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Trajectories of Online Racial Discrimination and Psychological Functioning among African American and Latino Adolescents

Brendesha M. Tynes,
University of Southern California Rossier School of Education

Devin English,
The Center for HIV/AIDS Educational Studies & Training (CHEST), Hunter College, City University of New York (CUNY)

Juan Del Toro,
New York University

Naila A. Smith,
Dickinson College

Fantasy T. Lozada,
Virginia Commonwealth University

David Williams
Harvard University

Abstract

This study investigated trajectories of individual and vicarious online racial discrimination (ORD) and their associations with psychological outcomes for African American and Latinx adolescents in 6th–12th grade ($N = 522$; $M_{grade} = 9^{th}$) across three waves. Data were analyzed using growth mixture modeling (GMM) to estimate trajectories for ORD and to determine the effects of each trajectory on wave 3 depressive symptoms, anxiety, and self-esteem. Results showed four individual and three vicarious ORD trajectories, with the majority of participants starting out with low experiences and increasing over time. Older African American adolescents and people who spend more time online are at greatest risk for poor psychological functioning.

Keywords

online racial discrimination; internet; adolescence; trajectories; depressive symptoms

There has been increased hate activity in online and offline settings with the campaigns and elections of the last two US presidents (Potok, 2016; Stephens, 2013; Zook, 2012) which can have mental health consequences for adolescents of color. Though quite a large number of studies have examined the implications of offline experiences, particularly with respect to racial discrimination (Benner & Graham, 2011; Greene, Way, & Pahl, 2006; Smith-Bynum,

Correspondence regarding this article should be addressed to Brendesha Tynes at University of Southern California Rossier School of Education, 3470 Trousdale Pkwy, Los Angeles, CA, 90089, btynes@rossier.usc.edu.

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Lambert, English, & Ialongo, 2014), we know less about online settings. This is despite the fact that 95% of adolescents have access to a smart phone and nine out of 10 go online at least "multiple times per day" (Anderson & Jaing, 2018). Moreover, African American and Latinx youth spend more time with media broadly than their White counterparts (Rideout, Lauricella, & Wartella, 2011), with 54% of Latinx youth reporting they go online "almost constantly" compared to 41% of Whites (Anderson & Jaing, 2018). This extended use coupled with the necessity to reveal your identity in some social media spaces may make people of color more vulnerable to negative race-related experiences (Kahn, Spencer, & Glaser, 2013). It is unclear whether adolescents' of color discrimination experiences have patterns that change over time, whether there are differences by age or sex, and whether these experiences are associated with mental health outcomes.

This study draws on a revised version of Bronfenbrenner's bio-ecological model that includes the techno-subsystem (Johnson & Puplampu, 2008) as a dimension of the microsystem. The techno-subsystem includes computers, internet, cell phone, ebooks, television, etc., and a child's proximal reciprocal interactions with technology. This model stresses the importance of attending to different types of users and suggests varying outcomes based on experiences across time. We also draw on Quintana and McKown's (2008) integrated model of the influences of race and racism on the developing child. The authors argue that the bulk of research on racial discrimination has focused on direct (i.e., individual) experiences and while important, the child does not necessarily need to be personally involved for the discriminatory or racist experience to impact psychological adjustment. Although not experienced directly, Quintana and McKown (2008) note that vicarious exposure to racial discrimination may be associated with poor mental health. We combine both frameworks to examine how individual and vicarious discriminatory experiences unique to the techno-subsystem impact student psychological functioning.

The Nature and Prevalence of Online Racial Discrimination

Online racial discrimination (ORD) is a specific form of racial discrimination that occurs on internet-based platforms and via text. It includes disparaging remarks, symbols, images or behaviors that inflict harm through the use of computers, cell phones and other electronic devices (Tynes, Rose, & Williams, 2010). As such, ORD specifically targets a person's race or ethnicity and can include individual experiences (e.g., being the direct target of discriminatory remarks) or vicarious experiences (e.g., hateful tweets that an adolescent inadvertently witnesses). The nature of these experiences overlaps in some cases and may differ in others for African American and Latinx communities. Both racial-ethnic groups are called racial slurs and stereotyped as unintelligent, as criminals, and as lazy (Tynes, Umana-Taylor, Rose, Lin, & Anderson, 2012). Where experiences may diverge is African Americans being represented as animals (e.g. President Obama's face on a monkey) or mocked in historically dehumanizing ways such as blackface (Tynes & Markoe, 2010; Tynes et al., 2012). They are also often overrepresented in degrading images and text (e.g., memes) that are produced as racial humor (Yoon, 2016). Latinx communities, in contrast, may be mocked for having perceived stereotypical careers like landscaping (Tynes & Markoe, 2010) or large families. As in offline settings, they are also constructed as perpetual foreigners who

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are in the country illegally and questioned about their language abilities (Huynh, Devos, & Smalarz, 2011; Lee, Lee, & Tran, 2017).

National surveys of adults show that twenty-five percent of African American and ten percent of Latinx adults experience ORD (or say they experienced online harassment because of their race; Duggan, 2017). Studies of adolescents show higher prevalence rates for experiences that are both personally directed as well as those that are vicarious (Tynes, Giang, Williams, & Thompson, 2008; Tynes, Seaton, & Zuckerman, 2015). Using a longitudinal sample of 340 African American, Latinx, Asian and biracial adolescents, online survey data revealed an increase in individual and vicarious experiences across three waves (Tynes et al., 2015). Forty two percent of the sample indicated they experienced at least one individual discriminatory incident the first year, 55% the second year, and 58% the third year. Sixty-four percent of racial-ethnic minority youth indicated that they had experienced at least one vicarious discriminatory incident in the first year, with 69% the second year, and 68% the third year. Moreover, mid to late adolescents have increased rates of each type of experience. More research is needed to better understand how patterns of discrimination over time may be indexed by race-ethnicity, gender, and age.

Online Racial Discrimination and Psychological Outcomes

Research has evinced a link between racial discrimination and a myriad of negative psychological (e.g., Flores, Tschann, Dimas, Pasch, & de Groat, 2010), physiological (e.g., Clark & Gochett, 2006), and educational (e.g., Benner & Graham, 2011) outcomes for African American and Latinx youth (for reviews see Pascoe & Smart-Richman, 2009; Schmitt, Branscombe, Postmes, & Garcia, 2014). A systematic review of 121 studies found racial discrimination is related to negative mental health for 76% of outcomes assessed, including depression, anxiety, and negative self-esteem (Priest, Paradies, Trenerry, Truong, Karlsen, & Kelly, 2013). These results are consistent with Benner and colleagues' (2018) meta-analysis of 214 studies across 11 indicators of well-being in which strongest associations are found with externalizing behaviors and small to moderate correlations with socio-emotional distress. Among the socio-emotional distress outcomes, depression and internalizing symptoms have strongest correlations whereas positive well-being and self-esteem are more modest. Taken together, as this study shifts to online settings, extant reviews make the case for focusing on depressive symptoms, anxiety, and self-esteem since they are among the most commonly studied and most pressing because of the strength of their associations (Paradies et al., 2015).

Similar to traditional offline racial discrimination, ORD is associated with negative outcomes for African American and Latinx adolescents. For example, individual ORD is associated with greater depression and anxiety over and above offline measures (Tynes et al., 2008). In a study of 6^{th} -12^{th} grade Latinx participants, individual ORD is linked to increased depressive symptoms, but for vicarious experiences there is a negative association (Umana-Taylor et al., 2015). This contrasts with findings from another study of adolescents that shows no association between vicarious ORD and psychological adjustment (Tynes et al., 2008). It further differs from a study of perceived online racism among adults which shows that both individual and vicarious experiences are associated with increased

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psychological distress (Keum & Miller, 2017). Thus far, however, ORD and psychological outcomes have primarily been investigated with cross-sectional designs (we note one longitudinal study of ORD and academic motivation-Tynes, Del Toro, & Lozada, 2015 and the descriptive preliminary analysis of prevalence rates previously noted– Tynes et al., 2015). Because of the mounting evidence that general online victimization predicts mental health outcomes over time (Rose & Tynes, 2015), it is important to understand whether these associations hold for race-related discrimination online.

Trajectories of Racial Discrimination Offline vs Online

A growing number of longitudinal studies have focused on discrimination among adolescent populations (Bellmore, Nishina, You, & Ma, 2013; Benner & Graham, 2011; Greene et al., 2006; Smith Bynum et al., 2014), yet there are notable gaps in the literature. First, studies tend to focus on populations either in middle or high school; few examine changes in discrimination using samples that include early, middle, and late adolescents (e.g. Hughes et al., 2016). This is important given the inconsistencies in findings for the offline literature. For example, studies suggest early adolescents from diverse ethnic-racial groups on average report decreases in discrimination from peers from the 6^{th} to 8^{th} grades, but stability in discrimination from adults (Niwa, Way, & Hughes, 2014) whereas others find increases during this period (Hughes et al., 2016). Similar variation has been found among older adolescents, either showing increasing (Benner & Graham, 2011; Benner & Kim, 2009), declining (Bellmore et al., 2012; Hughes et al., 2016) or stable experiences of discrimination across the high school years (Smith-Bynum et al., 2014; Greene et al, 2006). Differences may in part be based on school contextual factors or geographic region where the sample is drawn. With adolescents spending increased amounts of time online it is important to identify specific trajectories of online discrimination experiences across early to late adolescence.

No studies to date have focused on racial discrimination trajectories in the online context. By examining specific online trajectories, we gain the ability to identify sub-populations of youth who may be more vulnerable to experiencing ORD and at which periods. For instance, Smith-Bynum and colleagues (2014) conducted a longitudinal study of African American adolescent 7–10^{th} graders' offline experiences with racial discrimination and depressive and anxious symptoms. Using growth mixture modeling, they found three trajectories: increasing, decreasing, and stable low. In addition, they found that African American boys were more likely to be targeted as they aged. Gleaning this information for an online context will be useful in clinical and school settings to tailor discussions, treatment, and internet safety curricula. In addition, including participants with age ranges across adolescence is critical with respect to ORD given adolescents' developing abilities to recognize their own and others' race-related cognitions (Quintana, 1998; Bigler & Brown, 2005) and changing digital practices across this period (Anderson & Jaing, 2018). For example, despite the fact that nearly all have access to a smartphone, older teens 15–17 are slightly more likely to use Snapchat, Instagram, Facebook, and Twitter than younger ones ages 13–14 (Anderson & Jaing, 2018). These differences in online platforms use may make particular age groups (i.e., early vs late adolescents) more susceptible to experiencing varying degrees of exposure to racial discrimination across time.

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Finally, beyond identifying which groups may be more vulnerable and at what developmental period, we examine both individual and vicarious trajectories. To date, although multiple sources of discrimination (peer vs adult) have been explored, most studies examine discrimination as a unidimensional construct, with exceptions that include Hughes and colleagues (2016) who have examined both overt and covert forms and English (2017) who studies teasing along with both overt discrimination experiences and microaggression. This gap in the literature is important to fill given the differences in associations with psychological functioning by type of ORD (Umana-Taylor et al., 2015; Tynes et al., 2008). Moreover, this is critical given African Americans, for example, are more likely to witness severe forms of ORD such as threats (Duggan, 2017).

The Present Study

Following the theoretical framework and findings from extant literature, this study examines individual and vicarious trajectories of ORD. While accumulating empirical evidence indicates that racial discrimination contributes to well-documented health disparities between White adolescents and adolescents of color (Benner et al., 2018), research studies have investigated a limited set of experiences and ecologies common to these youth. In particular, although the internet is a social environment that can impact a range of developmental outcomes (Subrahmanyam & Smahel, 2011), there is notably little longitudinal research examining ORD for adolescents of color. Moreover, research has not investigated different patterns of exposure to ORD across time even though extant studies indicate that youth experience differential outcomes associated with increasing, decreasing, and stable longitudinal patterns of offline racial discrimination experiences (e.g., Smith-Bynum et al., 2014). Thus, this study is an investigation of trajectories of individual/direct and vicarious experiences of ORD and their associations with psychological outcomes for a sample of African American and Latinx adolescents. Based on empirical literature, the authors hypothesize that African American participants will be more likely than Latinx participants to experience increasing ORD trajectories, particularly boys. Given the differences in platform usage, Latinx participants may have more low to moderate experiences that decrease over time. It is also expected that increasing trajectories for both individual and vicarious experiences will be associated with later depressive and anxiety symptoms, and lower self-esteem. Decreasing trajectories will be associated with better psychological functioning. Because many adolescents officially gain access to social media spaces as early as 13, younger participants will be more likely to be in increasing trajectories.

Method

Sample

Data for the present study were drawn from the Teen Life Online and in Schools Project, a mixed-method, three-wave longitudinal study examining risk and protective factors associated with the online experiences of an ethnically and racially diverse sample of 6^{th} to 12^{th} grade students. We recruited participants from 12 Midwestern public schools (in urban, suburban, and small urban areas) at wave 1 and two additional schools as middle schoolers

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transitioned to high school. At wave 1, the number of participants from each school ranged from 8 to 95 with an average of 44 participants from each school. Of the 14 schools, four were multiracial with relatively equal percentages of Black and White students and up to 30% Latinx students; four were majority White schools, two were majority Latinx schools, and four were majority Black schools. Median income for the neighborhoods ranged from $38,000 to $71,000. The percentage of students receiving free and reduced lunch at each school ranged from 40% to 94%. Online survey data for the three waves were collected annually across four years in the fall from 2010–2013.

The current study consists of an analytic sample of 526 youth (56% girls) who were ages 10 – 19 ($M = 14.47$; $SD = 1.99$) and identified as African American (62.6%) or Latinx (37.4%) at Wave 1. Youth were predominantly US-born (99% African American, 92% Latinx), with Latinx participants being primarily of Mexican descent. Mothers in this sample were relatively well educated (9% less than high school education, 39% completed high school, 37% completed college, 15% completed graduate school). Participants reported they used the internet, on average, between 5 and 6 days per week for 4 hours per day.

Participants included in the sample had at least one wave of complete data for one of the independent variables. Four participants who had complete data for the individual ORD subscale, but not the vicarious ORD subscale, and another four participants who had complete data for the vicarious ORD subscale but not the individual subscale were included in the sample for the growth models for the respective ORD subscales. Participants with missing data on both ORD scales ($n = 48$) were not included in the analytic sample. These 48 participants did not significantly differ from the analytic sample at wave 1 in terms of gender, mother's education, depressive symptoms, anxiety symptoms, self-esteem, individual ORD, or vicarious ORD. However, there were differences based on school, grade, and race-ethnicity such that Latinx students attending middle school were most likely to be excluded from the sample because of missing data. This was likely due to a predominantly Latinx middle school dropping out of the study due to overscheduling in wave 2 which meant that 63 of the 76 participants from this school dropped out from wave 1 to wave 2. In all, of the 328 participants who identified as Black at wave 1, 253 (77%) participated at wave 2, and 168 (51%) participated at Wave 3. Of the 194 who identified as Latinx participants at Wave 1, 122 (63%) participants participated at Wave 2, and 95 (49%) participated at Wave 3.

Procedure

We recruited participants from 6th –12th grade classrooms in schools via 10-min presentations and distribution of informational flyers and consent forms in English and Spanish. Classrooms were selected to represent a range of academic abilities. Recruitment materials stated the study focused on learning more about students' experiences on the internet. Data were collected primarily during homeroom, computer class, lunch, or study hall. Research assistants administered 45-minute long surveys to consented students via Survey Monkey at computer stations or with laptops in schools. Surveys included participant assent and questions about discrimination and victimization experiences, internet use and experiences, cultural values, and psychosocial functioning. Schools received a stipend and

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participants received $15 Amazon.com gift certificates for their participation during the first year, $20 during the second year, and $25 during the third year.

Measures

Online racial discrimination (ORD).—We assessed perceived past-year experiences with ORD using the Online Victimization Scale (OVS; Tynes et al., 2010). The OVS includes 4 items that tap perceived individual ORD (e.g., People have said mean or rude things about me because of my race or ethnic group online; People have shown me a racist image online) and 3 items that tap perceived vicarious ORD (e.g., People have cracked jokes about people of my race or ethnic group online; People have said things that were untrue about people in my race or ethnic group). Responses were provided on a 5-point scale, anchored by (0) never and (4) almost daily. Because there was very little use of the higher response options, we coded the items as (0) did not experience and (1) experienced. Composite scale scores were computed by summing across responses to the items. Coefficient alphas (α) for Waves 1 to 3, respectively, were .74, .77, and .78 for individual ORD and .88, .90, and .92 for vicarious ORD. The OVS has been used to assess ORD experiences among African American and Latinx youth, specifically (Tynes et al., 2010).

Depressive symptoms.—An abbreviated, 12-item version of the Center for Epidemiologic Studies Depression scale (CES-D) was used to assess the frequency of past-week experiences with depressive symptoms (Roberts & Sobhan, 1992; see also Radloff, 1977). This version of the CES-D includes items that tap depressed affect (e.g., I felt depressed), somatic complaints (e.g., I could not get ‘going’), interpersonal difficulties (e.g., People were unfriendly), and positive affect (e.g., I enjoyed life; reverse-scored to reflect a lack of positive affect). Responses were provided on a 4-point scale, anchored by (0) rarely or none of the time and (3) most or all of the time. Composite scale scores were computed by averaging across responses to the items (αs = .63 and .75 for Waves 1 and 3, respectively).

Self-esteem.—We used the 10-item Rosenberg Self Esteem Scale (Rosenberg, 1965) to assess adolescents’ perceptions about themselves. This scale includes items that tap positive self-evaluation (e.g., On the whole, I am satisfied with myself) and negative self-evaluation (e.g., At times, I think I am no good at all). Responses were provided on a 4-point scale, anchored by (0) Strongly disagree and (3) Strongly Agree. Composite scale scores were computed by averaging across responses to the items (αs = .83 and .87 for Waves 1 and 3, respectively). The scale has been used on Latinx (Supple & Plunkett, 2011) as well as African American samples (Oney, Cole, & Sellers, 2011).

Anxiety symptoms.—An abbreviated, 4-item version of the Tension subscale of the Profile of Mood States-Adolescents (Terry, Lane, Lane, & Keohane, 1999) was used to assess symptoms of anxiety at the time of survey administration. Symptoms listed included “panicky,” “anxious,” “worried,” and “nervous”. Responses were provided on a 5-point scale, anchored by (0) Not at all and (3) Extremely. Composite scale scores were computed by averaging across responses to the items (αs = .82 and .88 for Waves 1 and

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3, respectively). This scale has been used previously with African American and Latinx samples (Tynes et al., 2008).

Analytic Plan

We conducted analyses within a structural equation modeling (SEM) framework with M*plus* Version 8.2 (Muthén & Muthén, 1998–2017), using growth mixture modeling (GMM; Muthén, 2004; Muthén & Shedden, 1999) to identify the optimal number of trajectory classes for individual and vicarious ORD, separately. GMM is one of a group of exploratory analytic approaches called mixture models, which are used to classify subpopulations of participants within a larger group of participants. GMM uses patterns of responses over time to classify participants into trajectory classes and estimate growth curves for each class (Muthén & Muthén, 2000). In line with best practices (Jung & Wickarama, 2008; Van De Schoot, Sijbrandij, Winter, Depaoli, & Vermunt, 2017), the process of GMM started with estimating a single-class intercept-only model that characterized initial levels of ORD but with no estimation of change over time. Next, we estimated both a single-class model with an intercept and a linear growth function. We did not test a quadratic growth model since we only used three waves of data in this study (Curran & Bollen, 2006). We used the log-likelihood ratio test and chi-square difference tests to determine whether the intercept-only or the model with both the intercept and linear slope fit the data better (Satorra & Bentler, 2010). Analysis proceeded with the estimation of a 2-, 3-, 4-, 5, and 6-class models for each type of ORD. We estimated up to six models to ensure that we fit two additional models beyond what statistical and conceptual criteria indicated were the best fitting model (Van De Schoot et al., 2017). To ensure that class solutions did not converge on local maxima, and in line with best practices for GMM model estimation (Hipp & Bauer, 2006), we specified 500 starting values for each parameter.

We estimated all initial growth models with both fixed effects (i.e., mean intercepts and slopes) and random effects (i.e., variance around the mean intercepts and slopes) within class—an approach referred to as latent growth mixture models (LGMM; Muthén, 2006). Estimating random effects is appropriate when researchers reasonably expect within-class variation around growth parameters and the sample limitations permit the estimation of random effects (i.e., there are not problems with convergence; Van De Schoot et al., 2017). However, because all individual ORD models showed nonsignificant variances around the intercept for all classes, we fixed the random intercept to be zero across all classes. This is a common and acceptable approach to model identification to promote model convergence and parsimony (Ram & Grimm, 2009). In addition to estimating within-class random effects, we also allowed random effects to vary across classes since there was no conceptual reason to expect variation in growth factors to be constant across subgroups (Van De Schoot et al., 2017).

We ran all models as unconditional growth mixture models (i.e., with no covariates included as part of the model enumeration process) since recent evidence indicates that class enumeration with unconditional models provides the most accurate class specification across diverse causal patterns within population models (Nylund-Gibson & Masyn, 2016). Consistent with recommendations for the optimal fit indices for unconditional class

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enumeration, we used the Bayesian Information Criterion (BIC) and the bootstrapped likelihood ratio test (BLRT; Nylund-Gibson & Masyn, 2016). We also considered the sample size adjusted BIC (ABIC) and entropy to identify the optimal number of classes, as studies suggest they help to identify fit to the data and class separation (Nylund, Asparouhov, & Muthén, 2007; Ram & Grimm, 2009). To ensure that outliers did not have an adverse effect on the enumeration process, we examined Cook's D statistic (Cook, 1977) to assess for highly influential cases. M*plus* 8.2 produces Cook's D along with model results as a measure of the influence of individual observations on the parameter estimates. Although there are no strict cut-offs for Cook's D values that indicate highly influential observations, we used the convention of a D value greater than 1 as a strong indicator of an outlier (Jobson, 2012), and examined whether participant D values were highly consistent across individual and vicarious OVS models, indicating a highly influential participant (i.e., they had consistently high D values).

In line with recent recommendations for best practices in growth mixture modeling (Bakk & Vermunt, 2015; Nylund-Gibson, Grimm, Quirk, & Furlong, 2014), following class enumeration we used the three-step maximum likelihood (ML) procedure (Vermunt 2010a, 2010b) within M*plus* 8.2. to examine both predictors and distal outcomes associated with class membership. This method, also referred to as the three-step approach with adjustment for classification errors (Van De Schoot et al., 2017), involves three-steps to evaluating predictors and outcomes of class membership: 1) the best-fitting unconditional model is estimated and the posterior probabilities along with the class assignment are saved; 2) the conditional probabilities for class assignment are estimated under the assumption of true latent class membership and translated into fixed parameter estimates that represent the association between the latent class variable and the class assignment variable; 3) a new latent class model is estimated with the assigned class memberships from step 2 as a single indicator and the conditional probabilities fixed to the estimates produced through Step 1 and 2. As such, this step offers the ability to have covariates predict class membership or to have class membership predict distal outcomes (Bakk & Vermunt, 2016).

We tested gender, race-ethnicity, age, the interactions between those variables, and time spent online as predictors of ORD class membership using the R3STEP command with M*plus* (Asparouhov & Muthen, 2014a). The R3STEP command estimates covariates as predictor variables in a multinomial logistic regression with class membership as the outcome variables as the third step of three-step ML process. We also tested associations between class membership and depressive symptoms, self-esteem, and anxiety at Wave 3 to examine if class membership predicted our outcomes of interest using the BCH command in M*plus* (Asparouhov & Muthen, 2014b). The BCH command is used for continuous distal outcome variables and uses a weighted multiple group analysis to test for differences in outcome variables across class membership.

Missing data.—Prior to analysis, we examined patterns of missing data and found the following rates of retention: 522 in Wave 1 (100%), 374 (72%) in Wave 2, and 263 (70%) in Wave 3. To handle missing data, we used full information maximum likelihood estimation in all analyses, which uses all available data to estimate the model. This approach operates under the assumption that the data are missing at random (MAR; Arbuckle, 1996; Little,

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1995) and is a widely accepted strategy for handling missing data (Muthén & Shedden, 1999; Schafer & Graham, 2002). We concluded that MAR was a reasonable assumption for this study since the participants who completed all three waves did not differ from those who did not complete wave 3 across any study variables measured at wave 1, including measures of ORD, depressive symptoms, anxiety symptoms, self-esteem, or the demographic variables.

Results

Descriptive Statistics

Means, standard deviations, and bivariate correlations among ORD and outcomes variables are presented in Table 1 (demographic information provided in Participants section). These results show that, on the aggregate, individual ORD, vicarious ORD, depressive symptoms, and anxiety symptoms increased from wave 1 to wave 3, while self-esteem decreased slightly from wave 1 to wave 3. In order to understand heterogeneity in these patterns we conducted GMM.

Growth Mixture Modeling of ORD Trajectory Classes

Individual online racial discrimination.—Results of the likelihood ratio tests for the single-trajectory model for individual ORD indicated that the linear slope model was a better fit for the data than the intercept-only model, $\Delta\chi^2(5) = 176.98$, $p < 0.001$. Therefore, we used a linear slope model as the baseline model in subsequent analyses. Next, we estimated a series of 2-, 3-, 4-, 5, and 6-class models starting initially with freely estimated intercepts and slopes. In each of these models, the variance around the intercept was not significant, thus we constrained the variance around the intercept to be 0, as is commonly done to ensure model convergence and parsimony (e.g., Ram & Grimm, 2009). Fit indices and class information for all class results can be found in Table 2. The BLRT p-value was significant for each class solution suggesting an improved fit for higher class solutions. Results showed the BIC and ABIC decreased and the entropy increased from the single-trajectory model up to the 5-class model. The BIC and ABIC increased and the entropy decreased from the 5-class model to the 6-class model, however, suggesting that the 5-class model was a better fit to the data than the 6-class model. We therefore chose to consider the 4 and 5 class models for the optimal solution. Given equivalent entropy values across these two class solutions, we examined the classes for analytic and conceptual clarity. We identified that one class in the 5-class solution had about 2% of the total sample and did not depict a unique pattern of change to the other four classes (i.e., there was substantial overlap with the moderate-decreasing trajectory depicted in Figure 1). Since class count and conceptual clarity are essential to optimal class enumeration (Jung & Wickarama, 2008; Muthén, 2004), and class solutions with vastly different class memberships risk inaccurate estimates of cluster sizes and growth trajectories as a function of the class size of the difference (Depaoli, 2013), we decided on the 4-class solution—i.e., the solution with the best combination of statistical and conceptual indicators of model fit.

Figure 1 presents the final model with (1) High-Decreasing, (2) Moderate-Decreasing, (3) Low-Increasing, and (4) Moderate-Increasing individual ORD trajectories. The High-

Decreasing trajectory (8% of the sample) consisted of adolescents whose experiences of individual ORD began at a high level at wave 1 that substantially decreased over time. The fixed intercept ($M = 3.44$, $SE = .08$, $p < .001$), fixed slope ($M = -.82$, $SE = .15$, $p < .001$), and random slope ($\sigma^2 = .32$, $SE = .15$, $p < .05$) were all significant for this class. The Moderate-Decreasing trajectory (12% of the sample) included adolescents who experienced individual ORD at a moderate level at wave 1 that moderately decreased over time. The fixed intercept ($M = 2.00$, $SE = .001$, $p < .001$), fixed slope ($M = -.40$, $SE = .12$, $p < .001$) and the random slope ($\sigma^2 = .34$, $SE = .12$, $p < .01$) were all significant for this class. The Low-Increasing trajectory (59% of the sample) included adolescents who experienced individual ORD at a low level at wave 1 that moderately increased over time. The fixed intercept ($M = .01$, $SE = .00$, $p < .01$), fixed slope ($M = .46$, $SE = .04$, $p < .001$), and random slope ($\sigma^2 = .13$, $SE = .06$, $p < .05$) were all significant for this class. The Moderate-Increasing trajectory (21% of the sample) included adolescents who experienced individual ORD at a moderate level at wave 1 that moderately increased over time. The fixed intercept ($M = 1.00$, $SE = .001$, $p < .001$), fixed slope ($M = .18$, $SE = .08$, $p < .05$), and random slope ($\sigma^2 = .27$, $SE = .09$, $p < .01$) were all for this class. See Table 3 for demographic composition of each of the individual discrimination classes.

Vicarious online racial discrimination.—We also estimated a single-trajectory model for vicarious ORD to identify the overall growth pattern across the three waves of the study. Results of likelihood ratio tests indicated that the linear slope model was a better fit to the data than the intercept-only model, $\Delta\chi^2(4) = 189.86$, $p < 0.001$. As such, we used the linear slope model as the baseline model in subsequent analyses. Next, we estimated a series of 2-, 3-, 4-,5-, and 6-class models with freely estimated intercepts and slopes. Fit indices and class information for all class results can be found in Table 2. Results showed the BIC and ABIC decreased until the 3-class model and increased with the 4- and 5-class models. The BLRT p-values were significant for class models 1 to 3, but non-significant for the 4- and 5-class solutions. Additionally, the 3-class solution depicted three unique and conceptually-relevant trajectories. Therefore, we selected the 3-class model for vicarious ORD.

Figure 2 presents the final model with (1) High-Stable, (2) Low-Increasing, and (3) High-Decreasing vicarious ORD trajectories. The High-Stable trajectory (32% of the sample) consisted of adolescents whose experiences of individual ORD began at a high level at wave 1 and increased slightly across time. The fixed intercept ($M = 2.72$, $SE = .05$, $p < .001$), fixed slope ($M = .08$, $SE = .03$, $p < .02$) and random intercept ($\sigma^2 = .16$, $SE = .07$, $p < .05$) were all significant for this class. The random slope approached significance ($\sigma^2 = .06$, $SE = .03$, $p = .06$). The Low-Increasing trajectory (55% of the sample) consisted of adolescents whose experiences of individual ORD began at a low level at wave 1 and moderately increased over time. The fixed intercept ($M = .30$, $SE = .03$, $p < .001$), fixed slope ($M = .53$, $SE = .05$, $p < .001$), random ($\sigma^2 = .16$, $SE = .07$, $p < .05$), and random slope ($\sigma^2 = .44$, $SE = .04$, $p < .001$) were all significant for this class. Finally, the High-Decreasing trajectory (13% of the sample) consisted of adolescents whose experiences of vicarious ORD started high at wave 1 and decreased precipitously across time. The fixed intercept ($M = 2.65$, $SE = .11$, $p < .001$), fixed slope ($M = -1.22$, $SE = .07$, $p < .001$), random intercept ($\sigma^2 = .15$, $SE = .08$, $p < .05$),

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and random slope (σ^2 = .08, SE =.04, p < .05) were all significant for this class. See Table 3 for demographic composition of each of the vicarious discrimination classes.

Outlier Analysis.—None of the 522 cases had a Cook's D greater than 1 across either the Individual or Vicarious ORD models. Moreover, none of the cases had a D value greater than .20 for both the individual and vicarious subscales, suggesting that there were no participants who were relatively highly influential across both measures. As such, it did not appear that there were participants who may have consistently and indiscriminately endorsed high or low values across subscales. As such, we did not find strong evidence that there were outliers adversely affecting the class enumeration process.

ORD Class Predictors and Outcomes

Predictors.—For individual ORD, results from the multinomial logistic regression using the 3-step ML procedure to predict class membership are presented in Table 4. Younger participants were more likely to be in the Low-Increasing versus the Moderate-Increasing trajectory. Also, at trend levels, girls were more likely to be in the Moderate-Decreasing trajectory than the High-Decreasing trajectory, boys were more likely than girls to be in the Moderate-Increasing trajectory versus the High-Decreasing trajectory, and participants who spent more time on the internet during their week were more likely to be in the Moderate-Increasing trajectory than the Low-Increasing trajectory.

Regarding interaction results for the individual ORD trajectories, the interaction between gender and race-ethnicity did not significantly predict any class membership differences. The results for the interaction between gender and age showed that older boys were more likely than older girls to be in the Moderate-Increasing than the High-Decreasing trajectory, older boys were more likely than older girls to be in the Moderate-Decreasing than the High-Decreasing trajectory, and older boys were more likely than older girls to be in the Moderate-Decreasing than the Low-Increasing trajectory. For the age by race interactions, results showed that older African American participants were more likely than older Latinx participants to be in the High-Decreasing trajectory than the Moderate-Decreasing, Low-Increasing, and Moderate-Increasing trajectories. At trend levels, older boys were more likely than older girls to be in the Low-Increasing trajectory than the High-Decreasing trajectory and older boys were more likely than older girls to be in the Moderate-Increasing trajectory than the Low-Increasing trajectory. No other interactions significantly predicted individual ORD trajectory membership.

For vicarious ORD, results from the three-step ML procedure with multinomial logistic regression (See Table 5) to predict vicarious ORD class membership indicated that younger participants were more likely to be in the Low-Increasing trajectory than the High-Stable trajectory. In addition, participants who spent more time online were more likely to be in the High-Stable trajectory than either the Low-Increasing or High-Decreasing trajectories. None of the interactions significantly predicted vicarious ORD trajectory membership.

Outcomes.—For individual ORD, results from the 3-step procedure to predict outcomes at Wave 3 using class membership (See Table 6) indicated that participants in the Low-Increasing class had lower mean scores in depressive symptoms than the High-Decreasing

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class; the Low-Increasing and the High-Decreasing classes did not differ from the Moderate-Increasing and Moderate-Decreasing classes. There were no significant differences in self-esteem and anxiety symptoms.

For vicarious ORD, results from the 3-step procedure to predict outcomes at Wave 3 using class membership (See Table 6) indicated that participants in the High-Stable class had higher depressive symptoms than the other two classes; the Low-Increasing class reported higher depressive symptoms than the High-Decreasing class. Adolescents in the High-Stable class reported lower self-esteem than their peers in the High-Decreasing class; adolescents in the Low-Increasing class did not differ from their peers in the High-Stable and the High-Decreasing classes. Additionally, adolescents in the High-Stable class reported more anxiety symptoms than the Low-Increasing class; those in the High-Decreasing class did not differ from the High-Stable or the Low-Increasing classes.

Discussion

The current study investigated trajectories of individual and vicarious experiences of online racial discrimination (ORD), and predictors and outcomes of the ORD trajectories among a sample of African American and Latinx youth. The study hypotheses were partially supported in that there were four trajectories of individual ORD (High-Decreasing, Moderate-Decreasing, Low-Increasing, and Moderate-Increasing) and three trajectories of vicarious ORD (High-Stable, Low-Increasing, and High-Decreasing). Additionally, boys were more likely than girls to be in the Moderate-Increasing trajectory than in the High-Decreasing trajectory and younger participants were more likely to be in the Low-Increasing trajectory versus the Moderate-Increasing trajectory. Main effects of gender, race, and age were qualified by two-way interaction effects on membership in these trajectories. Specifically, older adolescent boys were more likely to be in the Moderate Increasing individual ORD trajectory than older adolescent girls. In addition, our findings show that older African Americans were more likely than older Latinxs to be in the High-Decreasing class than Moderate Decreasing and that older Latinxs are more likely to be in the Low-Increasing trajectory than High-Decreasing.

With respect to subpopulations' patterns of exposure across time, results are consistent with extant literature. Like Smith-Bynum et al., (2014) we found both increasing and decreasing trajectories. However, they found a stable-low trajectory whereas the present study found no stable trajectories of individual ORD and only a high stable trajectory of vicarious ORD. Findings also align with respect to groups that are most vulnerable to discriminatory experiences. Smith-Bynum et al., (2014) noted it was African American boys who were increasingly targeted as they got older. In this study, older boys (African American and Latinx) were similarly more likely to be in the Moderate-Increasing trajectory than girls. In addition, it was older African Americans as a group that were more likely to be represented in the High-Decreasing trajectory. This may be because while African Americans reported being online "almost constantly" at relatively equal levels (34% vs 32% for Latinxs) closer to the time of data collection, they were more likely to have access to smartphones and to use video games (Lenhart, 2015) where they may have been more susceptible to experiencing more discrimination initially. Similarly, our hypothesis that

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Latinx participants would more likely be represented in a low-moderate class that decreases over time was partially supported. Instead of as a whole racial-ethnic group, however, it was specifically older Latinx participants which may be attributed to the fact that a small number of participants developed strategies to protect themselves at varying rates from online experiences, as they got older (as may be the case with African Americans).

The majority of the sample started out with zero to very little experience with both individual and vicarious ORD and saw increases over time. Early adolescents were most likely to be in the Low-Increasing trajectory for both individual and vicarious forms of ORD. This finding aligns with extant studies that show an increase in racial discrimination offline during this time period (Hughes et al., 2016), but contrasts with other research that shows a decrease from the 6^{th} to 8^{th} grades (Niwa, Way, & Hughes, 2014). This increasing exposure may be related to early adolescent access. Many social media platforms, for example, require individuals to be a minimum age of 13 (though some may have profiles as early as 10 or 11).

Findings further suggest that membership in the individual High-Decreasing and the vicarious High Stable classes confers greater psychological risk than membership in other classes. Participants who are most vulnerable include older African Americans and those that spend increased amounts of time online, suggesting a central role of not just age and race but the internet as a developmental context. Daniels (2013) has argued that racism is built into the infrastructure of the internet. In addition to the infrastructure, pseudo-anonymity may make individuals more disinhibited in their expressions of prejudice and discrimination online (Glaser & Kahn, 2005). Extended time in online spaces can lead to increased exposure to a climate of race-related online hate. This is particularly important in light of recent research that has linked an increase in mood disorders and suicide-related outcomes in adolescents from 2005–2017 to a rise in electronic communication (Twenge, Cooper, Joiner, Duffy, & Binau, 2019).

This study is the first to find longitudinal associations between racial discrimination in online settings and mental health. Findings in cross-sectional studies show poorer outcomes with respect to individual experiences, but have been less consistent on those that are witnessed (Keum & Miller, 2017; Tynes et al., 2008). With analyses of trajectories, this study was able to show that those in the High Stable vicarious trajectory were worse off on each of the outcomes assessed. This parallels findings on the most recent scale to be developed on perceived online racism (Keum & Miller, 2017).

Implications

Findings suggest that ORD is a present and meaningful stressor across the period of adolescence for African American and Latinx youth. Though there is heterogeneity, the majority of children are experiencing increases in the stressor across time. Interestingly, it was older adolescents who may be further along in the development of their abilities to think critically about race (Quintana, 2008) but also those who spend more time online who are at greatest psychological risk.

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Study Limitations

Limitations of the current study include moderate attrition rates from Wave 1 to Wave 3. This is partially due to the fact that one of our predominantly Latinx schools dropped out of the study after year 1. In addition, ORD, depressive symptoms, anxiety, and self-esteem measures were all self-report. Though the larger study includes the collection of online interviews, school reported grades, observations and artifacts, only survey data were analyzed for this study. This is arguably the best way to understand perceptions of exposure to negative messages about an individual's race. Lastly, this study did not estimate quadratic effects with only three waves of data. Due to the small sample size, within-race/ethnicity heterogeneity was also not addressed.

Future Directions

Despite limitations, this study underscores the need to make online expressions of racial discrimination a central part of racial discrimination research. Future studies should examine heterogeneity and unique racial/ethnic experiences across different Latinx and Black communities. Researchers should also focus on possible predictors of change in the slope and membership in ORD trajectories. In addition, researchers should investigate the offline and online moderators (e.g., online activism, critical consciousness) that may buffer against or exacerbate the negative mental health consequences of ORD exposure. In addition, the intersecting experiences of race, gender or gender-nonconforming youth will be important to explore.

Conclusion

Educators and mental health professionals should (1) recognize that the ability to intervene on or educate youth about these experiences requires extensive training and reading, (2) once trained, assess students'/clients' media diets and determine experiences related to race-ethnicity specifically for each racial-ethnic group, (3) keep open lines of communication about daily viewing and emotions connected to images/videos/text, (4) help students develop a strong positive racial-ethnic identity, particularly for ages 10–13, along with counternarratives about their group that can be used as a toolkit when students encounter racist material, and (5) use findings from this study to inform interventions and programs designed to enhance digital literacy, reduce depressive symptoms, and anxiety and enhance self-esteem. Those programs that do not include comprehensive coverage of race-related experiences and strategies for coping, neglect some of the most common experiences African American and Latinx youth have online.

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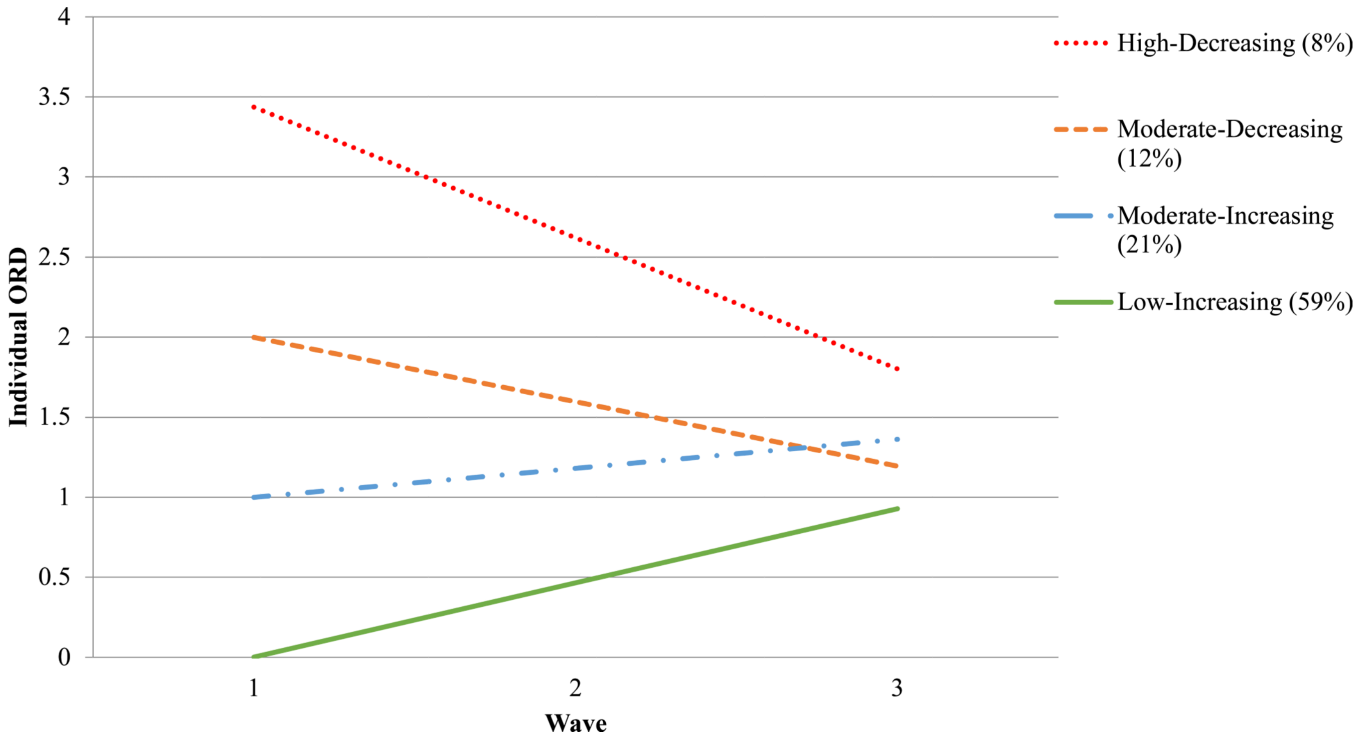

Figure 1.
Latent class trajectories of estimated means for individual ORD from wave 1-wave 3.

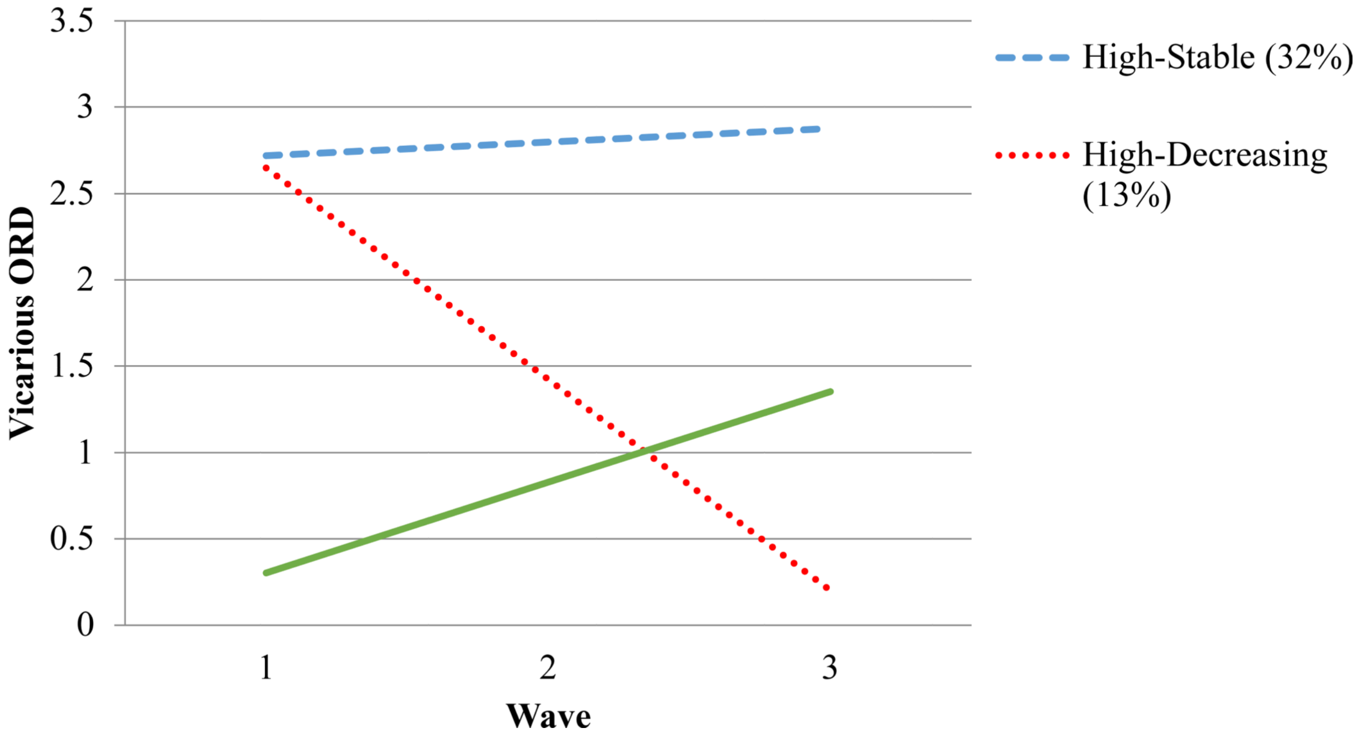

Figure 2.
Latent class trajectories of estimated means for vicarious ORD from wave 1-wave

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Table 1.

Correlation, Means, and Standard Deviations of ORD and Outcome Variables

Variable	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.
Individual ORD												
1. W1	--											
2. W2	.32***	--										
3. W3	.34***	.39***	--									
Vicarious ORD												
4. W1	.63***	.25***	.29***	--								
5. W2	.22***	.64***	.35***	.30***	--							
6. W3	.31***	.25***	.67***	.35***	.40***	--						
Depressive Symptoms												
7. W1	.21***	.15***	.27***	.30***	.20***	.25***	--					
8. W3	.10	.10	.24***	.19**	.13*	.34***	.50***	--				
Self-Esteem												
9. W1	-.07	-.09	-.16**	-.23***	-.14**	-.25***	-.57***	-.33***	--			
10. W3	-.04	.04	-.15**	.12	.09	-.22***	-.42***	-.62***	.45***	--		
Anxiety Symptoms												
11. W1	.20***	.14*	.14*	.19***	.14**	.12	.39***	.28***	-.33***	-.26***	--	
12. W3	.11	.17**	.17**	.04	.10	.29***	.30***	.56***	-.24***	-.36***	.31***	--
Mean	1.37	1.52	1.70	0.74	0.89	1.14	0.85	0.94	2.12	2.10	0.69	0.83
SD	1.28	1.30	1.33	1.08	1.14	1.28	.44	.50	.57	.59	.82	.99

Note. ORD = Online Racial Discrimination. W1 = Wave 1; W2 = Wave 2; W3 = Wave 3.

* $p < .05$,

** $p < .01$,

*** $p < .001$.

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Table 2.

Growth Mixture Modeling Results for Individual and Vicarious Online Racial Discrimination

Classes	BIC	ABIC	Entropy	BLRT *p*-value	Group Sample Size
Individual ORD					
1-class	3478.60	3453.21	--	--	522
2-class	3307.57	3275.82	0.92	.00	417, 105
3-class	3179.91	3135.47	0.96	.00	168, 311, 43
4-class	**2642.32**	**2585.18**	**0.99**	**.00**	**43, 62, 312, 105**
5-class	2482.32	2412.49	0.99	.00	62, 312, 105, 13, 30
6-class	2580.95	2501.59	0.83	.00	14, 47, 91, 265, 62, 43
Vicarious ORD					
1-class	3775.53	3750.14	--	--	522
2-class	3488.24	3446.97	0.98	.00	289, 233
3-class	**3370.94**	**3313.81**	**0.87**	**.00**	**184, 291, 47**
4-class	3869.40	3796.39	0.00	1.00	123, 122, 132, 145
5-class	3900.69	3811.81	0.00	1.00	92, 106, 98, 105, 121
6-class	3906.94	3814.89	0.00	1.00	61, 77, 74, 104, 94, 112

Note. Bolded line are the final class solutions decided on using substantive and analytic information.

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Table 3.

Demographic Composition of Individual and Vicarious ORD classes

Individual ORD Classes				
	Low-Increasing	Moderate-Increasing	Moderate-Decreasing	High-Decreasing
Age	14.44 (2.02)	15.00 (1.80)	14.81 (1.95)	14.78 (2.16)
Time Online	4.29 (2.26)	4.72 (2.36)	4.31 (2.15)	5.79 (2.50)
Gender				
Boy	138 (60%)	42 (18%)	25 (11%)	25 (11%)
Girl	173 (60%)	63 (22%)	37 (13%)	18 (6%)
Race/Ethnicity				
Black	194 (59%)	73 (22%)	37 (11%)	27 (8%)
Latinx	118 (62%)	32 (17%)	25 (13%)	16 (8%)

Vicarious ORD Classes			
	Low-Increasing	High-Decreasing	High-Stable
Age	14.39 (2.03)	14.72 (2.06)	14.94 (1.84)
Time Online	4.11 (2.16)	4.87 (2.71)	4.99 (2.32)
Gender			
Boy	136 (59%)	18 (7.9%)	75 (33%)
Girl	154 (53%)	29 (10%)	109 (37%)
Race/Ethnicity			
Black	181 (55%)	31 (9.5%)	116 (35%)
Latinx	110 (57%)	16 (8%)	68 (35%)

Note. Mean and standard deviation are provided for continuous variables (Age, Time Online). n and % are provided for categorical variables (Gender, Race/Ethnicity).

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Table 4.

Logistic Regression Predicting Online Racial Discrimination Individual Class Membership by Demographic Characteristics

Individual ORD

Variable	HD vs. MI ß	HD vs. MI SE	HD vs. MI OR	HD vs. MI 95% CI	MD vs. MI ß	MD vs. MI SE	MD vs. MI OR	MD vs. MI 95% CI
Age	−.05	.10	0.95	.65–1.25	−.02	.08	.98	.82–1.14
Gender	*.65*†	*.38*	*.52*	*-.60–1.64*	−.05	.33	1.05	.40–1.70
Race	−.21	.38	1.23	.11–2.35	−.45	.36	1.56	.85–2.27
Time Online 1	.07	.22	1.07	0.42–1.72	−.01	.19	.99	.62–1.36
Age x Gender	**−.42** *	**.11**	**.66**	**.33−.99**	.04	.12	1.04	.80–1.28
Age x Race	**.34** *	**.21**	**1.40**	**.80–2.00**	−.08	.10	0.93	.73–1.13

Variable	LI vs. MI ß	LI vs. MI SE	LI vs. MI OR	LI vs. MI 95% CI	MD vs. HD ß	MD vs. HD SE	MD vs. HD OR	MD vs. HD 95% CI
Age	**−.12** *	**.06**	**.89**	**.77–1.01**	.03	.11	1.03	.81–1.25
Gender	.17	.23	.84	.39–1.29	*−.71* †	*.42*	*2.03*	*1.21–2.85*
Race	−.21	.25	1.24	.75–1.73	−.24	.42	1.27	.45–2.09
Time Online 1	*−.24* †	*.14*	*.79*	*.52–1.06*	−.08	.23	.93	.48–1.38
Age x Gender	*−.16* †	*.09*	*0.85*	*.67–1.03*	**.46****	**.17**	**1.58**	**1.25–1.91**
Age x Race	.05	.07	1.05	.91–1.19	**−.41** **	**.16**	**0.66**	**.35−.97**

Variable	LI vs. HD ß	LI vs. HD SE	LI vs. HD OR	LI vs. HD 95% CI	LI vs. MD ß	LI vs. MD SE	LI vs. MD OR	LI vs. MD 95% CI
Age	−.07	.09	0.93	.75–1.11	−.10	.08	1.03	.87–1.19
Gender	−.48	.35	1.62	.93–2.31	.22	.29	.95	.38–1.52
Race	−.01	.34	1.01	.34–1.68	.23	.30	.64	.05–1.23
Time Online 1	−.31	.19	0.74	.37–1.11	−.23	.16	1.01	.70–1.32
Age x Gender	*.26* †	*.15*	*1.29*	*1.00–1.58*	**−.20** *	**.10**	**.82**	**.62–1.02**
Age x Race	**−.29** *	**.14**	**.75**	**.48–1.02**	.12	.09	1.13	.95–1.31

Note. HD = High-Decreasing, MI = Moderate-Increasing, MD = Moderate-Decreasing, LI = Low-Increasing. Race = Race/ethnicity; Reference groups: Girl (Gender), Latinx (Race). Gender x Race interactions are not included in this table because none were significant.

† $p < .10$,

* $p < .05$,

** $p < .01$,

*** $p < .001$. Significant results are in bold. Trend results are italicized.

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Table 5.

Logistic Regression Predicting Online Racial Discrimination Vicarious Class Membership by Demographic Characteristics

	Vicarious ORD											
	HS vs. HD				LI vs. HD				LI vs. HS			
Variable	ß	SE	OR	95% CI	ß	SE	OR	95% CI	ß	SE	OR	95% CI
Age	.06	.13	1.06	.81–1.31	-.08	.11	.93	.71–1.15	**-.14***	**.06**	**.87**	**.75-.99**
Gender	.03	.52	.97	-.05–1.99	-.32	.42	.73	-.09–1.55	.29	.24	.75	.28–1.22
Race	-.44	.57	1.56	.44–2.68	.21	.46	1.24	.34–2.14	.23	.25	.79	.30–1.28
Time Online 1	**.58***	**.29**	**1.78**	**1.21–2.35**	.02	.20	1.02	.63–1.41	**-.56****	**.16**	**.57**	**.26-.88**
Age x Gender	.47	.28	1.60	1.05–2.15	.35	.25	1.42	.93–1.91	-.12	.09	.89	.71–1.07
Age x Race	-.27	.20	.76	.37–1.15	-.27	.19	.77	.40–1.14	.01	.07	1.01	.87–1.15

Note. HS = High-Stable HD = High-Decreasing, LI = Low-Increasing. Race = Race/ethnicity; Reference groups: Girl (Gender), Latinx (Race). Gender x Race interactions are not included in this table because none of them were significant.

† $p < .10$,

* $p < .05$,

** $p < .01$,

*** $p < .001$. Significant associations are bolded. Significant results are in bold. Trend results are italicized.

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Table 6.

Results for Association between Individual and Vicarious Online Racial Discrimination Class Membership and Psychological Outcomes

Parameter	Depressive Symptoms			Self-Esteem			Anxiety Symptoms		
	Mean	S.E.	χ^2(df)	Mean	S.E.	χ^2(df)	Mean	S.E.	χ^2(df)
Individual ORD Class Membership			6.40(2) †			3.39 (2)			.65 (2)
Moderate-Increasing	.93[ab]	.06		2.12	.08		.77	.13	
Moderate-Decreasing	1.03[ab]	.08		2.04	.10		.80	.14	
Low-Increasing	.89[a]	.04		2.13	.05		.83	.08	
High-Decreasing	1.18[b]	.13		1.91	.12		.98	.23	
Vicarious ORD Class Membership			16.59 (2) ***			4.71 (2) †			7.96 (2) *
High-Stable	1.20[a]	.08		1.96[a]	.08		1.17[a]	.15	
Low-Increasing	.88[b]	.04		2.11[ab]	.05		0.70[b]	.08	
High-Decreasing	.65[c]	.10		2.29 [b]	.11		0.68[ab]	.24	

Note.

$^{\dagger}p < .10$,

$^{*}p < .05$,

$^{**}p < .01$,

$^{***}p < .001$

Groups with different superscripts differ at p < .05 based on a chi-square test. Groups that share a common superscript do not.

We measured outcome variables at wave 3.