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Racism in Digital Era: Development and Initial Validation of the Perceived Online Racism Scale (PORS v1.0)

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The purpose of this study was to develop the Perceived Online Racism Scale (PORS) to assess perceived online racist interpersonal interactions and exposure to online racist content among people of color. Items were developed through a multistage process involving a comprehensive literature review, focus-groups, qualitative data collection, and survey of online racism experiences. Based on a sample of 1,023 racial minority participants, exploratory and confirmatory factor analyses provided support for a 30-item bifactor model accounted by the general factor and the following 3 specific factors: (a) personal experience of racial cyber-aggression, (b) vicarious exposure to racial cyber-aggression, and (c) online-mediated exposure to racist reality. The PORS demonstrated measurement invariance across racial/ethnic groups in our sample. Internal reliability estimates for the total and subscale scores of the PORS were above .88 and the 4-week test–retest reliability was adequate. Limitations and future directions for research are discussed.

Public Significance Statement
The findings help advance research regarding people's experiences of online racism and how they relate to well-being. The measure will be a helpful tool toward better understanding and mitigating the unique risks associated with online racism.

Keywords: online racism, racism, perceived racism

Racism is an everyday reality resulting in maltreatment, unjust burden, and discrimination for people of color in the United States. Racism is deeply rooted in a system of dominance and power that creates White societal privileges and advantages while discriminating against racial/ethnic minority populations who are viewed as inferior, deviant, and undesirable. Racism affects people of color at individual, group, and institutional/systemic levels (Harrell, 2000; Jones, 1997). The individual (e.g., calling someone a racial slur) and group (e.g., negatively stereotyping an entire group of race) experiences are often times explicit, direct, and obvious. However, institutional/systemic forms of racism, such as policies that provide people of color less access to societal goods, services, and opportunities, are more subtle, indirect, and less obvious. Whether direct or indirect, the psychological, physical, and social costs of racism for people of color (Pascoe & Smart Richman, 2009) have been well documented.

Recently, scholars have contended that explicit racist speech has become commonplace on the Internet (Daniels, 2013; Hughey & Daniels, 2013; Lewis, Cogburn, & Williams, 2015). For instance, the web site "Geography of Hate" tracked over 150,000 publically available racist tweets across the U.S. in just 1 year (Stephens, 2013). The Internet has been dubbed a "safe haven" where concerns of political correctness and being labeled as "racist" are greatly diminished due to ineffective content moderation and the increased anonymity and virtual distance offered online (Van Blarcum, 2005). Online anonymity minimizes the influence of societal norms and inhibitions that usually dictate offline face-to-face interactions (Suler, 2004). The virtual distance framework posits that online social interactions can involve psychological and emotional detachment as social encounters occur online, via the screens on the electronic devices (Lojeski & Reilly, 2008). These conditions create an atmosphere in which users feel free to publically and frequently disclose their racist ideologies without accountability (Hardaker, 2010).

Yet, online racism has received limited attention in the literature even though the majority of the global population and nearly 73% of Internet users in the U.S. are online every day and higher rates

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of usage have been observed among racial minority adults such as African Americans and Latino/as (Pew Research Internet Project, 2014). Therefore, in order to advance studies on online racism, our goal was to develop and evaluate the psychometric properties of the Perceived Online Racism Scale (PORS).

Initial Studies on Online Racism

Since the inception of the Internet, racism has manifested in various forms across continually evolving online social platforms (Daniels, 2013; Hughey & Daniels, 2013). For example, Back (2002) introduced the concept of cyber-racism in order to describe how White nationalists have used the Internet to justify and promote White supremacist ideologies. Further, the rapid advancement of Internet technologies has created many different ways in which people may perpetuate and perceive racism in online social platforms. In particular, a growing number of studies have documented the common and explicit interpersonal exchanges of blatant and subtle racist messages between Internet users on social media platforms (Chaudhry, 2015; Cleland, 2013; Gerstenfield, Grant, & Chiang, 2003; Harrison, Tayman, Janson, & Connolly, 2010; Steinfeldt et al., 2010; Tynes, Reynolds, & Greenfield, 2004; Weaver, 2011). The nature of these messages have been more blatant than subtle, often characterized as forms of online aggression such as "flaming" (hostile online exchanges). Recently, Tynes, Rose, and Williams (2010) adapted a seven-item subscale of the Online Victimization Scale (OVS; Tynes et al., 2010) in order to assess individual and vicarious domains of interpersonal online racism for adolescents. Quantitative studies using the OVS have found significant relationships between online racism and poor psychosocial functioning (e.g., depression, anxiety) in adolescents (Tynes, Giang, Williams, & Thompson, 2008; Umana-Taylor, Tynes, Toomey, Williams, & Mitchell, 2015).

Toward a Theory of Online Racism

In light of growing evidence on the harmful nature of online racism, there are several factors that differentiate online racism as a potentially major chronic stressor in today's digital era when compared with offline racism. First, online racism is more *pervasive* than offline racism. There is an abundance of online racist content created on a daily basis that can be easily and perhaps inadvertently encountered by other users (Bonilla & Rosa, 2015; Kirkpatrick, 2011). For example, racist messages, photos, and videos are constantly being produced and shared by users and are easily available for people of color to encounter. Similar to the way in which the relatively recent phenomena of the 24-hr online news cycle fundamentally changed the way in which the general public consumes and understands local, national, and international events (Lin & Atkin, 2014), we believe that this never-ending "pipeline" of online racism fundamentally changes the way in which people of color experience racism. Thus, people are now exposed—often in real time—to constant cycle of a continually growing universe of racism content and events from across the globe, whether offline to online, small to major, or local to regional, from the convenience of their electronic devices.

Second, compared with offline racism event, an online racism event can have more *permanent* presence as it requires an active and involved process to moderate and remove such content from the Internet (Bickart & Schindler, 2001). For example, whereas removing a racist paper flyer taped to person's office door may be straightforward, removing a racist comment posted on that same person's social media page is much more difficult as such content—even if deleted from the page—may exist in perpetuity on Internet servers and through sharing and reposting by others online. In addition, although offline racism events typically occur at a discrete point in time and are mostly reexperienced through memories and reminders of the event, online racism is not bound to a discrete point in time because the actual events continue to exist online and are available for individuals to relive and reexperience (as opposed to remembering it). We contend that the relative permanence of online racism and the possibility of repeated exposure makes it more harmful than offline racism.

Third, unlike offline racism, which is static, online racism can evolve over time and across various digital formats. Notably, online racist content may transform into a "trending" or "viral" content due to repeated sharing across online communities and users (Becker, Naaman, & Gravano, 2011). More importantly, the nature of these content can change and/or intensify over time as people provide their own perspective on an experience. For example, past racial controversies, such as issues of police brutality on racial/ethnic minorities have received widespread attention as a result of this process (Graham, 2015). Additionally, online racism evolves as the digital landscape provides perpetrators of racism numerous convenient ways in which to create and share racist content across various online social media platforms and multimedia formats such as texts, photos, and videos, (Hughey & Daniels, 2013). For example, an online racism experience such as receiving a racist comment on a user's social medial page can be adapted and shared using various memes (e.g., photo with a racist caption, #hashtags).

Measurement of Perceived Online Racism

Despite growing attention, a major barrier in advancing online racism research has been the lack of a conceptually rigorous measure that produces reliable and valid scores. None of the current measures adequately assess the unique aspects of online racism. Appropriately assessing online racism may be beyond the scope of conducting simple modifications of commonly used general racism measures. For example, measures such as the Perceived Ethnic Discrimination Questionnaire (Brondolo et al., 2005) or the General Ethnic Discrimination Scale (Landrine, Klonoff, Corral, Fernandez, & Roesch, 2006) contain items that are specific to offline activities such as experiences at stores (e.g., "Clerk or waiter ignored you") or face-to-face interactions (e.g., "Been nice to you to your face, but said bad things about you behind your back"). An ecologically valid measure of online racism should reflect the racism that is uniquely manifested in online activities and shared and transmitted in variety of digital formats. Unlike face-to-face offline interactions, online racism is experienced in the form of texts, comments, memes, photos, and/or videos that exist in perpetuity and are shared among many people. Sharing, in particular, has become a potent societal influence due to its effectiveness in propagating ideas and incidents at an exponential rate, thereby bringing attention to "trending" content (Becker et al., 2011).

In our search, the OVS (Tynes et al., 2010) was the only scale that has been developed and used to advance online racism research. However, it is not without limitations. First, the scope of the OVS' content is quite limited as it only focuses on the blatant interpersonal victimization (i.e., remarks or behaviors adolescents employ to inflict harm online; Patchin & Hinduja, 2006) that occur in cyber-bullying among adolescents. The small number of items are also lacking in assessing the major online activities through which the victimizations can occur. Therefore, the OVS fails to capture the breadth of online racism beyond adolescents' interpersonal experiences. The measure also does not assess subtle aspects of racism (e.g., racial microaggression) that may be salient on the Internet. In addition, the OVS produced scores with inadequate reliability estimates ($\alpha = .66$; Tynes et al., 2010). Finally, more than half of the OVS's development samples consisted of White participants and it is unclear whether the OVS produces reliable and valid scores for the racial minority populations.

Against this backdrop, our goal was to develop a more comprehensive and psychometrically sound measure of perceived online racism for use with multiple racial/ethnic minority groups. We aimed to develop items that reflected the aforementioned pervasive, permanent, and evolving aspects of online racism in several domains that were deduced from the literature. First, as with the OVS, both direct (e.g., personal) and vicarious (e.g., observation of other people's interactions) interpersonal online racism have been identified in the literature. In particular, vicarious forms of online racism may be especially salient and pervasive on the Internet as racist exchanges are common and widely available for other people to observe—and experienced vicariously—given the open access nature of the Internet. Second, we aimed to examine subtle aspects of online racism. Although blatant aspects of online racism have been mostly evidenced in the literature, subtle messages of racial microaggressions and those implying colorblind ideologies have also been observed in studies (e.g., Cleland, 2013; Gerstenfield et al., 2003; Harrison et al., 2010; Steinfeldt et al., 2010). Third, we aimed to measure the noninterpersonal informational aspect of online racism given the pervasive and relatively permanent presence of racist information on the Internet (Daniels, 2013; Hughey & Daniels, 2013). People may encounter such content, often repeatedly, without the geographic and temporal boundaries of the source material. For example, people may encounter: (a) reports of controversial online or offline racist events such as police brutality on racial/ethnic minorities (Holmes, 2000); (b) information on systemic issues of racism such as disparities in access to quality health care (Feagin & Bennefield, 2014); (c) online White supremacy groups propagandizing racist culture via online communications (Daniels, 2009); and/or (d) negative or stereotypical portrayals of people of color in everyday online media (Chau & Xu, 2007). This may be an important aspect of online racism as these types of information, especially those on group or systemic oppression, may not be as tangible or noticed offline; thus, they are often overlooked in racism studies which have overwhelmingly focused on offline individual racism.

The Present Study

Based on our review, we aimed to develop and test the initial psychometric properties of the Perceived Online Racism Scale (PORS) via several phases. We developed the items for PORS and conducted factor analysis to identify and validate the most appropriate factor structure. We then tested the construct validity of PORS scores by analyzing its relationship to other racism constructs and mental health indicators. Lastly, we examined the reliability of PORS in producing consistent scores and across four week interval (test–retest reliability).

Method

Scale Development

Guided by best practices in measure development (DeVellis, 2016), several steps were taken to generate items for PORS. We reviewed relevant literature in racism, cyber-psychology, and computer-mediated communication in identifying common themes relevant to online racism. We also reviewed online social platforms (e.g., social media, online forums) and content (e.g., online blogs, online news articles) to further identify online activities and content relevant to online racism. Further, we conducted a short anonymous online survey (advertised through social network sites and snowball sampling) asking 132 self-identified racial minority individuals describe their racism experiences on the Internet. Using inductive thematic analysis, the following themes emerged: interpersonal communication of racist messages (e.g., sending posts, videos, photos, and sharing content); encounters with online racist multimedia (e.g., photos, videos); observations of other racial/ethnic minority members being harassed in online interactions; online groups propagandizing racist ideologies (e.g., White supremacy); information on systemic racial/ethnic inequality (e.g., health care practices); "trending" content depicting offline or online racial violence; and the rampant and explicit nature of online racism compared with offline interpersonal racism. Broadly, the themes characterized racism experiences pertaining to (a) online interactions represented by both interpersonal and vicarious contexts and (b) exposure to online information such as systemic and public issues of racism.

Additionally, we reviewed racial microaggression measures such as the REMS (Nadal, 2011) and the Inventory of Microaggressions Against Black Individuals to develop items assessing subtle experiences of online racism. We also reviewed scales such as the group impact (GRP) subscale from the Racism and Life Experiences Scale (Harrell, Merchant, & Young, 1997) in order to guide item development for exposure to information on group and systemic aspects of online racism.

Throughout the development process, we focused on the major modes of online communication (e.g., text posts, pictures, videos) and common activities in various online social platforms (e.g., social media, online discussion forums) in order to generate online racism content that was salient and generalizable over time and context. We were cautious about platform specific (e.g., Facebook) items due to the rapidly evolving nature of the Internet.

We developed an initial pool of 134 items. These items were subject to several rounds of internal focus groups with the authors' research lab members experienced in studying racism and measure development. Two additional experts in racism, stigma, and measurement development also provided feedback on the initial item pool. Based on this feedback, we removed 14 items and revised the remaining 120 items to enhance content representativeness and relevance, conciseness, grammar, reading level, and to eliminate redundancy. This revised item pool was then sent to another five expert reviewers specializing in the study of racism, measurement, and online communication. Based on expert feedback regarding content validity and item clarity, 16 items were further removed. The final item pool consisted of 104 items. An online reading level calculator indicated sixth grade level for the items. Overall, 76 items characterized racism experiences in online interactions and 28 items represented the ways people encounter online racist content. Further, 52 of the 76 online interaction items were based on racial microaggression. All of the items started with the following stem: "In the past 6 months, I have. . . ." Responses were rated on a 5-point scale ranging from 1 (*never*) to 5 (*all the time*). The prompt for the measure read: "We are interested in your personal experiences of racism in online settings as you interact with others and surf the Internet. As you answer the questions below, please think about your online experiences in the past 6 months."

Procedure

The study was approved by the Institutional Review Board (#775818–1). Participants were invited to participate in an online survey consisting of study variable measures and demographic items hosted by Qualtrics. The survey was advertised through multiple online communication platforms such as listservs, discussion forums, and social network sites (e.g., Facebook). The inclusion criteria for the study were: (a) 18-years-old or older; (b) self-identify as a racial/ethnic minority (e.g., African American/Black, Asian American/Asian, Hispanic American/Latino/a etc.); and (c) live in the U.S. Participants were compensated 50 cents via Amazon's Mechanical Turk (MTurk) and entered into a raffle for a chance to win an Amazon gift card. We decided to recruit participants using MTurk because it allows researchers to conduct targeted recruitment for underrepresented populations (Huff & Tingley, 2015). Studies have shown that MTurk allows researchers to collect large amounts of data efficiently from a diverse sample of population with comparable data reliability and quality compared to traditional methods (Buhrmester, Kwang, & Gosling, 2011; Casler, Bickel, & Hackett, 2013). The survey took 15 to 20 min to complete and included four validity check items (e.g., "Please choose always") throughout the survey.

Participants

The average age of the participants was 27.42 ($SD = 9.77$) and ranged from 18 to 67. About 33% (306) of the participants self-identified themselves as Black/African American, 20% (185) as East Asian/East Asian American, 17% (163) as Hispanic/Latino/a American, 13% (125) as Southeast Asian/Southeast Asian American, 11% (108) as Multiracial, 2.5% (26) Native American Indian/Alaskan Native, 2% (19) Middle Eastern, 1% (nine) Native Hawaiian, and .5% (five) other. About 59% (555) of the participants were women, 39% (372) men, and 2% (19) transgender. Majority of the sample were heterosexual (85%; 803), followed by 6% (55) bisexual, 3% (30) gay, 2% (23) lesbian, 2% (15) uncertain, 1% (11) asexual, and 1% (nine) queer. Approximately 26% (249) identified as non-native English speaker and 36% (338) as a first-generation college student. About 41% (388) reported receiving college education, 36% (336) had college degrees, and 14% (130) had graduate or professional degrees (e.g., M.A., Ph.D., M.D.). About 34% (319) were full-time employed, 39% (367) were students, and 19% (177) were part-time employed. The average income was $57,800. Participants were from diverse states with 33% (312) Mid Atlantic, 21% (199) West Coast, 19% (180) South, 20% (189) East Coast, and 7% (66) Midwest. In terms of Internet use, participants' average number of hours online per day was 6.39 ($SD = 4.02$). On average per day, 2.49 hr ($SD = 2.61$) was spent on social network sites (e.g., Facebook), 1.20 hr ($SD = 2.08$) on forums and chat services, 1.79 hr ($SD = 3.13$) on browsing online media, and .94 hr ($SD = 1.96$) on gaming.

Measures

Psychological distress. Participants' level of psychological distress was measured using the Mental Health Inventory-5 (MHI-5; Veit & Ware, 1983). The MHI-5 contains five items with higher scores indicating higher levels of psychological well-being and lower scores indicating higher levels of psychological distress. For the current study, we reverse scored the items so that higher scores indicate higher levels of psychological distress. Participants report on the frequency of the feelings related to mental health over the last month (e.g., "Have you felt downhearted and blue?"). Responses are rated on a 6-point scale ranging from 1 (*all of the time*) to 6 (*none of the time*). The responses are summed and range from 5 to 30. MHI-5 has been linked with stressful life events and decreased social support and life satisfaction. Reliability coefficients for racially diverse populations have ranged upward of .84 (Fischer & Bolton Holz, 2010; Heubeck & Neill, 2000). The Cronbach's alpha for the current sample was .85.

Perceived stress. We used the 10-item Perceived Stress Scale (PSS-10) to assess the extent to which situations in life are perceived as stressful (Cohen, Kamarck, & Mermelstein, 1983). The PSS-10 was designed to assess how unpredictable, uncontrollable, and overloading the life situations are for the participants over the last month. Participants rate their exposure to the stressful situations on a 5-point scale ranging from 0 (*never*) to 4 (*very often*). A sample item reads "How often have you been angered because of things that were outside of your control?" The responses are summed (ranging from 0 to 40), with higher total scores indicating greater perceived stress. Internal reliabilities for the PSS-10 ranged from .78 to .91 in a racially/ethnically diverse nationally representative sample (Cohen & Janicki-Deverts, 2012). Perceived stress has been significantly and positively correlated with negative affect (e.g., anxiety), depression, and coping behaviors. The Cronbach's alpha for the current study was .86.

Perceived racism (offline). The Perceived Ethnic Discrimination Questionnaire-Community Version Brief (PEDQ-CVB; Brondolo et al., 2005) is a 17-item measure of general perceived racial discrimination with the following subscales: exclusion/rejection (four items; e.g., "Have others ignored you or not paid attention to you?"), stigmatization/disvaluation (four items; e.g., "Have people not trusted you?"), work/school discrimination (four items; e.g., "Have you been treated unfairly by coworkers or classmates?"), treatment/aggression (four items; e.g., "Have others actually hurt you or tried to hurt you?"), and police (one item). PEDQ-CVB was selected for our study as it was designed as a general measure that can be used with adults in the community across racial/ethnic groups, and educational backgrounds. The full scale was used for our study. Participants rate their perceived exposure to discrimination items on a 5-point scale ranging from 1 (*almost never*) to 5 (*almost always*). Responses are summed and averaged. Higher scores represent higher levels of perceived racial/ethnic discrimination. An additional instruction was introduced stating "Please think about your offline experiences (not online) of racism." The PEDQ-CVB has been shown to converge with other racism measures and linked to negative mental health (Brondolo et al., 2005). Full scale reliability estimates have ranged upward of .90 in multiple racial/ethnic groups (Brondolo et al., 2005; Fang, Friedlander, & Pieterse, 2016). The Cronbach's alpha for the current sample was .94.

Belief in an unjust world. The 5-item Unjust Views Scale (UVS; Lench & Chang, 2007) assesses both personal ("The awful things that happen to me are unfair") and general beliefs ("People who do evil things get away with it") in an unfair world. Participant responses can range from 1 (*strongly disagree*) to 5 (*strongly agree*). Item scores are summed and averaged. Higher scores indicate greater belief in an unfair world. The measure demonstrated discriminant validity with belief in a just world and positively correlated with use of denial, anger, pessimism, and other disengagement coping strategies (Lench & Chang, 2007; Liang & Borders, 2012). The reliability estimates with racially diverse samples have ranged from .72 to .80 (Lench & Chang, 2007; Liang & Borders, 2012). The Cronbach's alpha for the current study was .65.

Racism-related stress. General racism-related stress was assessed using the 18-item General Ethnic Discrimination Scale (GED; Landrine et al., 2006). The GED is a measure of perceived racial discrimination for various racial/ethnic groups and are based on offline contexts (e.g., work, public places, and school). Participants rate each statement for past year exposure, lifetime exposure, and stress appraisal. A sample item reads "How often have you been treated unfairly by teachers and professors because of your race/ethnic group?" The scale uses a 6-point scale ranging from 1 (*never* or *not at all stressful*) to 6 (*almost all the time* or *extremely stressful*). The scores are summed and higher scores indicate greater stressfulness or exposure to racial discrimination events. While the items were based on offline experiences, we provided additional instruction for participants to focus on their offline experiences in answering the items. The GED has demonstrated high internal consistency (Cronbach's alphas .90 and above) and significantly associated with negative mental health outcomes such as psychological distress across racial/ethnic groups (Bastos, Celeste, Faerstein, & Barros, 2010; Landrine et al., 2006). The Cronbach's alphas for all three subscales were above .93 in our sample.

Data Screening and Preparation

A total of 2,339 participants accessed the survey. Of these, 732 (31%) were removed as they did not meet the inclusion criteria (hence, did not record any responses), and another 583 (25%) cases were removed for answering at least one of the four validity check items incorrectly. One case was further removed for missing more than 10% of the data (Schlomer, Bauman, & Card, 2010), resulting in a sample size of 1,023 participants who completed the PORS (note that only 946 of participants provided adequate data on other study variables and demographics). Little's missing completely at random test suggested that data were missing completely at random, $\chi^2(985) = 969.960$, $p = .628$. We imputed the missing values using the expectation-maximization algorithm in SPSS. We randomly assigned participants to a development or validation sample. The development sample ($n = 545$) was used for EFA and the validation sample ($n = 478$) was used for CFA. Representation of race, gender, and age in both samples were similar to the total sample descriptors.

Results

Step 1: Exploratory Factor Analysis (EFA)

To identify the initial factor structure of PORS, we conducted an EFA based on best practice guidelines using the development sample (DeVellis, 2016; Fabrigar, Wegener, MacCallum, & Strahan, 1999). EFA was conducted using principal axis factoring extraction and oblique promax rotation in SPSS 21.0 because we expected the factors to correlate with each other as part of the online racism experience. We also conducted parallel analysis, which is a simulated factor retention technique to determine the appropriate initial number of factors to be retained and interpreted (O'Connor, 2000).

Parallel analysis. Bartlett's test of sphericity was $\chi^2(5,356) = 47999.56$, $p < .001$, and the Kaiser-Meyer-Olkin measure of sampling adequacy was .98, indicating that data were sufficiently factorable. The scree plot indicated a sharp "bend of the elbow" around the third to fifth factor mark. However, examination of the eigenvalues obtained through parallel analysis suggested the retention of eight factors based on the eigenvalues that were greater than those obtained from simulating random data (O'Connor, 2000). Based on 10,000 random data sets, the first eight factors had raw data eigenvalues (42.90, 8.72, 3.24, 1.83, 1.49, 1.39, 1.24, 1.06) that were greater than the simulated random eigenvalues (1.27, 1.19, 1.14, 1.09, 1.05, 1.01, .98, .95).

Factor structure extraction. The eight-factor solution had a poor fit to the data. Thus, we proceeded to examine the factor loadings and remove problematic items (Tabachnick & Fidell, 2007). Items were sequentially removed, only retaining items with primary loadings higher than .50 and cross-loadings equal to or less than .20 (Osborne & Costello, 2009). We reexamined the fit statistics and loadings after each round of item removal on a case-by-case basis guided by interpretability of the domains (Worthington & Whittaker, 2006). Throughout this process, no items loaded at the .50 level on Factor 8 and this factor was removed. Items with primary loadings on Factors 4, 5, 6, and 7 also exceeded the .20 cross-loading cutoff; these factor solutions were ultimately not retained as each had less than three items that loaded at the .50 level after sequentially eliminating cross-loading items (Tabachnick & Fidell, 2007). We were comfortable eliminating these factor solutions given that the fourth factor and beyond were likely nuisance factors resulting from overextraction (Brown, 2015; Fabrigar et al., 1999) and the minimal additional variance accounted for in PORS items by factors 4, 5, 6, and 7 were 1.9%, 1.7%, 1.4%, 1.2%, and 1%, respectively. Conversely, the first three factors continued to emerge robustly in the process of elimination, resulting in a 41-item three-factor solution.

The three-factor structure provided a theoretically meaningful simple structure (see Table 1). To name the factors, the

Table 1
Item Factor Loadings (Pattern Matrix Coefficients) for the Perceived Online Racism Scale

Items	EFA				CFA: Bifactor			
	1	2	3	h^2	g	1	2	3
Factor 1: Personal experience of racial cyber-aggression								
50. Received racist insults regarding my online profile (e.g., profile pictures, user ID).	.84	.03	−.02	.72	.57	.58		
15. Been kicked out of an online social group because I talked about race/ethnicity.	.83	−.02	−.13	.58	.41	.62		
19. Been intentionally invited to join a racist online social/hate group.	.83	−.13	−.08	.55	.28	.61		
61. Received replies/posts suggesting that I should avoid connecting online with friends from my own racial/ethnic group.	.80	.10	−.12	.61	.51	.60		
23. Received racist insults about how I write online.	.79	−.08	.02	.58	.46	.63		
52. Been threatened of being harmed or killed due to my race/ethnicity.	.75	.05	−.06	.55	.44	.65		
31. Received replies/posts hinting that my success is surprising for a person of my race/ethnicity.	.72	−.03	.10	.58	.53	.44		
67. Received a message with a racist acronym such as FOB (Fresh Off the Boat) or PIBBY (Put In Black's Back Yard).	.70	−.01	−.07	.44	.49	.55		
30. Been harassed by someone (e.g., troll) who started a racist argument about me for no reason.	.67	−.03	.14	.55	.62	.52		
69. Received a racist meme (e.g., racist catchphrases, captioned photos, #hashtags etc.).	.65	.09	.01	.50	.59	.49		
76. Been tagged in (or shared) racist content (e.g., web sites, photos, videos, posts) insulting my race/ethnicity.	.65	.05	.09	.55	.62	.49		
36. Received posts with racist comments.	.64	−.03	.22	.59	.63	.42		
3. Received replies/posts hinting that what I share online cannot be trusted due to my race/ethnicity.	.63	.02	.05	.45	.51	.48		
33. Been unfriended/lost online ties because I disagreed with racist posts.	.60	.07	.08	.48	.65	.36		
Factor 2: Online-mediated exposure to racist reality								
101. Been informed about a viral/trending racist event happening elsewhere (e.g., in a different location).	−.07	.84	−.05	.60	.51		.56	
93. Been informed about unfairness in healthcare for racial/ethnic minorities (e.g., biased quality of treatment, insurance issues).	.06	.73	−.04	.53	.52		.50	
100. Seen online videos (e.g., YouTube) that portray my racial/ethnic group negatively.	.07	.73	−.07	.51	.67		.32	
94. Encountered online resources (e.g., Urban Dictionary) promoting negative racial/ethnic stereotypes as if they are true.	.05	.70	.01	.55	.58		.45	
88. Been informed about unfairness in financial gains for racial/ethnic minorities (e.g., earning less money than Whites for doing the same work, unfair housing, and loan opportunities).	−.14	.69	.13	.53	.48		.56	
82. Been informed about unfairness in education for racial/ethnic minorities (e.g., higher suspension rates for racial/ethnic minority students).	−.09	.69	.13	.55	.56		.53	
99. Been informed about a viral/trending racist event that I was not aware of.	.05	.69	−.12	.40	.50		.35	
80. Seen online news articles that describe my racial/ethnic group negatively.	.03	.67	.06	.53	.64		.41	
92. Seen photos that portray my racial/ethnic group negatively.	.04	.65	.04	.50	.64		.37	
77. Encountered a viral/trending online racist content (e.g., many likes, stars).	−.08	.65	.08	.53	.55		.45	
3. Encountered online hate groups/communities against non-White racial/ethnic groups.	.14	.65	−.02	.51	.63		.35	
Factor 3: Vicarious exposure to racial cyber-aggression								
64. Seen other racial/minority users receive racist comments.	−.09	.05	.83	.68	.70			.39
51. Seen other racial/minority users being treated like a second-class citizen.	−.06	.10	.79	.69	.69			.47
22. Seen other racial/minority users being treated like a criminal.	.02	.08	.72	.63	.62			.46
44. Seen other racial/minority users receive racist insults regarding their online profile (e.g., profile pictures, user ID).	.18	.00	.66	.60	.72			.36
4. Seen other racial/minority users being threatened to be harmed or killed.	.11	.11	.58	.53	.58			.48

Note. Factor loadings for Exploratory Factor Analysis (EFA) with promax rotation ($n = 545$) and Confirmatory Factor Analysis (CFA) for the bifactor model ($n = 478$). All items loaded significantly in the CFA onto the proposed factors ($p < .001$).

authors proposed several literature-based factor names to the authors' research lab members. A consensus process was used to discuss the fit of the names to the items and content representation. Items with the highest loadings were also used as themes to guide factor labeling. The first factor was named *personal experience of racial cyber-aggression* (PERCA; 18 items) and represented people's direct personal experiences of online racism in their interactions with others. The second factor was named *online-mediated exposure to racist reality* (OMERR; 13 items) and represented exposure to online content through which individuals witness the reality of racism in society. Item content comprised of information such as racist incidents happening in another geographic location or online information illuminating various systemic racial inequalities. The third factor was named *vicarious exposure to racial cyber-aggression* (VERCA; 10 items) and represented vicarious and indirect experiences of online racism via the observation of others being victimized as targets of racial aggression in online interactions. The variance explained by each factor was 40.19%, 10.94%, and 3.69%, respectively. Reliability estimates were .951, .937, and .932, respectively.

Optimization of scale length. Our goal was to maximize the utility of the measure by considering the trade-offs between scale length, reliability, and content representation. We deleted items based on the following criteria (Worthington & Whittaker, 2006): (a) have the lowest factor loadings, (b) have the highest cross-loadings, (c) contribute least to the internal consistency of the scale scores, and (d) have low conceptual consistency with other items on the factor. The optimization process resulted in a 30-item measure: 14 items for personal experience, five items for vicarious exposure, and 11 items for online-mediated exposure (see Table 1). Variance explained by these factors were 40.56%, 11.41%, and 3.12%, respectively. The factors were correlated moderately high with each other: $r_{\text{PERCA-OMERR}} = .486$, $p < .001$; $r_{\text{PERCA-VERCA}} = .572$, $p < .001$; $r_{\text{OMERR-VERCA}} = .700$, $p < .001$ (see Table 4 for descriptive statistics).

Step 2: Confirmatory Factor Analysis (CFA)

To cross-validate the three-factor oblique model of PORS, we conducted a CFA with the validation sample using Mplus 7.11. Model fit was evaluated by the following fit indices (Fabrigar et al., 1999; Hu & Bentler, 1999): (a) comparative fit index (CFI; >.95 for good fit; .92 to .94 for adequate fit); (b) the standardized root-mean-square residual (SRMR; close to <.08 for acceptable fit); (c) and the root mean square error of approximation (RMSEA; close to <.08 for acceptable fit). These fit indices were also used to examine several a priori competing models we tested in order to rule out rival hypotheses regarding the PORS factor structure. The competing models were compared based on (a) Satorra-Bentler scaled chi-square difference test (S-B chi-square test); (b) Bayesian information criterion (BIC) values; and (c) Akaike Information Criterion (AIC) values. Smaller values of BIC and AIC values suggest better fit, with higher values of more than 10 units suggesting lack of empirical support for goodness of fit (Burnham & Anderson, 2004).

CFA. Because the omnibus test of multivariate normality (Small, 1980) suggested that validation sample ($N = 478$) data were not normal, $\chi^2(60) = 1376.90$, $p < .001$, we employed a maximum likelihood estimation with standard errors and chi-square test statistic that are robust to non-normality. The CFA suggested adequate to good fit for the three-factor oblique model (see Table 2). All items loaded significantly ($p < .001$) on the hypothesized latent factors and ranged from .61 to .83.

Test of competing models. We compared our three-factor oblique model to a number of a priori alternative models. We examined one-factor, three-factor orthogonal, and bifactor (with one general and three domain specific factors; Reise, 2012) models (see Figure 1). The S-B chi-square tests indicated that the oblique three-factor model had a significantly better fit to the data than the orthogonal model, SB $\chi^2(3) = 461.342$, $p < .001$, and the one-factor model, SB $\chi^2(3) = 1571.577$, $p < .001$. The superior fit of the three-factor oblique model was also demonstrated as the alternative models had greater AIC and BIC values of more than 10. However, the AIC value of the bifactor model was 100 units less than the three-factor oblique model. The S-B chi-square test also indicated that the bifactor model had a better fit to the data than the three-factor oblique model, SB $\chi^2(27) = 124.755$, $p < .001$ and was therefore retained (see Table 2).

Bifactor model. Our bifactor model assumed that a conceptually meaningful general factor accounted for variance in all PORS items and that three conceptually meaningful domain specific PORS factors accounted for variance in respective subsets of PORS items. All items significantly loaded onto the general factor in the range of .28 to .72 and the specific factors in the range of .32 to .65. Of the 30 items, 24 items loaded onto the general factor at .50 or above. Concurrently, 13 out of 14, seven out of 11, and three

Table 2
Goodness-of-Fit Indicators for Structural Equation Modeling Analyses

Models/samples	*df*	χ^2	RMSEA	90% CI	CFI	SRMR	BIC	AIC
Oblique three-factor	402	944.024**	.053	[.049, .058]	.927	.055	34780.77	34392.39
Orthogonal three-factor	405	1306.890**	.068	[.064, .072]	.873	.253	35230.75	34855.48
One-factor	405	2758.066**	.11	[.106, .114]	.668	.118	37124.59	36749.32
Bifactor	375	822.489**	.050	[.045, .055]	.937	.043	34792.49	34292.14
Configural model	1,500	2976.005**	.067	[.063, .070]	.919	.055	65836.801	63538.635
Metric model	1,668	3308.026**	.067	[.063, .070]	.915	.067	65028.465	63534.657
Scalar model	1,746	3498.895**	.067	[.064, .071]	.906	.070	64689.881	63569.525
Asian ($N = 319$)	375	601.403**	.044	[.037, .050]	.942	.065	21770.66	21318.83
Black ($N = 306$)	375	734.83**	.056	[.050, .062]	.929	.048	23676.35	23229.52
Latino/a ($N = 163$)	375	610.336**	.062	[.053, .071]	.902	.074	12133.28	11762.03
Multiracial ($N = 108$)	375	532.063**	.062	[.050, .074]	.920	.059	8124.41	7802.56
Measurement model	1,371	3768.68**	.043	[.041, .045]	.906	.055	140013.43	138926.53

MI model comparison	$\chi^2(df)$	*p*	ΔCFI	ΔRMSEA	ΔSRMR
Configural vs. metric	332.022 (168)	<.001	.004	0	.012
Metric vs. scalar	190.868 (78)	<.001	.009	0	.003
Scalar vs. configural	234.061 (82)	<.001	.013	0	.015

Note. RMSEA = root-mean-square error of approximation; CI = confidence interval for RMSEA; CFI = comparative fit index; SRMR = standardized root-mean-square residual; BIC = Bayesian information criterion; AIC = Akaike information criterion; MI = measurement invariance.
** $p < .01$.

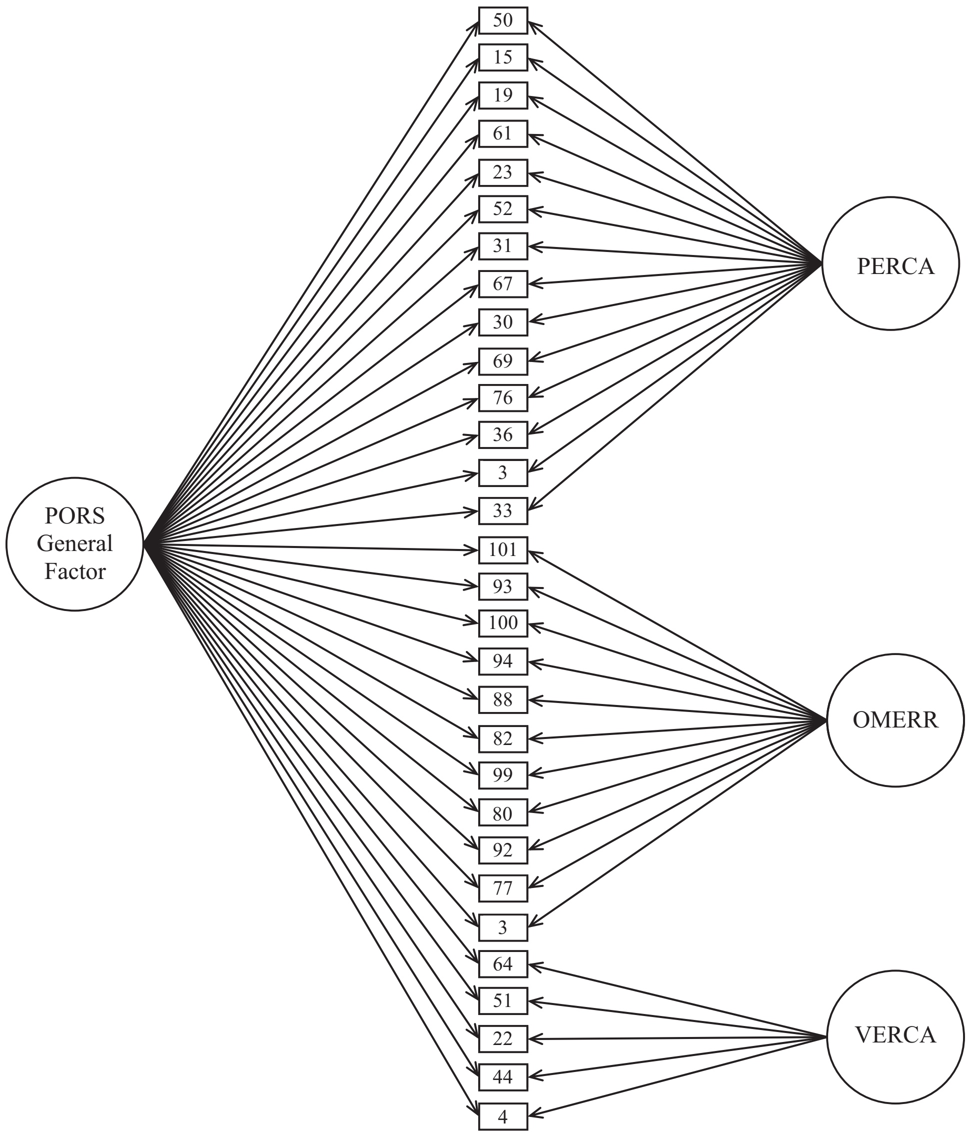

Figure 1. Bifactor model of the Perceived Online Racism Scale (PORS) with the general factor and three specific factors. The three-factor model excludes the general factor. The one-factor model includes all items. PERCA = personal experience of racial cyber-aggression; VERCA = vicarious exposure to racial cyber-aggression; OMERR = online-mediated exposure to racist reality.

out of five items loaded above .40 for the personal experience, online-mediated exposure, and vicarious exposure factors, respectively. Thus, the magnitude of the loadings offered support for our assumption that the general and domain specific factors were conceptually meaningful (Reise, 2012). The three domain specific factors were correlated moderately high with each other: $r_{\text{PERCA-OMERR}} = .514$, $p < .001$; $r_{\text{PERCA-VERCA}} = .613$, $p < .001$; $r_{\text{OMERR-VERCA}} = .724$, $p < .001$ (see Table 4 for descriptive statistics).

Step 3: Measurement Invariance

We conducted multigroup CFA to evaluate measurement invariance of PORS to test whether the measure operated in an equivalent manner across the major racial/ethnic groups in our sample (Black, Asian, Latino/a, Multiracial). Invariance testing is conducted via comparison of a series of models with increasing constraints: baseline configural model (no constraints), metric model (factor loadings constrained), and scalar model (factor loadings and item intercepts constrained). Model fit was assessed by the same fit index used in our CFA (Hu & Bentler, 1999). Evaluation of the invariance was conducted by assessment of changes in the fit index. A change in CFI (ΔCFI) less than .01, change in RMSEA (ΔRMSEA) less than .015, and change in SRMR (ΔSRMR) less than .03 suggests no significant decrease in model fit and supports measurement invariance (Chen, 2007). We did not consult S-B chi-square tests as we anticipated these tests to be significant (suggesting noninvariance) given that chi-square tests are known to be sensitive to sample size and even a small difference may be found to be significant with increasing sample sizes (Cheung & Rensvold, 2002).

Invariance testing. Fit statistics for invariance tests are displayed in Table 2. The sample sizes for the Black, Asian, Latino/a, and Multiracial samples were 306, 319, 163, and 108, respectively. The baseline bifactor configural model had an adequate fit to the data across the groups. The configural model was compared to the metric model that constrained factor loadings across the groups. The metric model had an adequate fit to the data and the changes in fit index indicated no significant decrement in fit from configural to the metric model (ΔCFI $= -.004$, ΔRMSEA $= 0$, ΔSRMR $= -.012$). We proceeded to compare the metric model to the scalar model that constrained factor loadings and intercepts across the groups. The scalar model had an acceptable fit to the data and the changes in fit index indicated no significant decrement in fit from metric to the scalar model (ΔCFI $= -.009$, ΔRMSEA $= 0$, ΔSRMR $= -.003$). We decided to accept our results as evidence for measurement invariance as the changes in CFI, RMSEA, and SRMR across the increasingly constrained models did not indicate significant decrement in model fit (Chen, 2007; Cheung & Rensvold, 2002).

Latent means. Given this evidence of PORS measurement equivalence across the four groups, we conducted latent mean comparisons. We set the factor means at 0 for the Multiracial group. Both Black and Asian groups reported significantly higher total means than Multiracial individuals (see Table 4). Interestingly, Black individuals reported significantly lower means for the vicarious and online-mediated exposure subscales than Multiracial individuals (see Table 4).

Step 4: Construct Validity

We used structural equation modeling (SEM) in Mplus 7.11 to establish initial validity evidence for the bifactor model of PORS (one general factor and the three domain specific factors) by examining its relationship with other racism constructs (general perceived racism, racism-related stress) and mental health indicators (psychological distress, perceived stress, belief in an unjust world). We employed a maximum likelihood estimation with standard errors and chi-square test statistic that are robust to non-normality. The total sample was used for validity testing ($N =$ 1,023). For convergent and criterion-related evidence, we examined the latent variable correlations of PORS with our validity variables (Note: convergent evidence with racism-related stress was tested with bivariate correlations of observed scores as limited data [$N = 46$] was collected from the follow-up survey). Predictive evidence was tested by regressing each of our mental health indicators on the PORS. To test incremental evidence, the general perceived racism variable was added to each of these latent regression models to see if PORS would still significantly predict our mental health variables over and above an existing measure of racism. Effect size evaluations were guided by Cohen, Cohen, West, and Aiken, (2013).

Preliminary analysis. Prior to our analyses, we established a measurement model that included all of the PORS factors and validity variables. The measurement model had an acceptable to good fit to the data (see Table 2) and all items loaded onto the latent variables ($p < .001$). We also assessed the data we collected on some of our mental health variables by comparing the means with those found in other studies because MTurk participants have endorsed clinical symptoms greater than traditional nonclinical samples (Arditte, Çek, Shaw, & Timpano, 2016). We compared the mean of our MHI-5 data with scores ($M = 3.13$, $SD = .86$, $N =$ 264) from Fischer and Bolton Holz (2010) and found no significant difference, $t(453) = 5.563$, $p = .960$. We compared the mean of our UVS data with scores ($M = 2.77$, $SD = .73$, $N = 170$) from Liang and Borders (2012) and found no significant difference, $t(232) = 2.834$, $p = .397$.

Convergent evidence. We hypothesized that the PORS scores would correlate positively with scores from a general perceived racism measure (PEDQ-CVB) given that both are racism constructs and should be related. We also anticipated a positive correlation between PORS and racism-related stress (GED-S) as we have outlined online racism as a major chronic stressor in the lives of people of color. We anticipated the correlations to be highest for the personal experience subscale followed by the vicarious exposure subscale given that the major contexts of the PEDQ-CVB and GED-S scales were direct/personal in assessing racism. We tentatively hypothesized that the magnitude of the correlations would be lowest with the online-mediated exposure subscale given that this factor represents exposure to contents rather than online interactions. Conversely, we also anticipated that PORS' focus on online activities may result in nonsignificant correlations of PORS with both PEDQ-CVB and GED-S.

As hypothesized, PEDQ-CVB was significantly and positively correlated with the general factor and all of the subscales. The largest effect was found for the personal experience factor whereas the smallest effect was found for the online-mediated exposure factor. The effect sizes ranged from small to medium, with the general factor having the largest effect. Regarding GED-S, all of the observed scores of PORS were significantly and positively correlated with observed offline racism-related stress scores. The GED-S was significantly correlated with PORS total score, $r =$ .57, $p < .01$, personal experience factor, $r = .54$, $p < .01$, vicarious exposure factor, $r = .34$, $p < .01$, and online-mediated exposure factor, $r = .50$, $p < .01$. Interestingly, the vicarious exposure factor had the smallest effect and we found a comparable medium effect size for both online-mediated exposure and personal experience factors. The mean score for the GED-S was 35.63 ($SD = 18.13$) and ranged from 17 to 102.

Criterion-related evidence. We hypothesized that PORS scores would positively correlate with psychological distress (MHI-5) and perceived stress (PSS) given the negative impact of offline racism on mental health (Pascoe & Smart Richman, 2009). Similarly, we hypothesized that PORS would positively correlate with belief in an unjust world (UVS) given prior research linking offline racism to beliefs in unjust world (Liang & Borders, 2012). Among the subscales, we anticipated that the effect sizes of the correlations would decrease from largest to smallest (or even nonsignificant), in the order of personal experience, vicarious exposure, and online-mediated exposure factors. This anticipation was based on online communication research suggesting that greater personal relevance with online content may predict greater perceived risk of that material for an individual (Cohen, 2001; Snyder & Rouse, 1995). We anticipated that the personal experience factor would be most relevant and distressing, followed by vicarious exposure and online-mediated exposure factor.

The general factor significantly and positively correlated with MHI-5, PSS, and UVS, ranging from small to medium effect sizes. Both PSS and UVS had similar magnitudes while the effect was smallest with MHI-5. For the specific factors, we observed small to medium effect sizes and differential correlations with the three mental health variables. The vicarious exposure factor was significantly correlated with MHI-5 and PSS. The personal experience factor was significantly correlated with MHI-5 and UVS. Contrary to our hypothesis, the vicarious exposure factor had the largest effect with MHI-5. The online-mediated exposure factor was only correlated with MHI-5. As anticipated, we found the lowest effect for this correlation.

Predictive evidence. Given the negative mental health implications of racism (Pascoe & Smart Richman, 2009), we hypothesized that the total score and the three domain specific factors would significantly predict each of our mental health indicators (MHI-5, PSS, UVS). As with criterion-related evidence, we again hypothesized that the effect sizes of the relationships would decrease from largest to smallest (or even nonsignificant), in the order of personal experience, vicarious exposure, and online-mediated exposure factors.

The general factor significantly predicted MHI-5 ($b = .20$, $p < .01$, $R^2 = .15$), PSS ($b = .29$, $p < .01$, $R^2 = .17$), and UVS ($b = .31$, $p < .01$, $R^2 = .10$). Beyond the general factor, the personal experience factor significantly predicted MHI-5 ($b = .23$, $p < .01$, $R^2 = .07$) and UVS ($b = .21$, $p < .01$, $R^2 = .07$). The vicarious exposure factor significantly predicted MHI-5 ($b = .26$, $p < .01$, $R^2 = .03$) and PSS ($b = .17$, $p < .01$, $R^2 = .03$). No significance was found for the online-mediated exposure factor, although we observed marginal significance in predicting MHI-5 ($b = .11$, $p = .054$). As with our criterion evidence, the vicarious exposure factor had the largest effect size in predicting MHI-5 among the specific factors.

Incremental evidence. Given that PORS focuses on online racism, we tested whether this differentiation from offline contexts may account for unique variance that is not captured by an existing measure of offline racism. Thus, we hypothesized that the PORS would explain unique variance in MHI-5, PSS, and UVS above and beyond PEDQ-CVB. However, we anticipated that the unique variance would most likely be found with the vicarious exposure or the online-mediated exposure factors as personal experience factor seem to bear most semblance to the interpersonal context of the PEDQ-CVB.

When PEDQ-CVB was added to the latent regression model, only the vicarious exposure factor accounted for additional unique variance in MHI-5 ($b = .22$, $p < .01$, $R^2 = .03$). Although personal experience factor accounted for additional unique variance in PSS ($b = -.11$, $p < .01$, $R^2 = .06$), we observed an inverse relationship. We suspected that there was a suppression effect given that the magnitude of the relationship increased to significance and a sign change (positive to negative) was observed for the path coefficient when PEDQ-CVB was added into the model. We refrained from further inference of this finding as scholars have cautioned that a meaningful interpretation of the unexpected directional relationship is unwarranted when there is reason to suspect statistical suppression (Cheung & Lau, 2007).

Step 5: Reliability

We evaluated the impact of content sampling error (via Cronbach's alpha) and time of measurement error (via test-retest estimates) on the reliability of PORS scores. We anticipated PORS scores to be stable across short periods of time based on our discussion on the pervasive and permanent nature of online racist content. To examine test–retest reliability of PORS scores, we asked a randomly selected subset of participants from the total sample to complete a brief follow up online survey four weeks after completion of the original survey. The survey included validity check items and an additional measure to examine further convergent evidence with racism-related stress (GED-S). Of the 100 participants we contacted, 71 participants started the survey and 51 completed the survey (72%; contact the first author for demographic information). No participants were missing any data but five were removed due to incorrectly answering the validity items. The final sample size for the follow-up sample was 46. We calculated the correlations between Time 1 and Time 2 (4 weeks later) scores of PORS.

Descriptive statistics, latent variable correlations, factor means and Cronbach's alphas are presented in Tables 3 and 4. PORS factor based scale scores produced Cronbach's alpha coefficients of .88 and higher. Regarding test–retest reliability, we calculated the correlations between Time 1 and Time 2 (4 weeks later) scores

Table 3
Latent Variable Correlations, Observed Score Descriptive Statistics, and Cronbach's Alphas for PORS, Validity Measures, and Age

Variable	1	2	3	4	5	6	7	8	α	*M*	*SD*	Range
1. PERCA	—								.95	63.02	21.22	30–150
2. VERCA	.00	—							.94	21.75	10.03	14–70
3. OMERR	.00	.00	—						.90	11.93	5.12	5–25
4. General	.00	.00	.00	—					.92	29.33	10.02	11–55
5. PEDQ-CVB	.46**	.13**	.08*	.59**	—				.94	1.84	.72	1–5
6. MHI-5	.24**	.26**	.11*	.20**	.42**	—			.85	13.95	4.70	5–30
7. PSS	.04	.16*	.08	.32**	.39**	.78**	—		.86	17.55	6.70	0–40
8. UVS	.21**	.17	.03	.31**	.49**	.52**	.48**	—	.65	2.60	.74	1–5
9. Age	.00	−.03	−.03	.01	.01	−.01	−.02	−.01		27.43	9.77	18–67

Note. PORS = Perceived Online Racism Scale; PERCA = personal experience of racial cyber-aggression; VERCA = vicarious exposure to racial cyber-aggression; OMERR = online-mediated exposure to racist reality; PEDQ-CVB = perceived ethnic discrimination questionnaire-community version brief (general measure of perceived offline racism); MHI-5 = Mental Health Inventory-5; PSS = Perceived Stress Scale; UVS = Unjust Views Scale; *SD* = standard deviation.
* $p < .05$. ** $p < .01$.

Table 4
Factor Means, Standard Deviations, and Cronbach's Alphas

Sample	PERCA			VERCA			OMERR			PORS-total		
	M	*SD*	α	*M*	*SD*	α	*M*	*SD*	α	*M*	*SD*	α
EFA Sample (*N* = 545)	21.42	9.80	.94	11.96	5.08	.98	29.35	10.01	.88	62.72	21.07	.95
CFA Sample (*N* = 478)	21.86	10.13	.95	11.76	5.11	.90	29.31	9.91	.92	62.92	21.20	.95
Black (*N* = 306)	*−.26*	*1.30*	.95	*−1.05**	*1.12*	.90	*−.60**	*1.11*	.92	*.70***	*1.04*	.95
Asian (*N* = 319)	*.17*	*.67*	.93	*.60*	*1.26*	.88	*.28*	*1.13*	.91	*−.62***	*.85*	.94
Latino/a (*N* = 163)	*−.27*	*.87*	.93	*−.75*	*1.14*	.88	*−.467*	*1.17*	.92	*.18*	*.97*	.94
Multiracial (*N* = 108)	*0*	*1*	.95	*0*	*1*	.91	*0*	*1*	.91	*0*	*1*	.96
4-week test–retest												
Time 1 (*N* = 46)	19.26	8.19	.92	11.63	5.59	.92	28.96	9.13	.88	59.85	20.05	.94
Time 2 (*N* = 46)	18.61	7.07	.90	11.65	4.70	.90	28.87	10.04	.93	59.10	18.13	.94

Note. PERCA = personal experience of racial cyber-aggression; VERCA = vicarious exposure to racial cyber-aggression; OMERR = online-mediated exposure to racist reality; PORS = Perceived Online Racism Scale; EFA = Exploratory Factor Analysis; CFA = Confirmatory Factor Analysis; *SD* = standard deviation. Italicized values indicate latent means and standard deviations.
* $p < .05$. ** $p < .01$.

of PORS general factor and the subscale scores. The correlations between Time 1 and Time 2 administrations of PORS were .81, .72, .85, and .80 for the subscales of personal experience, online-mediated exposure, vicarious exposure, and the total score, respectively.

General Discussion

The Perceived Online Racism Scale was developed to assess the unique ways in which people experience racism while interacting in online social platforms and browsing online content. Using best practices in measure development, we examined the psychometric properties of the PORS in a total sample of 1,023 racial minority participants. The PORS items were developed using several sources of information (extant literature, preexisting racism measures, online examples, and brief survey of diverse individuals' experiences of racism on the Internet) to tap ecologically relevant ways that people perceive racism in today's digital society. The items underwent several revisions and expert review.

Our factor analytic tests found that a bifactor model of the PORS, with three specific factors and one general factor, was superior to a number of plausible competing models. The personal experience of racial cyber-aggression factor reflects the direct online racial aggression that individuals can face in their online interactions with others. The vicarious exposure to racial cyber-aggression factor represents observation of racial aggression experienced by other racial/ethnic minority Internet users in their online interactions. The online-mediated exposure to racist reality factor represents people's exposure to online content (e.g., racist incidents happening in another location or online information illuminating various systemic racial inequalities) through which they may realize and witness the apparent reality of racism in society. Finally, the general PORS factor represents common aspects of online racism not specific to any individual online mode or experience.

PORS factor based scale scores produced Cronbach's alpha coefficients of .88 and higher and we found that PORS scores were stable over a 4-week period of time. We also found measurement invariance of PORS across race/ethnicity indicating PORS measurement equivalence across the four racial/ethnic groups (Black, Asian, Latino/a, Multiracial) and that differences in the scores reflect true results rather than response bias. Lastly, the PORS scores were associated with scores on measures of racism, racism-related stress, perceived stress, psychological distress, and beliefs in an unjust world in a way consistent with theory.

Because we modeled the PORS as a bifactor structure with a general factor sharing variance in all of the items in addition to unique variance across the three subscales, the PORS general factor and the subscale scores cannot merely be calculated by summing up the scores for the items representing these domains. This would be acceptable for the general factor score (summing up scores of all the items) but would be problematic for subscale scores as the variance shared in the general factor would confound the unique variances of the subscales. This may lead to issues of multicollinearity and reduction of power in data analysis. To account for this, researchers may use structural equation modeling (SEM) to specify a bifactor model to assess the general factor and the specific factors independent from each other. If not using SEM and going with the observed scores, we suggest ipsative scoring (Tracey, 2012). Ipsative scoring corrects the subscale score by subtracting the mean of the total scale score in order to address the overall mean elevation due to the effects of the general factor. Thus, the total mean scores should be subtracted from each subscale scores to calculate the true subscale scores.

The PORS general factor score was significantly linked to all of our mental health indicators. In general, these findings align with studies in cyber-bullying suggesting online racial victimization as a significant predictor for poor mental health among adolescents (Tynes et al., 2008; Tynes et al., 2010). However, we found novel results on the mental health implications of online racism upon examination of the subscales. Whereas Tynes, Giang, Williams, and Thompson (2008) found no significant relationships between vicarious online racial victimization and mental health for adolescents, vicarious exposure emerged as a significant psychological stressor for adults in our study. Although we anticipated that vicarious exposure may be less potent in predicting psychological distress than personal experiences based on the relevance framework, vicarious exposure was linked to both psychological distress and perceived stress in greater magnitude.

Furthermore, vicarious experiences of online racism may be particularly important as we found that this was the only factor that explained additional unique variance in psychological distress beyond an existing measure of offline racism. We believe that this finding is a quintessential example of the pervasive nature of online racism—an important aspect of online racism experiences that may differ from offline racism experiences for the general adult population. The Internet provides convenient access to a vast amount of vicariously felt racism experiences that one simply does not encounter offline. The sheer volume of these experiences, therefore, may be the most potent racism-related stressor on the Internet. This is especially problematic given that vicarious racism is associated with feelings of helplessness and anger (Harrell, 2000). Sustaining these negative reactions consistently over time may be especially harmful, particularly for frequent users of the Internet.

Interestingly, factors that seemed more personally relevant (personal experience and vicarious exposure factors) were the major predictors of mental health outcomes whereas online-mediated exposure factor was minimally significant. This suggests that users may experience greater distress when the racist contents are more personally relevant. This is congruent with online communication research suggesting that personal identification with online content may predict greater perceived relevance and risk of that material for an individual (Cohen, 2001; Snyder & Rouse, 1995). The online-mediated exposure factor reflects experiences that are not as personal in nature and may be less likely to instill a sense of identification. This may help to explain how online-mediated exposure factor scores did not predict our mental health outcomes after accounting for the general PORS factor. Conversely, we did find that this factor correlated with racism-related stress with large effect compared with the other subscales. It is possible that a racism-specific or online-related measurement of stress may be more relevant in assessing the online-mediated realization of racism in society.

Regarding the content of our measure, most of the items we developed to assess subtle online racism (i.e., racial microaggressions, RM) were not retained in factor analysis. These items loaded onto the factors we eventually (i.e., Factors 4, 5, 6, 7, and 8) removed and did not emerge as meaningful domains in our study. Thus, majority of PORS items, particularly with our personal experience and vicarious exposure subscales, represent blatant forms of racism. Theoretically, we interpreted the instability of these factors as a sign that our racial microaggression items were either inadequate in their representation or suggest that subtle racism experiences are not as salient on the Internet. It is possible that the items we generated based on existing literature and adapted from preexisting offline measures may not have truly represented how RM manifests online. We posit several reasons pointing to the uncertainty of RM in our assessment of perceived online racism. First, the nonverbal behaviors and social cues that an individual may consider in determining whether certain ambiguous messages or acts are deemed as RM may be missing (Sue et al., 2007). Nonverbal behaviors such as lack of eye contact and physical distancing are useful cues for an individual to determine whether she/he (and other members of their racial group) is being excluded in offline group interactions due to their race/ethnicity. The lack of these cues (and others) makes it difficult if not impossible to assess whether such assumption is valid. Second, people may find it easier to miss RM given that the lack of the social and physical cues may stir less uncertainty and stressfulness in trying to decipher whether certain messages or acts are invalidations. Lastly, blatant forms may overshadow subtle forms of online racism because explicit, controversial materials are often the subject of "trending" content on the Internet (Becker et al., 2011).

Regardless, we believe that this result raises an interesting and fundamentally important aspect of online racism compared to offline racism. Given the uncertainty of the meaningfulness in current conceptualizations of subtle racism for the online context, it is possible that explicit and blatant forms predominantly characterize the nature of online racism. This seems especially congruent with literature suggesting that much of the hate speech and aggression on the Internet may be driven by increased online anonymity that can lead to online disinhibition. Suler (2004) suggests that online disinhibition is further classified as being toxic, or as "rude language, harsh criticisms, anger, hatred, even threats" (p. 321) that people would be less likely to express in offline interactions. The blatant nature of online racism raises an interesting paradox that the meaningfulness of subtle and covert forms of offline racism such as racial microaggression or colorblindness—as they are currently conceptualized—may be diminished in online contexts. Ultimately, we believe that there is a need to reconceptualize subtle racism when generalizing this construct to the online context.

Our study has several limitations that should be considered when evaluating the current findings. First, the PORS is limited in scope and assessment regarding subtle racism experiences on the Internet. It would be important for future studies to consider subtle aspects of online racism from a phenomenological perspective given that current theories of subtle racism may not directly translate to online settings. Second, although we recruited over 1,000 participants and found measurement invariance across our racial/ethnic groups, Latino/a and Multiracial groups were underrepresented in our study. Both metric and scalar models bordered on acceptable fit, suggesting that future validation studies with larger samples for these and other groups (e.g., Native Americans) should be conducted. Another limitation related to sampling is our use of MTurk. Though we found that the means of our validity variables (MHI-5, UVS) were comparable with the norms found in other studies, results should be interpreted with caution. Third, although our items contained varying question stems, all the stems for the vicarious exposure factor items were same. This suggests potential method variance in how the items aggregated for this factor. Fourth, although the PORS assesses multiple aspects of online racism, it may still be limited in its utility given the breadth of online activities. Although we developed items that represent the more common— but not platform specific—means of online interactions and access to content, the Internet is a fast-changing place and regularly promotes new ways for people to connect with others and access information. While we believe that our item content represents the majority of current and the not too distant future of online racism experiences, with time these activities may be replaced with other sets of online behaviors. Thus, future research can explore the need to revise PORS contents as the way in which people use the Internet evolves.

Despite these limitations, the PORS can facilitate research on the social, physical, and psychological implications of online racism. Future research could investigate the effects of online racism on other areas of well-being and psychological distress. The personal experience subscale may be used to study the mental health implications of facing interpersonal hostility in online interactions such as the effect on state expressions of anger (Brondolo et al., 2005). With the vicarious and online-mediated exposure subscales, researchers could investigate the overall mood and self-esteem levels that may be negatively affected from helplessly observing other racial/ethnic minorities being discriminated and consuming information about the racial injustice in society. Collectively, it would be important to consider how frequent encounter of online racism may translate into individuals' views on racial justice in society and offline attitudes such as hypervigilance about racism (Carter, 2007) and learned helplessness (Abramson, Seligman, & Teasdale, 1978). In terms of physical health, longitudinal studies can track and document the influence of online racism on relevant physiological changes that have been connected to racism (Brondolo et al., 2005).

In assessing the potential differentiation in people's scores on PORS subscales, future research could examine how varying levels of anonymity may influence people's perceptions of online racism across various online social platforms. For example, people are more easily identifiable in social network sites (e.g., Facebook) that use personal identifying information compared with online discussion forums that lack such detail. Information communicated via social media platforms (e.g., Facebook) has been found to carry more personally meaningful influence (Schweisberger, Billinson, & Chock, 2014) given that most users are identifiable and connected via existing offline relationships. Thus, experiencing online racism from identifiable individuals than from anonymous individuals may actually be more stressful for the victim given the greater personal relevance and risk. Additionally, it would be interesting to assess the influence of variables related to Internet use. For example, studies could examine how the amount of Internet use or Internet dependency could moderate the degree to which people report on their perceived racism. Future studies on these differentiating factors would be helpful to understand the mean differences in PORS scores we found among our racial/ethnic groups.

For practical implications, online racism may coincide with the cyber-bullying that adolescents may experience (Patchin & Hinduja, 2006). PORS may serve as a useful clinical tool based on future validations with adolescents. In particular, racial/ethnic minority adolescents' exposure to online racism may be important to examine regarding their racial identity development and critical consciousness of the racial dynamics in society. For adults, counselors working with clients experiencing racism-related stress or extreme unjust views of society can use our measure as anchors for exploring the racism that they may be facing not only offline, but also on the Internet. In doing so, the three domains of the PORS may illuminate the different ways in which the client may be affected. These discussions may be especially important for those who sustain a substantial online presence.

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