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Trajectories of Academic Achievement in High Schools: Growth Mixture Model

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Abstract

The current study investigated patterns of growth in academic achievement trajectories among American high school students (N = 12,314) that were obtained from a nationally representative, public-use dataset (the High School Longitudinal Study of 2009) in relation to key demographic information (*i.e.*, gender, grade level, socioeconomic status [SES] in ninth grade, and ethnicity) and a distal outcome (*i.e.*, applying for college). Unconditional growth mixture model showed that the three-class model was most appropriate in capturing the latent heterogeneity (*i.e.*, low-achieving/increasing, moderate-achieving/decreasing, and high-achieving/slightly increasing). Two covariates (*i.e.*, gender and SES in ninth grade) were positively associated with the intercept growth factor (*i.e.*, initial GPA) in two of the three achievement classes (*i.e.*, high-achieving and moderate-achieving). In contrast, two other covariates (*i.e.*, Hispanic and African American) were negatively associated with the intercept growth factor in all of the achievement classes. The multinomial logistic regression coefficients identified an increase in the likelihood of belonging to the following achievement classes: (1) Moderate-achieving, if the students were male or African American and of low SES, (2) Low-achieving, if the students were male and of low SES, and (3) High-achieving, if the students were female and of an ethnicity other than African American and high SES. The probability of not applying for college was higher among the low-achieving and the moderate-achieving classes compared with the high-achieving class (223 words).

Keywords: Academic achievement trajectory, Growth modeling, Applying for college, High school

1. Introduction

Academic achievement, as measured by grade point average (GPA), is an indication of academic success and the achievement of pedagogical goals. GPA also can affect high school graduates' career choices and their ability to enroll in college. It has been well documented in the literature that growth in academic achievement varies among students during high school and that students maintain heterogeneous GPA growth trajectories across their four years of schooling (Bowers & Sprott, 2012; Hodis, Meyer, McClure, Walkey, & Weir, 2011; Lee & Rojewski, 2013; Muthén, 2008), resulting in the grouping of these students into distinct latent achievement classes. For example, some students may start with modest level and show a linear increase, others may have a high initial status and display a constant growth, and others may hold relatively average initial status and perform poorly over time, becoming part of the disengaged students who are more likely than their peers to drop out of school (Muthén, 2008). A considerable heterogeneity in the intercept growth factor (*i.e.*, initial status) and the slope growth factor (*i.e.*, change in GPA over time) is apparent from this example. Failure to account for such latent heterogeneity results in misleading conclusions and biased findings (J. Wang & X. Wang, 2012). Heterogeneity also was identified in the shape of academic growth (*i.e.*, linear or nonlinear). Previous studies have yielded inconsistent results about the exact shape of academic growth, particularly during the four years of high school. While some studies have found evidence of linear growth (Bowers & Sprott, 2012), other studies have shown support for nonlinear (*e.g.*, quadratic; Choi, Elicker, Christ, & Dobbs-Oates, 2016).

The value of modelling these latent achievement classes (as measured by GPA growth) is their ability to predict a distal outcome (*i.e.*, applying for college); however, many other student-related covariates are associated with a student's decision to enroll in college. For example, a recent study showed that students with a high GPA but low socio-economic status (SES) had a lower rate of completing the college admissions process (Sackett et al., 2012). An additional support has been highlighted in the recent Education Pay report, substantiating the association between SES and college enrollment in the United State (Ma, Pender, & Welch, 2016). According to the report, 82% of students in the high-income quintile (above $100,010) applied for and enrolled in college. In contrast, 58% of the students in the lowest SES quintile (*i.e.*, below $20,582) enrolled in college. It is controversial to observe how contextual variables (in this case, SES) contribute in projecting students' future academic paths, despite they are not under the students' control. Researchers also have found that other demographic variables(*i.e.*, gender and ethnicity) are not only associated with whether students decide to enroll in college but also are predictive of latent class structures based on the latent heterogeneity of GPA growth (Bowers & Sprott, 2012; Gottfried, Nylund-Gibson, Gottfried, Morovati, & Gonzalez, 2017; Hodis et al., 2011).

The High School Longitudinal Study of 2009 (HSLS:09) from the U.S. Department of Education is one of several recent national datasets that have examined the above-mentioned variables(*i.e.*, ninth to twelfth grades GPA, applying for college and demographics such as gender, SES, and ethnicity) among Millennials (born between 1981 and 1996) and Generation Z (born since 1997) high school students (Duprey et al., 2018). Analyzing this dataset provides the opportunity for capturing brand new insights about achievement growth and its association with college enrollment. The HSLS:09 dataset includes a diverse range of individual (*i.e.*, student-related) variables and contextual variables (*i.e.*, parent-related, teacher-related, and school-related) that influence students' decisions about what to major in in college (Ingels et al., 2011). The current study, however, focused on only three components of the large dataset: (1) Student-related covariates, (2) Academic achievement composite scores, and (3) Applying for college. The study then sought to answer three questions, each of which was related to one of the three components selected from the HSLS:09 dataset: (1) Do high school students exhibit heterogenous GPA growth trajectories, resulting in the formation of distinct latent achievement classes? (2) Do three student-related covariates (*i.e.*, Gender, SES, and ethnicity) correlate with the estimated heterogenous latent achievement classes? and (3) To what extent can applying for college be predicted by the heterogeneity of GPA growth trajectories?

The simultaneous approach of answering these three research questions can be accomplished by Growth Mixture Model (GMM). This can be attributed to the parsimonious and flexible approach of the GMM relative to other traditional methods. Given that, GMM achieves multiple tasks, which are: (1) Estimating the average-level and individual-level of intercept (*i.e.*, initial status) and slope (*i.e.*, change across time) growth factors, (2) Estimating the variability between persons in their growth factors, (3) Forming classes based on the latent heterogeneity, and (4) Substantiating the estimated class-structure by modeling the associations to theory-driven selected covariates and predicting a distal outcome (Muthén, 2008).

A thorough review of the literature in which the GMM was used to analyze GPA growth underscored the relative lack of studies on GPA growth among high school students. Most of the studies examined GPA growth among elementary school students and were limited to math and reading skills. Data for these studies came from the Early Childhood Longitudinal Study (ECLS-K) for kindergarten through eighth grade (Lu, 2016; Palardy & Vermunt, 2010; Wu, Morgan, & Farkas, 2014). Only seven studies modeled the GPA growth among high school students using GMM (Bowers & Sprott, 2012; Gottfried et al., 2017; Hodis et al., 2011; Lee & Rojewski, 2013; Liu & Lu, 2011; Muthén, 2008). Of these seven studies, only one used the HSLS:09 dataset to examine GPA growth (Barr, 2015). This one study, however, used a mediation model rather than the GMM to examine growth in math achievement. The number of estimated achievement class-structure identified by researchers varied among the studies reviewed. Three studies (43%) found a two-class structure (Gottfried et al., 2017; Hodis et al., 2011; Lee & Rojewski, 2013), while two other studies (29%) found a three-class structure (Liu & Lu, 2011; Muthén, 2008). Only one study (14%) showed a four-class structure (Bowers & Sprott, 2012). A clear and consistent conclusion about the patterns of growth (*i.e.*, linear or nonlinear) could not be determined from the literature.

In terms of the covariates examined, all of the reviewed studies, except for one (Liu & Lu, 2011), investigated the effects of the covariates on achievement class-structure. The results of these studies showed that the achievement classes were regressed on various covariates. The most frequently studied covariates can be grouped as follows: (1) Student-related, (2) Family-related, and (3) School-related. The two covariates that most of the studies had in common were gender and SES (Bowers & Sprott, 2012; Gottfried et al., 2017; Hodis et al., 2011; Lee & Rojewski, 2013; Muthén, 2008), although other covariates (*e.g.*, ethnicity, student locale, and negative students' behavior such as being expelled or arrested) also were examined.

The covariates with high or significant predictive values were gender and SES. Gender was a significant predictor of achievement class-structure in four of the studies reviewed (Bowers & Sprott, 2012; Hodis et al., 2011; Lee & Rojewski, 2013; Muthén, 2008). SES was a strong predictor of achievement class-structure in five studies (Bowers & Sprott, 2012; Hodis et al., 2011; Lee & Rojewski, 2013; Muthén, 200). For instance, Bowers and Sprott (2012) found that the high-achieving class (*i.e.*, students who started high school with a high GPA and remained high) included more females and students with high SES, while the low-increasing achievement class (*i.e.*, students who started high school with low GPA and experienced a positive linear growth in GPA) included more males and students with low SES. Other covariates were understudied relative to gender and SES. For example, only two studies examined the association between ethnicity and achievement class structure (Bowers & Sprott, 2012; Muthén, 2008).

For a distal outcome, most of the studies investigated the school drop-out rate (Bowers & Sprott, 2012; Hodis et al., 2011; Muthén, 2008). The current study, however, focused on applying for college as the distal outcome because the aim was to better understand the factors that influence the decision of students (Millennials and Generation Z in particular) in the United States to enroll in college (Henry, Knight, & Thornberry, 2012). The economic, psychological, and social ramifications of not earning a college degree are exacerbated among Millennials. The Pew Research Center (2014), for example, showed that in the United States, the earnings of employees with a high school diploma were $17,500 less than the earnings of employees with a bachelor's degree among Millennials. This disparity in income potentially limits other choices (*e.g.*, healthcare, housing) that Millennials will need to make at some point in their lives. People without a college degree, for example, tend to have a less healthy lifestyle, are more likely to engage in substance abuse and aggressive behavior, and are more likely to suffer from depression (Henry et al., 2012; OECD, 2017). Other ramifications include escalating rates of incarceration (Moretti, 2007).

Therefore, the purpose of this study was three-fold, which includes: (1) Examining the heterogeneity of GPA growth trajectories, (2) Identifying the associations between student-related covariates and estimated heterogenous latent classes, and (3) Predicting the probability of applying for college as a distal outcome by each latent class. These aims were investigated among the recently collected national representative sample of Millennials (HSLS:09) using several GMMs.

2. Literature Review

2.1 Academic Achievement in High School

The level of academic achievement in high school plays a decisive role in the career opportunities available to students in the United States and their ability to become contributing members of society. For example, students who performed poorly in high school are more likely to be unemployed, develop a substance use disorder, and engage in delinquent behavior after graduation (Henry et al., 2012). Li, Lerner, and Lerner (2010) argued that a negative growth trend in academic achievement (*i.e.*, decline) among adolescents in the United States is alarming. This decline in student achievement underscores the need to examine the factors that influence high school students' academic performance and then develop ways to reverse the trend. One important factor to consider is the growth of individual students' GPA over the four years of high school and how an upward trajectory in academic achievement over time can increase students' chances for employment opportunities that offer more than mere subsistence wages and instead can provide some financial security.

Previous studies, however, have shown considerable heterogeneity in students' GPA growth across the four years of high school. For instance, Bowers and Sprott (2012) analyzed the GPA growth among 5,400 high school students who were part of a national longitudinal dataset: The Education Longitudinal Study of 2002. The researchers' findings supported a four-class structure for students' academic achievement: Class 1 (*i.e.*, mid-decreasing [*i.e.*, starting GPA was at a moderate level and declined over time]; 10.8% of the sample), Class 2 (*i.e.*, low-increasing [*i.e.*, starting GPA was at a low level and increased over time]; 13.8% of the sample), Class 3 (*i.e.*, mid-achieving [*i.e.*, starting GPA was at a moderate level and remained relatively constant over time]; 39.7% of the sample), and Class 4 (*i.e.*, high-achieving [*i.e.*, starting GPA was at a high level and remained high over time]; 52.1% of the sample). Classes 2 and 3 (*i.e.*, mid-achieving and low-increasing, respectively) accounted for 91.8% of the students who dropped out of high school. In contrast, Class 4 (*i.e.*, high-achieving) accounted for a considerably smaller percentage of dropouts at 8.2%. Muthén (2008) found similar results when he examined data on 2,757 students in Grades 7 through 10 who were part of the Longitudinal Study of American Youth. Muthén (2008), however, created a three-class structure for growth in GPA: Class 1 (*i.e.*, high-achieving growth; 52% of the sample), Class 2 (*i.e.*, moderate-achieving growth, 28% of the sample), and Class 3 (*i.e.*, low-achieving growth, 19% of the sample). This variability in achievement growth has the potential to affect students' personal and academic outcomes and decisions in the future.

Extensive research has shown that the factors associated with high school students' GPA growth can be grouped into three categories: (1) Student-related (*e.g.*, gender, SES, ethnicity, IQ, and negative behavior), (2) Family-related (*e.g.*, parent education and family SES), and (3)

School-related (*e.g.*, school size, school climate, and student-teacher ratio). Other studies have shown that gender and SES were highly correlated with academic growth and were the most significant predictors of students' achievement class membership. For example, females typically were identified in high-achieving class, whereas males were part of the low- and moderate-achieving classes (Bowers & Sprott, 2012). Hodis et al. (2011) supported this association, finding that the Class 1 (*i.e.*, high-achieving class that characterized by high GPA and graduation from high school with a diploma) contained a larger number of females than other achievement classes. In contrast, most of the students in Class 2 (*i.e.*, showed a steeper decline in GPA) were males. Other researchers have found that high SES is significantly related to greater academic achievement (Barr, 2015) and that students with high SES status were more likely to be classified in high-achieving class to have high aspirations (Lee & Rojewski, 2013). Ethnicity, according to Muthén (2008), was highly correlated with students' achievement class. For example, African American students significantly more likely than students of other ethnicities to be in the low-achieving class. In addition, Bowers and Sprott (2012) revealed that Hispanic students predominated in the mid-decreasing achievement class, while Asian students predominated in the high-achieving class. African American students, on the other hand, were less well represented in the high-achieving class. The current study aimed only to examine the regression coefficients of student-related variables using a simple form of the GMM rather than the multilevel GMM when considering school-related variables.

2.2 College Enrollment in the United States

College enrollment and completion of postsecondary education is identified by four stages (*i.e.*, college preparation, college access, financing college, and college retention; Deil-Amen & Turley, 2007). The current review examined the student-related factors that are identified in the first stage (*i.e.*, academic preparation for college), which typically involves four years of high school. Access to and enrollment in college are determined in large part by high school GPA and standardized test scores (*i.e.*, SAT score) in the United States (Sackett et al., 2012). Other personal and contextual variables, however, also influence students' decision to apply to various colleges and to register at the selected institution. An analysis of outdated national datasets (*e.g.*, the National Education Longitudinal Study of 1988) showed that family income (as a measure of SES), paternal and maternal education levels were associated with students' pursuit of postsecondary education (Akerhielm, 1998). The analysis also showed that females were more likely than males to complete postsecondary education.

From the examination of another old dataset (*i.e.*, the 1990/1994 Beginning Post-Secondary Survey), Stratton, O'Toole, and Wetzel (2006) found that full-time enrollment in college was associated with academic performance in high school, parental education, household characteristics, and economic factors. In contrast, part-time enrollment in college was related to racial and ethnic characteristics. Students who were male and whose parents had less than a formal education and of Hispanic ethnicity were more likely to enroll at an institution of higher education on a part-time basis. These findings mainly highlighted the association between gender, SES, and college enrollment. Other researchers, however, focused on the relationship between ethnicity and postsecondary education. Akerhielm (1998), for example, found that college attendance was the lowest level among Native Americans, African Americans, and Hispanics. In an examination of a predominately African American sample of high school students, Temple (2009) found that the African American students did not apply to college for reasons related to SES, cultural and social capital, family structure, unconstructive expectations, lack of guidance, lack of support, and lack of general college knowledge.

2.3 Study Aim and Research Questions

As has been noted, the literature has pointed out diverse factors that influence high school graduates' decisions of completing higher education and college enrollment. One of the main factors is GPA growth while in high school. Previous studies also place great emphasis on another three student-level covariates (*i.e.*, gender, SES, and ethnicity). These factors (*e.g.*, SES) determine, rather than merely influence, whether students decide to enroll in college and complete the requirements for a degree (Sackett et al., 2012). Previous research also has emphasized the presence of latent heterogeneity in students' academic growth and the formation of multiple latent achievement-classes. Thus, estimating and understanding these classes and their associations with students' decisions to apply to college were necessitated by using a recent national dataset (*i.e.*, the HSLS:09). The goal was to expand the understanding of student-related factors, including GPA growth in high school and student-level demographic data, that are associated with college enrollment among Millennials and Generation Z students (Pew Research Center, 2019).

The GMM is the well-suited approach for investigating GPA growth in the present study for the following reasons. First, the GMM models not only intra-personal changes (*i.e.*, within-person growth) over time and interpersonal growth (*i.e.*, between-persons variability in growth) but also latent heterogeneity with respect to latent growth factors (*i.e.*, latent intercept and slope), resulting in classifying students into classes (Muthén, 2008). In other words, the GMM analyzes a non-normal mixture that comprises several normally distributed sub-populations (*i.e.*, classes). Furthermore, GMM provides a more in-depth representation of the sample's underlying variability that results in the formation of latent classes, which can be predicted by time-invariant covariates (*i.e.*, gender, SES in ninth grade, and ethnicity) and time-varying covariates(*e.g.*, age). None of the latter were examined in the current study. As well, the obtained classes that can predict a distal outcome (*i.e.*, applying for college).

The current present study, therefore, sought to investigate the latent heterogeneity in the GPA growth trajectories among a nationally representative sample of high school students in the United States, controlling for specific background covariates using a conditional GMM (see Figure 1). Two patterns of growth were modeled, including linear and nonlinear growth. To this end, the following questions were addressed:

(1) To what extent do different composite GPA growth trajectories exist during high school (*i.e.*, Grades 9-12) in the U.S.?

(2) To what extent are students' demographic variables (*i.e.*, gender, SES in ninth grade, and ethnicity) associated with estimated latent achievement-classes and GPA growth factors?

(3) Do the estimated latent classes predict high school graduates' decisions to apply to college?

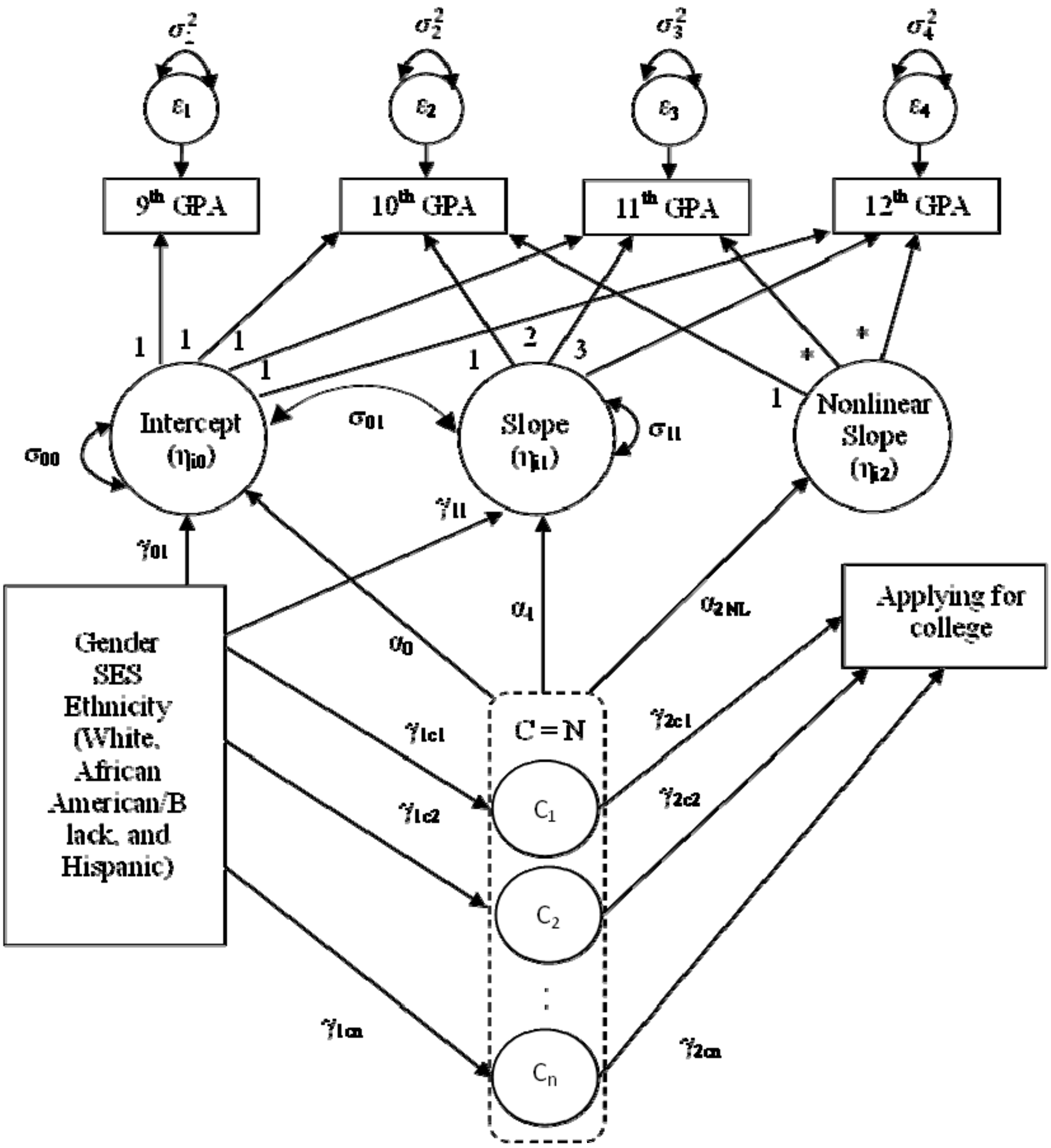

Figure 1. Proposed *N*-class GMM of the high school's academic achievement growth

3. Methods

3.1 Participants

A total of 12,314 high school students were selected from second follow-up phase of a nationally representative, public-use dataset known as the HSLS:09 (Duprey et al., 2018). The HSLS:09 was chosen because it investigates the individual and contextual factors that influence students' decisions regarding their college major (Ingels et al., 2011). The data hold a hierarchical structure. It has been collected using a stratified, two-stage random sample design. The selected subsample was identified after eliminating incomplete responses (*i.e.*, missing data, unit non-response, item legitimate skip, component not applicable, and the student did not attempt). There were 5,911 (48%) males and 6,403 (52%) females. The majority of participants were Whites (n = 10,590). Minority of the participants were Black/African American (n = 1,796) and Hispanic (n = 1,724).

3.2 Measures

The student questionnaire was reviewed in the second follow-up of HSLS:09 public dataset (Duprey et al., 2018). Variables of interest were four waves of academic achievement in Grades 9, 10, 11, and 12 as measured by GPA. Three demographic information were investigated (*i.e.*, gender, SES composite score in ninth grade, and ethnicity). Gender was a dichotomous variable (*i.e.*, 0 = Male and 1 = Female). The ninth-grade SES was computed using three variables (*i.e.*, parent/guardian's education [X1PAR1EDU and X1PAR2EDU], occupation [X1PAR1OCC2 and X1PAR2OCC2], and family income [X1FAMINCOME]). Ethnicity was dummy coded into six groups. Three ethnic groups—White, Black/African American, and Hispanic—were included and dummy coded. The full HSLS:09 dataset recognizes three additional ethnicities (*i.e.*, Asian, Native Hawaiian/Pacific Islander, and American Indian/Alaska native), but information on these groups was not available in the public-access version of the dataset. A dichotomous distal outcome (*i.e.*, 0 = never applied or registered; 1 = applied for college) was examined.

3.3 Data Analysis

Demographic descriptive statistics were examined using the Statistical Package for Social Sciences (SPSS) for Windows Version 24.0. The data were screened (*e.g.*, missing data, normality, and outliers) before the main analyses were conducted (Tabachnick & Fidell, 2007). GMM was used to model the growth trajectories using Mplus 8 (Muthén & Muthén, 2017). To enumerate a correct number of classes, a two-step approach was followed (Muthén, 2004). First, several unconditional GMMs with an increasing number of classes were compared in ordered to select the model with the best class-structure and optimal growth trend (Ram & Grimm, 2009; J. Wang & X. Wang, 2012). In the second step, a conditional model with the best class-structure was fitted, identifying the significant covariates. Simultaneously, applying for college was regressed on categorical latent classes.

Related to the first step, Berlin, Parra, and Williams (2014) suggested conducting some preliminary analyses. That is, a Latent Growth Curve Model (LGCM) was fitted, exploring whether a single class could represent the data. In other words, this model identifies whether there is no significant heterogeneity in the growth factors. Poor model fit and significant growth factor variances reflect a considerable latent heterogeneity, implying the presence of distinctive classes. In a subsequent step, three main models were analyzed (*i.e.*, Latent Class Growth Analysis [LCGA; the within-class variance was constrained to zero], the GMM with class invariant variance and covariance [GMM-CI], and the GMM with class varying variance and covariance terms [GMM-CV]). The three models with an increasing number of classes were examined.

The analytical weights were examined, including sampling and replicate weights (*i.e.*, balanced repeated replication, BRR). The sampling weight (W3W1STUTR) was used because the current study investigated multiple variables that were measured in two phases (*i.e.*, base year and high school transcript update-2013; Duprey et al., 2018). The sampling weights accounted for the variability caused by stratification sampling and legitimate skipping of items, resulting in an accurate parameter estimate. In contrast, the replicate weights (W3W1STUTR 1-200) can estimate precise standard errors. The replicate weights, however, were not included when the data were analyzed with the Mplus software. Mplus allows the inclusion of replicate weights only cases of complex analysis (Type = Complex). The analysis type for the current study was a mixture rather than complex. Furthermore, the sampling weights were eliminated from the analyses when estimating the Likelihood Ratio Tests (LRTs) indices (*i.e.*, LMR, VLMR, and BLRT). Otherwise, sampling weights were used to estimate the model parameters, the Information Criteria (ICs), and entropy indices.

The model parameters were estimated using Maximum Likelihood with an expectation-maximization (EM) algorithm as an optimizing algorithm that is implemented in Robust Standard Errors estimator (ESTIMATOR = MLR). Previous studies have mentioned various convergence issues (*e.g.*, negative variance, local maxima, and improper solutions). Negative variance errors were solved by constraining class variance to zero (Ram & Grimm, 2009). To fix local maxima and improper solutions, one of the suggested solutions was to increase the default number of starting values and the final optimizing iterations (*i.e.*, Mplus default values are 20 and 4, respectively; Hu, Leite, & Gao, 2017; Lubke & Muthén, 2006). For instance, Hu and colleagues (2017) used 400 and 100 for initial values and optimizing iterations, respectively, whereas Kim (2014) used lower numbers for initial values and optimizing iterations (*i.e.*, 200 and 20, respectively). Thus, the current study modified the multiple default GMM analysis options, which were: (1) STARTS = 500, 100, (2) LRTBOOTSTRAP = 50, and (3) LRTSTARTS = 0 0 100 25.

Acknowledging the enumeration issues related to the GMM, several indices were assessed to evaluate the optimal number of achievement classes (*e.g.*, Bauer & Curran, 2003; Chen, Luo, Palardy, Glaman, & McEnturff, 2017; Nylund, Asparouhov, & Muthén 2007; Tofighi & Enders, 2007). These indices belong to the following categories: (1) Information Criteria (ICs), (2) Entropy statistics, and (3) Likelihood Ratio Tests (LRTs). In particular, Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Sample Adjusted BIC (SABIC), Entropy, Lo-Mendell-Rubin test (LMR), Vuong- Lo-Mendell-Rubin Likelihood Test (VLMR), and Bootstrap Likelihood Ratio Test (BLRT) were estimated. Overall, a parsimonious model with the lowest values for *ICs* signals a good fit (Tofighi & Enders, 2007). Entropy values of .40, .60 and .80 indicate poor, medium, and high classification, respectively (Muthén, 2004; Wang & Bodner, 2007). For the LRTs, a significant p-value implies a rejection of the k-1classes' model and, thus, acceptance of the k-class model. Additional considerations were examined during the process of selecting the model with best number of classes, including: (1) Parsimony of the model, (2) Class size (*i.e.*, model with very small classes [< 5%] was rejected), (3) Average posterior probabilities (*i.e.*, the diagonal values in the matrix of average latent class probabilities for most likely latent class membership should be closer to one and ≥ .70; J. Wang & X. Wang, 2012), and (4) Interpretability of each class trajectory as supported by substantive theory (Berlin et al., 2014).

4. Results

4.1 Descriptive Statistics, Correlations, and Assumptions Checking

Descriptive statistics (see Table 1) were examined in addition to outliers (z±2.58). Zero-order Pearson correlation coefficients between the variables were reviewed. The results showed that normality was met for all variables; however, the normality of "applying for college" was accepted based on liberal criteria (< 3 for skewness and < 10 for kurtosis; Kline, 2011). The hypothesized correlations were statistically significant (see Table 2).

Table 1. Descriptive statistics for selected variables (N = 12,314)

Variables	Scale	Sample statistics					
		M	*SD*	Min	Max	Skewness	Kurtosis
1. 9th-grade GPA	continuous	2.97	.78	.25	4.00	-.60	-.22
2. 10th-grade GPA	continuous	2.94	.79	.25	4.00	-.54	-.16
3. 11th-grade GPA	continuous	2.95	.76	.25	4.00	-.64	.04
4. 12th-grade GPA	continuous	3.05	.74	.25	4.00	-.85	.64
5. Gender	dichotomous	1.52	.50	1	2	-.08	-1.99
6. 9th-grade SES	continuous	.18	.79	-1.82	2.57	.29	-.21
7. White	dichotomous	.76	.43	0	1	-1.19	-.57
8. Black/African American	dichotomous	.15	.35	0	1	2.01	2.03
9. Hispanic	dichotomous	.14	.35	0	1	2.08	2.31
10. Applying for college	dichotomous	.92	.28	0	1	-2.99	6.99

Table 2. Pearson correlation coefficients between the selected variables (N = 12,314)

Variables	1	2	3	4	5	6	7	8	9	10
1. 9th-grade GPA	-	.81**	.72**	.65**	.16**	.36**	.07**	-.27**	-.16**	.29**
2. 10th-grade GPA		-	.79**	.69**	.16**	.34**	.08**	-.20**	-.14**	.30**
3. 11th-grade GPA			-	.74**	.16**	.34**	.08**	-.18**	-.13**	.30**
4. 12th-grade GPA				-	.18**	.31**	.10**	-.18**	-.12**	.30**
5. Gender					-	-.03**	.01	.02	.01	.10**
6. 9th-grade SES						-	.07**	-.14**	-.24**	.20**
7. White							-	-.52**	-.02*	-.05**
8. Black/African American								-	-.02	.02*
9. Hispanic									-	-.04**
10. Applying for college										-

Note. $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

4.2 Unconditional Models Results

Following the steps that were recommended by Berlin and colleagues (2014), the LGCM was fitted to the data. The results showed that the LGCM had a relatively poor model fit, as evidenced by the significant Chi-square ($\chi^2[5] = 186.84$; $p < .001$), implying a difference between the sample covariance and the model-implied covariance matrices. RMSEA was .05 (90% confidence interval [CI] = .05 – .06), which supports an acceptable model fit. The SRMR, however, was .07, suggesting a poor model fit. The CFI and the TLI were .97 and .96, respectively. In addition, the variances of growth factors were statistically significant (.58, $p < .001$ and .02, $p < .001$, for intercept and slope growth factors, respectively). These findings implied a significant latent heterogeneity that cannot be captured by a single class.

Next, the LCGA, the GMM-CI, and the GMM-CV with an increasing number of classes were examined (*i.e.*, two-class, three-class, four-class, and five-class models; see Table 3). Two patterns of growth were examined (*i.e.*, linear and nonlinear). The results showed a better fit for freely estimated slopes (*i.e.*, nonlinear growth) relative to linear slopes, thus, nonlinear findings were interpreted. The findings of LCGA suggested that the five-class model had the best fit relative to other LCGA models. Meaning, this model had the lowest AIC, BIC, and SABIC (77242.12, 77390.49, and 77362.93, respectively). The LMR-LRT and the BLRT were significant, supporting the goodness-of-fit for the *k*-class model (*i.e.*, five classes) relative to the *k-1* class model (*i.e.*, four classes). Entropy and average posterior probabilities were ≥ .70, implying high classification accuracy. Lastly, the class sizes were reasonable (*i.e.*, ≥ 5%).

The interpretability of the five classes, however, was questionable (see Figure 2). Meaning, the classes showed relatively similar growth slopes (*i.e.*, increasing to constant slopes) and different intercepts (*i.e.*, average initial values of academic achievement). Previous studies have found at least one class with a decreasing slope (Bowere & Sprott, 2012; Muthén, 2008). Results from a majority of the previous research also substantiated a three-class or four-class structure. These findings contradicted the five-class LCGA model. Previous research also has found that over-extraction of classes occurs more often with LCGA models than it does with other models (*e.g.*, GMM-CI and GMM-CV; J. Wang & X. Wang, 2012). The tendency for over-extraction explains the optimal fit indices for the five-class LCGA model in the current study.

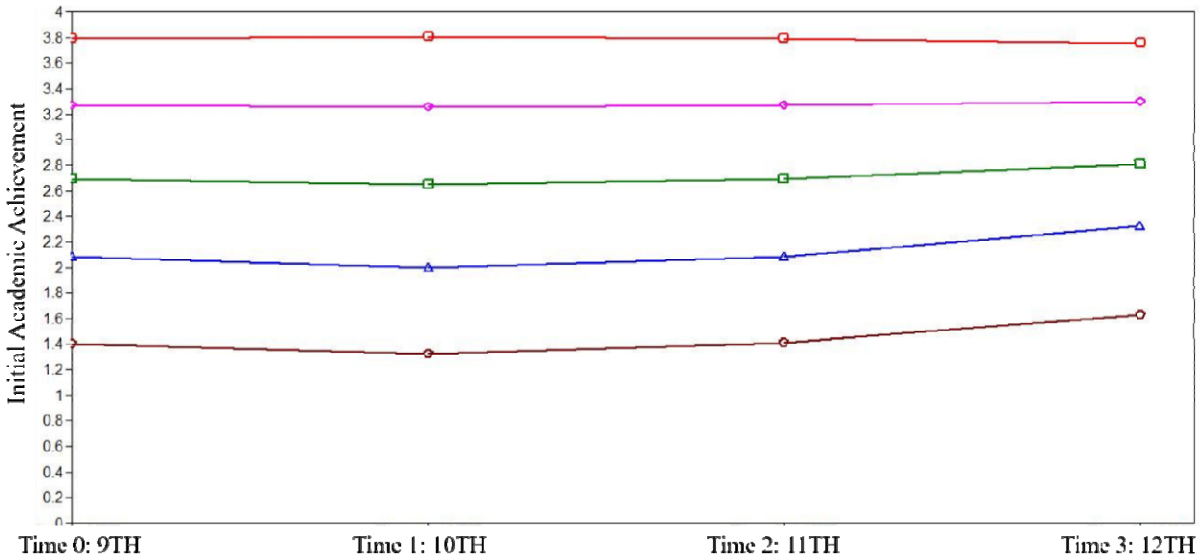

Figure 2. Five-class LCGA with best model fit

Table 3. LCGA, GMM_CI, and GMM_CV models with freely estimated slopes

Fit Statistics	Two-class	Three-class	Four-class	Five-class
A. LCGA				
LL(No. of parameters)	-44831.73(11)	-40733.12(14)	-39198(17)	-38601.06(20)
AIC	89685.46	81494.25	78431.14	**77242.12**
BIC	89767.06	81598.11	78557.25	**77390.49**
SABIC	89732.11	81553.62	78503.23	**77326.93**
Entropy	.88	**.86**	.83	.80
LMR-LRT(*p*)	23243.23(.00)	7917.02(.00)	2964.20(.00)	**1154.17(.00)**
BLRT(*p*)	-56864.65(.00)	-44831.73(.00)	-40733.12(.00)	**-39198.57(.00)**
Group size (%) C1	7690(62%)	2122(17%)	4249(35%)	2709(22%)
Group size (%) C2	4624(38%)	5372(44%)	4036(33%)	1895(15%)
Group size (%) C3		4820(39%)	2928(24%)	3199(26%)

Group size (%) C4			1101(8%)	3909(32%)
Group size (%) C5				602(5%)
B. GMM-CI				
LL(No. of parameters)	-37518.71(14)	-37617.43(17)	-37387.89(20) [a]	-37220.59(23)[a]
AIC	75065.42	**75268.86**	74815.79	74487.19
BIC	75169.28	**75394.98**	74964.17	74657.82
SABIC	75124.79	**75340.95**	74900.61	74584.73
Entropy	.65	**.73**	.75	.74
LMR-LRT(*p*)	2883.45(.00)	**790.48(.00)**	443.38(.00)	323.16(.00)
BLRT(*p*)	-38991.05(.00)	**-38026.66(.00)**	-37617.43(.00)	-37387.89(.00)
Group size (%) C1	4003(33%)	**2222(18%)**	350(2%)	859(7%)
Group size (%) C2	8311(67%)	**8937(73%)**	975(8%)	1274(10%)
Group size (%) C3		**1155(9%)**	3032(25%)	1947(16%)
Group size (%) C4			7957(65%)	372(3%)
Group size (%) C5				7862(64%)
C. GMM-CV				
LL(No. of parameters)	-37790.51(14)[b]	-36687.33(23)[bcd]	-36809.79(26)[bcd]	-36809.79(31)[bcd]
AIC	75609.02	73420.66	73671.59	73681.59
BIC	75712.88	73591.28	73864.48	73911.57
SABIC	75668.39	73518.19	73781.85	73813.06
Entropy	.73	.58	.60	.66
LMR-LRT(*p*)	37484.95(.00)	786.87(.18)	107.04(.28)	.00(.53)
BLRT(*p*)	-56864.65(.00)	-37087.73(.17)	-36864.45(.28)	-36809.79(.53)
Group size (%) C1	9675(79%)	5744(47%)	384(3%)	2920(24%)
Group size (%) C2	2639(21%)	3479(28%)	2920(24%)	384(3%)
Group size (%) C3		3091(25%)	5281(43%)	0(0%)
Group size (%) C4			3729(30%)	5281(43%)
Group size (%) C5				3729(26%)

Note. [a] small latent classes' probabilities. [b] Inadmissible solution (*i.e.*, negative variance). [c] Convergence problems (*i.e.*, local maxima). [d] The model was not normally terminated and the results cannot be trusted.

In comparison, the GMM-CI showed a better fit compared with the LCGA models as indicated by lower values for AIC, BIC, and SABIC and a significant LMR-LRT and BLRT, all of which supports the decision to reject the five-class LCGA model in the current study

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(see Table 4, section B). Of the GMM-CI models, the three-class, four-class, and five-class models were candidates to capture the latent heterogeneity accurately. The four-class and five-class models had the lowest AIC, BIC, and SABIC. The entropy values for the four-class and five-class models were medium (*i.e.*, .75 and .74, respectively). The LMR-LRT and the BLRT were significant, which supports a good model fit; however, the size of the classes and their average posterior probabilities were smaller than the optimal range (*i.e.*, < 5% for both Class 1 in the four-class and Class 3 in the five-class GMM), which suggest a poor classification. In contrast, the three-class model had a smaller AIC, BIC, and SABIC relative to the LCGA model and nearly similar values compared to other GMM-CI models. The finding of a significant LMR-LRT and a significant BLRT in the current study supported the decision to accept the three-class model. In addition, entropy, average posterior probabilities, and class sizes were good. These results suggest that the three-class GMM-CI had the most accurate enumeration (see Figure 3), aligning with previous research findings (Liu, & Lu, 2011; Muthén, 2008).

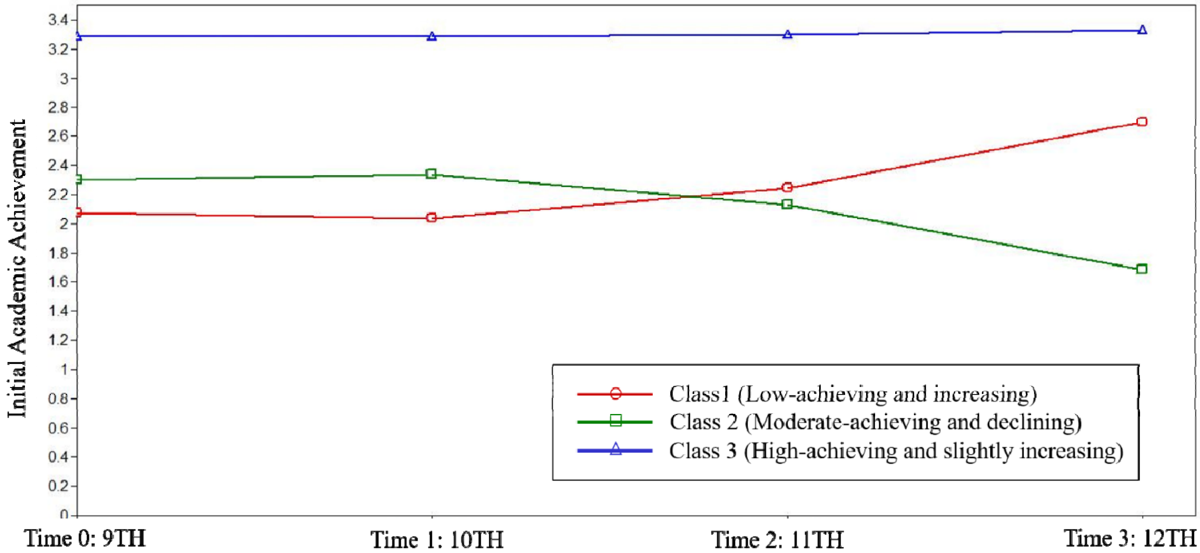

Figure 3. Three-class GMM-CI model

For the GMM-CV, many estimation issues (*i.e.*, negative variance, local maxima, and small E steps in the iteration process) were discovered. The following remedies were among those applied in an attempt to resolve the issues: (1) Fixing the variance to zero in the classes that had non-positive variance, (2) Increasing the initial values and the final optimizations (STARTS), and (3) Increasing the MITERATIONS. Despite the application of these remedies in an exploratory approach, the findings cannot be trusted because the analyses of three-class, four-class, and five-class GMM-CV models were terminated non-normally (see Table 4, section C). Therefore, no further discussion of GMM-CV is provided here.

In regard to the first research question, the findings concluded that the three-class GMM-CI showed the best model fit and had the most accurate class-enumeration. As shown in Table 4, there was significant variability in the intercepts and slopes of the classes. On average, students in Class 1 started with low academic achievement in ninth grade ($\eta_I = 2.07, p < .001, n = 2{,}222$) but increased their GPA during the four years of high school ($\eta_S = .04, p < .01$). Thus, Class 1 was named as "Low-achieving and increasing". Students in Class 2 were moderate achievers in ninth grade ($\eta_I = 2.30, p < .001, n = 1{,}155$) and showed a significant GPA decline over time ($\eta_S = -.04, p < .01$). This class was the most problematic and named as "Moderate-achieving and declining". Lastly, students in Class 3 were relatively highly performs with an average intercept ($\eta_I = 3.29, p < .001, n = 8{,}937$) and showed a very small increase in performance over time ($\eta_S = .003, p < .05$). This class was named as "High-achieving and slightly increasing".

Table 4. The unstandardized parameters of three-class GMM-CI

GMM-CI	Intercept		Slope		Covariance
	Mean	Variance	Mean	Variance	
Class1 (Low-achieving and increasing)	2.07^{***}	$.22^{***}$	$.04^{**}$	.00	$.002^{*}$
Class 2 (Moderate-achieving and declining)	2.30^{***}	$.22^{***}$	$-.04^{**}$	.00	$.002^{*}$
Class 3 (High-achieving and slightly increasing)	3.29^{***}	$.22^{***}$	$.003^{*}$	.00	$.002^{*}$

Note. $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

4.3 Conditional GMM Results

In addressing the second research question, a conditional three-class GMM was used to investigate the associations between four covariates (*i.e.*, gender, Hispanic, African American, and ninth-grade SES) and latent growth factors and between those same covariates and class membership (see Table 5). The conditional three-class GMM also was used to examine the relationship between class membership and applying to college. In Class 1 (*i.e.*, low-achieving and increasing), the variables Hispanic and African American were negatively associated with the intercept growth factor, meaning that Hispanic and African American students had a lower average initial GPA among the students in Class 1. The four covariates were significantly associated with the intercept growth factor among the students in Class 2 (*i.e.*, moderate-achieving and declining) and among the students in Class 3 (*i.e.*, high-achieving and slightly increasing). That is, female students and students with a higher ninth-grade SES had a higher average initial GPA than other members of the same class, whereas Hispanic and African American students had a lower initial ninth-grade GPA than other members of the same class. The four covariates, however, were not significantly associated with change in GPA over time (*i.e.*, slope growth factor) in the three classes. This lack of association implies that the students in all three classes had a similar growth in GPA regardless of their demographic characteristics. Overall, these results suggest that latent class membership moderated the association between the covariates and the within-class intercept growth factor but not the slope factor.

Table 5. Multivariate regression estimates on the intercepts and slopes for the latent classes

	Class 1 (Low-achieving and increasing)	Class 2 (Moderate-achieving and declining)	Class 3 (High-achieving and slightly increasing)
A. Intercept latent factor			
Gender	.07	.18**	.16***
Hispanic	-.15**	-.20**	-.15***
African American	-.31***	-.26***	-.38***
9th-grade SES	.01	.14**	.13***
B. Slope latent factor			
Gender Female	.000	.004	-.001
African American	-.002	-.004	.000
Hispanic	-.001	-.003	-.002
9th-grade SES	-.001	.000	.000

Note. $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

The multinomial logistic regression coefficients identified the likelihood of belonging to a certain latent class relative to a reference class, which was in the case was Class 3 (*i.e.*, high-achieving and slightly increasing). Odds were calculated for the significant coefficients, facilitating the interpretation of the findings (see Table 6; Muthén, 2008). The odds of classification in Class 1 (*i.e.*, low-achieving and increasing) increased by .56 when students were male and by .29 when students had a low ninth-grade SES. The majority of students in Class 2 (*i.e.*, moderate-achieving and declining) were male, African American, and had a low ninth-grade SES. In contrast, the majority of students in Class 3 (*i.e.*, high-achieving and slightly increasing) were female, less African American, more other ethnicity groups (*e.g.*, white), and a high ninth-grade SES.

Table 6. Multinomial logistic regression model estimation of the likelihood of latent class trajectory categorization in comparison to high achieving and slightly increasing as a reference class

	Class 1 (Low achieving and increasing)		Class 2 (Moderate achieving and declining Class)	
	Coefficient	Odds	Coefficient	Odds
Gender	-.58***	.56	-1.03***	.34
Hispanic	-06		.00	
African American	-.15		.41*	1.51
9th-grade SES	-1.24***	.29	-.99***	.37

Note. * $p < .05$, ** $p < .01$, *** $p < .001$.

The third research question addressed the prediction of applying to college (0, never applied or registered; 1, applied or registered) by latent class-structure. The threshold estimates were: -.87, $p < .001$ for Class 1; -.99, $p < .001$ for Class 2; and -4.48, $p < .001$ for Class 3. The probability of not applying to or enrolling in a college for Class 1 was .30, $p < .001$ and for Class 2 was.27, $p < .001$, which are approximately similar. The probability of not applying to college was considerably smaller for Class 3 (.01, $p < .001$).

5. Discussion

The literature has authenticated the latent heterogeneity in high school academic achievement growth, resulting in various classes that could influence differently students' decisions about whether to enroll in college or not. Treating high school students as a homogenous group in terms of their GPA growth may result in biased and inaccurate associations between GPA and applying for college. Most importantly, previous studies have acknowledged the influence of demographic variables (*i.e.*, gender, ninth-grade SES, and ethnicity) in the relationship between GPA growth and applying to college. For the population groups are known as Millennials and Generation Z, a deeper understanding of the associations between these variables and latent-class structure and applying to college was needed. The current study therefore used a recent national dataset, the HSLS:09, to explore these issues. Therefore, the purpose of the study was threefold: (1) Identify the latent heterogeneity and accurately estimate an achievement-class structure, (2) Explore the associations between demographic variables (*i.e.*, gender, ethnicity, and ninth-grade SES) and achievement growth factors, and (3) Predict which students are most likely not to apply to college based on their membership in a particular achievement class. Several GMMs were examined during the study. This section summarizes the findings in sequential order as follows.

Related to identifying latent heterogeneity, one of the promising results of the LGCM showed a significant latent heterogeneity in high school students' academic growth, indicating that Millennials and Generation Z cannot be viewed as a homogenous group. Consequently, a comparison of three models (*i.e.*, LCGA, GMM-CI, and GMM-CV) with an increasing number of classes (*i.e.*, two, three, four, and five classes) was conducted. The results showed that the three-class GMM-CI had the best model fit and the most accurate class-enumeration. The three classes are: (1) Low-Achieving and Increasing Class, (2) Moderate-Achieving and Declining Class, and (3) High-Achieving and Slightly Increasing Class.

Significant differences were identified in the growth factors (*i.e.*, intercept and slope) of the three classes. Meaning, students in three classes had a different initial GPA in ninth-grade and demonstrated different levels of change (either increasing or decreasing) in GPA over time. This achievement class-structure aligns with previous research (Liu & Lu, 2011; Muthén, 2008), which identified three achievement classes (high-achieving, mid-achieving, and low-achieving) among students in middle school and two lower grades in high schools (*i.e.*, Grades 7 through 10; Muthén, 2008). The current study extended this line of research to high school students (Grades 9 through 12) by estimating their initial GPA (*i.e.*, in ninth grade) and freely estimating patterns of GPA growth among those students. The three-class structure that emerged from the current study of older students (*i.e.*, high school), while believed to be valid differs from the four-class structure Bowers and Sprott (2012) identified in their research. They included an additional class (*i.e.*, mid-achieving with constant growth) that was not found in the current study. This contradiction can be attributed to small class size (*i.e.*, < 5% for Class 1 in the four-class GMM) and unacceptable average posterior probabilities (*i.e.*, ≤ .70; J. Wang & X. Wang, 2012) in the current study, suggesting poor classification and resulting in rejecting four-class GMM.

The results of the conditional three-class GMM represent two key findings. First, significant associations were found between theory-driven covariates and the intercept growth factors. The strength of these associations varies across the three latent classes that emerged from the current study. For example, only Hispanic and African American were negatively associated with the intercept growth factors in Class 1 (low-achieving and increasing), while the four covariates associated with the intercept growth factors in the other two classes (*i.e.*, Class 2 and Class 3). Second, no significant associations were identified between the slope growth factor and the selected covariates. Student-related covariates did not moderate the change in GPA over time, which indicates that the students showed an indistinguishable change in GPA over time in the three classes regardless of students' individual characteristics.

With respect to gender, the average initial ninth-grade GPA for females was not significantly different from that of males in Class 1 (*i.e.*, low-achieving and increasing); however, the average initial ninth-grade GPA for females in the other two classes (*i.e.*, Class 2: moderate-achieving and declining and Class 3: high-achieving and slightly increasing) was higher than it was for males. When SES is taken into account, students with a high SES in ninth grade had a higher average initial ninth-grade GPA than their peers with low SES in Class 2 (*i.e.*, moderate-achieving and declining) and Class 3 (*i.e.*, high-achieving and slightly increasing). In contrast, no significant association was found between average initial GPA and ninth-grade SES for students in Class 1 (*i.e.*, low-achieving and increasing).The findings related to gender and SES are consistent with the results of previous studies (Bowers & Sprott, 2012; Gottfried et al., 2017; Hodis et al., 2011; Lee & Rojewski, 2013; Muthén, 2008) in that males and students with lower SES are more likely to begin ninth grade with lower initial academic achievement. Consequently, they were more likely to be classified in the low-achieving class, as shall be discussed shortly. This pattern is applicable among Millennials as supported by the current study.

Additional novel findings related to ethnicity have emerged from the current study, which should help to fill gaps in the literature about the association between ethnicity and GPA growth (Bowers & Sprott, 2012; Muthén, 2008). The current study found, for example, that for all three classes, being Hispanics and/or Black/African American was associated with a low initial average ninth-grade GPA in the three classes. These results add to previous research that investigated only Blacks/African Americans (Muthén, 2008) by showing that Hispanics in all three classes start ninth grade with low academic achievement.

The odds of students being in Class 1 (*i.e.*, low-achieving and increasing) as opposed to the comparison group, Class 3 (*i.e.*, high-achieving and slightly increasing), were higher when the students were male and were in a low SES in ninth-grade. The odds of students being in Class 2 (*i.e.*, moderate-achieving and declining) as opposed to the comparison group increased when students were male, Black/African American, and of a low SES in ninth grade. The majority of students in Class 3 were female. These students were less likely to be Black/African American and more likely to be of some other ethnicity (*e.g.*, white) and to have a high SES in ninth grade. These findings are consistent with the majority of reviewed studies, which showed that gender and SES significantly associated with academic growth in high school (*i.e.*, Barr, 2015; Gottfried et al., 2017; Hodis et al., 2011; Lee & Rojewski, 2013). The current study, however, put a greater emphasis on ethnicity. For example, the odds of a student being in Class 2 (*i.e.*, moderate-achieving and declining) increased by 1.51 if the student was Black/African American. This finding highlights the need for interventions that empower the academic achievement among black/African American students starting from ninth grade and echoes the findings of Davis and Otto (2016), which showed that college enrollment was lowest among Black/African American males relative to other ethnic groups.

Another novel finding from the current study is that achievement-class membership predicted students' attempts to apply for college. That is, the probability of not applying to college was .30 ($p < .001$) for students in Class 1 (*i.e.*, low-achieving and increasing) and .27 ($p < .001$) for students in Class 2 (*i.e.*, moderate-achieving and declining). The probability of not applying to college for students in Class 3 (*i.e.*, high-achieving and slightly increasing) was considerably lower (.01, $p < .001$) relative to the other two classes. These findings add new insights about how high school GPA growth influence college enrollment and students' future outcomes. The literature has covered in-depth the ramifications of dropping out of high school and dropping out of an institution of higher education. Several potential issues face students who choose not to enroll in a college: lower wages (Pew Research Center, 2014); fewer opportunities for well-paid jobs; increased rates of unemployment (Ma et al., 2016); greater likelihood of substance abuse, aggression, depression, misbehavior, and a generally unhealthy lifestyle (OECD, 2017); and escalating rates of imprisonment (Moretti, 2007). For instance, Ma and colleagues (2016) found that smoking rates were higher among high school graduates (26%) compared to college graduates (8%). They also found that college graduates

(69%) included exercise as part of a healthy lifestyle compared to (45%) of high school graduates.

5.1 Implications

The results of the current study shed light on the variability of academic achievement growth among Millennials and Generation Z students using a recent national dataset (HSLS:09). The study also clarified the associations among theory-driven covariates, latent achievement-class structure, and college enrollment. In addition to the abovementioned theoretical implication, the current study addressed many practical implications, suggesting solutions to the ramifications of the well-documented decline in GPA growth among high school students (*i.e.*, Henry et al., 2012; Li et al, 2010) and the tendency of students in certain achievement-classes not to enroll in college (Henryet al., 2012; Ma et al., 2016; Moretti, 2007). Initiatives that strengthen the academic growth of high school students in Class 1 (*i.e.*, low-achieving and increasing) and Class 2 (moderate-achieving and declining) are suggested. Educational interventions are recommended particularly for males, blacks/African Americans, and students of both genders in a low SES. The interventions should focus on empowering the students' academic growth and paving the road for future opportunities related to college enrollment. Specific interventions should target academic outcome (*e.g.*, tutoring, study strategies, and setting productive academic goals) and affective traits (*i.e.*, mentoring, empowering students' self-confidence, teaching motivational techniques including grit and behavioral interventions).

5.2 Limitations

The current study also has several limitations. The current study examined only time-invariant student-related covariates. It also examined only three ethnic groups (*i.e.*, white, black/African American, and Hispanic) because other ethnic groups were suppressed in the public version of the HSLS:09 dataset that served as the basis for the study. This study ignored the third nested level (*i.e.*, repeated measures nested within students and students nested within schools) due to the use of the public version of HSLS:09, which conceals identifiers (IDs) for higher-level units of nesting (*i.e.*, schools; Moerbeek, 2004). That is, contextual information related to school was not examined in the current study. The literature has highlighted other reasons for using GMM rather than a multilevel GMM, which includes: (1) Solving the frequent convergence issues that arise with model estimation even when the model involved is complex and intended to investigate student-related and school-related covariates simultaneously (Van Landeghem, De Fraine, & Van Damme, 2005) and (2) Long computation time during data analysis (Meyers & Beretvas, 2006). The current study conducted the simplest form of GMM available, in keeping with previous studies have done (Bowers & Sprott, 2012; Gottfried et al., 2017; Hodis et al., 2011; Muthén, 2008).

Ignoring a higher level of nested data (*i.e.*, students nested within schools) by conducting GMM and not the multilevel GMM has a trivial impact on the class enumeration (*i.e.*, identifying the correct number of classes) as suggested by one simulation study (Chen, Kwok, Luo & Willson, 2010). This simulation study showed that ignoring the higher nested level of data by using a traditional GMM yielded accurate estimates of fixed effects estimates and regression coefficients. As well, it did not impact the enumeration of achievement classes at the student level; however, the use of the traditional GMM did result in lower classification accuracy, overestimation of observed measurement error variance, and a biased standard error. The students' achievement-classifications in the current study therefore, shall not be used to make direct conclusions about the students' performance, as the current study reveals only a general association between latent class-structure and college enrollment. The ability to generalize the findings of the current study also is limited because records with missing data and records pertaining to students who did not attempt to complete the four repeated measures of GPA were eliminated from the dataset.

Recommended topics for future research include (1) The examination of the effects of time-varying, family-related, and school-related covariates on the heterogeneity of GPA growth trajectories among high school students; (2) The examination of academic achievement growth among other ethnic groups, such as Asian and Native American; (3) The use of a Multilevel Growth Mixture Model to account for the hierarchal structure of the data in national datasets (Chen et al., 2010); (4) The application of missing data treatments, including Full Information Maximum Likelihood and Multiple Imputation (Li & Lomax, 2017); and (5) The implementation of quasi-experimental studies that examine the effectiveness of initiatives to improve academic achievement among males, African Americans, and all students with a low SES.

5.3 Conclusion

The students whose data were used in the study demonstrated significant heterogeneity in their academic growth over the four years of high school, forming three latent classes. The heterogeneity in the initial average GPA was associated with several demographic variables, which increase the odds of classifying students in a certain latent class. The influences of gender, SES, and ethnicity were salient in the three classes but especially in the Class 2 (*i.e.*, moderate-achieving and decreasing class). Simultaneously, the three classes predicted the probability of not applying to college, thus implying the dual influences of demographic variables in relation to the students' academic growth and their decisions about applying to college. The development of appropriate interventions was suggested to mitigate the influences of external demographic characteristics on students' academic growth and provide equitable opportunities for college enrollment. Such interventions can reduce the ramifications of not applying to college and put students on a path to a better future as individuals and as a nation.

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