Editorial Essay

Using QuantCrit to Advance an Anti-Racist Developmental Science: Applications to Mixture Modeling

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Abstract

How researchers use statistical analyses shapes their research toward or away from an anti-racist agenda. In this article, we demonstrate how developmental scientists can use the QuantCrit framework to critically examine the process of conducting quantitative analyses. In particular, we focus on mixture modeling to clearly demonstrate how the integration of QuantCrit can be achieved within a statistical technique. We first summarize the tenets of QuantCrit and how it has turned the lens of critical race theory onto quantitative methodology. Second, we provide a summary of the key concepts of mixture modeling. The main section of the article is organized according to three "moments" that occur in quantitative research: (1) development of the research question(s) and identification of analysis variables; (2) decision-making about the role of race in planned analyses; and (3) interpretation of the results through a theoretical framework. We describe each moment, illustrate how researchers can use QuantCrit principles within it, and offer as examples empirical articles from adolescent research where these strategies have been implemented during

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mixture modeling. It is our hope that readers will identify moments in their own analyses in which these (and other) principles could be applied.

Keywords

QuantCrit, mixture modeling, anti-racism, critical race theory

Statistical analyses have long been used to support research designed to demonstrate that people of color were inherently inferior compared to white people[1] (Cokley & Awad, 2013; Zuberi, 2003). Although overtly racist applications of statistics have decreased, statistical analyses are still wielded as a tool of racial oppression across fields in the social sciences (Zuberi & Bonilla-Silva, 2008), including developmental science (Burman, 2015; Syed et al., 2018). However, it is not the statistical tools themselves that are racist (as a set of mathematical operations, they have no inherent value), but rather, how they are used. What we do with statistical analyses shapes our research toward or away from anti-racism. That is, by interrogating the decisions that are made during the analysis process, it is possible to move toward conducting quantitative research in ways that combat racist ideas and promote racial justice and equity (Berman & Paradies, 2010).

The framework of QuantCrit,[2] which integrates critical race theory (CRT) with quantitative methodology (Garcia et al., 2018; Gillborn et al., 2018), can be used to guide this examination of analysis-related decisions. QuantCrit applies to quantitative methods the core tenets of CRT: the centrality of racism in everyday life, a critique of liberal ideologies such as race-neutrality and meritocracy, and the urgency of uplifting the narratives of people of color that counter dominant narratives (Crenshaw, 2011; Delgado & Stefancic, 2017). QuantCrit applies these ideas to the conduct of statistical analyses to show that viewing numbers, categories, and data as unaffected by context and inherently true normalizes racial inequity and perpetuates racism (Garcia et al., 2018; Gillborn et al., 2018).

In this article, we demonstrate how developmental scientists can use the QuantCrit framework to critically examine their process of conducting quantitative analyses. Carefully regarding how quantitative work can shift toward anti-racism is important for combating racist assumptions about youth of color. Youth of color are often not afforded a developmental perspective (Spencer et al., 2015; Swanson et al., 2003). They are treated as static and miniature versions of their adult selves, a view that both exacerbates and solidifies the pathologization of youth of color (Spencer et al., 2015; Swanson et al., 2003). Furthermore, youth of color are often studied in a decontextualized manner. Their immediate contexts may be considered, but rarely are the

wider historical and sociopolitical contexts taken into account when posing research questions about youth of color (Spencer et al., 2015; Swanson et al., 2003). In contrast, white youth are afforded the privilege of being viewed through a developmental perspective such that they are seen as engaged in maturation processes across diverse domains of human development (Spencer et al., 2015). Furthermore, contexts within which white youth develop are predominantly constructed to preserve white dominance while at the same time shielded from cross-examination of the ways in which whiteness is being privileged. Centering QuantCrit as a developmental scientist can help interrupt the perpetuation of racist narratives about adolescents of color and can bring a more critical perspective to our understanding of the development of white youth.

To illustrate the applications of QuantCrit for developmental scientists, we chose to focus on mixture modeling (e.g., latent profile analysis and growth mixture modeling; Masyn, 2013), an analytical approach used to investigate the potential for unobserved subgroups within a dataset. We decided to highlight mixture modeling because of the relevance of these techniques for developmental science (Lanza & Cooper, 2016), their increasing popularity in the field, and our extensive experience with using them in our own analyses (e.g., Johnson et al., 2014, 2018). We do not intend this choice to imply, however, that QuantCrit principles are only applicable to mixture models or are more applicable to mixture models than to other types of analyses. On the contrary, we encourage readers to consider how the material we present here applies to whatever quantitative analyses they currently have in their repertoire.

We begin with an overview of the tenets of QuantCrit and how it has turned the lens of CRT onto quantitative methodology. Next, we provide a brief summary of the main concepts of mixture modeling to provide a foundation for understanding the strategies and examples presented in the rest of the article. The main section of the article is organized according to three "moments" of mixture modeling; we present the complex and often synergistic aspects of research in this manner to show how shifts toward anti-racism can be made at various points in the analysis process. For each moment, we highlight mixture modeling articles from the adolescent development literature to illustrate how some researchers tackle the issues we raise and make use of QuantCrit strategies in their work.

QuantCrit: Examining Quantitative Methods Through Critical Race Theory

QuantCrit draws from the scholarship of CRT scholars as well as early works by social scientists, such as Du Bois's (1899/1996) *The Philadelphia Negro*,

which challenged other works from that era that enshrined white supremacist ideology through statistics (see the list of suggested readings at the end of this article for works reviewing the use of statistics to reinforce racial oppression). Via five key tenets, QuantCrit proposes a framework for using quantitative research in a critical race-conscious way so as to challenge racist ideologies. Scholars who use a QuantCrit approach strive to use quantitative methods toward anti-racism by engaging in rigorous, continuous, self-reflexivity throughout the research process and unpacking systems of oppression as they relate to the phenomena under study.

Centrality of Racism (Tenet 1)

CRT as a transdisciplinary project rose out of anti-racist legal scholarship and is concerned with the examination of and transformation of racism in society (Crenshaw, 2011; Delgado & Stefancic, 2017). A core principle of CRT, and therefore a foundation of QuantCrit, is the recognition that racism is a firmly entrenched, permanent aspect of social life (Delgado & Stefancic, 2017; Ladson-Billings & Tate, 1995). Accordingly, the presence of white supremacy threatens all knowledge projects, including quantitative research (Garcia et al., 2018; Zuberi, 2003). Not paying attention to racism during the research will legitimize or remake existing race inequities (Gillborn, 2010; Gillborn et al., 2018).

Numbers Are Not Neutral (Tenet 2)

Similar to how critical race theorists reject notions of race neutrality as an ideology that entrenches racial inequities (Delgado & Stefancic, 2017; Ladson-Billings & Tate, 1995), QuantCrit scholars reject the idea that numbers "speak for themselves" (Garcia et al., 2018). They stress that numbers are never neutral, because they are used by humans, and therefore filtered through human biases. Calling into question the so-called neutrality of numbers is important in statistics because the epistemological lens that often underlies the use of statistical analyses magnifies the consequences of racist applications of quantitative data analyses (Zuberi & Bonilla-Silva, 2008). Statistical analyses are often framed within a post-positivist perspective that views numbers as infallible portrayals of reality and conclusions based on quantitative analyses as incrementally arriving at a single, objective truth (Kincheloe & Tobin, 2009; Strega, 2005). By drawing on these ideas, faulty conclusions based on racist interpretations of quantitative research have been used as compelling evidence for making significant decisions (e.g., in education policy; Gillborn, 2010) and can

easily be used to advance the interests of white supremacy (Gillborn et al., 2018; Zuberi & Bonilla-Silva, 2008).

Even when numbers are not explicitly used to advance racist ideas, numbers can be interpreted through a racist ideological lens if they are not carefully contextualized within an analysis of dimensions of power, with the consequence of normalizing racial inequality (Gillborn et al., 2018). For example, statistical differences between white youth and youth of color in academic outcomes have often been interpreted as a result of purportedly biologically-based attributes, such as intelligence or work ethic, rather than as a result of systemic racism within neighborhoods, within educational systems, in classroom settings, in the institutions of standardized testing, and so on (Zuberi, 2003). Power and Frandji (2010) present yet another practice in the use of statistics in education that appears benign or neutral yet promotes the narrative that certain racial groups are inherently lower performing compared to others. They point out that measuring educational achievement as above or below what would be predicted from prior academic achievement (i.e., whether students under- or over-achieve) makes lower achievement at the group level appear "inevitable and insurmountable" and enshrines educational inequities (Power & Frandji, 2010, p. 393).

Categories Are Never Natural (Tenet 3)

A third principle of QuantCrit is the insistence that researchers must critically evaluate the categories they construct for analysis, especially categories related to race (Garcia et al., 2018; Gillborn et al., 2018). Although *race* is not a stable and concrete matter (Helms et al., 2005; Smedley & Smedley, 2005), *racism* is deeply embedded in society and therefore is always operating (Bonilla-Silva, 2001; Omi & Winant, 2014; Zuberi & Bonilla-Silva, 2008). However, it is embedded in a complex, fluid manner, making it difficult to measure and not obviously amenable for statistical inquiry (Garcia et al., 2018; Gillborn et al., 2018). Not including or addressing race in research suggests that it is unimportant. On the other hand, only addressing race through the inclusion of racial categories without explicit discussions of racism may suggest racial inequities are natural. Such research often reinforces whiteness as a dominant standard by comparing participants of color to white participants (Zuberi, 2003).

Gillborn et al. (2018) clearly illustrated the socially constructed nature of categories in the analyses of the likelihood of attending elite universities in the United Kingdom, wherein different conclusions were reached depending on how "people of color" in the sample were aggregated or disaggregated. Being cognizant of the socially constructed nature of race

and the dynamics of power that operate in racialized social relationships reduces the likelihood of making erroneous essentializing interpretations about race.

Voice and Insight Are Vital (Tenet 4)

CRT scholars reexamine history through the lens of communities of color, upholding the ways in which people of color have challenged dominant white narratives through counter storytelling (Ladson-Billings & Tate, 1995; Solórzano & Yosso, 2002). Similarly, users of QuantCrit understand that the voice, insight, knowledge, and experiences of communities of color must be prioritized in the conduct and interpretation of data analyses.

Scholars have drawn on the lived experiences of groups that are marginalized in educational systems to provide compelling counterstories to deficit-based interpretations of data about non-white underachievement (Covarrubias, 2011; Sablan, 2019; Yosso, 2006). One application of QuantCrit to provide a counternarrative has been the formation of a Critical Race Occupational Index as an alternative to the widely used Duncan Socioeconomic Index of occupational prestige (Pérez Huber et al., 2018). The Duncan Socioeconomic Index quantifies the "prestige" of occupations; the occupations that score the highest are those that are most accessible to wealthy white men. Non-white groups score poorly on this index, which has been used to question the value of college degrees for marginalized people. Pérez Huber and colleagues (2018) employed the knowledges embodied within their communities to propose a Critical Race Occupational Index, which instead strives to capture occupations considered valuable by communities of color, especially Latinx[3] groups—occupations that center care, service, and teaching.

Using Numbers for Social Justice (Tenet 5)

Once we reject the notion that statistical research is bias-free and instead acknowledge its prior and continuous use as a tool of racial oppression, we can begin to use quantitative analysis in the service of social justice aims, including advancing racial equity (Garcia et al., 2018; Gillborn et al., 2018). Using QuantCrit as a guide, researchers using quantitative methods can engage in praxis, wherein we critically reflect on our practice and uses of quantitative methods during the process. In this way, our quantitative work may begin to more justly capture the nuances and depth of the lived experiences of communities of color while simultaneously interrogating prevailing racist thinking and beliefs.

Brief Overview of Mixture Modeling

In this section, we first provide a brief overview of mixture modeling for readers who may not be familiar with these types of analyses. Readers who want to learn more about specific types of mixture models, including the logistics of how to conduct them, can consult the list of suggested readings at the end of the article. Mixture models are part of the larger family of latent variable models (Muthén, 2001). Latent variable techniques are used to account and correct for measurement errors in observed variables (Muthén, 2002). Much research in developmental science involves latent variables of the continuous variety, where participants vary in the *amount* of something (e.g., adolescents' feelings of social responsibility). In contrast, mixture models involve latent variables that are categorical, where participants vary in a *type* or *pattern* of something (e.g., different forms of civic actions that adolescents engage in most frequently; Muthén, 2001). These categories of the latent variable correspond to the subgroups in the dataset.

An important aspect of mixture models is that the subgroups are not directly observed. In other words, there is no one item in the dataset that indicates subgroup membership. Instead, the groups must be inferred from variables that are directly observed or asked about. We refer to these "inputs"—that is, what goes into the mixture model to comprise the groups— as **indicators**. Indicators may consist of single items in the data set (e.g., single items for volunteering, activism, and contacting government officials) and/or be created from multiple items (e.g., composite scores computed from several items from a scale of social responsibility).

Another important aspect of mixture modeling is that the number of subgroups in the population is not known prior to the analysis (and, in reality, can never be definitively known; e.g., Cudeck & Henly, 2003). The task of the analyst, then, is to identify the number of subgroups that provide the best fit to the sample data through what is termed the **enumeration process**: testing models that include different numbers of groups (and potentially different model specifications) and to choose the *best fitting model* based on statistical (e.g., model fit indices) and substantive (e.g., theoretical interpretability) criteria. We specifically chose the phrase "best fitting model" and avoided the language of choosing the "correct" or "true" number of groups. In fact, whether and to what extent the results reflect a true number of subgroups in the population is a long-standing and rather heated debate within both methodological and substantive circles (e.g., Bauer & Curran, 2003; Cudeck & Henly, 2003). The purpose of this article, however, is not to enter into this debate nor to convince readers either for or against the use of mixture models. Our position is that mixture models are one useful way to address

developmental science research questions (e.g., Petras & Masyn, 2010); for readers who choose to use these techniques, we offer our perspectives on how they can be used as part of an anti-racist research agenda through situating them within the principles of QuantCrit.

There are many types of mixture model techniques. They share a common purpose of investigating the potential presence of subgroups; what the subgroup is *about*, however, varies between different types. For example, latent profile analyses (McLachlan & Peel, 2000) are used to identify participants who are similar in their pattern of responses to a set of continuous items (e.g., frequencies of participation in different civic activities; Johnson et al., 2014). Growth mixture modeling (Ram & Grimm, 2009) is used to identify individuals who have similar types and rates of change (e.g., patterns of civic socialization across adolescence; Karras-Jean Gilles et al., 2020). Other mixture techniques used by developmental scientists include latent transition analyses (Nylund, 2007; Vermunt & Magidson, 2002) and regression mixture analyses (Van Horn et al., 2015; Wedel & DeSarbo, 1994).

The final aspect that we emphasize here is that mixture models incorporate uncertainty in group membership (i.e., they are probabilistic; Masyn, 2013). For any given model, each individual has a probability of being classified into each subgroup. For example, if a four-group model is specified, then the resulting model will include four groups, each with a prototypical (i.e., overall) response pattern. Depending on their individual response pattern, each participant receives a probability of belonging to each of the groups identified in that model. Ideally, individuals have a high probability of being classified into only one group and a low probability of being classified into the other groups. If a model with a different number of groups is specified, these probabilities will change. Accordingly, classification accuracy (how closely individual response patterns are able to be matched to one specific group) can be used to evaluate the quality of a specific model.

When integrating the QuantCrit framework to their work, researchers may capitalize on mixture modeling techniques. In mixture modeling, the assumption that a sample is drawn from a homogeneous population (with respect to the variables and relationships under study) is relaxed. Accordingly, researchers can explore variations (i.e., heterogeneity) in the phenomena of interest within their sample. This approach is particularly important among research with youth of color who are often not afforded a perspective that is developmental or heterogeneous (Spencer et al., 2015; Swanson et al., 2003). Although the use of comparative analyses (e.g., between-group mean comparisons) is not inherently problematic (Syed, 2020), the interpretations from comparative work can and have been used to draw unidimensional and essentializing conclusions about people of color while upholding white people as

the norm against which others are compared. Again, while this is an issue of framing and interpretation rather than an issue with the statistics themselves, the use of comparative methods in deficit-oriented ways has been and continues to be an issue (Spencer et al., 2015; Swanson et al., 2003). Mixture models can be used as tools for conducting nuanced, multidimensional analyses about people of color; for example, researchers have used mixture models to counter exaggerated stereotypes about African American youth (Neblett et al., 2016).

Although assumptions of mixture modeling make it amenable for addressing the recommendations of QuantCrit, mixture modeling techniques also have features that are vulnerable to being used to uphold racist ideas. Just as with other quantitative analyses, there are multiple points during the analytic process in which researchers can shape the outcomes of the analysis. For example, the best fitting model to the data is determined by "the parsimony principle . . . such that the model with the fewest number of classes that is statistically and *substantively adequate and useful* [emphasis added] is favored" (Masyn, 2013, p. 571). The characteristics of mixture modeling allow us to demonstrate the core theory of QuantCrit: that the potential for researchers to influence the application of the statistics means that a researcher practicing self-reflexivity and making decisions with intention may be able to shape their use of those statistics toward an anti-racist agenda.

Mixture Modeling Through a QuantCrit Lens: Three Moments for Intervention

To offer anti-racism strategies that researchers can use in their own analyses, we traced the steps analysts take during a mixture model analysis to identify moments for intervention (see Figure 1). We identified three moments where researcher influence is paramount: (1) development of the research question(s) and identification of analysis variables; (2) decision-making about the role of race in planned analyses; and (3) interpretation of the results through a theoretical framework. We scrutinized each moment through the lens of QuantCrit to identify how researchers may pivot their research toward anti-racism. Although we have partitioned the research process into these three moments for clarity of presentation, we acknowledge that they are integrated such that each influences the others throughout the usually non-linear research process. Interpretations of a model, for example, are in response to the research question, which is itself constrained by and feeds into decisions about sample and measurement. We offer these three moments, then, as a starting point for discussion; we hope that readers will draw on them to identify more moments in their own analyses, where these (and other) principles could be applied.
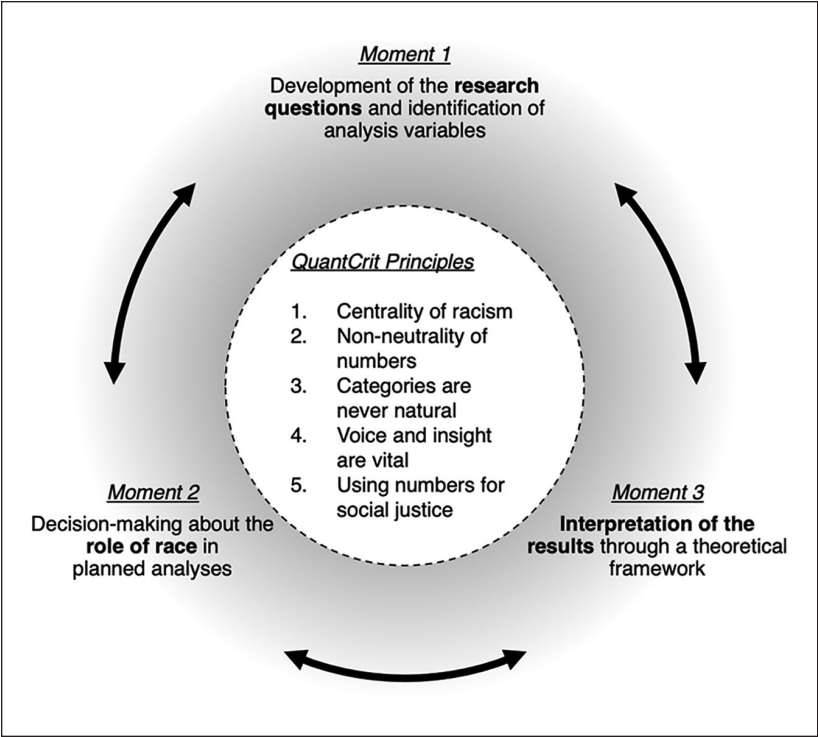
Figure 1. Quantitative research is a cyclical process with multiple, interrelated processes; we highlight three of them in our article. Researchers can pivot their analyses toward anti-racism by centering the core principles of QuantCrit.

Within each moment below, we offer examples of empirical work where these strategies have been implemented.

Moment 1: Development of the Research Question(s) and Identification of Analysis Variables

The first moment that we describe usually occurs at the beginning of a study or analysis and involves the development of the research question. The decisions made in these early steps in the research process present a powerful opportunity for researchers to intentionally invoke an anti-racist stance. In developing the research question, the researcher also identifies variables that will be used to answer their questions. In mixture modeling,

some of these variables of interest become the indicator variables put into the mixture model.

A foundation of CRT, and thereby of QuantCrit, is that racism permeates social life—it is both pervasive and incessant. The implications of this tenet for quantitative research are that if researchers do not actively take an anti-racist stance, their analysis will tend toward legitimizing and perpetuating racial oppression. One purposive way to center the effects of racism in research is to take a reflexive stance about the questions being asked, in part through interrogating our positionalities vis-à-vis the research topic (Day, 2012; Parson, 2019). This practice has been incorporated for many years in qualitative research, where the researcher's position in relation to the study is acknowledged as influencing all aspects of the study (Pillow, 2010). The position of QuantCrit is that self-reflexivity is also crucial to doing quantitative research, although it is mostly considered outside of its purview (and therefore largely missing in its development, training, and applications; Hope et al., 2019; Tabron, 2019).

Researchers' positionalities are affected by social identifiers or locations including (but not limited to) race, gender, sex, class, ethnicity, and religion. These are important standpoints to consider, as each includes perspectives, either explicit or unexamined, that can influence the research in ways that may perpetuate hegemonic relationships between the researcher and others who are more marginalized or minoritized in society. Just as a lack of awareness of positionality may recreate racial oppression, the opposite is also the case: reflexive and transparent examination about what is guiding inquiry can move research away from racist narratives.

In approaching the development of the research question, the guidance of a theoretical framework that explicitly examines issues of oppression may be valuable. Particularly with questions that are suited for mixture modeling where variations within a group are being queried, a theoretical framework that takes into consideration how structural forces influence disparities in developmental outcomes is essential. Instead of conceptualizing variations in an outcome as influenced by characteristics deemed inherent to the individual or group, theoretical frameworks that take systemic inequity into account conceptualize variation as operating from and through forces of oppression. Examples of such frameworks that are well established within developmental science include García Coll's integrative model (García Coll et al., 1996) and Spencer's phenomenological variant of ecological systems theory (PVEST; Spencer et al., 2015). Both theories account for social stratification, especially along racial lines, and the cascading effects of this stratification on development. Embedding research questions within such a framework can help ensure that the roles of oppression are present in the way development is being investigated.

For example, Yu et al. (2019) asked questions about the psychological adjustment and educational outcomes of African American and Latinx children using PVEST as a theoretical guide. Accordingly, they included racial-ethnic and cultural constructs in conceptualizing what may lead to positive outcomes. As outlined in PVEST, the researchers took into consideration structural challenges such as racial discrimination in thinking about the development of African American and Latinx children, while also allowing for variation in how the constructs manifested. Thus, they included not only broad positive youth development (PYD) constructs that do not explicitly acknowledge the role of oppression in the lives of children of color but also constructs that are related to the adjustment of children of color, such as racial-ethnic pride and perceived racial-ethnic barriers. Yu and colleagues used these constructs within a latent profile analysis that was designed to explore the strengths and resources that children of color may draw on to achieve developmental successes. Among children in their study, those who had high PYD, high racial-ethnic pride, and low perceived racial-ethnic barriers had more favorable outcomes compared to two other groups: children with high PYD, high racial-ethnic pride, and high perceived racial-ethnic barriers, and children with low PYD, low racial-ethnic pride, and low perceived racial-ethnic barriers. These results added to the knowledge base regarding what contributes to the development of PYD for children of color: the evidence from this study suggests that it is important for children to feel proud of their racial-ethnic background and not feel that there are significant barriers to their development due to their racial-ethnic identity.

In addition to using a framework that theorizes about oppression, researchers should carefully consider the assumptions and beliefs that they hold about youth of color. In thinking about the research question as well as variables for analysis, taking a strengths-based view of youth of color can move researchers toward anti-racist research practices. Rather than assume that people of color primarily need to be resilient in the face of structural barriers that could lead to maladaptation, researchers can ask questions about how youth may produce transformative changes impacting their own development and the wellbeing of their communities. A view of youth of color as agentic and able to be engaged in social change (Ginwright & Cammarota, 2002) can offer ideas for inquiry such as that pursued by Lardier et al. (2019), who used latent class analysis to investigate the cognitive empowerment and ethnic identity of youth of color. In the introduction to their article, Lardier et al. (2019) explicitly described their stance toward their participants:

> Whether youth are advocating for gun reform following the horrific school shooting in Parkland, Florida or are DREAMers throughout the U.S. advocating

for reforms to bring forward a clean DREAM Act, the commonality is their sense of empowerment to engage in social change. These youth are. . .critical observers of their world, they are unwilling to sit silent . . . (p. 1531)

Lardier et al. (2019) selected indicators for the mixture model that aimed to capture the youths' cognitive empowerment—their understanding of the sociopolitical system such that it empowers them to strategically and effectively engage in social change—and ethnic identity. Such constructs are intended to capture the particular culturally-relevant strengths of communities of color (Yosso, 2005); for example, ethnic identity at the individual level has been shown to counteract the deleterious effects of discrimination, while at the community level, it can inspire opportunities to discuss contexts of oppression and engage collectively in social change (Hipolito-Delgado & Lee, 2007). Thus, a stance against racist portrayals of youth of color can foster research on the strengths and contributions of youth of color.

Furthermore, Lardier et al. (2019) and Yu et al. (2019) provide examples of how to think carefully about the measures selected. Through engaging with theoretical frameworks that address oppression, and by challenging the narrative of youth of color as deficit, the researchers moved toward employing measures of "success" that are conscious of the experiences of people of color and attuned to the way many standards of success are normed in the service of more privileged groups. Constructs such as racial identity, awareness of barriers due to one's race, and feeling empowered in the sociopolitical domain aim to capture what it means to navigate and confront a society where racism and other forms of oppression exist.

It is also important to consider how the measures themselves were developed and the evidence for their validity and appropriateness for use with particular groups. Many measures that are presented as globally "validated" may in fact have been developed without the considerations we have just described (i.e., without consideration to the role of racism in measure development) and may, at best, not resonate with the experiences of people of color, or, more menacingly, explicitly draw on deficit narratives or stereotypes. Contending with racism during the conceptualization of a research project through the choices made about guiding frameworks, questions that will be asked, and what variables will be measured and how, can be a powerful first step toward anti-racism.

Moment 2: Decision-Making About the Role of Race in Planned Analyses

The second moment includes choices regarding variables indicating race, which may include decisions about specifying the sample for a particular

study. Through questioning normalized approaches for treating race in quantitative analyses, we can intentionally shift toward anti-racism. Practices such as not including race, comparing between races, and "controlling for" race are all common strategies in quantitative analyses that are often predicated on assumptions that serve to perpetuate racism.

In general, QuantCrit theorists eschew approaches that have embedded in them an analysis of the "effect of race" (Holland, 2008). Most often explorations of the "effect of race" are carried out by examining race as a (categorical) covariate or by making comparisons between youth of color and white youth in ways that perpetuate deficit models of youth of color. While there can be anti-racist rationales for conducting comparative research (Syed, 2020), much comparative work fails to make explicit the logic with which comparisons between racial groups are being made, which can serve to propagate racist narratives about people of color while reifying white standards.

Without a doubt, race has very real effects on the development of all youth. Current classifications by race are mostly based on stereotyping of phenotypes, such as skin color and hair texture. Furthermore, individual experiences differ based on the recognition of their race by themselves, other people, and institutions. How people are classified racially impacts experiences of privilege and discrimination across contexts. Striving toward anti-racist research means remembering that race is a system of hierarchy and dominance constructed to establish and maintain colonization and slavery. The socially constructed nature of race is further emphasized by the fluidity of racial categories, both across geography and throughout history.

Accordingly, when researchers present quantitative differences between youth of color and white youth without contextual analysis, the interpretation—whether intended or not—is that these differences are *attributable* to the participants' race. By ignoring the socially constructed nature of race and the context of racism, such analyses attribute the impact of racism to individuals rather than historical and political structures of racial oppression. Thus, the analysis can propagate an erroneous, racist, claim that membership within a particular socially constructed racial category makes a person inevitably less competent or more "at risk." The results maintain deficit-focused orientations toward youth of color and uplift a dominant interpretation of race as a characteristic of individuals and communities.

Adding race as a control variable also carries with it multiple implications that do not fully account for the way racism operates: mainly, adding race as a covariate implies that race makes a difference but only at the mean level (i.e., that there are no relationships between race and other variables in the model; Martin & Yeung, 2003). The reality of racism operating

through variables is ignored (i.e., that processes and relationships between variables may differ between groups). Including interactions between race and other variables overcomes this limitation in part but still can contribute to an approach that focuses on examining differences between white and non-white groups.

Mixture modeling approaches offer alternative ways to consider samples and the inclusion of race-related variables. One potentially powerful use of these techniques is to examine the heterogeneity that exists within specific groups that experience oppression, including youth of color. Instead of comparing youth with minoritized and marginalized identities against the dominant white standard, mixture models can address how variables may relate differently among members of a group (i.e., within-group heterogeneity). Thus, nuances of developmental processes among groups who experience oppression can be demonstrated, and the blanket deficit-focus stories can be counteracted. We acknowledge that it is important to bring white youth under this scrutiny as well—we must examine the ways that there are within-group differences within the dominant racial group with respect to development.

Importantly, decisions about whether to focus on specific groups are important to make in the planning stages of a study. As with all quantitative analysis methods, mixture models have sample size requirements that depend on many aspects of the research design. In general, mixture models are a "large sample technique" in the same way that other latent variable methods are, in that they require more participants than analyses that do not involve latent variables (e.g., ordinary least squares regression, and cluster analysis). Most simulation studies suggest that mixture models work best with at least a few hundred participants, so researchers who want to focus on particular groups should plan for that in the study design. Without such advance planning, researchers may be left with sample sizes for particular groups that are too small to permit within-group mixture models; this situation increases the temptation to use other ways of incorporating race into analyses (e.g., including binary white/nonwhite variables used to make group comparisons) that, as we described earlier, can perpetuate racist narratives.

The developmental science literature offers several excellent examples of how researchers have used mixture models to examine within-group heterogeneity. Kulis et al. (2016), for example, examined latent classes of identity constructs among urban American Indian youth. As a group, urban American Indian youth are immensely diverse with respect to migration history, tribal backgrounds, and region of residence (among others). However, the authors recognized the related nature of their experiences of oppression: for example, this group has rates of poverty that are almost double that of non-Hispanic

whites. Thus, in constraining their sample to this group, Kulis et al. demonstrated an alternative to reductive groupings that collapse together data from people with diverging racial experiences (Strunk & Hoover, 2019). The authors' decision to examine variation *within* this group of youth not only brought to light more precise understandings of their development but enabled the authors to focus on the youths' unique cultural strengths, removed from any comparisons against a white standard. In their words, the aim of their study " . . . is not to categorize the adolescents . . . the study aims to shed light on the complexity of [American Indian] heritage and the choices for constructing indigenous identities in urban settings" (Kulis et al., 2016, p. 218). Their latent class analysis identified five patterns of indigenous identity with differential associations with academic outcomes and other identity constructs. For example, the largest class was characterized by strong engagement with American Indian culture through connections with parental heritage, past and present reservation connections, and best friends who are American Indian. The average school performance of this class was stronger than in the class that had a low engagement with American Indian culture and endorsed colonial notions such as blood quantum.

A second example comes from Romero and O'Malley (2020) who explored Latinx middle school students' school climate perceptions. Their latent class analysis identified a large group of youth (nearly half of the sample) with positive school climate perceptions, which counteracts a prominent negative narrative about Latinx students having negative perceptions of their school climate. Their exploration of heterogeneity in school climate perceptions revealed important complexities: for instance, the group with the most positive school climate perceptions overall was the only one where youth reported feeling like they had a role in making decisions at school. These findings have important implications for schools as well as theoretical development related to school climate perceptions. Notably, the authors acknowledge that although they focused specifically on Latinx youth, they did not address the immense ethnic diversity within this group because such information was not collected from the participants. This statement highlights the need to collect relevant identification from participants to adequately address within-group heterogeneity.

Our final example for this moment comes from a study of youth health disparities by Liu et al. (2018). They drew from a nationally representative sample, which included Black, Latinx, and white youth. However, instead of making comparisons between these groups on the same standard, they investigated relationships independently within each of these racial categories by conducting a separate latent class analysis for each group. This decision was both theoretically and empirically informed. The authors were guided by

García Coll's integrative model (García Coll et al., 1996), which argues that racial stratification results in different processes of development for youth who experience racial oppression. Empirically, a test of measurement invariance found that a model which assumed identical latent classes for all groups was a poor fit to the data. Without measurement invariance, and without a theoretical rationale for measuring whether different racial groups score "higher" or "lower" on their outcome, looking for such differences between the groups would not only be incorrect, it would generalize to the population conclusions about the racial groups that are taken out of context.

The researchers used the analytical approach of modeling latent classes independently for each racial category group and identified a class where reports of health promotive factors were high in all three of the racial category groups. The strength of associations between health promotive factors and outcomes was stronger for white youth than for youth of color. The researchers go on to contextualize their findings by suggesting that the effects of health promotive factors may be attenuated for youth of color due to effects of racial oppression on health or that some promotive factors that they investigated may be inversely associated with important supports for youth of color.

Moment 3: Interpretation of the Results Through a Theoretical Framework

Finally, we turn to the moment in research where the results are interpreted. In mixture modeling, the researcher must make sense of the groups that were identified. As outlined in QuantCrit, data do not "speak for themselves" in a neutral way. Instead, they must be translated by the researcher through a lens. Accordingly, researchers can move toward anti-racism by interpreting and explaining their findings with attention to the influence of privilege and power as well as to the assumptions and limitations of specific statistical techniques.

As statisticians and quantitative methodologists remind us, all statistical models rest on specific mathematical frameworks and assumptions; these models are one way that we, as researchers, simplify the extremely complex nature of whatever phenomenon we study. Probably everyone who uses a statistical technique agrees to that principle in theory. However, when we actually conduct analyses, and especially when we are confronted with results that match our expectations, we lose sight of it: as stated by Cudeck and Henly (2003), "the temptation is almost irresistible to make the following conclusion: the model holds; therefore, the behavior under investigation follows a process just like the one represented in this

analysis" (p. 378). In the specific situation of mixture modeling, the results provide what may be an especially appealing conclusion about the nature of humans, given our apparently inherent need to, or preference for, constructing categories (Bem, 1970). However, the identified subgroups depend on choices that analysts have made along the way, including the variables that are included and the way that the model is specified (Masyn, 2013). Therefore, the results of a mixture model are most appropriately interpreted as a representation of the data rather than a fixed statement about reality independent of researcher choices.

It is our perspective, however, that this rejection of the "trueness" of the groups is a philosophical position rather than an empirical one—acknowledging the limitations of statistical techniques (including but not limited to mixture models) does not render the results meaningless. In contrast, using a strengths-based theoretical framework that explicitly examines issues of oppression facilitates the ability of researchers to apply a social justice lens to the interpretation of the subgroups and make explicit the role of racism and other forces of oppression when contemplating the particular configurations within specific subgroups.

Research by Shramko et al. (2018) exemplifies this approach. In their review of the literature, the authors highlight that bullying and victimization interventions have failed to be successful for youth of color. Guided by concepts such as minority stress and intersectionality, they investigated how Latinx sexual minority youth experienced discrimination and victimization. A latent profile analysis showed that Latinx sexual minority youth attributed stressors to both their sexual minority and Latinx identities. This meshes with intersectionality theory, which suggests that multiple intersecting axes of oppression exist in society (Collins & Bilge, 2016). According to the authors, the implications of their findings are that interventions to prevent bullying and victimization need to explicitly focus on multiple identities within individuals (and the ways in which they intersect) to center the experiences of groups such as Latinx sexual minority youth and develop interventions that can be successful for them.

Making use of QuantCrit principles when interpreting results may necessitate moving away from established theories, especially when those theories frame communities of color in a deficit perspective. For example, Rivas-Drake and Witherspoon (2013) were interested in how neighborhood context affected racial identity development for Black youth. They conducted a latent profile analysis of neighborhood characteristics, which they then connected to youth racial identity outcomes. Literature on neighborhood effects prioritizes social disorganization theory, which predicted that neighborhoods with high rates of poverty and crime would lead Black youth

to manifest poor racial identity outcomes. Rivas-Drake and Witherspoon's (2013) results, however, were in contrast to those expectations. Black youth in neighborhoods with positive characteristics did indeed have positive racial identity outcomes (e.g., high positive private regard) over time—but so did adolescents who resided in neighborhoods that were characterized in the latent profile analysis as unsafe but with opportunities for positive social connections. In interpreting these findings, the authors acknowledged the overemphasis on deficits in social disorganization theory and instead turned to the PVEST framework and García Coll's integrative model to consider the role of both promotive and risk factors. They concluded that neighborhoods that may be considered "deficit" due to the lack of safety nevertheless facilitated the formation of strong bonds that informed youths' understandings of race in their lives.

Conclusion

Statistical analyses are important techniques in the research methods toolbox of developmental scientists. However, the history of the use of these techniques in the service of racism means that developmental scientists who want to use them as part of the movement toward anti-racism must do so with intention. The framework of QuantCrit (Garcia et al., 2018; Gillborn et al., 2018) is one way to organize these efforts. QuantCrit applies the core tenets of CRT (Crenshaw, 2011; Delgado & Stefancic, 2017) to the conduct of statistical analyses. In doing so, it emphasizes that numbers, categories, and data are never neutral, but if we acknowledge the pervasiveness of racism and interrogate how it shows up in ourselves and our analysis choices, we can begin to use statistical research toward social justice aims. We urge readers to reflexively engage with the notion that all quantitative analyses can perpetuate racism, without exemption. Thus, a useful question to begin with may be: *How does racism show up in my research and the ways in which I carry out research?*

Readers undertaking the work required to transform their research may want to continuously engage with certain questions to align, and realign, their work with anti-racism. When considering what research questions to pose, it may be helpful to ask: *From what lens are we viewing this problem, and with what variables are we exploring the problem? How have our positions in society, our research training, and our views contributed to this research approach? Are we relying on racist tropes and stereotypes?* When thinking about the inclusion of race in analyses, questions to spur intentionality may include: *Are we using the race variable in ways that are simply convenient or customary, or have we thought through the particular ways in which race*

influences our analyses? Have we planned our study to allow for different ways of including race in analyses? We also urge readers to consider how moments before and after the analysis process—including but not limited to recruitment of participants and communication of findings—likewise interact with and contribute to racism.

In this article, we discussed how developmental scientists might use the QuantCrit framework in the context of mixture modeling (e.g., latent profile analysis, growth mixture modeling; Masyn, 2013). Mixture models have features that make them well suited for the application of QuantCrit principles, such as offering an explicit way to investigate within-sample heterogeneity. This method is not a foolproof road to anti-racist quantitative analyses, however. We described three "moments" in the research process, where analysts can make choices consistent with an anti-racist orientation. For each moment, we described some of the ways that researchers could pay attention to how racism seeps in and, accordingly, ways to reorient toward anti-racism. In each case, we offered examples of how these strategies have been used by developmental scientists. There are many more excellent examples, and we hope that readers will use the moments and principles we have described here as a starting point for conducting mixture model analyses as part of anti-racist quantitative developmental science.

Suggested Resources for Further Reading

On the Use of Statistics for Racial Oppression

Saini, A. (2019). *Superior: The return of race science.* Beacon Press.

Winston, A. S. (Ed.). (2004). *Defining difference: Race and racism in the history of psychology.* American Psychological Association.

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On Mixture Modeling

Collins, L. M., & Lanza, S. T. (2009). *Latent class and latent transition analysis: With applications in the social, behavioral, and health sciences.* John Wiley.

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Notes

1. Throughout the article, we have chosen to capitalize Black when discussing race, while white is left in lower case. This rhetorical choice is supported by the Associated Press style guide and serves to recognize and uplift Black identity. Although white too is a constructed racial identity, capitalizing this word as a proper noun is a practice associated with those who condone white supremacy; therefore, we have decided to forego capitalizing white in this article.
2. Critical Race Quantitative Intersectionality is a similar framework developed by the Critical Race Intersectional Think Tank (Covarrubias et al., 2018). It has a heavier emphasis on intersectionality.
3. We use the gender non-binary term Latinx when referring to those who identify as having roots in Latin American countries, to include both those who identify as male and female as well as those who identify as another gender.

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