Relationship between teacher's racial beliefs in education and their beliefs in deficit narratives

Ally Cameron

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The purpose of this research project is to explore the question: **Do high school math teachers' classroom-related racial beliefs influence their beliefs in deficit narratives?** To answer this question, I will attempt to analyze two estimands: 1) *what is the direct effect of teachers' average score on the minimization of race construct on their average score on the deficit narratives construct*, and 2) *what is the direct effect of teachers' average score on the race conscious construct on their average score on the deficit narratives construct.* More discussion on constructs follows below.

Researchers have shown that many teachers consciously or unconsciously lower their expectations for minoritized learners, which can contribute to their placement in lower academic tracks (Berry, 2008; Kyburg et al., 2007; Strayhorn, 2010). This lowering of expectations for minoritized learners is usually characterized by teachers' use of racialized deficit narratives. Racialized deficit narratives are defined as viewing minoritized learners and their families as deficient and/or less competent than white students. Deficit narratives in K-12 mathematics education are formed and maintained in schools (Pollack, 2012; Williams et al., 2020), policy decisions (Berry, 2021; Martin, 2009), and existing mathematics education research (Martin, 2009). Within schools, racially minoritized learners are often denigrated as troublemakers (Brown & Donnor, 2011), mathematically inferior (Martin, 2019), and the target of blame for the exclusionary nature of mathematics. When minoritized youth see themselves over-represented in general and remedial classrooms yet underrepresented in advanced STEM courses in their schools, there is a lasting effect on their perception of what a mathematician or scientist looks like and whether they can see themselves as one (Visintainer, 2020). Deficit narratives can have lasting effects on minoritized learners' sense of belonging, as well as how they interact and engage in mathematics spaces.

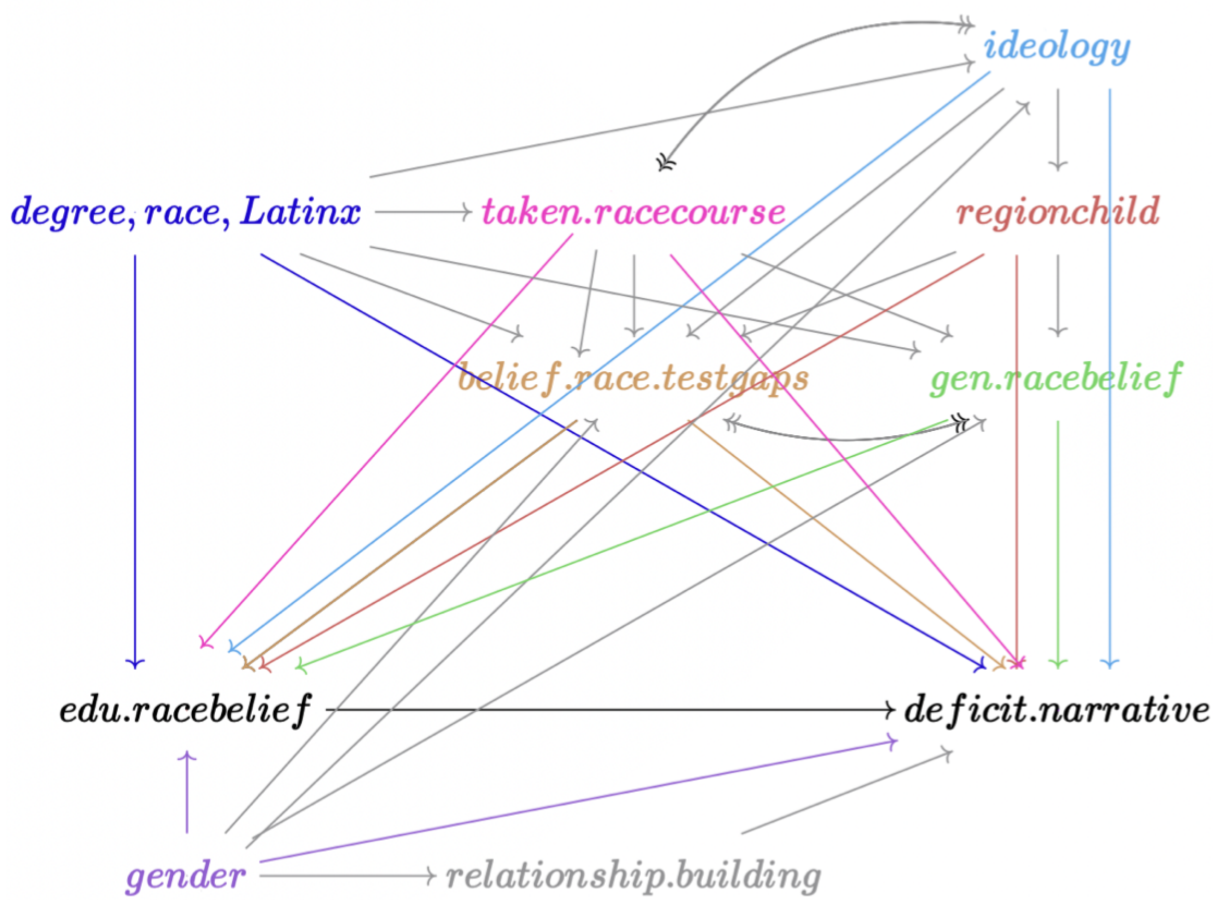
The current research aims to quantitatively explore the relationship between teacher's education-related racial beliefs and belief in deficit narratives. The resulting relationship between these beliefs has implications for the perceptions teacher's have towards minoritized students and the strategies they use when engaging students of color. Future research will aim to understand the relationship between deficit narratives and inclusive teaching practices.

Data and Methods

Research Design. This study uses pilot data from a national survey of secondary mathematics teachers. The survey includes original questions and items from existing surveys, both of which were informed by existing literature, focus group interviews with mathematics teachers, and regular working group meetings. This survey is the first large-scale teacher survey with *race-oriented measures* to investigate mathematics teachers' beliefs, views about minoritized learners and their families, and the range of teaching practices they use in their classroom.

Participants. To recruit participants, first, we randomly selected around 400 traditional public and charter secondary schools from the Common Core of Data, stratified by Black student enrollment quartiles. Next, we compiled a list with the name and email address of all high school mathematics teachers working in these schools using publicly available data sources. Each teacher was sent a personalized invitation to participate in the survey, as well as a $5 gift card of their choice. We also recruited teachers to participate via open email invitations sent to the listservs of multiple professional associations (e.g., local and state chapters of the National Council of Teachers of Mathematics) and posted to social media (e.g., Twitter, Facebook affinity groups). Our final pilot sample includes 227 high school math teachers, 123 from the random sample, and 88 from the nonrandom sample.

Variables. To analyze the effect of teachers average score on the minimization of race and race consciousness constructs on teacher's average score on the deficit narrative construct I use a generalized linear model (GLM). Below is a diagram illustrating the logic that informs the GLMs for analyzing the relationships between these variables.



The main takeaway from this diagram is that all of the variables in color are confounders, and thus will be controlled for in the model.

In green are two constructs related to general racial beliefs of teachers (Table 2.2). In orange is a construct measuring teachers' beliefs around racial test gaps (Table 2.4). In black, educational race beliefs (Table 2.1) and deficit narratives (Table 2.3) are also informed by constructs. All of these variables from constructs are scaled to account for potential multicolliniearity and the difference in units of the scales. The constructs were determined using the principal-component factor method for an exploratory factor analysis. Factor loadings above .55 were included within each construct. The tables illustrating the variables and factor loadings can be found in the Appendix.

In dark blue are the demographic variables that have similar causal paths. Degree is capturing an individual's highest degree attainment and is measured with six categories (i.e., 0 = no college degree, 1 = Associate's degree, 2 = Bachelor's Degree, 3 = Master's degree, 4 = Education Specialist Degree, 5 = high-level professional degree). Race is measured with seven categories (i.e., 1 = White Non-Latinx, 2 = Black, 3 = American Indian, 4 = Asian, 5 = Pacific Islander, 6 = Mixed-Race, 7 = White Latinx). Latinx is a binary variable, where one is individuals of Latinx ethnicity. However, after assessing the variance inflation factor (VIF) for all variable, the VIF for Latinx was greater than 6 and was dropped from the model. When the VIF is over 5, there is a stronger risk for multicollinearity which would negatively impact my results. In purple is gender, which is also a binary variable where one is females and zero is males.

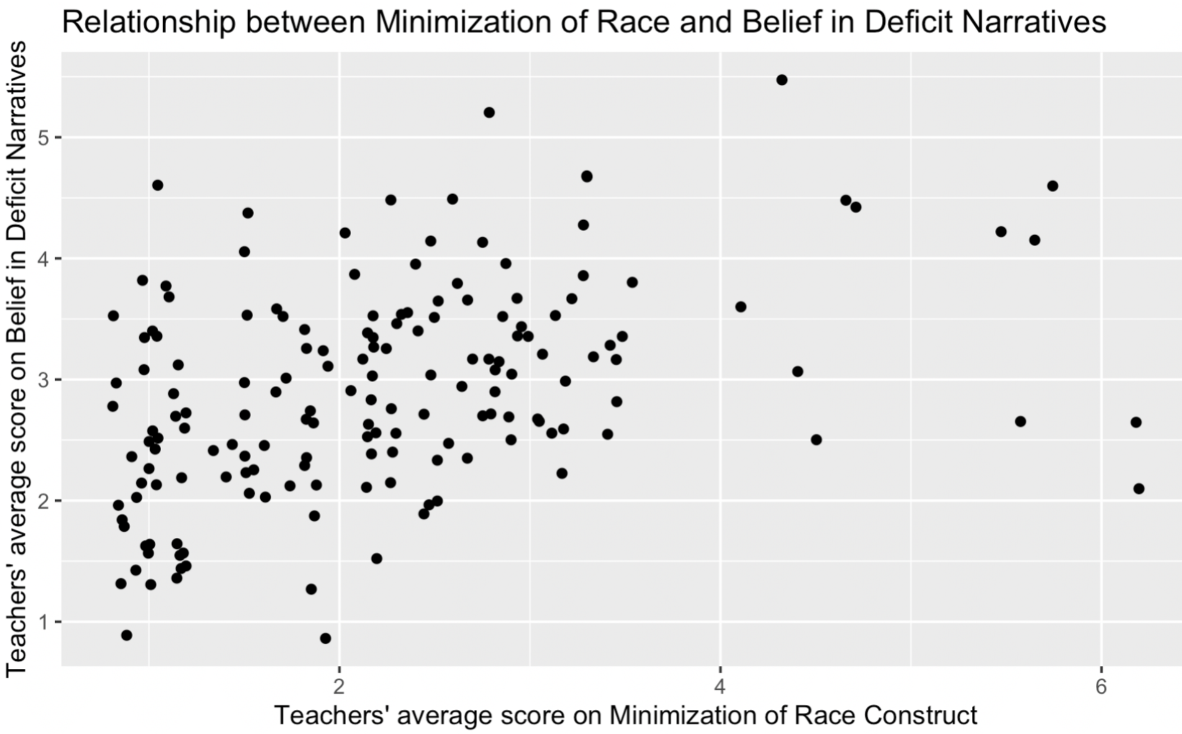
In blue is teachers' political ideology. Ideology is measured with seven categories (i.e., 1 = extremely liberal, 2 = somewhat liberal, 3 - lean liberal, 4 = in the middle, 5 = lean conservative, 6 = somewhat conservative, 7 = extremely conservative). In red is the region teacher's grew up in. This is measured with 5 categories (i.e., 1 = Northwest, 2 = Midwest, 3 = South, 4 = West, 5 = Outside of the U.S.).

In pink is two binary variables that also have similar causal paths. These variables measure whether teachers took a race course in either graduate school or undergraduate school. Both of these variables were coded where one means that teacher's did take a race course in either of these settings.

Results

Before running models, I assessed the relationship between the teachers average score for each construct on educational race beliefs and their average score on the construct on deficit narrative beliefs. These graphs use the non-scaled data to make the discussion of these graphs easier to interpret in the context of average scores for each construct; however, within the model the variables that use constructs are scaled so that the mean is equal to zero.

Minimization of Race and Belief in Deficit Narratives. First, looking at the relationship between minimization of race and belief in deficit narratives. We can interpret the relationship as: a) a positive linear relationship, or b) a non-linear relationship where the positive relationship begins to slow around the average minimization of race construct score of 4.



Model 1: If we assume the first relationship (a), the model can be expressed in mathematical terms as:

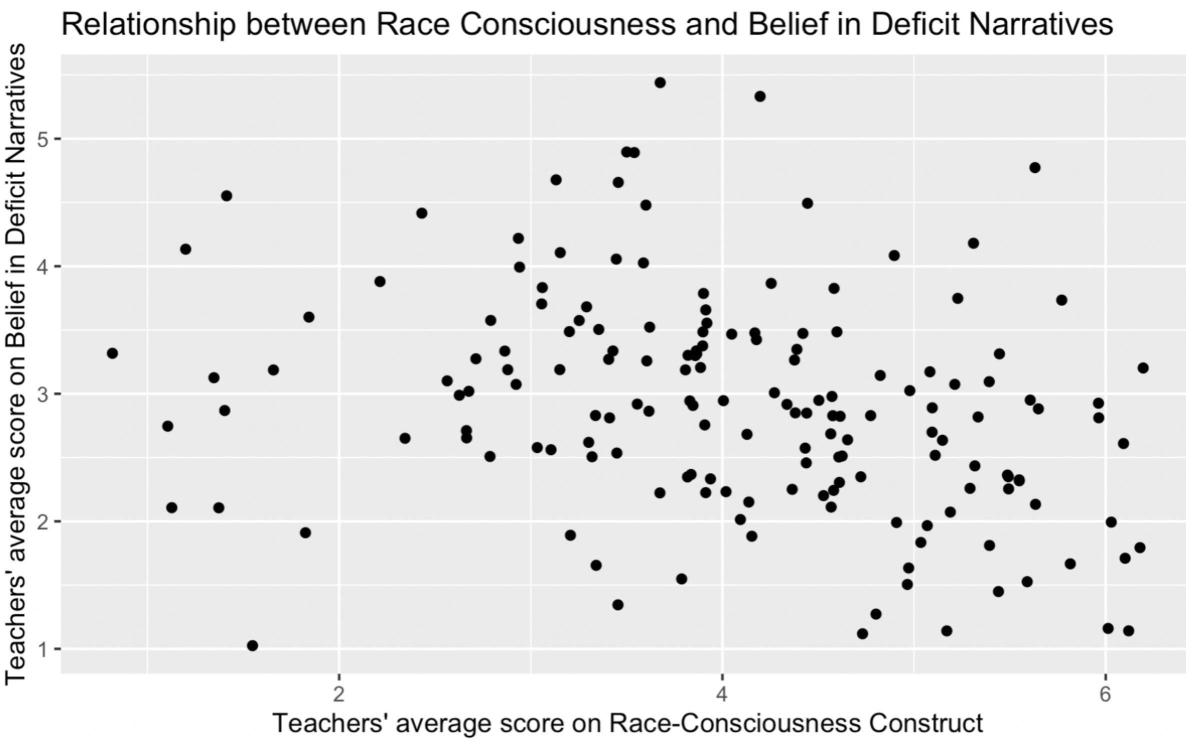
$$\begin{aligned} Deficit = \beta_0 + \beta_1 * edu.minimization + \beta_2 * gen.evasive + \beta_3 * gen.CRT + \beta_4 * belief.test.gaps + \beta_5 * ideology \\ + \beta_6 * gender + \beta_7 * grad.racecourse + \beta_8 * college.racecourse \\ + \beta_9 * degree + \beta_{10} * race + \beta_{11} * regionchild + \epsilon \end{aligned}$$

Model 2: If we assume the second relationship (b), the model can be expresssed in mathematical terms as:

$$\begin{aligned} Deficit = \beta_0 + \beta_1 * edu.minimization + \beta_2 * edu.minimization^2 + \beta_3 * gen.evasive + \beta_4 * gen.CRT \\ + \beta_5 * belief.test.gaps + \beta_6 * ideology + \beta_7 * gender + \beta_8 * grad.racecourse + \\ \beta_9 * college.racecourse + \beta_1 0 * degree + \beta_{11} * race + \beta_{12} * regionchild + \epsilon \end{aligned}$$

The ϵ in each equation is the error term.

Race Consciousness and Belief in Deficit Narratives. Next, looking at the relationship between race consciousness and belief in deficit narratives. We can interpret the relationship as: a) a negative linear relationship, or b) a non-linear relationship where the negative relationship begins slowly and picks up around the average race consciousness score of 4.



Model 3: If we assume the first relationship (a), the model can be expressed in mathematical terms as:

$$\begin{aligned} Deficit = \beta_0 + \beta_1 * edu.conscious + \beta_2 * gen.evasive + \beta_3 * gen.CRT + \beta_4 * belief.test.gaps + \beta_5 * ideology \\ + \beta_6 * gender + \beta_7 * grad.racecourse + \beta_8 * college.racecourse \\ + \beta_9 * degree + \beta_{10} * race + \beta_{11} * regionchild + \epsilon \end{aligned}$$

Model 4: If we assume the second relationship (b), the model can be expresssed in mathematical terms as:

$$\begin{aligned} Deficit = \beta_0 + \beta_1 * edu.conscious + \beta_2 * edu.conscious^2 + \beta_3 * gen.evasive + \beta_4 * gen.CRT \\ + \beta_5 * belief.test.gaps + \beta_6 * ideology + \beta_7 * gender + \beta_8 * grad.racecourse + \\ \beta_9 * college.racecourse + \beta_1 0 * degree + \beta_{11} * race + \beta_{12} * regionchild + \epsilon \end{aligned}$$

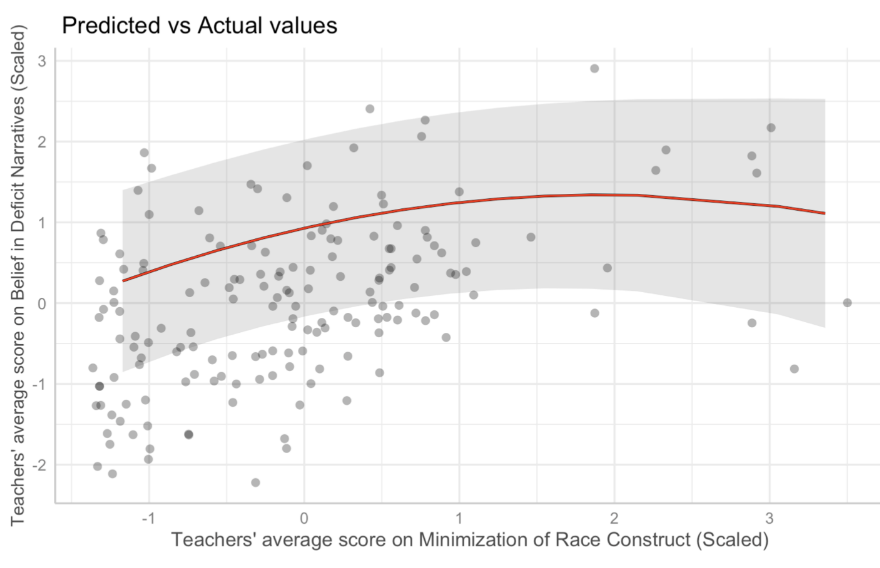
Again, the ϵ in each equation is the error term.

Model Comparison. To compare the models for each education-related race belief construct and the deficit narrative beliefs construct we will assess their goodness-of-fit using Bayesian Information Criterion (BIC). A model with a lower the BIC is preferred because it provides a better balance between model fit and model complexity. Below is a table that shows the BIC for each model.

Model	BIC
M1: ed_minimize	522.23
M2: I(ed_minimize^2)	519.83
M3: ed_conscious	533.75
M4: I(ed_conscious^2)	525.80

Based on the BIC values for each model, I chose to use the models that use the squared term (model 2 and model 4) for my analysis and interpretation.

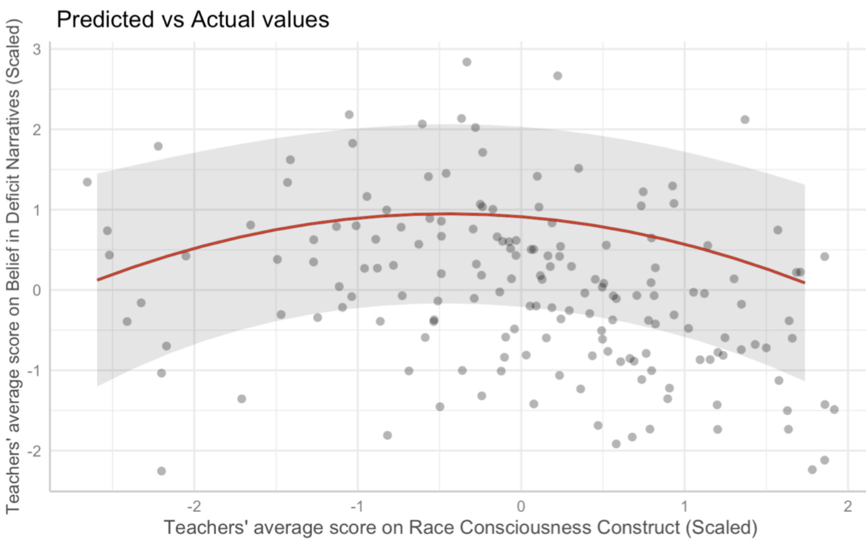
Results from the Model 2. Model 2 estimates the direct effect of teachers' average score on the minimization of race construct on their average score on the deficit narratives construct. Below, on the right, is an abridged version of the model summary that shows the model's estimates of this effect. Since there is a squared term, interpreting this model in words is harder. A loose interpretation of this summary is: a one standard deviation increase in teacher's average score on minimization of race construct results in an increase (in standard deviations) from the mean of the average score on the deficit narratives construct; however, this rate of change is decreasing as we get farther away from the mean. We can see this relationship visually in the graph on the left.



	(1)
(Intercept)	0.928+
	(0.558)
ed_minimize	0.429***
	(0.100)
I(ed_minimize^2)	−0.112*
	(0.044)
Num.Obs.	166
R2	0.448
AIC	429.6
BIC	519.8
Log.Lik.	−185.791
F	4.141
RMSE	0.74

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Results from the Model 4. Model 4 estimates the direct effect of teachers' average score on the race conscious construct on their average score on the deficit narratives construct. Below, on the right, is an abridged version of the model summary that shows the model's estimates of this effect. Since there is a squared term, interpreting this model in words is harder. A loose interpretation of this summary is: a one standard deviation increase in teacher's average score on race conscious construct from the mean results in a decrease (in standard deviations) from the mean of the average score on the deficit narratives construct; however, this negative rate of change decreases the more standard deviations we go from the mean (for the negative values). We can see this relationship in the graph on the left.



	(1)
(Intercept)	0.911
	(0.572)
ed_conscious	−0.162
	(0.104)
I(ed_conscious^2)	−0.180***
	(0.053)
Num.Obs.	166
R2	0.427
AIC	435.6
BIC	525.8
Log.Lik.	−188.776
F	3.814
RMSE	0.75

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Discussion and conclusion

While the increase in belief in deficit narratives for the minimization of race construct and the decrease in belief in deficit narratives of the race conscious construct, both illustrated by the non-squared coefficient are unsurprising. What is more surprising is that these relationships seem *non-linear* in the first place. However, this may be due to the lack of data for the lower average scores for the race conscious construct and the lack of data for the high average scores for the minimization of race construct. In future work, it would be nice to assess this relationship with spline models to better understand the relationship. However, after more data is collected, rerunning these models may also better add to our understaning of the relationship between education-related racial beliefs and beliefs in deficit narratives.

Additionally, I am making a large assumption that the relationship between the education-related race constructs and the deficit narrative constructs are **not** due to a larger "symptom" such as political ideology in our currently polarized environments leading people of certain ideologies to follow certain scripts and beliefs. However, I believe that assessing the relationship between these beliefs is necessary because of the implications deficit beliefs have on teaching practices. Additionally, in future research I plan to access the relationship between deficit narratives and inclusive teaching practices to strengthen this claim.

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Appendix

Factor Loadings for Variables based on Constructs

Table 2.1 Reliability and Factor Structure of Racial Attitudes in the Classroom Subscales from Exploratory Factor Analysis

Racial Beliefs in the Classroom Items	Factor 1a	Factor 2a
1. I don't think of my students in terms of their race or ethnicity.	0.2848	**-0.5851**
2. There is too much emphasis placed on multicultural awareness and training for teachers.	0.5445*	**-0. 6026**
3. Only teachers who work with students from different racial/ethnic backgrounds should have specific training on cultural diversity.	**0.7686**	-0. 1507
4. Adapting course content to students' cultural backgrounds is unnecessary because math is a universal language.	**0.7533**	-0. 3501
5. Taking time to find and include examples of the cultural, historic, and everyday lived experiences of my students distracts from teaching what matters most.	**0.7727**	-0. 1201
6. I feel prepared to have conversations about race in my classroom.	0.2733	0. 5097*
7. Teachers should adapt their teaching to the distinctive cultures of African American, Latina/o/x, Asian, and Native American students.	-0.2209	**0. 8038**
8. Schools should implement specific strategies to ensure that the racial composition of advanced math courses is reflective of their general student body.	-0.2004	**0.7445**
9. Disparities in the racial composition of advanced math courses are about poverty, not race.	0.3683	0.1628
10. Students should always be encouraged to resolve conflicts with each other by finding common ground.	-0.0067	-0.0724
Cronbach's Alpha	0.7535	0.7223

Factor loadings of |.55| and above are bolded. Factor loadings above |.5| are noted with an asterisk.

Factor 1a reflects a mindset leaning towards minimization of race
Factor 2a reflects a mindset leaning toward racial consciousness

Table 2.2 Reliability and Factor Structure of General Racial Attitudes Subscales from Exploratory Factor Analysis

General Racial Belief Items	Factor 1b	Factor 2b
1. People are more likely to come together when we focus on our similarities rather than our differences.	**0.7026**	0.1707
2. It is a problem if people think of themselves mostly as members of groups rather than as individuals.	**0.8129**	-0. 1057
3. Racial/ethnic diversity improves experiences and interactions within schools and classrooms.	-0.1018	**0. 7663**
4. Focusing too much on people's different backgrounds is divisive.	**0.7877**	-0. 3437
5. Talking about racism could open a can of worms, and little good is likely to come of it.	**0.6621**	-0. 3949
6. Racial and ethnic minorities in the U.S. have certain advantages because of the color of their skin.	0.5153*	-0. 3276
7. It is important that people begin to think of themselves as American, not as African American or Mexican American.	**0.7062**	-0. 3160
8. It is important for public schools to teach about the history and contributions of racial and ethnic minorities.	-0.1630	**0.7660**
9. Students in the U.S. should be required to take at least one ethnic studies course to graduate high school.	-0.2193	**0.7589**
10. Everyone who works hard, no matter what race they are, has an equal chance to succeed.	**0.7225**	-0.1485
Cronbach's Alpha	0.7535	0.7223

Factor loadings of |.55| and above are bolded. Factor loadings above |.5| are noted with an asterisk.

Factor 1b reflects a race evasive mindset
Factor 2b reflects a pro-CRT mindset

Table 2.3 Reliability and Factor Structure of Teacher Beliefs in Deficit Narratives from Exploratory Factor Analysis

Teacher Beliefs		Factor
1.	I expect my students to do their best all the time.	0.0391
2.	I am proud of the work I do.	-0.0732
3.	I am going to stay in the teaching profession for as long as I can.	0.1486
4.	The amount a student can learn is primarily related to family background.	**0.7573**
5.	I really can't do much for my students because most of a student's motivation and performance depends on their home environment.	**0.6751**
6.	If I try really hard, I can get through to even the most difficult or unmotivated students.	-0.1847
7.	Whether my students succeed largely depends on the attitudes and habits they bring to class.	**0.5924**
8.	It is not fair to ask students who are struggling to take on challenging academic assignments.	**0.7103**
9.	Aware of the limits of their ability, I give my students assignments I know they can do so they don't become discouraged.	**0.6672**
10.	Students need to have a solid grasp of basic skills before they engage in complex learning tasks.	**0.6240**
11.	Being wrong is a normal and expected part of the learning process.	-0.0230
12.	Students must learn to work through their own self-doubt if they are to succeed.	-0.0334
13.	An important part of my job as a math teacher is to correct students' mistakes.	0.3608
14.	My beliefs about mathematics have no impact on the learning opportunities I provide for my students.	0.0566
	Cronbach's Alpha	0.7643

Table 2.4 Reliability and Factor Structure of Teacher Attitudes of National-Level Math Education Racial Beliefs Subscales from Exploratory Factor Analysis

National-Level Math Education Racial Beliefs	Factor 1
1. Closing racial test score gaps in mathematics	**0.7989**
2. Ending mathematics tracking in U.S. high schools	**0.5857**
3. Providing universal access to Algebra I in middle school	**0.6667**
4. Increasing the share of Black, Latina/o/x, and American Indian students who take advanced math courses, such as Calculus	**0.9080**
5. Increasing the representation of Black, Latina/o/x, and American Indian students in STEM majors and careers	**0.8930**
Cronbach's Alpha	.749

Code

Here is my data where I manipulated variables for the models.

```
library(haven)
library(tidyverse)
library(dplyr)
d1 <- read_dta(paste0("/Users/allysontcameron/Library/CloudStorage/OneDrive-",
               "DukeUniversity/2023/spring 2023/stats/final project info/",
               "NSHsMT Pilot Wave 1 Restricted Data Clean.dta") %>%
  haven::zap_labels()

d1 <- d1 %>%
  select(caseid ,gender, latinx, race_1, race_2, race_3, race_4, race_5,
         degree_1, degree_2, degree_3, degree_4, degree_5, degree_6,
         collegerace_1, collegerace_2, collegerace_3, collegerace_4,
         collegerace_5, racebelief1_1, racebelief1_2, racebelief1_3,
         racebelief1_4, racebelief1_5, racebelief2_1, racebelief2_2,
         racebelief2_3, racebelief2_4, racebelief2_5, racialbeliefs1_1,
         racialbeliefs1_2, racialbeliefs1_3, racialbeliefs1_4,
         racialbeliefs1_5, racialbeliefs2_1, racialbeliefs2_2,
         racialbeliefs2_3, racialbeliefs2_4, racialbeliefs2_5, ideology,
         gradrace, teacherbeliefs1_1, teacherbeliefs1_2, teacherbeliefs1_3,
         teacherbeliefs1_4, teacherbeliefs1_5, teacherbeliefs2_1,
         teacherbeliefs2_2, teacherbeliefs2_3, teacherbeliefs2_4,
         teacherbeliefs2_5, teacherbeliefs3_1, teacherbeliefs3_2,
         teacherbeliefs3_3, teacherbeliefs3_4, q255_1, q255_2, q255_3,
         q255_4, q255_5, regionchild) %>%
  mutate(latinx = if_else(latinx == 2, 0L, 1L))

# create multi-race variable
d1 <- d1 %>%
  mutate(race_6 = case_when(
  race_1 == 1 & race_2 == 1 & race_3 == 1 & race_4 == 1 & race_5 == 1 ~ 1,
  race_1 == 1 & race_2 == 1 & race_3 == 1 & race_4 == 1 ~ 1,
  race_1 == 1 & race_2 == 1 & race_3 == 1 & race_5 == 1 ~ 1,
  race_1 == 1 & race_2 == 1 & race_4 == 1 & race_5 == 1 ~ 1,
  race_1 == 1 & race_3 == 1 & race_4 == 1 & race_5 == 1 ~ 1,
  race_2 == 1 & race_3 == 1 & race_4 == 1 & race_5 == 1 ~ 1,
  race_1 == 1 & race_2 == 1 & race_3 == 1 ~ 1,
  race_1 == 1 & race_2 == 1 & race_4 == 1 ~ 1,
  race_1 == 1 & race_2 == 1 & race_5 == 1 ~ 1,
  race_1 == 1 & race_3 == 1 & race_4 == 1 ~ 1,
  race_1 == 1 & race_3 == 1 & race_5 == 1 ~ 1,
  race_1 == 1 & race_4 == 1 & race_5 == 1 ~ 1,
  race_2 == 1 & race_3 == 1 & race_4 == 1 ~ 1,
  race_2 == 1 & race_3 == 1 & race_5 == 1 ~ 1,
  race_2 == 1 & race_4 == 1 & race_5 == 1 ~ 1,
  race_3 == 1 & race_4 == 1 & race_5 == 1 ~ 1,
  race_1 == 1 & race_2 == 1 ~ 1,
  race_1 == 1 & race_3 == 1 ~ 1,
  race_1 == 1 & race_2 == 1 ~ 1,
  race_1 == 1 & race_3 == 1 ~ 1,
  race_1 == 1 & race_4 == 1 ~ 1,
```

```r
  race_1 == 1 & race_5 == 1 ~ 1,
  race_2 == 1 & race_3 == 1 ~ 1,
  race_2 == 1 & race_4 == 1 ~ 1,
  race_2 == 1 & race_5 == 1 ~ 1,
  race_3 == 1 & race_4 == 1 ~ 1,
  race_3 == 1 & race_5 == 1 ~ 1,
  race_4 == 1 & race_5 == 1 ~ 1,
  TRUE ~ 0))
#degree variable
d1 <- d1 %>%
  mutate(degree = case_when(
    degree_1 == 1 ~ 1,
    degree_2 == 1 ~ 2,
    degree_3 == 1 ~ 3,
    degree_4 == 1 ~ 4,
    degree_5 == 1 ~ 5,
    degree_6 == 1 ~ 0
  ))
# race course variable
d1 <- d1 %>%
  mutate(collegerace = case_when(
    collegerace_1 == 1 ~ 1,
    collegerace_2 == 1 ~ 1,
    collegerace_3 == 1 ~ 1,
    collegerace_4 == 1 ~ 1,
    collegerace_5 == 1 ~ 0))
# finishing race variable
d2 <- d1 %>%
  filter(race_6 != 1) %>%
  mutate(race_7 = if_else(latinx == 1 & race_1 == 1 & race_2 != 1 &
                          race_3 != 1 & race_4 != 1 & race_5 != 1, 1L, 0L),
         race_1a = case_when(
           race_7 == 1 ~ 0,
           race_7 == 0 & race_1 == 1 ~ 1,
           TRUE ~ race_1))
  # adding all race variables together in one variable a
d4 <- d2 %>%
  mutate(race = case_when(
    race_1a == 1 ~ 1, # white, non-Hispanic
    race_2 == 1 ~ 2,
    race_3 == 1 ~ 3,
    race_4 == 1 ~ 4,
    race_5 == 1 ~ 5,
    race_7 == 1 ~ 7)) # Hispanic, white
d3 <- d1 %>%
  filter(race_6 ==1) %>%
  mutate(race = case_when(
    race_6 == 1 ~ 6))

# finalizing most messed with variables
d <- bind_rows( d3, d4) %>%
  select(caseid, gender, latinx, race, degree, collegerace, ideology,
         racebelief1_2, racebelief1_1, racebelief1_3, racebelief1_4,
```

```
         racebelief1_5, racebelief2_1, racebelief2_2, racebelief2_3,
         racebelief2_4, racebelief2_5, racialbeliefs1_1, racialbeliefs1_2,
         racialbeliefs1_3, racialbeliefs1_4, racialbeliefs1_5,
         racialbeliefs2_1, racialbeliefs2_2, racialbeliefs2_3,
         racialbeliefs2_4, racialbeliefs2_5, gradrace, teacherbeliefs1_1,
         teacherbeliefs1_2, teacherbeliefs1_3,
         teacherbeliefs1_4, teacherbeliefs1_5, teacherbeliefs2_1,
         teacherbeliefs2_2, teacherbeliefs2_3, teacherbeliefs2_4,
         teacherbeliefs2_5, teacherbeliefs3_1, teacherbeliefs3_2,
         teacherbeliefs3_3, teacherbeliefs3_4, q255_1, q255_2, q255_3,
         q255_4, q255_5, regionchild)
```

This is the variable manipulation for construct variables.

```
  # first, let's reverse scales for negative values in construct
d <- d %>%
  mutate(racebelief1_1r = case_when(
    racebelief1_1 == 6 ~ 1,
    racebelief1_1 == 5 ~ 2,
    racebelief1_1 == 4 ~ 3,
    racebelief1_1 == 3 ~ 4,
    racebelief1_1 == 2 ~ 5,
    racebelief1_1 == 1 ~ 6
    ),
    racebelief1_2r = case_when(
      racebelief1_2 == 6 ~ 1,
    racebelief1_2 == 5 ~ 2,
    racebelief1_2 == 4 ~ 3,
    racebelief1_2 == 3 ~ 4,
    racebelief1_2 == 2 ~ 5,
    racebelief1_2 == 1 ~ 6
    ))

# create new variables with the average of the variables within each construct
# this should give us each teacher's average score for each construct.
d <- d %>%
  mutate(unscaled_ed_minimize = rowMeans(d[, c("racebelief1_3",
                                               "racebelief1_4",
                                               "racebelief1_5")]),
         ed_minimize = unscaled_ed_minimize %>%
           scale() %>%
           as.vector(),
         unscaled_ed_conscious = rowMeans(d[, c("racebelief1_1r",
                                                "racebelief1_2r",
                                                "racebelief2_2",
                                                "racebelief2_3")]),
         ed_conscious = unscaled_ed_conscious %>%
                                  scale() %>%
           as.vector(),
         # adjustments
         gen_evasive =  rowMeans(d[, c("racialbeliefs1_1", "racialbeliefs1_2",
                                       "racialbeliefs1_4",
                                       "racialbeliefs1_5","racialbeliefs2_2",
```

```
                                        "racialbeliefs2_5" )]) %>%
                                   scale () %>%
                                   as.vector(),
          gen_CRT = rowMeans(d[, c("racialbeliefs1_3", "racialbeliefs2_3",
                                   "racialbeliefs2_4")]) %>% scale() %>%
                              as.vector(),
          poc_math = rowMeans(d[, c("q255_1", "q255_2", "q255_3", "q255_4",
                                   "q255_5")]) %>%
            scale() %>%
            as.vector()) %>%
  select(caseid, female, latinx, race, degree, collegerace, ideology, gradrace,
         teacherbeliefs1_1, teacherbeliefs1_2, teacherbeliefs1_3,
         teacherbeliefs1_4,
         teacherbeliefs1_5, teacherbeliefs2_1, teacherbeliefs2_2,
         teacherbeliefs2_3, teacherbeliefs2_4, teacherbeliefs2_5,
         teacherbeliefs3_1, teacherbeliefs3_2,teacherbeliefs3_3,
         teacherbeliefs3_4, ed_minimize, ed_conscious, gen_evasive,
         gen_CRT, poc_math, regionchild, unscaled_ed_minimize,
         unscaled_ed_conscious) %>%
  drop_na()
# outcome variable

d <- d %>%
  mutate(unscaled_deficit = rowMeans(d[, c("teacherbeliefs1_4",
                                           "teacherbeliefs1_5",
                                           "teacherbeliefs2_2",
                                           "teacherbeliefs2_3",
                                           "teacherbeliefs2_4",
                                           "teacherbeliefs2_5" )]),
         deficit = unscaled_deficit %>%
           scale () %>%  as.vector ()) %>%
  select(caseid, female, latinx, race, degree, collegerace, ideology, gradrace,
         ed_minimize, ed_conscious, gen_evasive, gen_CRT, deficit,
         poc_math, regionchild, unscaled_ed_minimize, unscaled_ed_conscious,
         unscaled_deficit) %>%
  # also making categorical variables factors
   mutate(degree = as.factor(degree),
         race = as.factor(race),
         ideology = as.factor(ideology),
         female = as.factor(female),
         latinx = as.factor(latinx),
         collegerace = as.factor(collegerace),
         gradrace = as.factor(gradrace),
         regionchild = as.factor(regionchild))
```

Here is my code for creating the models.

```
# models for minimization of race mindset construct
m1 <- glm(deficit ~ ed_minimize + gen_evasive + gen_CRT + poc_math +
            ideology + female + gradrace + collegerace + degree + race  +
             regionchild,
          data = d,
          family = gaussian(link = "identity"))
```

```r
m2 <- glm(deficit ~ ed_minimize + I(ed_minimize^2) + gen_evasive +
            gen_CRT + poc_math + ideology + female + gradrace + collegerace +
            degree + race  + regionchild,
          data = d,
          family = gaussian(link = "identity"))
# models for race conscious mindset construct

m3 <- glm(deficit ~  ed_conscious + gen_evasive + gen_CRT + poc_math +
          ideology + female + gradrace + collegerace + degree + race +
           regionchild,
          data = d,
          family = gaussian(link = "identity"))
m4 <- glm(deficit ~ ed_conscious + I(ed_conscious^2) + gen_evasive +
          gen_CRT + poc_math + ideology + female + gradrace + collegerace +
            degree + race + regionchild,
          data = d,
          family = gaussian(link = "identity"))
```

Here is my assessment of multicollinearity.

```r
library(car)
# minimization of race
vif(m2)
# race consciousness
vif(m4)
```

Here is my model comparison.

```r
# model comparison for minimization of race mindset construct
BIC(m1, m2)

# model comparison for race conscious mindset construct
BIC(m3, m4)
```

Lastly, here is the code I used to interpret the models and to visualize the predicted data.

```r
# model summaries
modelsummary::msummary(m2, stars = TRUE,
                       coef_omit = "^(?!.*Intercept|.*ed_minimize)")
modelsummary::msummary(m4, stars = TRUE,
                       coef_omit = "^(?!.*Intercept|.*ed_conscious)")

# visualization of predictions
library(ggeffects)
theme_set(theme_light(base_family = "Avenir"))
# for minimization of race
ggpredict(m2, terms = "ed_minimize") %>% plot(add.data = TRUE) +
  geom_line(color = "red") +
labs(x = "Teachers' average score on Minimization of Race Construct (Scaled)",
       y = "Teachers' average score on Belief in Deficit Narratives (Scaled)",
        title = " Predicted vs Actual values") +
  theme(axis.title.y = element_text(size = 10))
```

```r
# for race consciousness
ggpredict(m4, terms = "ed_conscious") %>% plot(add.data = TRUE) +
  geom_line(color = "red") +
labs(x = "Teachers' average score on Race Consciousness Construct (Scaled)",
       y = "Teachers' average score on Belief in Deficit Narratives (Scaled)",
        title = " Predicted vs Actual values") +
  theme(axis.title.y = element_text(size = 10))
```