Disaster Medicine and Public Health Preparedness

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Original Research

Cite this article: Whipps MDM, Phipps JE, Simmons LA. Measuring evidence-based viral respiratory illness mitigation behaviors in pregnant populations: Development and validation of a short, single-factor scale during the COVID-19 pandemic. *Disaster Med Public Health Prep*. doi: https://doi.org/10.1017/dmp.2022.103.

Keywords:
COVID-19; pregnancy; mitigation; infectious disease transmission; health communication

Corresponding author:
Mackenzie D.M. Whipps,
Email: mdwhipps@ucdavis.edu.

SDMPH
SOCIETY FOR DISASTER MEDICINE & PUBLIC HEALTH

Measuring Evidence-Based Viral Respiratory Illness Mitigation Behaviors in Pregnant Populations: Development and Validation of a Short, Single-Factor Scale During the COVID-19 Pandemic

Mackenzie D.M. Whipps PhD, CLC, Jennifer E. Phipps PhD and Leigh Ann Simmons PhD, MFT, FAAHB

University of California, Davis, Department of Human Ecology, Perinatal Origins of Disparities Center, Davis, CA, USA

Abstract

Objective: Researchers and public health professionals need to better understand individual engagement in coronavirus disease 2019 (COVID-19) mitigation behaviors to reduce the human and societal costs of the current pandemic and prepare for future respiratory pandemics. We suggest that developing measures of individual mitigation behaviors and testing them among high-risk individuals, including pregnant people, may help to reduce overall morbidity and mortality by quickly identifying targets for messaging around mitigation until sufficient vaccination uptake is reached.
Methods: We surveyed pregnant people in California over 2 waves of the COVID-19 pandemic to explore mitigation behaviors. We developed and validated a novel Viral Respiratory Illness Mitigation Scale (VRIMS).
Results: Seven measures loaded onto a single factor with good psychometric properties. The overall sample scale average was high over both waves, indicating that most pregnant Californians engaged in most of the strategies most of the time. Older participants, minoritized participants, those living in more urban contexts, and those surveyed during a surge reported engaging in these strategies most frequently.
Conclusions: Clinicians and researchers should consider using reliable, validated measures like the VRIMS to identify individuals and communities that may benefit from additional education on reducing risk for COVID-19, future respiratory pandemics, or even seasonal flu.

On March 11, 2020, the World Health Organization (WHO) declared coronavirus disease 2019 (COVID-19) a pandemic.[1] Efforts to control community spread of the highly transmissible virus have been variable.[2–4] However, 1 issue remains clear: The success of any community-level mitigation strategy to control COVID-19 spread depends upon vast numbers of individuals drastically altering their day-to-day personal behavior. Where adherence to guidelines and policies such as mask wearing and physical distancing have been low, rapid community transmission and rates of illness have consistently been the highest.[5]

One challenge in understanding and assessing individual adherence to mitigation strategies has been the evolving guidelines on these behaviors. Initially, public health experts in the United States did not recommend the regular use of nonmedical masks in public. However, by June 2020 guidelines changed[6] as evidence had converged on several key strategies still overwhelmingly endorsed as critical: frequent hand washing; wearing masks in public; practicing good cough/sneeze hygiene; avoiding close contact with others outside the home of unknown vaccine status; and cleaning and sanitizing high-touch surfaces.[7] Additionally, COVID-19 is primarily spread by means of respiratory droplets, but the CDC and WHO still recommend frequent sanitation of surfaces, leading to some controversy.[8] These personal mitigation behaviors have been shown to reduce rates of COVID-19 community transmission,[9,10] and yet adherence has been inconsistent. Despite vaccine availability, uptake has been low, new variants continue to arise, and breakthrough infections are common, making other mitigation factors critically important. Thus, it is crucial for researchers and public health professionals to understand individual engagement in COVID-19 mitigation behaviors, both for reducing the human and societal costs of the current pandemic, and for preparing for future pandemics.[11] Such understanding begins with establishing the ability to measure the construct of individual mitigation behaviors reliably and validly.

The purpose of this research was to begin to establish a valid and reliable scale of viral respiratory illness (VRI) mitigation behaviors, particularly for the vulnerable pregnant population, with a next step to include validating this scale in a non-pregnant population.

A Pandemic-Related Pregnancy Stress scale has been developed[12] as well as a Postpartum Specific Anxiety Scale for use during global crises,[13] but these do not directly measure COVID-19 or other VRI mitigation behaviors. As of the writing of this paper, we are aware of only 1 study that has examined the psychometric properties of evidence-based COVID-19 mitigation scales outside of measures of reliability.[14] This scale—the COVID-19 Preventative Behaviors Index, or CPBI—was developed and evaluated in the United Kingdom, and measures *perceived likelihood* of following mitigation behaviors in the future as opposed to current practices and also includes items that may not be evidence-based (ie, intending to change their lifestyle, or intention to watch the news[14]). Other studies of COVID-19 mitigation have generally measured 1 specific behavior, like social distancing,[15,16] shelter-in-place orders,[17] and mask-wearing.[18] Some studies have utilized checklists to examine aggregate "compliance" with several different public health measures.[19,20] However, these checklists also contain behaviors that are not evidence-based (eg, participating in virtual events) and may even be actively discouraged by public health authorities (eg, stockpiling medical masks[19]). Incorporating as many of the evidence-based strategies as possible—while eschewing those strategies that are not—is an important facet of construct validity[21] that has yet to be robustly investigated.

In developing a mitigation scale for VRIs like COVID-19, we evaluated the need in light of several factors, including: (1) low vaccination rates worldwide and the rise of more infectious variants indicating the COVID-19 pandemic is far from over; (2) the increasing likelihood that another VRI pandemic will emerge within the next 2 decades; and (3) the morbidity and mortality associated with more common respiratory viruses, such as seasonal influenza and respiratory syncytial virus (RSV), can be reduced through the same mitigation behaviors as those examined in the current study. We also considered nomological validity,[22] or the importance of validating the extent to which a given measure matches up to the theory or evidence base that exists, and the extent that the new scale correlates to distinct, but theoretically related, constructs of interest within a *nomological net*.[21,22] If a new measure can be validated as such, it becomes a more useful tool in evaluating public health interventions that seek to change health behaviors and the course of community spread for COVID-19 or other VRIs.[21,23]

One way to examine whether a new measure is conceptually robust is to explicitly test a priori hypotheses about how an individual's score on such a scale would correlate with other constructs within this nomological net.[24] Engaging in evidence-based mitigation behaviors is likely related to knowing and understanding the health guidelines[25] and the credibility of the source of those guidelines.[26] Likewise, we would expect that a scale measuring VRI mitigation behaviors using the COVID-19 pandemic as its test case would positively correlate with intention to receive a COVID-19 vaccination,[27,28] while expressing "adherence fatigue" for continued following of public health guidelines would likely negatively correlate to this scale.[29] Last, studies have shown that health behaviors tend to cluster within individuals and those who engage in 1 health-promoting behavior are more likely to engage in others.[30,31] Thus, we might expect that more attention to viral respiratory illness mitigation is positively correlated with endorsing other healthful activities, like healthy nutrition, abstaining from harmful substances during pregnancy, and receiving a seasonal flu vaccine.

Finally, as of this writing, we are unaware of COVID-19 or other VRI mitigation scales that have been rigorously tested with pregnant populations specifically. Existing infectious disease theory suggests, and emerging evidence has shown, that COVID-19 infection significantly increases the risk of severe maternal, fetal, and neonatal morbidity and mortality for pregnant and postpartum populations.[32] Likewise, data have shown that pregnant people are at high risk from complications and death due to other VRIs, like the seasonal flu.[33] This vulnerable population deserves increased research attention, including rapidly developed and validating a mitigation scale for use in ongoing studies. Furthermore, pregnancy is considered a "teachable moment" when health education is more likely to "stick" and health behaviors are more likely to be initiated.[34] Studying COVID-19 mitigation behaviors in this population will contribute to the knowledge base for the general population, as well as provide a foundation for better understanding how pregnant people manage preventable risk from communicable diseases in general.

This study seeks to remedy the gaps in our current understanding by first developing, and then validating, a short VRI mitigation scale with a pregnant sample in the United States using the COVID-19 pandemic as its test case over 2 points in time. We then tested a wide array of behavioral and attitudinal measures that comprise a nomological net to develop a fuller picture of the construct validity for this new measure.

Methods

Participants

Pregnant Californians were offered a Web-based survey in both English and Spanish (the 2 most common languages in the state) during 2 waves of cross-sectional data collection; Wave 1 was collected between June 6 to July 29 of 2020, while Wave 2 was collected from December 24, 2020 to January 27, 2021. Surveys took approximately 20-30 min to complete, and participants were offered \$10 gift cards for their participation. Participants were recruited primarily using *StudyPages*, a service that leverages social media to solicit participation. Currently, pregnant individuals who resided in California and were between the ages of 18 and 45 were eligible. Informed consent was obtained by means of Web-based survey. University of California, Davis' Institutional Review Board approved the study. In total, 588 participants completed the survey during Wave 1 and 454 completed the survey during Wave 2.

Missing Data

Because this was a Web-based survey, we used several strategies to ensure high data quality. Participants who attempted to take the survey multiple times, who completed the survey in less than 10 min, or who did not reach the end of the survey instrument had their data removed before analysis. Participant age was asked twice, once at the beginning of the survey and once at the end; any participant without matching responses for these 2 items also was removed before analyses. In all, 216 participants were not included in the analytic sample as a result of these quality checks. The data also were screened for impossible values and outliers. Sporadic missing data were limited to under 10% for each variable and handled using list-wise deletion. The resulting analytic samples are comprised of 433 participants for Wave 1 and 387 participants for Wave 2. Demographic features of the analytic samples can be found in Table 1.

Measures

Survey items consisted of several categories: demographic features of the sample, 7 mitigation behaviors that make up the scale itself, and 13 items within the nomological net of the scale

Table 1. Demographic characteristics across data collection wave

	June-July 2020		December 2020-January 2021	
	n = 433		n = 387	
Characteristic	N	(%)	N	(%)
Maternal age				
18-24	53	(12.2)	27	(7.0)
25-34	255	(58.9)	224	(57.9)
35+	125	(28.9)	136	(35.1)
Participant is essential worker				
Yes	103	(23.8)	149	(38.5)
No	112	(25.9)	84	(21.7)
Not currently employed/no answer	218	(50.3)	154	(39.8)
Ethnicity				
Hispanic	149	(34.4)	151	(39.0)
Not Hispanic	280	(64.7)	236	(61.0)
Race				
White	233	(53.8)	199	(51.4)
Black/African American	20	(4.6)	18	(4.7)
Indigenous/First Nations	4	(.9)	2	(.5)
Asian/Pacific Island/Native Hawaiian	36	(8.3)	37	(9.6)
Other race	37	(8.6)	42	(10.9)
Multiracial	82	(18.9)	64	(16.5)
Urbanicity				
Rural	22	(5.1)	14	(3.7)
Semi-rural	51	(11.8)	33	(8.6)
Suburban	191	(44.1)	162	(42.3)
Urban	99	(22.9)	85	(22.2)
Major metropolitan	63	(14.6)	89	(23.2)
Trimester of pregnancy				
1st (0 - 13 weeks+6 days)	96	(22.2)	121	(31.3)
2nd (14 - 27 weeks+6 day)	188	(43.4)	172	(44.4)
3rd (28 - 42 weeks)	142	(32.8)	94	(24.2)
No answer/unsure	7	(1.6)	0	(.0)
Parity				
Primipara	206	(47.6)	183	(47.4)
Multipara	227	(52.4)	203	(52.6)

Note: Every participant did not respond to every item; therefore Ns do not necessarily sum to total analytic sample size

(4 hypothesized predictors of the mitigation scale, 3 items indexing attitudes or behaviors regarding the COVID-19 pandemic, and 6 health behavior items unrelated to COVID-19). See Appendix 1 for details on the specific items within these categories, and Table 2 for scale item wording.

Data Analysis

Testing Assumptions

We examined whether each sample (wave 1 and 2) was adequate to conduct exploratory and confirmatory factor analysis. Sample sizes must be over 300[35] and there must be more than 20:1 sample to variable ratio.[36] Each individual item in the scale should correlate at levels of .30 or higher with at least 1 other item in the scale, average inter-item correlations should be at least r = 0.15, Bartlett's test of sphericity should be significant ($P < 0.05$), and the items should have a Kaiser-Meyer-Olkin (KMO) value of .60 or higher.[37–39]

Exploratory Factor Analysis

We used exploratory factor analysis (EFA) using Principal Factors Analysis in Stata,[40] examining solutions with 1, 2, and 3 factors across the 7-item overall scale. There were several criteria we used to choose the model that fit the data best: (a) eigenvalues for included factors should be at least 1,[41] but ideally much larger[42]; (b) only retaining items that loaded onto a stable factor with a factor loading of more than 0.4[40]; and (c) only retaining items that showed a communality of at least 0.3.[43]

Confirmatory Factor Analysis

After conducting an exploratory factor analysis, we validated the chosen factor structure in the second wave of data using Confirmatory Factor Analysis (CFA). The sample size, sphericity, and KMO were tested to ensure that the sampling and data quality were adequate for these purposes.[35,36,38–40] That model was then tested for goodness-of-fit using 3 measures: (a) comparative fit index (CFI) and Tucker-Lewis index (TLI) over 0.95 indicating "good" model fit, and CFI and TLI between 0.90 and 0.95 indicating "adequate" model fit[44]; and (b) root mean square error of approximation (RMSEA) under 0.05 considered a "good" fit, and RMSEA values between 0.05 and 0.10 considered "acceptable".[45] Error terms among our items were allowed to correlate if there were theoretically sound reasons for the addition of these parameters. Finally, we report the internal consistency (using Cronbach's α;[46,47]) at each wave and over both waves. Cronbach's $\alpha > 0.8$ (but <0.9) are considered "good" and Cronbach's α between 0.6 and 0.8 are considered "acceptable" for this short, nonredundant scale.[48,49]

Exploring Demographic Corollaries of the Scale

After confirming an adequate goodness-of-fit and adequate internal consistency of the scale, we described how the mitigation scores varied across demographic characteristics by using either univariate ordinary least squares regression or 1-way analysis of variance. We also described whether and how scores changed over the 2 waves of data collection.

Testing Nomological Validity

We began testing the nomological validity of the scale by examining the relationships between the scale scores and distinct constructs of interest. These constructs fall into 3 categories: (a) predictors of COVID-19 mitigation, (b) other attitudes and behaviors that relate to the COVID-19 pandemic, and (c) other (nonpandemic) related health-promoting behaviors. A significant relationship between 2 constructs was considered present if the correlation reached a $P < 0.05$ significance level. We also assessed the strength of the correlations, which were considered "weak" if the absolute value was less than 0.20; "moderate" if the value was between 0.20 and 0.40; and "strong" if the correlation was more than 0.40.

Results

Testing Assumptions

Both wave 1 and wave 2 samples were adequate for conducting EFA and CFA analyses. The Bartlett test of sphericity was significant for both samples: $\chi^2 = 680.92$, $P < 0.001$ for wave 1; $\chi^2 = 488.79$, $P < 0.001$ for wave 2. For wave 1, KMO = 0.71; and for wave 2, KMO = 0.70. Sample sizes of 433 and 387 provided

Table 2. Summary statistics of specific viral respiratory illness mitigation strategies across waves

Viral Respiratory Illness Mitigation Behaviors, June-July 2020 (n = 433)	% Never or Rarely	% Sometimes	% Often or Always	Inter-item Correlations							
				1	2	3	4	5	6	7	Average
Specific Strategies											
1. I wear a mask in public	2	5	93	1.00							0.32
2. Household members wear a mask in public	5	7	88	0.54***	1.00						0.28
3. Social distance (6 feet) in public	3	7	89	0.56***	0.45***	1.00					0.32
4. Sanitize frequently touched surfaces	27	26	46	0.16***	0.17***	0.20***	1.00				0.26
5. Sanitize groceries/packages	46	15	38	0.16***	0.18***	0.22***	0.47***	1.00			0.27
6. Wash hands before eating	4	14	81	0.22***	0.11*	0.23***	0.38***	0.27***	1.00		0.29
7. Wash hands after coming in	4	8	87	0.29***	0.25***	0.28***	0.20***	0.31***	0.51***	1.00	0.31

Viral Respiratory Illness Mitigation Behaviors, December 2020-January 2021 (n = 387)	% Never or Rarely	% Sometimes	% Often or Always
Specific Strategies			
1. I wear a mask in public	1	1	98
2. Household members wear a mask in public	2	3	94
3. Social distance (6 feet) in public	1	5	93
4. Sanitize frequently touched surfaces	34	22	44
5. Sanitize groceries/packages	58	17	25
6. Wash hands before eating	3	9	86
7. Wash hands after coming in	4	8	87

large enough samples for factor analysis with a ratio of over 50 participants per variable in each wave. For wave 1, inter-item correlations range from 0.11 to 0.56, with all correlations significant at $P < 0.05$. Inter-item correlations average r = 0.29 with all other items in the scale, and each item correlated with at least 1 other item on the scale at or above r = 0.45 See Table 2 for correlations between individual items in the scale.

Exploratory Factor Analysis

Table 2 shows response rates for each item across both waves. Based on our a priori criteria, we extracted a single factor and retained all of the items. The eignenvalue for the 1-factor solution was 2.1 (2-factor solution = 0.7; 3-factor solution = 0.2). Table 3 shows results from EFA and CFA. The proportion of the scale variance explained by 1 factor is 0.89. In the 1-factor solution, all factor loadings are >0.4, and communality are all >0.3, confirming that each item shares common variance with the other items. By contrast, factor loadings for the 2nd and 3rd factors in the 2- and 3-factor solutions were largely below 0.4. Therefore, we created the scale as a unidimensional measure, labeled "Viral Respiratory Illness Mitigation Scale (VRIMS)".

Confirmatory Factor Analysis

Using wave 2 data ($n = 387$), we conducted a CFA using the *sem* package in Stata. A 1-factor structure was confirmed to be an adequate-to-good fit for the data. The RMSEA = 0.061, the model CFI = 0.97 and model TLI = 0.94. See Table 3 for standardized factor loadings for each item. As expected, error terms between certain items were significantly related: (a) the 2 mask-wearing items, (b) the 2 hand-washing items, and (c) the 2 surface-sanitizing items (all error term correlations significant $P < 0.001$). These error terms were allowed to correlate in the final CFA model.

Given the EFA and CFA results, scores on individual items were averaged, then the scale was standardized and centered for further analyses for the entire sample ($n = 820$). Figure 1 shows the distribution of this standardized/centered scale over the 2 waves of data collection. Scale averages shifted slightly over time: (a) wave 1 mean = −0.38, SD = 0.68; and (b) wave 2 mean = 0.39; SD = 0.53. One-way ANOVA showed that the wave 2 scale average is marginally higher than wave 1: F(817) = 3.28; $P = 0.071$. Over both samples, the measure showed acceptable reliability, with Cronbach's α = 0.72 (wave 1 $\alpha = 0.74$ and wave 2 $\alpha = 0.70$). The measure is negatively skewed and tail-heavy at both waves.

Exploring Demographic Corollaries of the Scale

VRIMS scores varied significantly by several demographic categories (see Figure 2). Older participants scored higher than younger participants ($\beta = 0.01$; $P = 0.017$), and Hispanic participants scored higher than non-Hispanic participants (F(813) = 18.14; $P < 0.001$). Participants living in more urban contexts scored marginally higher than those living in more rural contexts ($\beta = 0.04$; $P = 0.066$), while Black and Asian/Pacific Islander participants scored marginally higher than white and multiracial participants (F(692) = 2.34; $P = 0.05$). Primiparous participants scored lower than multiparous participants (F(816) = 5.83; $P = 0.016$). Essential worker status was not significantly related to VRIMS score.

Table 3. Results of Factor Analysis

	Exploratory Factor Analysis, n = 433		Confirmatory Factor Analysis, n = 387			
Variable	Item Loadings for 1-Factor Solution	Item Uniqueness	Standardized Item Loadings	p-value	95% CI	
Wear a mask in public	0.62	0.48	0.37	<0.001	0.25	0.50
Household members wear a mask in public	0.54	0.58	0.27	<0.001	0.15	0.40
Social distance (6 feet) in public	0.59	0.56	0.44	<0.001	0.32	0.57
Sanitize frequently touched surfaces	0.50	0.60	0.54	<0.001	0.42	0.65
Sanitize groceries/packages	0.48	0.64	0.45	<0.001	0.33	0.57
Wash hands before eating	0.57	0.52	0.59	<0.001	0.47	0.71
Wash hands after coming inside	0.56	0.58	0.54	<0.001	0.42	0.67

Note: Single-factor scale developed during wave 1 showed an acceptable fit for the data during wave 2: CFI = 0.97, TLI = 0.94, RMSEA = 0.061

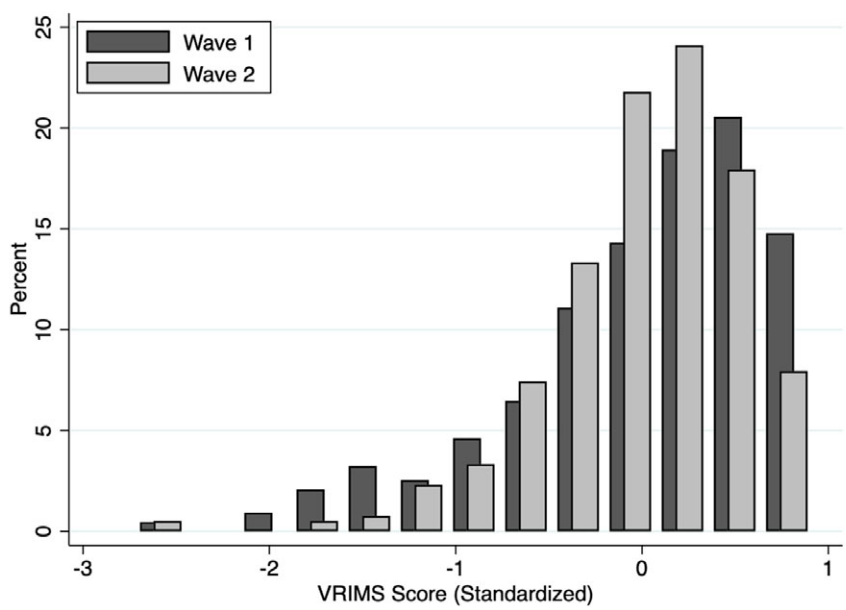

Figure 1. VRIMS score distribution by data collection wave.

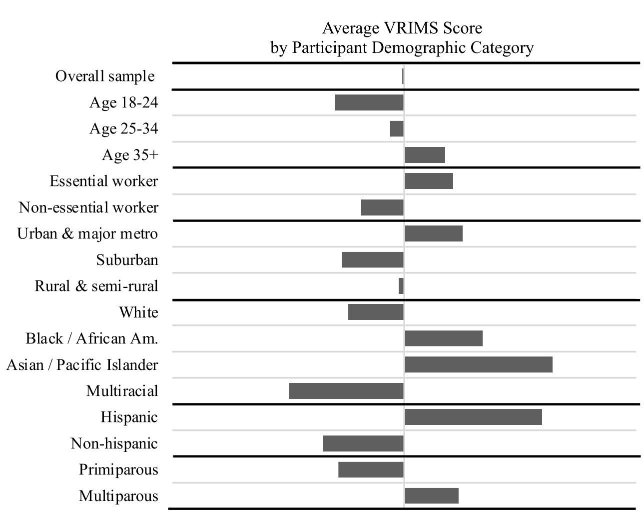

Figure 2. Average VRIMS score by participant demographic category.

Testing Nomological Validity

See Table 4 for hypothesized and observed nomological validity correlations. Overall, the hypothesized relationships were observed in expected directions with at least $P < 0.05$ significance. Receiving or intending to receive both the seasonal flu vaccination and the COVID-19 vaccination were important exceptions to this finding: 29.9% of wave 2 respondents indicated that they were unsure whether they would receive the COVID-19 vaccine if it were made available to them, and although the correlation between this intention and the VRIMS was in the expected direction, it did not reach statistical significance (0.08; $P = 0.19$). Additionally, drinking sugary beverages was not related to the VRIMS score ($r = 0.06$; $P = 0.11$), although the other health-promoting behaviors (that do not index viral respiratory illness mitigation) were significantly related in the expect direction.

Discussion

We developed and validated the VRIMS, a 7-item, unidimensional measure of adherence to recommended VRI mitigation behaviors,

Table 4. Hypothesized and observed relationships between VRIM Scale and other indicators of nomonological validity (n = 820)

	Hypothesized Correlation with Scale	Observed Correlation with Scale
I am living my life as before the pandemic	- -	- -
I understand COVID-19 risk reducing actions	+ +	+ +
I let family and friends visit	–	- -
Public health agencies a primary info source	+ +	+
Intention to receive COVID-19 vaccine[a]	+	ns
Difficulty continuing COVID-19 public health measures[a]	–	–
I pay attention to healthy nutrition	+	+ +
I take care of my physical health as I always have	+	+ +
Received or intend to receive seasonal flu vaccine[a]	+	ns
Smoking cigarettes	–	–
Drinking alcohol	–	- -
Eating sweets	–	–
Drinking sugary drinks	–	ns

Note: Hypothesized relationship between indications and VRIMS score denoted as follows: + weak positive correlation; ++ moderate or strong positive correlation; - weak negative correlation; - - moderate or strong negative correlation; ns non-significant correlation
[a]Items available only for wave 2 data collection

including mask wearing, social distancing, and handwashing using data from pregnant people in California across 2 waves of the COVID-19 pandemic. To our knowledge, this is the first such scale, available in English and Spanish, that measures the frequency of actual mitigation behaviors in the pregnant population or otherwise.[14] Results demonstrated good psychometric properties, including good internal consistency and reliability across multiple waves. The scale correlated as expected with other behaviors and attitudes regarding COVID-19 and with most other health-promoting behaviors (eg, healthy diet and physical activity). Additionally, total scores were higher during the second, "surge" wave in California when the state was under a universal "stay-at-home order", suggesting that the scale was sensitive to changes in behaviors based on shifts in rates of infection over time.

One interesting finding is that the VRIMS scores did not correlate with COVID-19 vaccination intentions. There may be a number of reasons for this, including that at the time of the survey, the COVID-19 vaccine trials had not included pregnant people, and the emergency use authorization (EUA) did not extend to this group.[50] At the time of the writing of this study, however, over 100,000 pregnant people had received the vaccine[51] after an initial study showed its safety in 10,000 pregnant people.[52] This policy shift may change the association of COVID-19 vaccination intentions and other mitigation strategies as captured in our scale, and future studies should investigate this. Conversely, other studies have shown that there is general vaccine hesitancy among pregnant people due to debunked research that has linked prenatal and early infancy vaccination to childhood disability and death,[53] which may be exacerbated by the unique circumstances under which the COVID-19 vaccine was developed. Public unease over the "fast pace" of production, distrust of pharmaceutical companies, and associated safety concerns may further confound the relationships between vaccination and other mitigation strategies.[54] Given the important role of vaccination in addressing not only this pandemic, but future respiratory pandemics and more common VRIs such as flu, future research should better elucidate vaccination decisions in the context of other modifiable risk-reducing behaviors.

While our study found that the VRIMS is a valid and reliable tool, future researchers should extend use of the scale and establish its validity in other populations and settings. We assessed mitigation behaviors at the individual level, independent of specific local management of the pandemic, including such factors as local case rates, industry closures, contact tracing, mass testing, and financial means to adhere to mitigation strategies.[55,56] Scale properties could potentially be different in localities where public health measures and individual supports for adherence were greater than in the United States. Furthermore, our data were exclusively from pregnant people in California. Other studies should investigate the scale's properties across different states, countries, and cultures, among non-pregnant people, and in nationally representative samples. Additionally, because this survey was conducted online, we may not have reached participants without stable Internet connectivity; in-person and phone-based surveys to validate other modalities may therefore be a fruitful next step.

Future studies should also test discriminant and predictive validity. For example, studies could examine how the CPBI, which measures likelihood of adhering to mitigation behaviors, compares with the VRIMS.[14] Likewise, our scale could be used to assess whether interventions to improve COVID-19 or other VRI mitigation behaviors result in expected changes in item and total scores. Studies also could test the sensitivity and specificity of the scale's total score for predicting exposure risk to better target public health messaging. While VRIMS is available in both English and Spanish, we did not have a large enough sample to specifically validate a Spanish version, and this should be pursued. Last, future studies should establish face validity by asking health-care and public health professionals how well the items represent the construct of mitigation as operationalized. While we have relied on evidence-based public health agency guidelines in the creation of the scale items to address this concern, there may be other, missing facets of VRI mitigation behaviors that could enhance utility of the scale for specific provider and public health audiences.

Our scale has the potential to benefit research and clinical practice now and in the future. The VRIMS is short, nonredundant, evidence-based, and unidimensional with good psychometrics. This makes future inclusion of the VRIMS in studies aimed at understanding and improving mitigation behaviors for COVID-19 and other VRIs simple without increasing participant burden. Likewise, as we better establish the utility of the VRIMS for identifying risk categories, clinicians may use the scale for targeted patient education. Given the rise of COVID-19 variants and lower than desired vaccination rates for other VRIs (eg, measles, seasonal flu), our scale could prove useful in future public health crises both locally and globally because the evidence-based guidelines for mitigating transmission of these illnesses are the same.[57]

Conclusions

The VRIMS is a short, unidimensional measure of evidence-based individual mitigation behaviors. The scale shows acceptable internal reliability, adequate psychometric properties, demonstrable construct and nomological validity, and consistency over time for a population of pregnant Californians. It is also easy to interpret and use, and could be used immediately as a monitoring or evaluation tool to aid in policy and intervention development, having shown good psychometric qualities across both a "surge" and "nonsurge" pandemic context. Future research can and should continue to test and refine this scale to use in the ongoing context of the COVID-19 pandemic, for future pandemics, and for outbreaks of common, seasonal respiratory illnesses such as influenza and RSV.

Supplementary Material. To view supplementary material for this article, 344 please visit https://doi.org/10.1017/dmp.2022.103.

Acknowledgments. The authors acknowledge Sharon Tafolla, who assisted with translation of the survey into Spanish, and Nikita Satish for assisting with literature review and editorial assistance.

Funding statement. Funding for the current study was provided by Hatch Project #CA-D-HCE-2582-H, Addressing Multifactorial Influences on Pregnancy Outcomes to Promote Health Equity. Funding for Dr. Whipps was provided by 5R01NR017659 (Simmons PI).

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