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Information-Accessing Behavior during Zika Virus Outbreak, United States, 2016

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We used latent class analysis to examine Zika virus–related information-accessing behavior of US residents during the 2016 international outbreak. We characterized 3 classes of information-accessing behavior patterns: universalists, media seekers, and passive recipients. Understanding these patterns is crucial to planning risk communication during an emerging health threat.

During the past 15 years, new media platforms have emerged as routine channels of health communication. Little is known about how persons navigate this dynamic and complex information landscape, especially during an emerging health threat with little scientific certainty and few or no medical countermeasures (1,2). The 2016 Zika virus outbreak provides for an examination of how people interact with this dynamic information landscape. As scientific understanding of the virus evolved, so did Zika

risk communication strategies. Previous reports have identified public sources of Zika information but have not considered the public's information-accessing behavior (3,4). We used latent class analysis (LCA) to characterize and differentiate types of information-accessing behavior and identify how these behavioral patterns shifted during the 2016 Zika virus outbreak.

LCA identifies clusters within the population on the basis of participants' responses to observed variables (5,6). We collected and pooled data from 3 representative samples of US households drawn from fully replicated, single-stage, random-digit dialing samples of households supplemented by lists of randomly generated cell phone numbers. The survey had a 4%–6% response rate. We conducted the surveys in April–May (1,233 participants), July–August (1,231 participants), and October–November (1,234 participants) of 2016.

The survey analyzed access to 6 categories of information sources: news (online or print); television or radio; social media, such as Facebook, YouTube, Reddit, or other apps; personal physician; government agencies; and friends, family, or co-workers. We used these data to form 6 binary variables indicating access to each category of information source. We then used these variables to determine 3 classes of information-accessing behavior.

In accordance with the best practices suggested by Nylund et al. (7), we used 6 criteria to determine the optimal number of classes (Appendix, <https://wwwnc.cdc.gov/EID/article/26/9/19-1519-App1.pdf>). New York University's Institutional Review Board approved this research.

Our LCA results suggested that information-accessing behaviors could be grouped into 3 distinct classes: universalists, media seekers, and passive recipients. We sorted each participant into a class on the basis of the number of sources he or she had accessed (Figure). Class 1 comprised universalists, that is, participants who actively accessed information from all sources included in the survey. Class 2 comprised media seekers, that is, participants who primarily accessed information from mass media. Class 3 comprised passive recipients of information; these participants accessed the fewest number of sources and had the highest probability of seeking information from broadcast media. Class membership was not necessarily static; an individual participant might exhibit different information-accessing behaviors at different time points within the Zika outbreak.

The acquisition patterns of Zika information shifted across time. At the first time point (April–May 2016), universalists constituted 23.0% of the US population, media seekers 20.7%, and passive recipients 54.3%. At the second time point (July–August 2016),

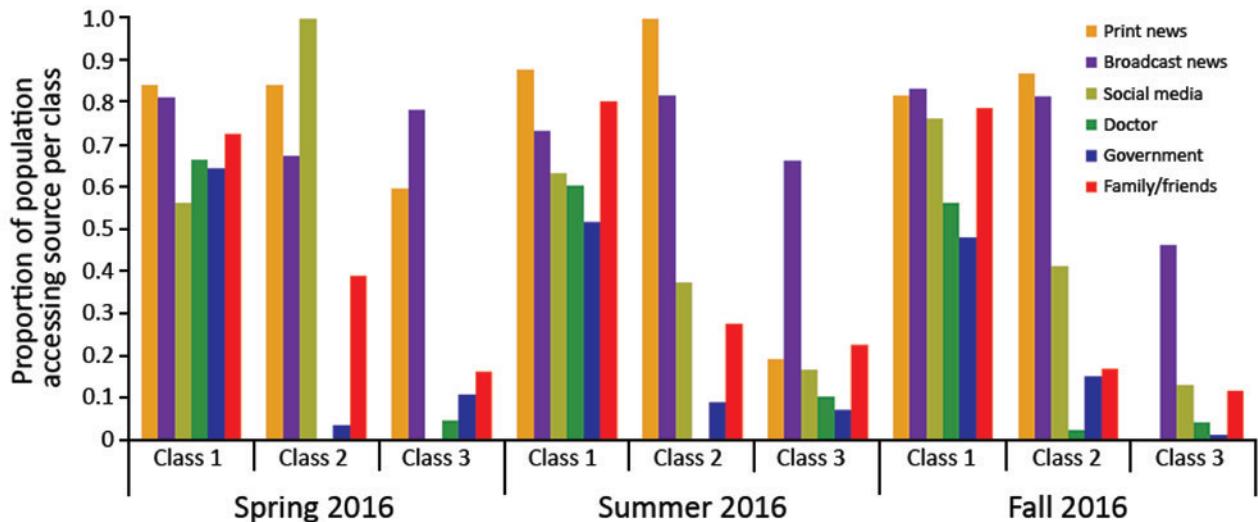


Figure. Latent classes of information access for Zika virus, United States, 2016. Proportion of the population that used a given category of information source in each class, across 3 time points of data collection.

universalists constituted 13.8% of the population, media seekers 51.5%; and passive recipients 34.8%. At the third time point (October–November 2016), universalists constituted 16.0% of the population, media seekers 52.0%, and passive recipients 32.0%.

As understanding of Zika virus evolved and media coverage shifted, the proportion of the population in each of the identified classes also shifted. Our finding that the proportion of the population in the universalist group was largest at the first time point suggests that in the earlier phases of the Zika outbreak, acquisition of information increased among the most highly attuned portions of the population. We hypothesize that as the mosquito season began, behavior patterns shifted from passive information acquisition to active information acquisition in the shift to media seeking (8). This hypothesis explains the shift from the large proportion of passive recipients at the first time point to the larger proportions of media seekers at the second and third time points.

These population shifts suggest large portions of the population were initially passive, perhaps uninterested, recipients of information about Zika. During the course of the surveys, a proportion of passive recipients and universalists may have become media seekers. In addition, we found that early adopters of emerging information could be retransmitters within their networks. Only universalists consistently accessed information from their own social network (including personal contacts and social media), the medical community, and government sources. Further exploration is needed to determine whether these findings are influenced by the actual lack of risk

for Zika in the United States or whether they are reflective of larger behavioral patterns.

Our analysis is limited by the number of information source categories included in the survey and the lack of source specificity. However, our study took a unique approach in characterizing patterns of information-accessing behavior. These findings can be used to inform risk communication strategies designed for population segments with different information-accessing behavior patterns.

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Severe Fever with Thrombocytopenia Syndrome Virus in Ticks and SFTS Incidence in Humans, South Korea

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During 2016–2018, we collected 3,193 ticks from rural areas in South Korea to investigate the prevalence of severe fever with thrombocytopenia syndrome virus (SFTSV). We detected SFTSV in ticks at an infection rate (IR) of 11.1%. We noted increases in the human IR associated with the monthly SFTSV IR in ticks.

Severe fever with thrombocytopenia syndrome (SFTS) is a tickborne zoonosis caused by the SFTS virus (SFTSV) (1); >1,000 SFTS cases have been reported in South Korea (2). The SFTS prevalence rate was 2.26/100,000 inhabitants on the mainland and 13.66/100,000 inhabitants on Jeju Island, South Korea (2). SFTSV has been detected in several species of ticks, including *Haemaphysalis longicornis*, *Amblyomma testudinarium*, and *Ixodes nipponensis* (3). A previous study reported that the minimum infection rate of SFTSV in infected ticks was lower (0.37%) on Jeju Island than in other collection areas (1.97%) (4). However, 7%–14% SFTSV seropositivity was identified in domestic and wild animals (4–5), and 2%–5% SFTSV seropositivity was identified in a healthy population in South Korea (6). Therefore, our aim was to investigate the SFTSV infection rate (IR) in ticks in the region with the highest endemicity, Jeju Island, and to analyze the relationship between the geographic distribution of ticks and SFTSV and human cases of SFTS.

During June 2016–January 2019, well-equipped trained researchers collected ticks from the natural environment of Jeju Island. The tick sampling sites included 5 rural areas: Aewol-eup (AW); Seon Hul-ri (SH); Jeo Ji-ri (JJ); and Ha Do-ri (HD) and Bo Mok-ri (BM) (Figure). These 5 areas were chosen to compare SFTSV IR in ticks in areas with the highest rates of human SFTS cases, SH, HD, and AW, and SFTSV IR in ticks in areas with lower human SFTS rates, JJ and BM. Ticks were manually collected 2 times per month, during the first and third weeks, by dragging a white cloth in woodlands for 2 hours in each area. We morphologically identified tick species and developmental stages by using an Olympus SD-ILK-200–2 stereomicroscope (Olympus Corporation, <https://www.olympus-lifescience.com>) (7) and extracted viral RNA by using a QIAamp Viral RNA Mini kit (QIAGEN Inc., <https://www.qiagen.com>) according to the manufacturer's instructions (Appendix, <https://wwwnc.cdc.gov/EID/article/26/9/20-0065-App1.pdf>).

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Appendix

Methods

Data Source

Three cross-sectional samples of the United States population were collected at three distinct time points—Spring (April/May), Summer (July/August), and Fall (October/November) of 2016—which included measures related to source of Zika information. Data was collected from a representative sample of U.S. households collected using a fully-replicated, single-stage, random-digit-dialing (RDD) sample households supplemented by a list of randomly generated cell phone numbers. The first structured telephone survey was of 1,233 U.S. residents, subsequent surveys sampled 1,231 residents and 1,234 residents respectively. Data will be analyzed using complex survey weights so results are representative of the population. Further information on weighting procedures have been described in detail in a previous manuscript (1).

Analytic Plan

Statistical methods such as LCA are especially useful to understand if there are underlying subtypes of individuals in the population for the phenomena at hand. LCA will be used to identify if there are “types” of information users within the population. LCA is a statistical tool to study a heterogeneous population consisting of several unidentified groups who behave differently regarding the problem at hand. LCA functions in terms of probability, specifically the probability that an individual belongs to a particular scoring pattern among the observed variables (2). While there are multiple interpretations of latent classes, the one being explored here is to classify respondents into being a member of a latent, unobserved class on the basis of their responses to one or more observed variables (3). LCA can reduce analytic complexity by identifying patterns of activity (4). Cluster analysis and LCA techniques have

been used within the fields of psychology, organizational behavior, and political science, and applied to examining health behaviors (2,5–11).

Model Selection

There is some debate in best practices for LCA model selection, especially when applying weighted population estimates when likelihood ratio tests may not be appropriately run since maximum likelihood estimates are not possible (12). In accordance with the best practices set out by Nylund, Asparaouhov, & Muthen (2007), several criteria were used to determine the optimal number of classes (13). The criteria applied here were:

1. Akaike and Bayesian information criteria (AIC and BIC) (14);
2. Lo-Mendell-Rubin adjusted likelihood ratio test;
3. Entropy;
4. the relative size of classes in each model;
5. substantive interpretability;
6. and replication of the LCA solution in all three samples.

Results

LCA results suggested a replicable three-class solution of information users in the population, with classes distinguished by the number of sources accessed. Appendix Tables 1–3 demonstrate the selection criteria used to compare 2–6 classes and reflect the three classes solution had the best goodness of fit at each time point. Results as to the proportion of the population in each class and accessing each source by time point are below in Appendix Tables 4–6.

Sample 1: Spring 2016

The proportion of the population in each of the three-classes is shown in Appendix Table 1. The average latent class probability, an indicator of membership within a latent class, measures how certain an individual is to be in one class compared to another, was high- 0.944, 0.893, and 0.906 respectively. Within Class 1, the probability of getting information from print news was 0.845, broadcast news was 0.814, social media was 0.564, doctor was 0.667,

government was 0.645, and family/friends was 0.729. Within Class 2, the probability of getting information from print news was 0.844, broadcast news was 0.675, social media was 1.00, doctor was 0.00, government was 0.035, and family/friends was 0.390. Within Class 3, the probability of getting information from print news was 0.597, broadcast news was 0.786, social media was 0.004, doctor was 0.047, government was 0.108, and family/friends was 0.164.

Sample 2: Summer 2016

The proportion of the population in each of the three-classes is shown in Appendix Table 2. From time 1 to time 2, the proportion of the population in each class shifted. Class 1, people who sought information from many sources, was 13.8% of the population, Class 2, those who primarily sought information from mass media and social media were 51.5% of the population, and Class 3, the least active information seekers, was 34.7% of the population. The average latent class probability, an indicator of membership within a latent class, measures how certain an individual is to be in one class compared to another, was still high- 0.890, 0.792, and 0.947 respectively. For Class 1, the probability of getting information from print news was 0.881, broadcast news was 0.735, social media was 0.635, doctor was 0.605, government was 0.518, and family/friends was 0.806. Within Class 2, the probability of getting information from print news was 1.00, broadcast news was 0.818, social media was 0.376, doctor was 0.00, government was 0.090, and family/friends was 0.277. Within Class 3, the probability of getting information from print news was 0.193, broadcast news was 0.665, social media was 0.169, doctor was 0.105, government was 0.073, and family/friends was 0.227.

Sample 3: Fall 2016

The proportion of the population in each of the three-classes is shown in Appendix Table 3. The proportion of the population in each class was similar to Sample 2. The average latent class probability, an indicator of membership within a latent class, measures how certain an individual is to be in one class compared to another, was also high- 0.852, 0.860, 0.872- respectively. For Class 1, the probability of getting information from print news was 0.818, broadcast news was 0.834, social media was 0.764, doctor was 0.564, government was 0.482, and family/friends was 0.789. Within Class 2, the probability of getting information from print news was 0.871, broadcast news was 0.816, social media was 0.414, doctor was 0.024, government was 0.151, and family/friends was 0.171. Within Class 3, the probability of getting

information from print news was 0.000, broadcast news was 0.463, social media was 0.131, doctor was 0.044, government was 0.014, and family/friends was 0.118.

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Appendix Table 1. Model fit statistics of latent class analysis models on Zika information accessing behaviors. United States, April–May 2016

No. classes	H0 value	H0 scaling correction factor for MLR	AIC	BIC	SBIC	Entropy	Pearson's χ^2 p value	LLR χ^2 p value	Average LC probability for most likely LC	Lo Mendell Rubin p value	Vuong Lo Mendell Rubin p value
2 class model	-4,070.212	2.0027	8,166.425	8,232.948	8,191.655	0.611	<0.01	<0.01	0.844, 0.911	<0.01	<0.01
3 class model	-4,021.901	1.6961	8,083.802	8,186.146	8,122.618	0.804	<0.01	<0.01	0.944, 0.893, 0.906	<0.01	<0.01
4 class model	-3,986.520	1.8278	8,027.040	8,165.204	8,079.441	0.829	0.04	<0.01	0.865, 0.849, 0.906, 0.946	0.36	0.36
5 class model	-3,964.701	1.5854	7,997.402	8,171.387	8,063.388	0.700	0.99	0.03	0.887, 0.816, 0.891, 0.560, 0.889	0.19	0.19

LC, latent class; AIC, Aikake Information criteria; BIC, Bayesian information criteria; MLR, multi-linear regression; LLR, log linear ratio

Appendix Table 2. Model fit statistics of latent class analysis models on Zika information accessing behaviors. United States, July–August 2016

No. classes	H0 Value	H0 Scaling Correction Factor for MLR	AIC	BIC	SBIC	Entropy	Pearson's χ^2 p value	LLR χ^2 p value	Average LC probability for most likely LC	Lo Mendell Rubin p value	Vuong Lo Mendell Rubin p value
2 class model	-3,968.288	2.0518	7,962.576	8,029.068	7,987.775	0.712	<0.01	<0.01	0.758, 0.953	0.02	0.02
3 class model	-3,932.758	1.7150	7,905.516	8,007.812	7,944.283	0.653	<0.01	<0.01	0.890, 0.792, 0.947	0.06	0.06
4 class model	-3,907.997	1.5895	7,869.994	8,008.093	7,922.330	0.738	<0.01	<0.01	0.920, 0.822, 0.864, 0.850	0.13	0.13
5 class model	-3,893.733	1.8898	7,855.467	8,029.369	7,921.371	0.695	<0.01	0.02	0.794, 0.779, 0.712, 0.922, 0.807	0.74	0.74

LC, latent class; AIC, Aikake Information criteria; BIC, Bayesian information criteria; MLR, multi-linear regression; LLR, log linear ratio

Appendix Table 3. Model fit statistics of latent class analysis models on Zika information accessing behaviors. United States, October–November 2016

No. classes	H0 Value	H0 Scaling Correction Factor for MLR	AIC	BIC	SBIC	Entropy	Pearson's χ^2 p value	LLR χ^2 p value	Average LC probability for most likely LC	Lo Mendell Rubin p value	Vuong Lo Mendell Rubin p value
2 class model	-3,934.742	1.7497	7,895.485	7,962.008	7,920.715	0.571	<0.01	<0.01	0.917, 0.797	<0.01	<0.01
3 class model	-3,864.304	1.5507	7,768.608	7,870.952	7,807.423	0.699	0.40	0.03	0.852, 0.860, 0.872	<0.01	<0.01
4 class model	-3,850.260	1.4955	7,754.520	7,892.685	7,806.921	0.645	0.98	0.21	0.818, 0.973, 0.682, 0.846	0.26	0.25
5 class model	-3,839.352	1.3971	7,746.703	7,920.688	7,812.690	0.608	1.00	0.58	0.780, 0.686, 0.812, 0.721, 0.929	0.21	0.22

LC, latent class; AIC, Aikake Information criteria; BIC, Bayesian information criteria; MLR, multi-linear regression; LLR, log linear ratio

Appendix Table 4. Latent class analysis proportions and Zika information sources. United States, April–May 2016

Class category	Class 1	Class 2	Class 3
Proportion of population in class*	0.23030	0.20710	0.54259
Information source, % use (SE)			
Print news	0.845 (0.041)	0.844 (0.072)	0.597 (0.026)
Broadcast news	0.814 (0.040)	0.675 (0.043)	0.786 (0.023)
Social media	0.564 (0.057)	1.000 (0.000)	0.004 (0.095)
Doctor	0.667 (0.071)	0.000 (0.000)	0.047 (0.020)
Government	0.645 (0.050)	0.035 (0.040)	0.108 (0.025)
Family and friends	0.729 (0.060)	0.390 (0.077)	0.164 (0.023)

*<2% of the population could not be adequately sorted into a class

Appendix Table 5. Latent class analysis proportions and Zika information sources. United States, July–August 2016

Class category	Class 1	Class 2	Class 3
Proportion of population in class	0.13775	0.51486	0.34739
Information source, % use (SE)			
Print news	0.881 (0.084)	1.00 (0.000)	0.193 (0.144)
Broadcast news	0.735 (0.060)	0.818 (0.030)	0.665 (0.032)
Social media	0.635 (0.088)	0.376 (0.050)	0.169 (0.031)
Doctor	0.605 (0.110)	0.000 (0.000)	0.105 (0.037)
Government	0.518 (0.083)	0.090 (0.024)	0.073 (0.032)
Family and friends	0.806 (0.099)	0.277 (0.047)	0.227 (0.033)

Appendix Table 6. Latent class analysis proportions and Zika information sources. United States, October–November 2016

Class category	Class 1	Class 2	Class 3
Proportion of population in class	0.16000	0.52000	0.32000
Information source, % use (SE)			
Print news	0.818 (0.046)	0.871 (0.086)	0.000 (0.000)
Broadcast news	0.834 (0.039)	0.816 (0.023)	0.463 (0.061)
Social media	0.764 (0.043)	0.414 (0.041)	0.131 (0.042)
Doctor	0.564 (0.116)	0.024 (0.017)	0.044 (0.014)
Government	0.482 (0.074)	0.151 (0.022)	0.014 (0.021)
Family and friends	0.789 (0.065)	0.171 (0.054)	0.118 (0.025)