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Legacy and social media respectively influence risk perceptions and protective behaviors during emerging health threats: A multi-wave analysis of communications on Zika virus cases

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ABSTRACT

Objective: Both legacy media, such as television and newspapers, and online social media are potentially important but incompletely understood sources of information in the face of emerging public health risks. This research aimed to understand media effects on risk perceptions and behaviors concerning the Zika virus in the United States.

Methods: We analyzed a multi-wave nationally representative survey (N = 29,062) and the volume of communications in social and legacy media (i.e., legacy media data from news sources and databases, N = 2,660 and social media data from Twitter, N = 1,605,752) in the United States between April and October 2016, dates coinciding with the early cases of local transmission of Zika in the United States (i.e., 25 weeks). The present study conducted econometric analyses (i.e., Granger causality tests) to assess the associations of legacy and social media coverage with risk perceptions and protective behaviors in the total sample and specific groups separated by pregnancy status/intent, geographic region, income, education level, age, and ethnicity.

Results: The results from the overall sample suggested that changes in the volume of information in legacy and social media (i.e., Twitter) were followed by different changes in community risk perceptions and protective behaviors. Specifically, social media coverage correlated with the level of risk perceptions, whereas the legacy media coverage correlated with the level of protective behaviors. Analyses across different subpopulations, including those of different pregnancy status/intent, geographic Zika risk, income, education level, age, and ethnicity, replicated the social media associations with risk perceptions in most cases. However, legacy media and protective behaviors were linked only in some vulnerable subpopulations (e.g., the less-educated populations).

Conclusion: Understanding how media coverage relates to Zika risk perceptions and protective behaviors will help to facilitate effective risk communications by healthcare professionals and providers, particularly when a health risk emerges.

1. Introduction

Media information about health risks depicts both long-standing threats (e.g., the risk of contracting the flu in winter) as well as emerging risks (e.g., the risk of the Zika virus in 2016) (for a discussion of emerging risks, see Kousky et al., 2010). Recipients of information about emerging threats have limited, or no knowledge of the threat (e.g., the disease) and thus may benefit from receiving health information, particularly when the information travels quickly, and the format is brief and accessible (Shearer and Gottfried, 2017). The present study draws on models of health communications to answer the following questions: What are the associations of the volume of legacy and social media data with risk perceptions and protective behaviors? Do these associations vary across subpopulations with higher (vs. lower) risk of Zika infection? Understanding the influences of social and legacy media coverage of a novel health risk is important for health prevention and control as well as an optimal communication policy (Srinivasan, 2010).

On November 6, 2015, the World Health Organization (WHO)'s Weekly Epidemiological Record pointed out that “recent outbreaks of

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Zika infection in different regions of the world underscore the potential for the virus to spread further in the Americas and beyond, wherever the vector is present." The Zika virus can be transmitted to people primarily through the bite of an infected mosquito of the *Aedes* genus, possibly through sexual transmission, and from a pregnant woman to her fetus. Other less confirmed modes of transmission are blood transfusions and exposure to infected patients in healthcare settings (CDC, 2017a; WHO, 2017). The first sexual transmission of the Zika virus in the United States was reported on February 2, 2016 (CDC, 2017a; WHO, 2017); by mid-to-late summer of that year, local cases were identified in Florida (CDC, 2017b). These patterns suggest the potential for rapid growth in areas where the *Ae. aegypti* and *Ae. albopictus* mosquitos live, and a high volume of inhabitants who travel to and from Zika-affected regions. Despite recordings of Zika infections as early as 1952, only recently was the Zika virus conclusively linked to Guillain-Barré Syndrome (PAHO/WHO, 2016), a rare neurological disorder in which the immune system attacks the peripheral nerves (Oduyebo et al., 2016), and to microcephaly, a rare condition in which the virus attacks the nervous system of fetuses and children (Mlakar et al., 2016; WHO, 2016).

Understanding risk perceptions of a public health crisis and the protective behaviors are critical for disease prevention and control: Outbreaks of Zika virus cases in the year 2016 represented an ideal opportunity to observe population levels of risk perceptions and behaviors and the extent to which social and legacy media coverage influence these levels. The present study of the 2016 media messages concerning Zika considered the view that emerging risk perceptions and protective behaviors in a population are best instilled by quickly updated information in social media. Fear appeals and risk perceptions have typically been studied in legacy media contexts (Becker, 1974; Rogers, 1983; Witte et al., 2001) but may exert effects in new media as well. A fear appeal refers to a persuasive message intended to arouse danger or threat perceptions to facilitate preventive motivation and protective behaviors (Earl et al., 2009; Rogers and Deckner, 1975; Tannenbaum et al., 2015). The public health research suggests that fear appeals can act as *cues to action* and elicit risk perceptions and health behaviors (Becker, 1974; Champion and Skinner, 2008). Whether risk perceptions and health behaviors are both affected by a message, however, depends on whether the health behavior is perceived as well-suited to reduce the risk (Fishbein et al., 1995; Rogers, 1983). When a behavior is perceived as efficacious at reducing the risk, messages that influence risk perceptions may also influence protective behaviors. In contrast, when protective behaviors cannot fully reduce the risk of infection, such as when an infection (e.g., Zika) is asymptomatic and reducing contact is difficult, protective behaviors and perceived risk may remain functionally independent (Rogers, 1983). All in all, however, the presence of a large volume of social and legacy media messages about the Zika virus may both increase risk perceptions and protective behaviors. Furthermore, perceived risk should depend on the level of actual vulnerability to infection (CDC, 2017b; McCarthy, 2016; PAHO/WHO, 2016), which, in the case of Zika virus, should be higher in households with current and/or intended pregnancy and in geographic areas of high activity of the *Aedes* mosquito.

Prior research has demonstrated that legacy media, such as television broadcasts and newspapers, shape perceptions of public health issues (Dudo et al., 2007). For example, exposure to H1N1 flu news on television has been linked to the heightened perceived risk of the pandemic disease in Taiwan (Chang, 2012). Currently, social media allows for receiving and sharing health information within a social network in a timely manner (Fox, 2014, 2011) and can also influence perceptions of risk and protective behaviors through informal influences within a community (Chew and Eysenbach, 2010; Choi et al., 2017). Yet, legacy and social media may exert differential effects in the context of the novel risk (see Bass et al., 2006; Johnson and Meischke, 1993; Kousky et al., 2010). When the first few Zika infections were confirmed, fast-paced social media, rather than legacy media, may have provided a more adequate channel to disseminate information than the more formal, slower legacy media channels.

Somewhat surprisingly, however, no studies to date have directly examined the differential impact of social and legacy media on perceptions of the risk for infectious diseases (i.e., whether these media are differentially associated with risk perceptions when a health risk emerges) (Choi et al., 2017; Song et al., 2017). Choi et al. (2017) asked participants to report social media exposure and found a positive relation between exposure and risk perceptions of Middle East Respiratory Syndrome (MERS). Meanwhile, another group of researchers conducted a big data analysis of social media messages about the MERS in South Korea in 2015 (Song et al., 2017). These studies neither addressed the connections between media coverage and community risk perceptions and behaviors nor provided answers to the question of differential effects of social and legacy media. This gap in knowledge is worth filling, because while the media are ideally positioned to influence risk perceptions and subsequent behavioral responses, legacy and social media may play different roles in alerting the public.

To determine whether the volume of legacy and social media coverage week by week corresponds to the levels of risk perceptions and protected behaviors, we conducted a survey of the U.S. population over a period of 25 weeks and recorded references to the Zika virus in legacy media (i.e., radio, television, newspapers) and on Twitter. These data allowed us to gauge the relations between the volume of media coverage, risk perceptions, and protective behaviors. The present study used econometric analyses to observe the associations of legacy and social media coverage with risk perceptions and behaviors in the U.S. population. Subgroup analyses were performed on survey responses of priority populations, including respondents in households with a member who is pregnant or intending to become pregnant and different demographic groups.

2. Method

2.1. Social and legacy media data

We measured the total legacy media coverage of Zika during April–October 2016 by conducting searches of the term "Zika" on news websites and legacy media databases, including Factiva, Newsbank, and Internet Archive. We limited the records to the following legacy media sources located in the United States (i.e., *The Wall Street Journal, The New York Times, USA Today, The Washington Post, The Miami Herald, The Orlando Sentinel, The Sun Sentinel, The Tampa Bay Times,* ABC, CBS, NBC, CNN, Fox News, and MSNBC). We also included local broadcasts created by these legacy media sources in the search results.

The Twitter data were collected with software developed by Crimson Hexagon. Because Crimson Hexagon includes Twitter's entire "firehose" (i.e., all publicly available tweets) (Hitlin, 2015), we used their dashboard service to obtain the number of tweets during April 11 and October 2 in 2016 by searching a list of keywords in English and Spanish. Given the character limits on Twitter, Twitter users might discuss Zika-related issues without using the word "Zika"; therefore, we used "Zika" and a list of related words in the search. We excluded retweets, limited the geographic location to the United States, and limited tweets written in English and Spanish. (The English keywords included: "Zika" or "dengue" or "yellow fever" or "Zika fever" or "Zika virus" or "flaviviridae" or "brains shrink" or "fetal brain disruption sequence" or "mosquitoes" or "birth defects" or "insect bites" or "mosquito bites" or "insect-borne virus" or "mosquito-borne flavivirus" or "microcephaly" or "Guillain-Barré Syndrome." The Spanish keywords included: "fiebre amarilla" or "Fiebre Zika" or "Virus Zika" or "Flaviviridae" or "Los cerebros se encogen" or "Secuencia de interrupción del cerebro fetal" or "Mosquitos" or "defectos de nacimiento" or "picaduras de insectos" or "picadura de mosquito" or "Virus transmitidos por insectos" or "Flavivirus transmitido por mosquitos" or "Microcefalia" or "Síndorme de Guillain-Barré".)

2.2. Survey data

A US-wide survey about the Zika virus was conducted weekly over a period of 25 weeks, between April 11 and October 2, 2016. On each week, the survey involved a dual-frame sample (i.e., a fully-replicated, single-stage, random-digit-dialing sample of landline telephone households, along with randomly-generated cell phone numbers) designed to represent the adult U.S. population, including Hawaii and Alaska. About 1000 interviews were conducted each week, of which at least 600 were obtained from cell phone respondents. Within each landline household, a single respondent (the youngest adult) was selected. Cell phone respondents were considered separately from landlines as the interview could take place outside the respondent's home. Surveys were conducted over a five-day period, in English and Spanish. The interviews were typically conducted from Wednesday through Sunday, to include both weekdays and weekends.

Each wave was weighted to provide nationally representative and projectable estimates of the adult population 18 years of age and older. The weighting process considered the disproportionate probabilities of household and respondent selection due to the number of separate telephone landlines and cell phones answered by respondents and their households, as well as the probability associated with the random selection of an individual household member. Following application of the weights, the sample was appropriately post-stratified and balanced by the key demographics of age, ethnicity, sex, region, and education. The sample was also weighted to reflect the distribution of phone usage in the general population, indicating the proportion of respondents who use a cell phone only, use a landline only, or a mix of both. There was no monetary remuneration for participation.

The survey included dichotomous responses and polychotomous scales. Among these measures were items assessing *risk perceptions* on a 5-point scale (1 = *extremely high risk* to 5 = *no risk*, i.e., *What is the risk that you will be infected with Zika in the next* 6 months*?*), and *protective behaviors* on a dichotomous-choice format (1 = *yes* and 2 = *no*, i.e., *In the past three months, have you done anything to protect yourself from getting Zika?*, *In the past three months, have you discussed Zika virus with a medical doctor or other healthcare professionals, or not?*) as well as on the scale (1 = *once*, 2 = *two times*, 3 = *three times*, 4 = *four times*, 5 = *five or more times*, i.e., *In the past three months, how many times have you discussed Zika virus with a medical doctor or other healthcare professional?*). The item measuring risk perceptions was reverse-coded so that a higher risk perception received a higher score, while the dichotomous items measuring protective behaviors were dummy-coded to represent the presence of a protective behavior (a score of 1) versus the absence of a behavior (a score of 0).

Additionally, respondents were asked questions about the pregnancy status of their household, i.e., *As far as you know, is anyone in your household currently pregnant?* and *As far as you know, is anyone in your household considering getting pregnant within the next* 12 months*?* Lastly, respondents reported their demographic and socio-economic information, including age, ethnicity, state of residence, household income, and the highest education level that they have completed.

2.3. Statistical procedures and analyses

Table 1 presents raw and standardized values of the variables of interests for all 25 waves, and Fig. 1 shows the standardized values for all waves. Details about each analysis are presented as they become relevant.

2.3.1. Legacy and social media

The searches on legacy media sites and databases resulted in over two thousand news records containing newspapers articles, and television/radio broadcasts, including both national and local channels. The raw number of records was calculated for each of the 25 waves based on their publication date, $Mdn = 93$, $M = 106.40$, $SD = 54.53$, and then standardized with a mean of zero. The search on Crimson Hexagon located over 1.6 million tweets during the study period. The average number of tweets was also calculated for each of the 25 waves, $Mdn = 8424$, $M = 9211.28$, $SD = 3938.31$, and these values were standardized as well.

2.3.2. Survey data

A total of 29062 adults (51% women, $M_{\text{age}} = 54$, $SD_{\text{age}} = 20.52$) responded to the survey. The average response rate over the data collection period was 7.5%, which is typical of this kind of study (Keeter et al., 2006; Kohut et al., 2012). The measures of risk perceptions and protective behaviors were calculated for each of the 25 weeks. Specifically, two measures of protective behaviors and discussions with healthcare professionals were standardized over the 25 weeks, and then these three measures were averaged to represent the level of protective behaviors. The standardized values of the variables of interest were calculated for the overall sample as well as for segments of interest based on pregnancy status (i.e., households with vs. without current and/or intended pregnancy), geographic regions (i.e., respondents residing in a high- vs. low-risk region of Zika infections), income (i.e., high vs. low household median income), education level (i.e., more vs. less education), age (i.e., young adult vs. adult vs. senior), and ethnicity (i.e., White vs. Black vs. Hispanic vs. 'other').

2.3.3. Correlation and Granger causality analyses

We first correlated risk perception and protective behavior over the 25 weeks of the study to see if the variables were associated or occurred in parallel. We then used the Granger causality technique to determine whether the volume of social (vs. legacy) media in a previous week (i.e., with the time lag of one, two, or three weeks) correlated with levels of risk perceptions and protective behaviors in the current week. We tested for lags of one week, two weeks, and three weeks to determine if the volume of media coverage was associated with levels of risk perceptions or behaviors a week, two weeks, or three weeks following particularized media coverage. In addition to establishing significance, the multiple linear regression models of the Granger causality tests assessed the strength of the associations.

3. Results

As shown in Table 1, the raw values of risk perceptions and one of the protective behaviors were around the midpoint of a 5-point scale in all 25 waves (risk perception: $Ms = 1.75$ to 2.04, $SDs = 0.81$ to 0.93 and discussing with healthcare practitioners: $Ms = 2.16$ to 3.02, $SDs = 1.41$ to 1.74). The correlation analysis suggested no significant association between risk perceptions and protective behaviors, $r = .41$, $p = .0997$, indicating that these two responses to the media were relatively independent (Fishbein et al., 1995). The results suggested that separate Granger causality tests with risk perceptions and protective behaviors as an outcome variable were appropriate. Post-hoc correlation analyses showed only continuous positive weak correlation coefficients between risk perception and protective behaviors from wave 13 to 25, $rs = .06$ to $.17$, $ps \le .05$.

3.1. Social and legacy media associations with risk perceptions and protective behaviors

The Granger causality tests in Table 2 show that social and legacy media were associated with risk perceptions, $F\ (1,\ 13) = 33.38$, $p < .001$, and protective behaviors a week later, $F\ (2,\ 18) = 4.00$, $p = .037$. The multiple linear regression model showed a strong association between social media and risk perceptions after 1 week, $b_{\text{lag1}} = 0.59$, $SE_{\text{lag1}} = 0.11$, 95% $CI_{\text{lag1}} = 0.34$ to 0.85, which accounted for 82% variance in risk perceptions in total, $p < .001$. Furthermore, the association between legacy media and protective behaviors a week later was of moderate strength, $b_{\text{lag1}} = 0.30$, $SE_{\text{lag1}} = 0.14$, 95%,

Table 1
Descriptive characteristics of all waves with raw and standardized values of the variables of interest during the year 2016.

Wave	Period	*N*	Mean age	Percent of females	Raw value					Standardized value			
					Risk perception	Protective behaviors[a]	Protective behaviors[b]	Legacy media	Social media	Risk perception	Protective behaviors	Legacy media	Social media
1	Apr/11 - Apr/17	1059	50 (18.48)	48%	–	0.08 (0.27)	2.74 (1.55)	68	7948	–	−0.10	−0.70	−0.32
2	Apr/18 - Apr/24	1009	50 (18.89)	50%	–	0.07 (0.25)	3.02 (1.74)	119	4662	–	0.51	0.23	−1.16
3	Apr/25 - May/1	1013	52 (19.12)	52%	–	0.07 (0.25)	2.64 (1.57)	39	5263	–	−0.46	−1.24	−1.00
4	May/2 - May/8	1009	52 (19.12)	51%	–	0.08 (0.27)	2.74 (1.61)	74	5377	–	−0.07	−0.59	−0.97
5	May/9 - May/15	1008	52 (18.67)	51%	–	0.07 (0.25)	2.19 (1.47)	60	6016	–	−1.62	−0.85	−0.81
6	May/16 - May/22	1029	52 (18.77)	52%	1.95 (0.87)	0.07 (0.26)	2.64 (1.60)	104	9020	0.44	−0.44	−0.04	−0.05
7	May/23 - May/28	1018	52 (19.23)	50%	–	0.13 (0.26)	2.47 (1.58)	134	9496	–	−0.38	0.51	0.07
8	May/29 - Jun/5	1033	52 (19.32)	51%	–	0.07 (0.26)	2.61 (1.52)	91	9127	–	−0.51	−0.28	−0.02
9	Jun/6 - Jun/12	1023	53 (18.74)	53%	1.90 (0.87)	0.07 (0.25)	2.50 (1.41)	127	8424	−0.16	−0.81	0.38	−0.20
10	Jun/13 - Jun/19	1012	51 (19.34)	53%	1.94 (0.90)	0.15 (0.26)	2.63 (1.52)	64	7273	0.30	0.20	−0.78	−0.49
11	Jun/20 - Jun/26	1018	53 (18.39)	52%	–	0.07 (0.26)	2.42 (1.51)	80	9578		−0.98	−0.48	0.09
12	Jun/27 - Jul/2	1017	52 (19.03)	49%	1.86 (0.85)	0.09 (0.28)	2.91 (1.67)	104	11056	−0.52	0.42	−0.04	0.47
13	Jul/3 - Jul/10	1024	52 (19.31)	52%	1.86 (0.82)	0.16 (0.27)	2.69 (1.61)	93	7716	−0.61	0.46	−0.25	−0.38
14	Jul/11 - Jul/17	1008	53 (18.75)	53%	1.79 (0.84)	0.16 (0.27)	2.35 (1.49)	54	7923	−1.35	−0.42	−0.96	−0.33
15	Jul/18 - Jul/24	1021	51 (18.88)	51%	1.78 (0.79)	0.15 (0.27)	2.76 (1.72)	44	8055	−1.48	0.54	−1.14	−0.29
16	Jul/25 - Jul/31	1011	52 (18.78)	54%	1.75 (0.82)	0.17 (0.28)	2.44 (1.53)	59	11789	−1.73	−0.08	−0.87	0.65
17	Aug/1 - Aug/7	1028	52 (18.87)	51%	1.81 (0.81)	0.16 (0.26)	2.16 (1.47)	145	22985	−1.15	−0.94	0.71	3.50
18	Aug/8 - Aug/14	1470	53 (18.96)	51%	2.04 (0.90)	0.20 (0.28)	2.56 (1.66)	236	14091	1.36	0.44	2.38	1.24
19	Aug/15 - Aug/21	1475	54 (18.68)	50%	2.02 (0.93)	0.20 (0.28)	2.62 (1.66)	134	12057	1.16	0.60	0.51	0.72
20	Aug/22 - Aug/28	1472	52 (19.07)	51%	1.95 (0.89)	0.18 (0.28)	2.54 (1.67)	53	12063	0.36	0.28	−0.98	0.72
21	Aug/29 - Sep/3	1453	53 (19.06)	53%	2.00 (0.88)	0.19 (0.29)	2.55 (1.58)	158	13152	0.91	0.32	0.95	1.00
22	Sep/4 - Sep/11	1475	53 (18.66)	49%	2.00 (0.88)	0.21 (0.30)	2.49 (1.57)	175	10645	0.93	0.41	1.26	0.36
23	Sep/12 - Sep/18	1450	53 (19.35)	51%	2.01 (0.92)	0.22 (0.30)	2.68 (1.73)	246	6465	1.07	0.92	2.56	−0.70
24	Sep/19 - Sep/25	1466	53 (19.17)	52%	1.98 (0.88)	0.21 (0.29)	2.59 (1.64)	108	4928	0.72	0.67	0.03	−1.09
25	Sep/26 - Oct/2	1461	52 (19.02)	51%	1.89 (0.86)	0.22 (0.29)	2.72 (1.66)	91	5173	−0.26	1.04	−0.28	−1.03

Note. Standard deviations in parentheses. Legacy media refers to the weekly number of records through the searches on sites and databases and social media refers to the weekly average of tweets through the search on Crimson Hexagon.

[a] Protective behaviors refer to the weekly averages of two dichotomous items.

[b] Protective behaviors refer to the weekly averages of the polychotomous item.

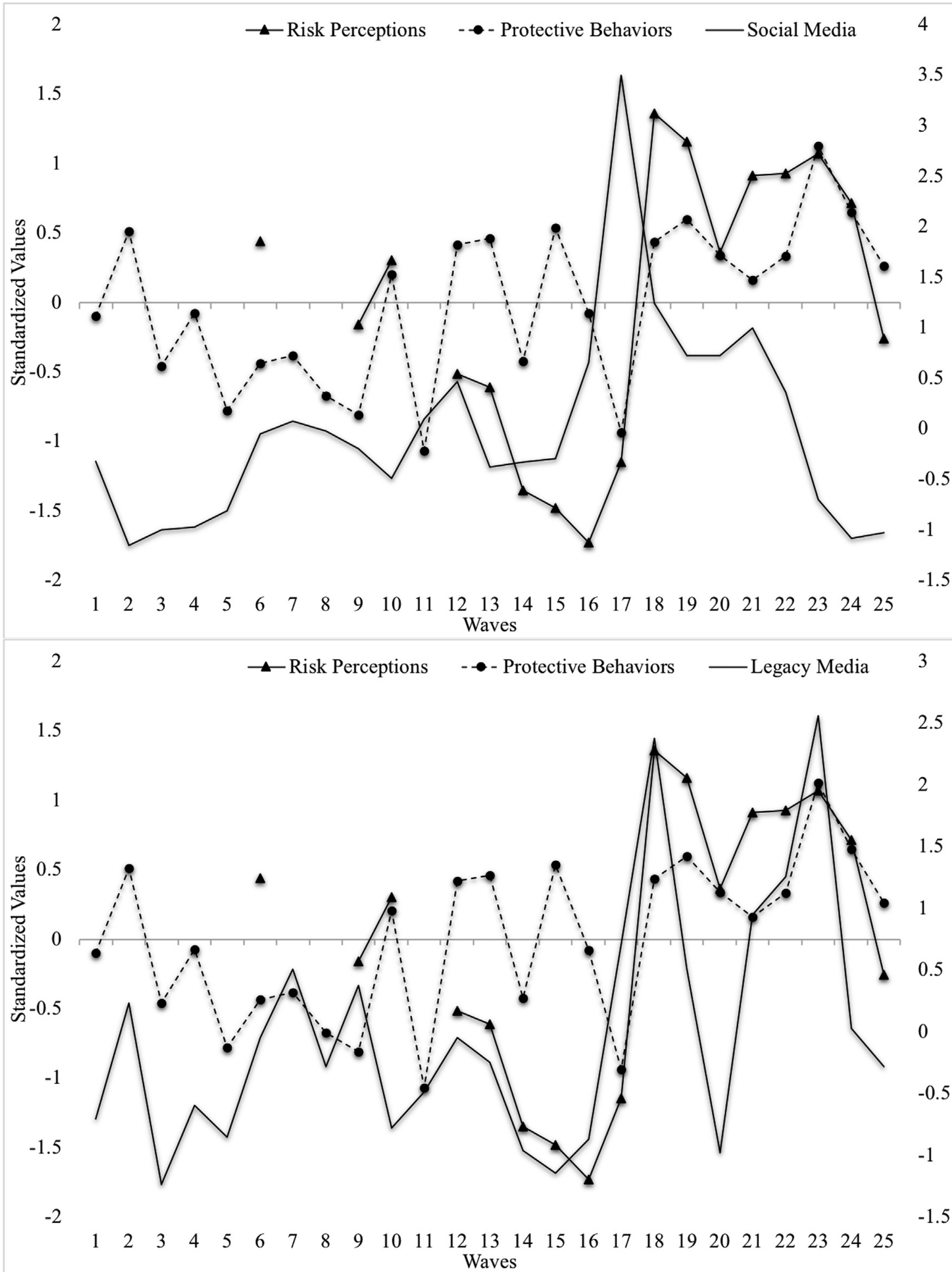

Fig. 1. Overall risk perceptions and protective behaviors with social media (upper panel) and legacy media (bottom panel) for 25 waves. Risk perceptions and protective behaviors are plotted on the left y-axis and the media is plotted on the right y-axis.

$CI_{\text{lag1}} = 0.01$ to 0.58, $b_{\text{lag2}} = 0.16$, $SE_{\text{lag2}} = 0.15$, 95%, $CI_{\text{lag2}} = -0.15$ to 0.47. This model accounted for 28% variance in protective behaviors, $p = .040$.

Table 3 shows the same analyses for subpopulations. These analyses were conducted to verify generalizability and detect any salient differences in the influence of lagged legacy and social media as a function of current/intended household pregnancy, geographic region, and demographic variables. A summary of our results is presented in the form of decision trees in Fig. 2. Importantly, the strong association between social media and risk perceptions a week later was present in all subpopulations except regions with low Zika-risk and in Black respondents (see Table 3 and the left panel of Fig. 2). The top panel of Table 3 presents the multiple linear regression results for social media and risk perceptions. Compared to the mostly homogeneous positive

Table 2
Results of granger causality tests between legacy (vs. Social) media, risk perceptions, and protective behaviors.

Variable	Legacy media *F*-value, *p*-value	Social media *F*-value, *p*-value
Lag length of one week[a]		
Risk perceptions	3.87, .071	**33.38, < .001**
Protective behaviors	3.75, .066	2.37, .139
Lag length of two weeks[b]		
Risk perceptions	1.52, .264	**14.02, < .001**
Protective behaviors	**4.00, .037**	2.28, .131
Lag length of three weeks[c]		
Risk perceptions	0.81, .526	**12.90, .003**
Protective behaviors	3.10, .059	1.74, .202

Note. Bold font style indicates a significance level of *p*-values ≤ .05.
[a] Degrees of freedom for *F*-tests of risk perceptions and protective behaviors were (1, 13) and (1, 21).
[b] Degrees of freedom for *F*-tests of risk perceptions and protective behaviors were (2, 10) and (2, 18).
[c] Degrees of freedom for *F*-tests of risk perceptions and protective behaviors were (3, 7) and (3, 15).

influences of social media on risk perceptions (see Fig. 2), however, legacy media was only significantly associated with risk perceptions in low Zika-risk regions, in less educated respondents, and in Hispanic respondents (see the top panel of Table 3 and the right panel of Fig. 2).

The analyses also recorded favorable influences of both social and legacy media on protective behaviors in households with current/intended pregnancy and among other ethnicities. As shown in the bottom panel of Table 3, lagged social media and protective behaviors were strongly associated in households with current/intended pregnancy, $b_{lag3} = 0.58$, $SE_{lag3} = 0.14$, 95%, $CI_{lag3} = 0.27$ to 0.88, and moderately associated among other ethnicities, $b_{lag1} = 0.31$, $SE_{lag1} = 0.14$, 95%, $CI_{lag1} = 0.02$ to 0.60. Likewise, legacy media and protective behaviors were also moderately associated in households with current/intended pregnancy, $b_{lag1} = 0.30$, $SE_{lag1} = 0.12$, 95%, $CI_{lag1} = 0.06$ to 0.54, and among other ethnicities (see Table 3). Further, lagged legacy media and protective behaviors correlated in high-risk regions, in less-educated populations, and in Hispanic respondents. These results indicate a unique and important favorable influence of legacy media in these subpopulations.

4. Discussion

At the start of a public health crisis, such as the 2016 Zika virus infections in the United States, selecting optimal communication media is important to inform the public, reduce anxiety and rumors of the virus/diseases, help people understand the situation, and prepare needed behavioral responses. The present study involved a nationally representative survey about the Zika virus, which we correlated with the volume of Zika coverage in U.S. legacy and social media over a period of 25 weeks. The results were clear: There is substantial evidence that changes in the volume of information in social media are followed by corresponding changes in the perceptions of risk, whereas changes in the volume of information in legacy media are followed by changes in protective behaviors. The findings underscore the importance of using both social and legacy media to raise awareness and promote healthy responses to an emerging health risk.

We present the findings for different subpopulations when using legacy or social media for Zika-related public health messages in two decision trees (Fig. 2). The associations in different demographic groups indicated that an increase of information flow in social media (see the left panel of Fig. 2) is more likely to produce changes in community risk perceptions in the populations that are most susceptible to Zika infection: Households with current/intended pregnancy and samples from regions with high Zika-risk, as well as low-income groups, less-educated populations, adults and seniors, Whites and 'other' ethnic populations. The increase of information flow on Twitter was also likely to increase protective behaviors in the households with current/intended pregnancy and 'other' ethnicities in the following week(s). That said, legacy media coverage remains essential in facilitating protective behaviors at the community level (see the right panel of Fig. 2). Specifically, changes in the volume of information in legacy media coincided with changes in protective behaviors in households with current/intended pregnancy, high Zika-risk regions, less-educated populations, Whites, and Hispanics. Furthermore, an increase in information flow in legacy media is linked to elevated risk perceptions in regions with low Zika-risk and among Hispanics.

This summary of the influences of social and legacy media across regions and subpopulations (Fig. 2) echoes national and international recommendations to communicate public health issues within a community. These recommendations include taking steps "to conduct an assessment of existing public communication capacity and existing research of community understanding, including demographics, literacy levels, language spoken as well as socio-economic and cultural backgrounds" (WHO, 2008) and "to understand audience by age/culture/level of experience or familiarity with the subject/language/geographic location" (Reynolds, 2007). Healthcare practitioners and journalists are encouraged to take population-specific needs into account when disseminating health-related messages on the media. For example, Zika-prevention messages targeting households with current/intended pregnancy and adolescents may be disseminated via both legacy and social media, whereas those that focus on frequent travelers with higher educational levels may be effectively issued via social media.

Our results correlating media with risk perceptions and protective behaviors are also consistent with Kousky et al., 2010 proposal that an emerging risk, rather than an experienced risk, energizes the information flow from other sources, such as scientific studies. More importantly, the present study suggests differential effects of social and legacy media. Whereas the volume of social media data showed robust positive associations with risk perceptions, the volume of legacy media correlated positively with protective behaviors in several subpopulations. These differences are likely due to differences in speed, volume, and numbers of information sources across the two types of media (CDC, 2017c; Denecke and Atique, 2016; Fung et al., 2015; Vos and Buckner, 2016), an issue that should be investigated in the future. The present study also adds to the understanding of public responses during an emerging health risk in the context of the health belief model (Becker, 1974; Champion and Skinner, 2008). The findings provide preliminary and empirical evidence of social media coverage acting as *cues of actions* to influence risk perceptions and protective behaviors. Despite the beneficial impacts, social media could also amplify maladaptive responses in the course of a crisis, as reported in studies of other health-unrelated crises (Jones et al., 2017; Mendoza et al., 2010). Future studies should examine this possibility.

Our correlational findings of course do not prove *causal* effects of social and legacy media coverage on risk perception and protective behaviors in the community, but they do offer innovative insights into public health implications. In particular, public health institutions such as WHO may use social media to quickly and efficiently inform the public when a health risk emerges. Strategic planning (Person et al., 2004) may be based on instant signals about the types of messages that are transmitting in the communities before rumors and stigmas spread. Moreover, public health institutions may work with the legacy media to avoid confusion and misunderstandings of constantly updating information (Hon et al., 2003; Karkowsky, 2016; Knapton, 2016). For example, providing extended recommendations and issuing press releases via legacy media are perhaps the optimal methods to influence the behavior of vulnerable populations.

Table 3
Results of granger causality tests and regression analyses between legacy (vs. Social) media, risk perceptions, and protective behaviors in different populations – by pregnancy status, Zika infection risk, income, education level, age, and ethnicity.

Demographic variable	Legacy media						Social media					
	Granger causality test *F*-value, *p*-value	Unstandardized coefficient	Standard error	95% *CI*	Adjusted R^2	*p*-value	Granger causality test *F*-value, *p*-value	Unstandardized coefficient	Standard error	95% *CI*	Adjusted R^2	*p*-value
Risk perceptions												
Pregnancy status[a]												
Households with current/ intended pregnancy	0.01, .909	−0.23	0.38	−1.06 to 0.59	.06	.284	**9.02, .010**	**0.54**	**0.22**	**0.07 to 1.02**	**.38**	**.029**
Households without current/intended pregnancy	**5.14, .041**	0.43	0.24	−0.10 to 0.97	**.54**	**.006**	**32.99, < .001**	**0.59**	**0.11**	**0.34 to 0.84**	**.82**	**< .001**
Geographic regions[b]												
High-risk	1.40, .258	0.23	0.23	−0.26 to 0.73	**.54**	**.005**	**27.54, < .001**	**0.53**	**0.11**	**0.29 to 0.76**	**.84**	**< .001**
Low-risk	**7.03, .012***	**0.69**[g] −0.34[h]	**0.23**[g] 0.23[h]	**0.16 to 1.23**[g] −0.90 to 0.20[h]	**.52**	**.052**	3.18, .098	0.36	0.22	−0.13 to 0.85	.14	.179
Income[c]												
Low income	3.00, .107	0.30	0.26	−0.26 to 0.87	**.49**	**.009**	**27.40, < .001**	**0.55**	**0.12**	**0.29 to 0.81**	**.81**	**< .001**
High income	4.18, .062	0.50	0.27	−0.10 to 1.11	**.48**	**.012**	**16.62, .001**	**0.57**	**0.15**	**0.23 to 0.90**	**.70**	**.001**
Education level[d]												
Less educated	**6.88, .021**	**0.62**	**0.24**	**0.09 to 1.16**	**.54**	**.006**	**11.73, .005**	**0.53**	**0.17**	**0.15 to 0.91**	**.60**	**.003**
More educated	0.62, .447	0.11	0.27	−0.49 to 0.71	**.38**	**.030**	**26.83, < .001**	**0.56**	**0.12**	**0.29 to 0.82**	**.79**	**< .001**
Age[e]												
Young adults	**6.55, .024**	**0.59**	**0.24**	**0.05 to 1.12**	.30	.056	**6.16, .027**	**0.52**	**0.22**	**0.04 to 0.99**	.30	.057
Adults	**4.95, .045**	0.46	0.25	−0.08 to 1.01	**.57**	**.004**	**29.00, < .001**	**0.56**	**0.12**	**0.30 to 0.82**	**.82**	**< .001**
Seniors	3.53, .083	0.48	0.32	−0.23 to 1.20	.18	.131	**14.21, .002**	**0.63**	**0.19**	**0.21 to 1.04**	**.51**	**.008**
Ethnicity[f]												
Whites	3.99, .067	0.42	0.26	−0.16 to 1.00	**.42**	**.019**	**38.75, < .001**	**0.63**	**0.11**	**0.38 to 0.88**	**.81**	**< .001**
Blacks	4.00, .067	0.47	0.32	−0.23 to 1.18	.26	.078	1.95, .186	0.27	0.23	−0.23 to 0.77	.21	.111
Hispanics	**7.33, .018**	**0.56**	**0.22**	**0.08 to 1.05**	**.49**	**.010**	**6.05, .029**	**0.47**	**0.21**	**0.01 to 0.94**	**.44**	**.016**
'Other' ethnicities	0.35, .563	0.32	0.29	−0.32 to 0.95	.03	.330	3.93, .055*	**0.69**[g] 0.27[h]	**0.23**[g] 0.24[h]	**0.15 to 1.23**[g] −0.30–0.85[h]	**.66**	**.018**
Protective behaviors												
Pregnancy status[a]												
Households with current/ intended pregnancy	**6.66, .017**	**0.30**	**0.12**	**0.06 to 0.54**	**.20**	**.039**	**8.84, .001^**	0.10[g] −0.04[h] **0.58**[i]	0.12[g] 0.16[h] **0.14**[i]	−0.16–0.36[g] −0.37 to 0.29[h] **0.27 to 0.88**[i]	**.62**	**.001**
Households without current/intended pregnancy	2.51, .128	0.24	0.15	−0.07 to 0.55	.05	.215	2.39, .137	0.21	0.14	−0.07 to 0.50	.05	.228
Geographic regions[b]												
High-risk	**10.13, .004**	**0.40**	**0.12**	**0.14 to 0.66**	**.42**	**.001**	3.76, .066	0.26	0.14	−0.02 to 0.54	**.27**	**.014**
Low-risk	0.37, .548	0.08	0.13	−0.19 to 0.36	-.08	.831	3.08, .094	0.21	0.12	−0.04 to 0.46	.04	.238
Income[c]												
Low-income	**4.66, .023***	0.24[g] 0.27[h]	0.13[g] 0.14[h]	−0.03–0.50[g] −0.02–0.57[h]	**.31**	**.028**	2.83, .107	0.21	0.12	−0.05 to 0.47	.11	.118
High-income	1.65, .213	0.19	0.15	−0.12 to 0.50	.03	.267	3.30, .083	0.25	0.14	−0.04 to 0.54	.10	.128
Education level[d]												
Less-educated	**6.72, .017**	**0.32**	**0.12**	**0.06 to 0.57**	**.17**	**.054**	1.00, .329	0.13	0.13	−0.14 to 0.41	-.05	.614
More-educated	1.90, .183	0.20	0.15	−0.10 to 0.51	.12	.096	3.47, .076	0.26	0.14	−0.03 to 0.54	**.18**	**.048**
Age[e]												

(*continued on next page*)

Table 3 (*continued*)

Demographic variable	Legacy media						Social media					
	Granger causality test *F*-value, *p*-value	Unstandardized coefficient	Standard error	95% *CI*	Adjusted R^2	*p*-value	Granger causality test *F*-value, *p*-value	Unstandardized coefficient	Standard error	95% *CI*	Adjusted R^2	*p*-value
Young adults	**4.19, .053**	0.26	0.13	−0.00 to 0.52	.13	.090	0.14, .716	0.05	0.14	−0.23 to 0.33	-.04	.571
Adults	2.94, .101	0.27	0.15	−0.06 to 0.59	.09	.149	3.19, .089	0.27	0.15	−0.04 to 0.58	.10	.134
Seniors	1.01, .326	0.12	0.12	−0.13 to 0.38	.03	.277	2.46, .132	0.19	0.12	−0.06 to 0.43	.09	.142
Ethnicity[f]												
Whites	**3.50, .052***	**0.32**[g] 0.09[h]	**0.14**[g] 0.15[h]	**0.02 to 0.62**[g] −0.23–0.40[h]	.23	.065	2.48, .130	0.21	0.13	−0.07 to 0.48	.03	.269
Blacks	2.56, .125	0.22	0.14	−0.07 to 0.51	.06	.200	2.32, .143	0.21	0.14	−0.08 to 0.50	.05	.223
Hispanics	**5.14, .034**	**0.33**	**0.15**	**0.03 to 0.64**	**.22**	**.027**	0.45, .510	0.11	0.16	−0.23 to 0.45	.05	.218
'Other' ethnicities	**3.60, .039^**	**0.29**[g] **−0.35**[h] **0.43**[i]	**0.14**[g] **0.15**[h] **0.16**[i]	**0.00 to 0.58**[g] **−0.66 to -0.04**[h] **0.08 to 0.77**[i]	**.39**	**.030**	**4.85, .039**	**0.31**	**0.14**	**0.02 to 0.60**	**.18**	**.048**

Note.

Absence *of* a symbol specification refers to a lag length 1, an asterisk refers to a lag length 2, and a caret refers to a lag length 3, the bold font style indicates the results were of a significance level of *p*-values ≤ .05.

[a] Pregnancy status: Respondents who answered "yes" to questions either about current or intended pregnancy in the next twelve months were grouped to the households with current/intended pregnancy whereas those who answered "no" to these questions were coded as households without current/intended pregnancy.

[b] Geographic regions: The state-level laboratory-confirmed symptomatic Zika virus disease cases and presumptive viremic blood donors reported to ArboNET were collected from the CDC, https://www.cdc.gov/Zika/geo/united-states.html. We identified Florida, New York, California, and Texas as geographic regions with high-risk because they contained over 50% of the reported cases in the United States. Respondents from these states were coded as from high-risk region, and the rest as from a low-risk region.

[c] Income: The median household income (i.e., US$55,775), reported in the 2015 American Community Survey was used as a threshold to identify high- and low-income populations. Using the answers of a question about household income (1 = Less than $15,000 to 15 = $250,000 or more), we divided respondents into the high-income group if an option 7 (i.e., $75,000 but less than $100,000) or higher was chosen, and those who selected an option 6 or lower were in the low-income group.

[d] Education level: More- (vs. less-) educated populations were defined as those with (vs. without) a college or university degree. Answers to the question about the level of education that the respondent completed were used for grouping. Respondents with a two-year associate degree from a college or university or a higher level were in the more-educated group whereas those without any college degree were in the less-educated group.

[e] Age: According to the age groups of the U.S. Census Bureau, respondents who reported between 18 and 24 years were classed as in the young adult populations, those who reported 25–64 years were classed as being in the adult populations, and those who reported being 65 years or older were categorized as being in the senior populations.

[f] Ethnicity: The responses to the question about individuals' identification of their own ethnicity, including "White non-Hispanic", "Black non-Hispanic", "White Hispanic" "Black Hispanic," and "Unspecified Hispanic" were used to form four ethnic categories, i.e., White, Black, Hispanic, and 'other' ethnicities.

[g] Lagged media with one week.

[h] Lagged media with two weeks.

[i] Lagged media with three weeks.

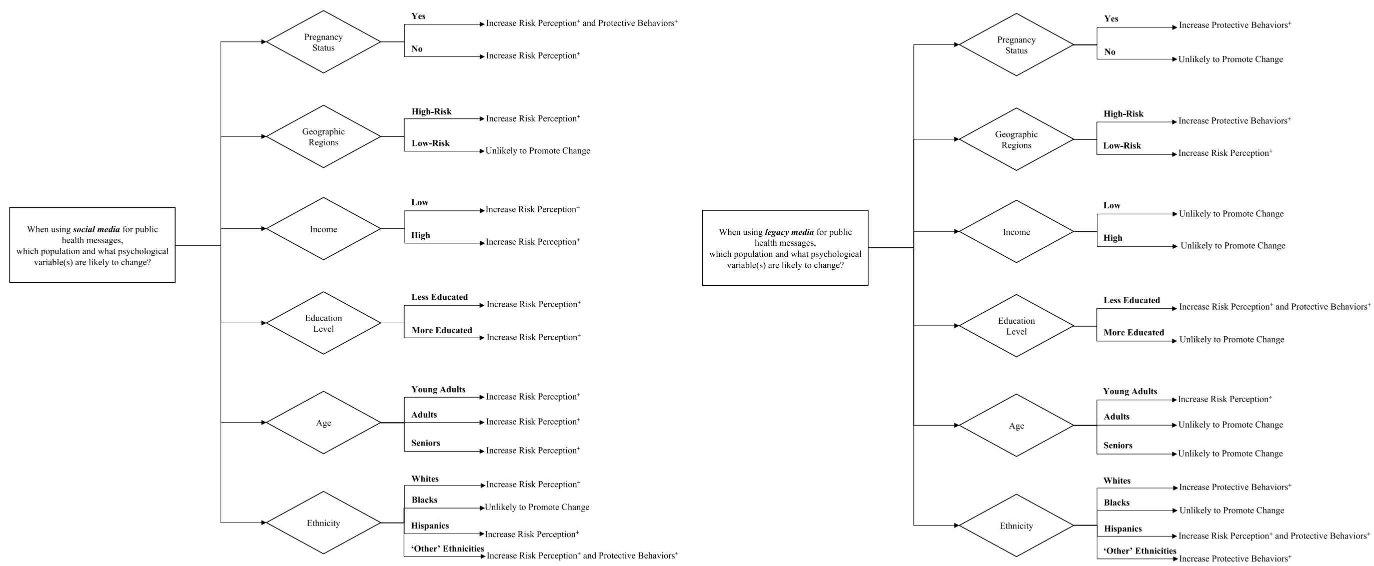

Fig. 2. Decision trees for social media (left panel) and legacy media (right panel) in different populations. A cross denotes the *p*-values of the unstandardized coefficients were $\leq .05$.

4.1. Limitations

This study offers insight into further research. We tracked the volume of information communicated in legacy and social media for only 25 weeks, a timespan which restricted the use of other forecasting techniques such as the Autoregressive Integrated Moving Average (ARIMA) models (Hyndman and Kostenko, 2007). Future work should track a longer period (or a shorter period for each wave), such as a wave per week for a year, and investigate other potential explanatory characteristics, such as the persuasiveness of the information delivered in the media (Albarracín et al., 2017a, 2017b; Fishbein and Cappella, 2006; Petty and Cacioppo, 1986). In the present study, the legacy media coverage only included English news reports, prints, and broadcasts, whereas legacy media coverage in Spanish was not available. Even though the sampled legacy media are likely representative of the entire legacy media coverage in the United States, and Hispanics often consume news in English (Lopez and Gonzalez-Barrera, 2013), future research should investigate the effect of the Spanish legacy media. Furthermore, the variables measured in the surveys were limited to the perception of the risk of infection over the next six months, and to protective behaviors such as taking mosquito-prevention measures and discussing Zika with healthcare professionals and providers. Other studies should expand the list of psychological variables to include efficacy beliefs (Brown, 2014; Rimal and Juon, 2010). Finally, our study focused on the community level instead of considering any change at the individual level. Future studies should combine surveys with tracks of legacy and social media exposure from individual participants to determine whether our findings replicate at the individual level. Nonetheless, this study provided valuable information about the role of legacy and social media in communicating about the risks of a geographically-dispersed disease.

5. Conclusions

Taken together, the present study provides empirical evidence on how social and legacy media relate to risk perceptions and protective behaviors across different subpopulations (i.e., pregnancy status/intent, geographic Zika-risk, income, education level, age, and ethnicity). Understanding these media effects is essential to communicate public health information and engage different populations in the community. In the face of emerging public health threats, risk communication that promotes attitudes and practices towards prevention and control can mitigate risks to the public.

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