts Assigning Blame on Twitter in English, Portuguese, and Spanish

| | Twitter | | | | | |
|---|---|---|---|---|---|---|
| | Gates | | Monsanto | | Rockefellers | |
| | No. of Posts | % Blame | No. of Posts | % Blame | No. of Posts | % Blame |
| English | 11,869 | 90% | 22,175 | 76% | 10,880 | 35% |
| Portuguese | 838 | 4% | 1,186 | 88% | 1,840 | 9% |
| Spanish | 2,810 | 90% | 8,202 | 100% | 14,225 | 92% |

about government funding for Zika. Indeed, Zika became politically charged in the United States because of the highly publicized debate over the Zika-related spending bill that eventually passed in September 2016, after considerable controversy (Fox, 2016). By contrast, in Portuguese, Brazilian executive and legislative groups were mentioned in blaming sentiments predominantly during the initial outbreak on Twitter.

In sum, the results of the blame-related analyses answer both our first and second research questions. With respect to the first research question (RQ1a and RQ1b), we found differences between Facebook and Twitter in the amounts of blame and in the groups mentioned in blaming sentiments for Zika-related problems. The analysis also provides answers to the first two components of our second research question (RQ2a and RQ2b); specifically, there were variations in both the amounts of blame and in the groups mentioned in blaming sentiments in the different languages under study.

### 5.2. Genetically Engineered Mosquitoes

From November 1, 2015 to February 1, 2017, we identified 326,469 relevant English-language tweets,

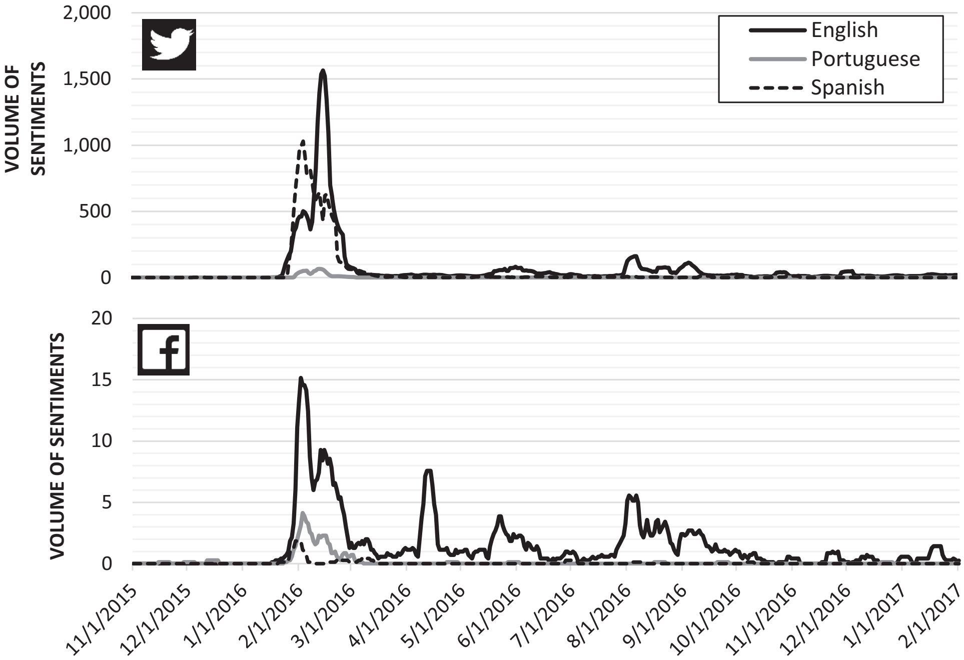


**Fig. 3.** Volume of blame associated with the private sector on Twitter and Facebook in English, Portuguese, and Spanish.
*Note*: Graph uses a seven-day average for data smoothing—the value for each day is the average for that value and the three days before and after.

**Table VI.** Volume of Zika-Related Content Mentioning Private-Sector Groups and the Proportion of the Posts Assigning Blame on Facebook in English, Portuguese, and Spanish

| | Facebook | | | | | |
|---|---|---|---|---|---|---|
| | Gates | | Monsanto | | Rockefellers | |
| | No. of Posts | % Blame | No. of Posts | % Blame | No. of Posts | % Blame |
| English | 170 | 91% | 388 | 87% | 273 | 87% |
| Portuguese | 5 | 20% | 12 | 67% | 20 | 45% |
| Spanish | | 67% | 40 | 28% | 28 | 50% |

46,772 relevant Portuguese-language tweets, and 55,437 relevant Spanish-language tweets referencing GE mosquitoes. For Facebook, the platform identified 2,002 relevant English-language posts and comments, 363 Portuguese-language posts and comments, and 151 Spanish-language posts and comments referencing GE mosquitoes on the pages of the selected news sources. The proportions of sentiments are listed in Fig. 5.

There were major variations among the sentiments expressed in each language and between Facebook and Twitter. On Twitter, the predominant sentiment expressed toward GE mosquitoes was neutral for all three languages. The proportion of neutral sentiments was similar for English (50%), Portuguese (46%), and Spanish (44%). For English and Spanish, the next most common sentiment was positive (29% and 30%, respectively), followed by negative (22% and 26%, respectively). However, for Portuguese, there were more negative sentiments (36%) than positive ones (18%).

Interestingly, patterns were different on Facebook. Instead of neutral, the predominant sentiment toward the GE mosquitoes on Facebook was negative in English (64%), Portuguese (45%), and Spanish (62%). Again, English and Spanish were similar for the proportion of negative, but on Facebook, the expression of positive (24% and

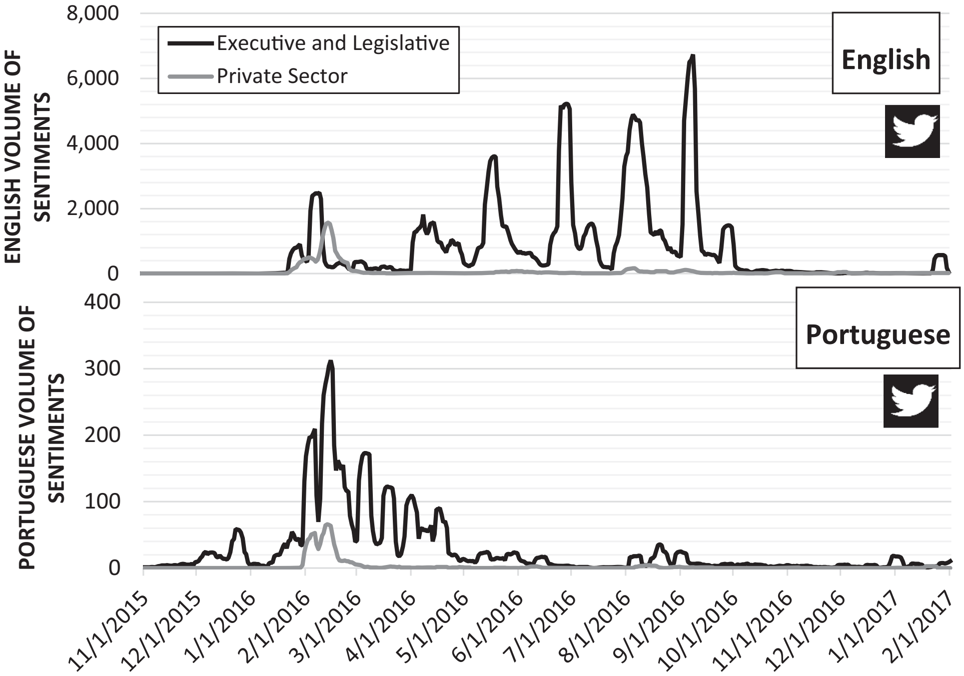


**Fig. 4.** Volume of blame associated with the private-sector and executive and legislative groups on Twitter in English.
*Note*: Graph uses a seven-day average for data smoothing—the value for each day is the average for that value and the three days before and after.

9%, respectively) and neutral (12% and 29%, respectively) sentiments was reversed. In contrast to Twitter, Portuguese content on Facebook had the largest proportion of positive sentiments (31%) of all three languages. These findings answer our remaining research questions (RQ1c and RQ2c), namely, there were differences between both Facebook and Twitter, as well as between English, Portuguese, and Spanish, in the discussions of GE mosquitoes for Zika control on social media.

## 6. DISCUSSION

Using the Zika outbreak as our context of inquiry, we demonstrated conversations about risk spreading beyond the topic of initial concern, the Zika virus, to other groups and issues. Specifically, we found two types of ripple effects previously discussed in the SARF literature; blame for Zika-related problems and negative perceptions of GE mosquitoes as a means to combat the Zika outbreak. In English and Portuguese, there was much more blame expressed on Facebook than on Twitter, but in Spanish, the amount of blame was relatively similar between the social media platforms. However, there was overall much less blame in Portuguese than in Spanish and English. For GE mosquitoes, content on Facebook was predominantly negative and Twitter content largely neutral in all languages. When compared to the other languages, the discussions about GE mosquitoes in Portuguese were more negative on Twitter and more positive on Facebook.

There are several limitations to consider before discussing the implications of our results. First, we did not have access to all content on Facebook. We are instead limited to a subset of posts and comments aggregated from high-traffic, public pages. Content from individuals' walls may differ from the data we analyzed. Another limitation was the use of keyword filters to establish the target of blaming sentiments. The volumes for the different groups (i.e., private-sector and executive and legislative groups) are mentions of the groups in sentiments that place blame. The blame of the sentiment could have been directed at another subject within the sentiment, although discussions with coders suggest that this is unlikely. Indeed, the coders individually evaluated over 1,000 posts and comments throughout the coding process for this project, and reported if the posts placed blame and mentioned one of the groups; these groups were largely the ones being blamed.

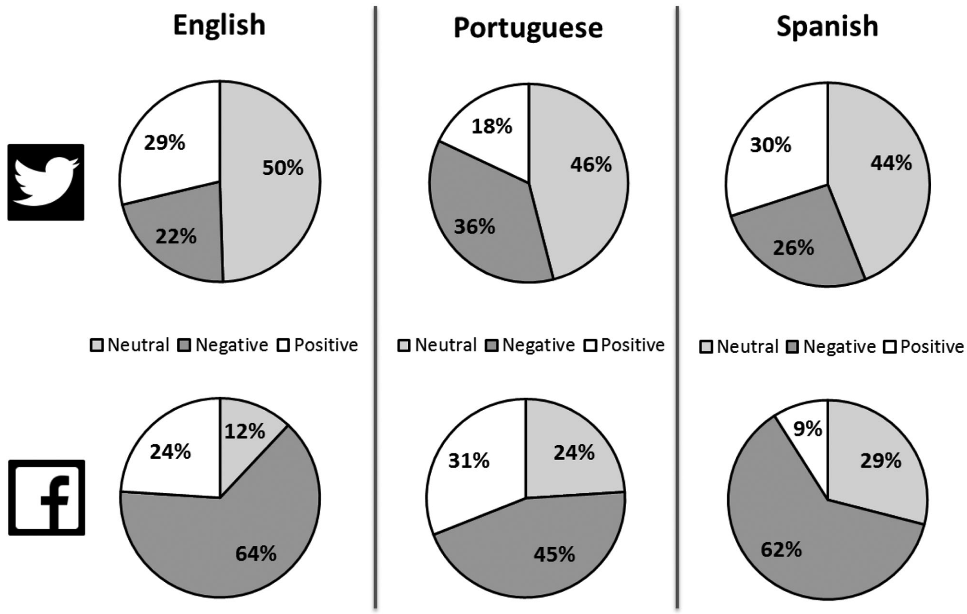


**Fig. 5.** Sentiment expressed about GE mosquitoes on Facebook and Twitter in English, Portuguese, and Spanish.

We also use a broad definition of blame that does not make distinctions between different types of targeting and responsibility being discussed. These distinctions may have important implications for managing and responding to risks, but our goal was to first determine if the sentiment was used, as well as measure how widely it was used on different platforms in multiple languages. As our results suggest, blame does appear in the discussions of risk on social media. Future research should explore the concept further to determine if different distinctions and more specific operationalizations also produce meaningful differences.

A final limitation is that our data only allow us to discuss the language-based differences in the context of discussions on social media platforms. We cannot speak to cultural differences in terms of individual-level risk perceptions or amplification of risk. This is because differences are likely a result of the differential and complex media systems among the countries that speak each language (Hallin & Mancini, 2004). For example, there may be less blame for Zika-related problems on social media because the platform is not widely adopted in Brazil. Or, on the other hand, different cultures may express different amounts of negativity in general. For this reason, it is important to note that our results are limited to the discourse surrounding Zika and GE mosquitoes on Facebook and Twitter.

### 6.1. Implications for Risk and Outbreak Communication

Despite these limitations, our study provides insights relating to the Zika outbreak and risk communication. We provide specific recommendations for practitioners involved in communicating about, or during, outbreaks, as well as those who communicate about other risk-related topics. First, our results illustrate how discussions about the Zika virus were very episodic, with spikes in volume on Twitter and Facebook centering around key events. These peaks largely follow the same pattern over time, but there are key points where these trends deviate for specific languages, platforms, and sentiments.

We will discuss these deviations and their implication in greater detail below, but, generally, these deviations appear to stem from responses to country-specific events. For example, there is a peak in volume only in Portuguese content when the first cases and suspicions of Zika emerged early on in Brazil. And in English, there are spikes that relate to events like local transmissions and political controversies. National-level politics appear to influence the overall Zika conversation in both the United States and Brazil, as our results demonstrated that English content was generally based in the United States and Portuguese content was almost entirely based in Brazil. This suggests that there is a somewhat "global" dialog that operated similarly over the course of the outbreak but certain fluctuations in the conversation were highly specific to one country. This may explain why there are less noticeable spikes for Spanish. While English generally represents the United States and Portuguese content almost entirely came from Brazil, the Spanish content covers several different countries. There may not have been specific events with the collective strength to really sculpt the dialog for all Spanish content.

As a result, public health officials should concentrate their efforts around these events, both at the global and national levels, to capitalize on the heightened discussion, provide quality information, and address concerns or misinformation. Communication strategies and teams should be prepared to join the conversation more actively at high peak times on social media, rather than on a fixed schedule with set quotas. Engaging more on social media more during peak times may be helpful because it increases the visibility of posts by attaching to a larger, more salient conversation.

Additionally, this approach ensures that more "controlled" or "professional" information makes it into the discussion at these times, which is especially important for social media. If misinformation circulates and either causes or adds to a spike in conversation, expert communicators should work to join or be more involved in the conversation at that time. If they do not, attention and discussion will likely fade quickly, and these experts will miss the opportunity to shape or add to the dialog in a substantive way.

Second, the conversation about Zika on social media expanded beyond just the virus itself to include both the private sector and government. The private sector was a large focus initially and even more so on Twitter than on Facebook news pages. While not the most prominent topic of conversation, identifying relatively large amounts of posts blaming groups for Zika-related problems illustrates the potential issue for risk communication of user-generated media that is not subjected to editorial processes. In this case, misinformation and conspiracy theories relating the Zika virus to various private-sector groups were circulated through social networks. These posts disputed the causes and risks associated with Zika, which, in turn, muddied the communication and information landscape surrounding the virus by making incorrect or highly speculative information accessible to audiences on Facebook and Twitter.

These conspiracies could have negative effects on social media audiences as they evaluate important decisions surrounding Zika-related risks, such as whether they should wait, and for how long, to have children or if they should avoid traveling to certain areas. This is especially dangerous when considering social media are significantly more important news sources for women and younger generations (Newman et al., 2016), the groups that have the highest potential risks from the Zika virus (Centers for Disease Control and Prevention, 2017).

In addition to the private sector, the government was also frequently mentioned in blaming sentiments. The debate surrounding Zika-related funding legislation in the United States caused a second major spike in the Zika discussion on both Facebook and Twitter. This later conversation was more politicized, with high amounts of blame being placed on government executive and legislative groups. These results suggest that in the United States within the course of eight months, a global disease outbreak turned into a political issue on social media. However, in Brazil, the blame and governmental discussions were more prominent during the initial outbreak. Public health and informational campaigns aimed at informing and updating audiences were potentially competing with political frames all throughout the outbreak.

The documentation of outside, nonrelated groups becoming a focus of blame demonstrates how the perceptions of risk expanded beyond just the risk of contracting the disease. This provides more challenges to public health officials because, in addition to managing perceptions and behaviors directly related to the Zika virus, they must also manage and navigate perceptions and misinformation tied to other groups. Thus, our results suggest that the communication of health campaigns on social media is operating in environments where it is competing with, and needs to address, potential misinformation and conspiracy theories.

These campaigns do not happen in a vacuum and public health and health communication practitioners need to be aware of how the topics of conversation shift and extend beyond the disease or crisis itself. The perceptions of the agencies or organizations involved in delivering information may be impacted by the discussions of other groups and parts of the government. Communication campaigns should maintain and adapt messages and strategies as the outbreak unfolds to make sure that their content is relevant and addresses the communication context, especially as it changes over time.

We also found several notable differences between Facebook and Twitter. These differences are especially pronounced among conversations about GE mosquitoes. The discussions on Twitter were predominantly neutral in all languages, while the largest category on Facebook was negative in each language. The conversations about GE mosquitoes were much less supportive on Facebook, especially in English and Spanish. Interestingly, there was a greater proportion of positive discussion on Facebook in Portuguese than on Twitter. Conversely, there was less blaming of specific groups on Facebook, which suggests that the Facebook pages of news agencies may not foster similar types of conversations as on Twitter.

One factor that may contribute to these differences is the structure and design of the platforms. Twitter has a character restriction that limits the amount of content a user can share. By contrast, Facebook allows users to share large amounts of content that could span several topics or express multiple sentiments within a single post or comment. The character restriction, or lack thereof, may contribute to how blame is expressed or technologies are discussed. Future research should explore ways in which platform-based differences may contribute to risk amplification.

In sum, we demonstrated how the conversation about the Zika virus ebbed and flowed while responding to different events and focused on different actors and issues. Messaging and information should build on and address the conversations that unfold to be more effective in reaching their audiences. Communication strategies need to be able to address and adapt to these issues because, unlike in traditional media, there is no centralization or way to "control" the conversation and messages. Overly broad or generic communication strategies will not likely be effective on social media, given the limited message control and constantly changing nature of social media discussions. The differences we found between platforms also suggest that communicators should be conscious of the platform on which they post their information. Different platforms attract different audiences and, as our results suggest, generate different conversations about risk and health. As a result, English-only and single-platform approaches to understand risk on social media are not necessarily generalizable to other languages or platforms.

### 6.2. SARF

Some scholars have specifically critiqued the presentation of mass media in the SARF as being oversimplified and communication processes presented as too static (Petts et al., 2000; Rayner, 1988). However, the SARF was not designed as a predictive model (Renn, 1991), but was instead to be treated as "a useful starting point from which to empirically investigate real world complexity in risk communication" (Bakir, 2005, p. 690). This design protects the SARF from being disproven or falsified, as it is not an actual theory and does not involve any predictions or hypotheses. However, this point also dramatically limits its utility, as it can also not be supported or affirmed. So, theoretical conclusions that can be drawn from the framework are, by definition, limited to conclusions about how useful the SARF is or is not when thinking about risk amplification.

Based on these parameters and our results, we conclude with two specific theoretical contributions related to the SARF. First, the framework serves as a helpful starting point for understanding how initial or more "expected" risks may spread and ripple beyond a specific risk. As discussed above, the conversations about the Zika virus on Facebook and Twitter expanded to include several other groups that were not directly connected to the outbreak. In the terms of the SARF, this documents the secondary effects of risk amplification, known as ripple effects. We documented these effects in all three languages, thus demonstrating social media platforms can act as a place for users to express and be exposed to the secondary impacts of risk amplification.

This is relevant to risk communication theory because it builds on past research on ripple effects (e.g., Susarla, 2003) by providing empirical evidence for their existence on social media, which are only beginning to be considered broadly within the framework (e.g., Fellenor et al., 2017). These findings are important for building risk communication theory and informing future research because they demonstrate how the focus of risk discussions and perceptions may change and deviate from what experts deem the "actual" risks. The ripple effects may also be helpful for determining how perceptions of one risk or technology can influence or "spill over" to the perceptions of other technologies (Akin et al., 2018).

Second, we did not find the SARF helpful for understanding variations in content data over time, as it would need to establish a "correct" or agreed upon level of risk from which perceptions are amplified or attenuated. The framework does not provide a useful theoretical foundation for interpreting variations over time, largely because the framework does not provide any testable hypotheses regarding media content. In this regard, no matter what we found in our analyses we could not have substantially contributed to the framework in this area. We argue future risk-related media studies direct attention to either other current theories, or work to develop new ones, which are falsifiable and aim to expand our understanding of how risk operates in evolving media landscapes.

### 6.3. Media Systems

Our research also provides key empirical data to the fields of Western and non-Western media studies. We focus our discussion about media systems primarily on Brazil and the United States, as our data best represent those countries specifically. Applying the concept of media systems outside of the initial countries analyzed was beyond the direct scope of the initial media systems framework (Hallin & Mancini, 2004, 2012). However, some researchers have argued the polarized pluralist model could generally apply to other areas of the world, like Latin America (Hallin & Papathanassopoulos, 2002). This extension has been criticized by other scholars for not accurately representing the factors at play (de Albuquerque, 2012). While Brazil does mirror some of the Mediterranean states in some ways (e.g., low newspaper circulation and high dependency on broadcast media), there are also key and substantial areas where it deviates (de Albuquerque, 2012), suggesting that the polarized pluralist model does not accurately represent the country's media system.

The theoretical foundation for media systems outside the West is so limited and fractured it makes expanding it difficult. However, what we do provide is content to serve as potential context in deciphering how the Latin American countries, most specifically Brazil, relate to a country already within the frame work, the United States. While Hallin and Mancini (2004) list content as a key factor for media systems, it is hardly represented in the analyses. We provide the content necessary for substantive comparisons and do so for social media, an area largely unaddressed by this area of research.

Our results suggest that there are differences between social media discussions about Zika between languages imbedded within various media systems. However, the differences between languages did not strictly follow the categorizations of media systems defined within some areas of research (Hallin & Mancini, 2004). For example, we found content in English, which generally represents the United States, and Spanish, which does not represent a specific country, to be more similar in some cases than Portuguese content, which largely represents Brazil. We found this even though traditional categorizations suggest that countries broadly represented by the Spanish content and Brazil would be more similar. However, these categorizations of systems were not designed to perfectly encompass the media within all countries and contexts (Hallin & Mancini, 2004).

Our research demonstrates that social media and online communication platforms are another source of media system variation that needs to be considered within traditional categorizations to make the concepts more useful and applicable to the field of media studies. Additionally, our research contributes to media studies discussions about globalization (Flew, Iosifidis, & Steemers, 2016). Even though social media platforms are discussed as "global" forms of communication, our results show that there is not always one clear and consistent conversation.

In conclusion, this research significantly contributes to the field of risk communication by documenting the risk-related discourse on two social media platforms in three languages. By expanding the applications of the SARF to new cultural contexts, we hope to have opened the door and helped facilitate future research in this area. This study provides both a foundation for studies within Latin America, and also, because of the comparative approach, provides a stronger bridge to risk communication research that has been done in Western and English-speaking contexts. We also hope future researchers continue to expand the applications of risk-related theories to more contexts and specific cases to enrich our understanding of how risks are spread, amplified, and attenuated.

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## APPENDIX A: BOOLEAN SEARCH STRING USED TO CAPTURE ALL POTENTIALLY RELEVANT POSTS FROM FACEBOOK AND TWITTER

| Language | Topic | Search String |
|---|---|---|
| English | Zika | ((zika) OR (zika*) OR (zica*) OR (zikv*) OR (zeka*)) AND -("Tata") |
| Portuguese and Spanish | Zika | ((zika*) OR (zica*) OR (zikv*) OR (zeka*) OR (**sika***) OR (**sica***)) AND -("Tata") |
| English | GMM | ((OX513A*) OR (((mosquit*) OR (mosqit*) OR (misquit*) OR (miskito*) OR (mosqut*) OR (mozzie*) OR (aedes*) OR (aegypti*)) AND ((oxitec*) OR (@Oxitec*) OR (#oxitex*) OR (oxytec*) OR (interexton*) OR (moscamed*) OR ("GM") OR (#GM*) OR ("GE") OR (#GE*) OR (GMO*) OR (LMO*) OR (#LMO*) OR (gene*) OR (engin*) OR (biotech*) OR ((bio*) AND (tech*)) OR (modifi*) OR (transgen*) OR (mutat*) OR (evolv*) OR (DNA) OR (RNA) OR (manip*) OR (inster*) OR (ster*) OR (reproduc*) OR (breed*) OR (viabl*) OR (offspring*) OR (termin*) OR (extinguish*) OR (edit*) OR (chang*) OR (research*) OR (tech*) OR (sci)))) AND -("Phosphoglucomutase") |
| Portuguese and Spanish | GMM | ((OX513A*) OR (((mosquit*) OR (mosqit*) OR (misquit*) OR (miskito*) OR (mosqut*) OR (aedes*) OR ("aegypti*")) AND ((oxitec*) OR (@Oxitec*) OR (oxytec*) OR (interexton*) OR (moscamed*) OR ("GM") OR (#GM*) OR ("GE") OR (#GE*) OR (GMO*) OR (gene*) OR (engenheirad*) OR (biotec*) OR ((bio*) AND (tec*)) OR (modifi*) OR (transgên*) OR (transgen*) OR (mutat*) OR (mutaç*) OR (mutac*) OR (evolv*) OR (evolu*) OR (DNA) OR (RNA) OR (manip*) OR (inster*) OR (ster*) OR (reprodu*) OR (viáve*) OR (viave*) OR (viabilid*) OR (prole*) OR (ovo*) OR (termin*) OR (elimin*) OR (edit*) OR (alter*) OR (pesquisa*) OR (científic*) OR (cientific*) OR (tech*) OR (tecnologia*) OR (ciência*) OR (ciencia*)))) AND -("phosphoglucomutase") |

## APPENDIX B: CODING CATEGORIES

### Blame-Related Categories

*Blame.* This category was for posts that attributed blame for the Zika virus or the problems associated with it. This includes posts that implied an individual, group, action, or technology was connected or responsible for the difficulties, losses, harm, damages, or complications that came from the Zika virus or its side effects. Additionally, posts supporting a Zika-related conspiracy theory were also placed into the *Blame* category. These were generally posts blaming Monsanto, GE mosquitoes, vaccines, chemicals, the Bill & Melinda Gates Foundation, or the Rockefeller Foundation for causing or being involved negatively with the Zika crisis. Posts that presented an individual, group, or institution as at fault for lack of actions were also placed into this category. For specific examples of posts that assign blame, see Table II.

*No Blame.* This category was for posts that did not attribute any blame for the Zika virus and its related problems. These posts were generally providing information, updates, or warnings about the Zika outbreak. This category was also used for posts that refuted conspiracies or misinformation related to the Zika virus. For specific examples of posts that do not assign blame, see Table II.

*Off-Topic.* This category is for posts that were captured by our search string that are not explicitly referencing the Zika virus and should not be analyzed. This includes things like keywords embedded within links, mentions of search terms that are clearly referencing another topic, or if the post is in a different language. Table II lists examples of off-topic posts that are used to train the ForSight platform what content is not relevant for our analyses relating to the Zika virus.

This category was also used for the analyses surrounding GE mosquitoes. Instead of posts not related to the Zika virus, the category was used for posts that did not explicitly reference GE or modified mosquitoes. This included things like keywords embedded within links or if the post is in a different language. The search terms for GE mosquitoes captured many posts about insects and GM foods/crops. Table III lists examples of off-topic posts that are used to train the ForSight platform what content is not relevant for our analyses relating to the Zika virus.

### GE-Mosquitoes-Related Categories

*Positive.* This category was for posts that mentioned GE mosquitoes in a positive way, were supportive, or were optimistic about the technology. Also, the post was deemed positive if it advocated and clearly focused on the benefits or helpfulness of the technology, or provided a clear expression of support. See Table III for examples of positive posts.

*Negative.* Conversely, posts that mentioned GE mosquitoes in a negative way, were not supportive, or were pessimistic were considered negative. If the post focused on the risks or harmfulness of the technology, it was also placed in this section. See Table III for examples of negative posts.

*Neutral.* This category was for posts that did not express valanced sentiments about GE mosquitoes. If the post is an update, like a news headline, it was considered neutral. See Table III for examples of neutral posts.

## APPENDIX C: FILTERS USED TO SORT RELEVANT SENTIMENTS BY MENTIONS OF DIFFERENT GROUPS

| Group | Search String |
|---|---|
| Executive and legislative (United States) | Congres* OR Senat* OR Democrat* OR republican* OR liberal* OR conservat* OR GOP* OR Obama* OR Barack* OR president* OR (white AND house) OR ((left OR right) AND wing*) |
| Executive and legislative (Brazil) | Congresso* OR Senad* OR PSDB OR PT OR PMDB OR PSOL OR liberal* OR conservador* OR Dilma* OR Rousseff* OR president* OR Michel* OR Temer* OR tucano* OR direita* OR petista* OR esquerda* |
| Private sector | Rockef* OR rockaf* OR rockf* OR Gates OR (bill AND melinda) OR Monsant* |

## APPENDIX D: FILTERS USED TO SORT RELEVANT SENTIMENTS BY MENTIONS OF DIFFERENT PRIVATE-SECTOR GROUPS FOR ALL LANGUAGES

| Group | Search String |
|---|---|
| Monsanto | monsant* |
| Bill & Melinda Gates Foundation | Gates OR (bill AND melinda) |
| Rockefeller Foundation | Rockef* OR rockaf* OR rockf* |

## APPENDIX E: RESULTS FROM INTERCODER RELIABILITY TRIALS

| Language | Platform | Topic | Percent Agreement | Krippendorff's Alpha |
|---|---|---|---|---|
| English | Facebook | Zika Blame | 85.30% | 0.629 |
| | | GE Mosquitos | 93% | 0.669 |
| | Twitter | Zika Blame | 91.20% | 0.787 |
| | | GE Mosquitos | 98% | 0.93 |
| Portuguese | Facebook | Zika Blame | 80% | 0.676 |
| | | GE Mosquitos | 87.20% | 0.709 |
| | Twitter | Zika Blame | 91.20% | 0.835 |
| | | GE Mosquitos | 89.40% | 0.562 |
| Spanish | Facebook | Zika Blame | 80.80% | 0.629 |
| | | GE Mosquitos | 92.80% | 0.445 |
| | Twitter | Zika Blame | 90.40% | 0.821 |
| | | GE Mosquitos | 91.20% | 0.677 |

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