Effects of Intrinsic and Extrinsic Motivation, Self-Efficacy, and Educational Expectations on Students' Post-Secondary Institutional Choice

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Abstract: The purpose of the present study was to examine the effects of intrinsic and extrinsic motivation, self-efficacy, and educational expectations on post-secondary institutional choices. These choices ranged from two-year institutions, four-year institutions, moderately selective four-year institutions, and highly selective four-year institutions. Restricted data from the nationally representative Education Longitudinal Study (ELS) of 2002 were used for the analysis. Using the ELS questions, 8 motivation constructs (general intrinsic, mathematics intrinsic, reading intrinsic, extrinsic, general academic achievement self-efficacy, mathematics self-efficacy, English self-efficacy, and educational expectations) were hypothesized. Structural equation modeling was used to investigate the direct, indirect and total effects of motivation on post-secondary institutional choice. Multiple group analyses were conducted to examine whether the results of these effects hold true across gender and race. The results indicated that institutional choice was positively influenced by self-efficacy on general academic achievement and mathematics, educational expectations, and reading intrinsic motivation, in addition to the ACT/SAT, GPA, and SES, and negatively influenced by extrinsic motivation. These effects hold true for regardless of students' gender and race.

Keywords: ACT/SAT, College choice, Education Longitudinal Study, GPA, Institutional selectivity, Motivation, SES.

1. INTRODUCTION

Students' academic achievement determines who can enroll in colleges or universities, but their socio-economic status (SES) and motivation factors play a role in determining where a student enrolls. Determining the contribution of motivation variables for students' post-secondary institutional choice is crucial to understanding what steps need to be taken to achieve an educational system that promotes equity rather than the systematic perpetuation of dominance based on SES. The purpose of the present study was to examine how extrinsic motivation (EM), intrinsic motivation (IM), self-efficacy (SE), and educational expectations (EXP) affect students' decisions regarding post-secondary institutional choice (IC) after controlling the effects of academic ability (Scores on the ACT or SAT [will be called "ACT" for simplification unless it is necessary to specify]), academic achievement (GPA), SES, race, and gender.

2. FACTORS THAT AFFECT STUDENTS' POST-SECONDARY INSTITUTIONAL CHOICE

2.1. Benefits of Post-Secondary Education

Greater proportions of Americans are pursuing higher education, but many academically qualified students do not make the transition [1]. The students who were seniors in 2004 indicate that 22% who earned a high school diploma or General Education Development (GED) equivalent had not enrolled at a post-secondary institution by 2006. Overall, 92% of the 2004 senior high school class had graduated with a diploma or had earned a GED, and 70% had enrolled in post-secondary education. However, the percentage of students who attended a post-secondary institution, and whether they attended highly or moderately selective post-secondary institutions, varies by race/ethnicity and increases as family income, parental education, and student educational expectations increase [2].

The various benefits of post-secondary education can be motivating factors for future students. These motivating factors include higher incomes, more fulfilling work environment, better health, longer life, and lower probability of unemployment [3-5]. In 2005, the median high school graduate income was $28,000, as compared to $65,000 for those with a bachelor's degree or higher [6]. Incomes vary by sex, race/ethnicity, and SES, but the income premiums associated with attaining a bachelors degree appears to be comparable [7]. Thus, the return on attaining a bachelor's degree is the same regardless of sex, race/ethnicity, or SES. However, the income premiums associated with attaining a degree increase based upon institutional selectivity [8].

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2.2. Institutional Selectivity

The most frequently defined institutional selectivity is estimated by average test scores of incoming students on standardized tests including the ACT [9]. Further, the most widely used institutional selectivity is the annual report by U.S. News & World Report (USNWR), which is based on the quality of undergraduate education of colleges and universities [10]. Although some studies show little relationship between USNWR rankings and good practices or quality of the education [9,11,12], institutional rankings of colleges and universities in the USNWR and others have a big impact on the public [13]. Student enrollment in a highly selective institution is related to students taking more course examination questions that measure higher-level thinking [14], higher educational attainment and productivity, career success including higher income and higher-status occupations [3,8,10,15-21], higher happiness and life satisfaction [22], more advantageous social networks that may help future careers [23,24], and a better marketplace for potential high-status marriage partners [13,23]. Further, students at highly selective institutions are more academically successful, stimulated and challenged by the interactions with other students in and out of the classroom, and give their professors opportunities to have higher academic expectations and demands [9], and attract more distinguished faculty members [25]. High institutional selectivity is also related to higher institutional expenditure (instructional support, academic support, and institutional grants) and higher retention and graduation rates [11,26].

In the present study, the criterion variable “choice of first attended post-secondary institution” was recoded to merge “choice not classified, 4-year institution” with “inclusive, 4-year institution” to form a single 4-year institution category. The final institutional choice variable is consisted of the following: 1 = 2-year institution, 2 = 4-year institution, 3 = moderately selective 4-year institution, and 4 = highly selective 4-year institution.

2.3. Effects of Race on Access to Post-secondary Institutions

African American and Hispanic students are less likely than Caucasian and Asian American students to attend college (two or four year), to take the ACT [27], and have lower access to selective institutions [25,28, 29], which is more true for male than female students [23,25]. Above and beyond SES and academic achievement, race influences the type of college a student attends [30]. However, when controlling for SES and academic achievement, an African American student's probability of enrolling in a four-year college or university is 25% higher than that of a comparable Caucasian student. This may suggest that African American students perceive a higher return for attaining a baccalaureate degree or this may be due to affirmative action programs that are more prevalent at four-year colleges [30]. Controlling for costs, benefits, financial resources, and academic ability, both African American and Hispanic students have a higher probability of college enrollment than Caucasian students have; suggesting that the actual lower enrollment rates are due to other things required for college enrollment, particularly test scores, curricular program, and educational expectations [7].

2.4. Effects of SES on Access to Post-secondary Institutions

The affect of race on access to post-secondary institutions is more significant than SES because there exists a gap based on SES in attending post-secondary education regardless of race [31]. SES has a greater effect on post-secondary choice than race, ethnicity, and gender. If low-income students choose to enroll, there is a high likelihood of enrolling in community college [27]. After taking background characteristics, educational expectations, and past academic performance into account, community college enrollment significantly reduces the probability of attaining a bachelor’s degree when compared to four-year institutions [32-35]. Prohibitive costs of selective colleges and universities, and different perceptions of opportunities and knowledge of the educational marketplaces may also explain SES inequality in selecting institutions [23].

Students from lower-SES are likely to attend lower-selectivity institutions and lower-spending institutions. However, academically strong students are likely to attend more selective institutions and higher spending institutions [36]. In an extensive review of literature from the 1960’s to the early 1990’s, Baker and Vélez [37] found that that higher SES allows students greater access to four-year institutions, but the relative importance of SES has decreased and that of academic achievement has increased. After controlling for SES and academic achievement, African American and Hispanic students are more likely than Caucasian and Asian American students to attend colleges [38]. African American and Hispanic Students who took more rigorous coursework and succeeded in those courses, attend more prestigious colleges and universities than

Caucasian students in less challenging courses. This indicates that SES and racial inequalities mostly occur indirectly due to differences in academic achievement [13].

2.5. Effects of ACT on Access to Post-secondary Institutions

SES effects have been further examined compared to effects of scores on standardized tests, including the ACT. Admittance to selective institutions is mostly based on high school GPA and test scores. Almost 90% of four-year institutions require either the ACT or SAT [39], and after high school GPA, these scores are considered the most important factor in the admissions decision. [39,40]. Additionally, four-year institutions are more likely than two-year institutions to place considerable importance on test scores, and highly selective institutions are more likely than less selective ones to heavily weigh test scores in the admission decision [40]. As noted earlier, these academic indicators are used when ranking colleges and universities [41-43].

There is a great deal of controversy regarding the use of ACT and SAT scores as criteria for college and university admission. The controversy revolves around the fact that standardized test scores correlate positively with SES [44]. In an extensive study, Sackett, Kuncel, Arneson, Cooper, and Waters [45] examined whether SES explains the relationship between test scores and post-secondary GPA, and found that SAT scores are positively related to SES (r = .42) and GPA (r = .47). When SES is controlled, the correlation between SAT scores and GPA are only slightly reduced, r = .47 to r = .44 [45], which indicates that SAT scores are measuring what they claim and are independent of the influence of SES.

According to their respective organizations, the ACT and SAT are assessment tests to evaluate previous learning [46,47]. However, they are used to predict the ability to succeed academically in college. Recent studies have examined their relationship to the theoretical factor of "g" [48-50]. The g factor is a latent construct representing variance common to many cognitive tests. How a test loads on the g factor directly relates to its predictive validity [51]. The factor loadings indicated that the ACT [48,50] and SAT [48,50] are highly related to g, which is also highly related to IQ. This suggests that the ACT and SAT could be used to estimate IQ, and the theoretical conceptualization of the ACT and SAT as indicators of ability is consistent with the theoretical framework of the present study, primarily to distinguish them from the academic achievement variable of GPA.

2.6. Effects of Motivation on Access to Post-secondary Institutions

Motivation is the driving force that causes people to achieve goals and is a key factor in learning as well as in achievement [52]. This may affect students achieving the goal of post-secondary education and institutional choice. Social cognitive models stress that people are motivated in multiple ways, and it is important to understand how and why people are motivated. One of the primary assumptions of social cognitive theory is that motivation is contextual. Therefore, not only are people motivated in multiple ways, but also their motivation varies according to the situation or context of the task. This means that motivation is a situationally sensitive construct and changeable [53,54]. Thus, understanding various motivation factors can be helpful to encourage them. The motivation factors for achieving the goal of post-secondary education and institutional choice can be made up of many factors including, extrinsic motivation (EM), intrinsic motivation (IM), self-efficacy (SE), and educational expectations (EXP).

2.6.1. EM, IM, and amotivation

IM is engaging in actions for their own sake without coercion, whereas EM is engaging in actions for external rewards, in which the activity is a means to an end [54]. In other words, IM is when you do something because you want to, and EM is when you do something because in order to get something you want, you have to. Ryan and Deci's self-determination theory [55] illustrates EM on one end, EM in the middle, and amotivation on the other end: On the IM end of the continuum, an activity is pursued because of an inherent desire for learning or interest or enjoyment of content. Within the EM area of the continuum, activities are engaged in to avoid punishment, gain rewards, prove self-worth, or gain self-esteem through achievement. On the amotivation, or lack of motivation, end of the continuum, there is no perceived connection between effort, goals, or purposes. This theory embraces the idea that motivation, or lack thereof, springs from self-interest. The extent to which an individual self-regulates to participate in achievement related behavior is directly related to their perceived amount of self-determination in pursuing their goal [55].

Previous research has concluded that IM can foster students' learning and achievement better than EM [54]. EM is positively related to students' reading fre-

quency [56] but it is negatively related to students' amount of reading after controlling for IM [57]. Additionally, EM is negatively related to text comprehension [57] and to students' reading achievement [58]. Extrinsically motivated students may exert only the minimum behavioral and cognitive effort they need in order to achieve an academic goal [59]. However, EM and IM are not always mutually exclusive [60,61]. Both EM and IM can coexist in one effort, as students can strive for good grades and the feeling of mastering the subject matter [62]. Both of them can also exist sequentially, as students can initially learn for external rewards including getting praise or good grades, but later can internalize the value and importance of learning [63]. Thus, a combination of both EM and IM is more beneficial to learning than either EM or IM alone [57,64].

In the present study, EM consists of the items following: "learns skills for job in school (LSJ); education is important to get a job later (EIJ); studies to get a good grade (SG); studies to increase job opportunities (IJO); studies to ensure financial security (SFS)." These five items were chosen as indicators of EM because each item asks the student about the importance of external rewards associated with academic success.

IM this study includes mathematics IM (MIM), reading IM (RIM), and general IM. GIM is "classes are interesting and challenging." MIM consists of items following: "math is important (MI); gets totally absorbed in math (AM); thinks math is fun (MFUN)." RIM consists of items following: reads in spare time (RST); gets totally absorbed in reading (AR); thinks reading is fun (RFUN). These six items were chosen as indicators of IM because each item asks the student about their inherent desire, interest, and/or enjoyment of content.

2.6.2. SE

Research has shown that SE is positively related to academic performance [65-67]. SE is different from self-esteem in that SE is one's self-perceived ability to successfully perform a specific task, and self-esteem is one's sense of self-worth [53]. SE is also different from confidence in that confidence is one's belief and does not necessarily specify what the certainty is about [68], SE is directly related to achievement in that if students have low SE and perceive that a particular task is too difficult, then they will not be very motivated to perform the task because they foresee failure [69]. Thus, SE influences students' choices, effort, and persistence in that students with low SE tend to put in less effort or give up in difficult situation than students with high SE [70-73]. Students with high SE tend to adopt a deep or strategic approach to studying whereas low SE adopt a surface approach, [74] and set lower goals, persevere less, and are less committed to goals than students with high SE [70-73], which might affect their IC.

In the present study, SE was represented by three latent constructs of MSE, ESE, and GSE with five items per construct. SE includes mathematics SE (MSE), English SE (ESE), and general academic achievement SE (GSE). MSE consists of items following: "can do excellent job on math tests (EJMT); can understand difficult math texts (UDMT); can understand difficult math class (UDMC); can do excellent job on math assignments (EJMA); can master math class skills (MMCS)." ESE consists of items following: "can understand difficult English texts (UDET); can understand difficult English class (UDEC); can do excellent job on English assignments (EJEA); can do excellent job on English tests (EJET); can master skills in English class (MSEC)." GSE consists of items following: "can learn something really hard (LRH); remembers most important things when studies (RMI); can get no bad grades if decides to (GNBG); can get no problems wrong if decides to (GNPW); can learn something well if wants to (LWELL)." These fifteen items were chosen as indicators of MSE, ESE, or GSE because each item asks the student about their perceived ability and to achieve specific tasks of academic success.

2.6.3. EXP related to EM, EX, and SE

EXP is created by assessing the value of education in terms of abilities, past academic performance, ambition, and family situation [75-79). They are formed relatively early [80] and are strongly influenced by parent EXPs [81-83] and SES [75]. The variety of influences that create the EXP make it, in a sense, a construct of the previously mentioned constructs. For instance, SES can act as an EM. Similarly, parental EXP while initially extrinsic in nature can become intrinsic if the child integrates and internalizes those EXP as his or her own. Additionally, the enjoyment of learning or attending school may be intrinsic to the child. Finally, a belief in a student's ability based on past academic performance is his or her SE.

EXP change little after high school graduation and have strong relationships with gender and parents SES [75]. Further, these EXP form as early as the sixth grade [80], and parental EXP are an important factor in determining post-secondary enrollment [81-83]. Kurlaender [27] found that students who have consistently indicated a desire to obtain a bachelor's degree are more likely to begin their post-secondary

education at a four-year institution than at a community college.

ELS 2002 data from the 2004 senior class shows a trend that indicates a relationship between their EXP in the 10th grade and their level of academic attainment two years after their anticipated high school graduation. Of the students whose educational expectation was "high school or less", 26.2% were enrolled in a post-secondary institution. Of the students whose educational expectation was "some college", 48.7% were enrolled in a post-secondary institution. Of the students whose educational expectation was "bachelor's degree", 75.1% were enrolled in a post-secondary institution. Of the students whose educational expectation was "graduate/professional degree", 85.7% were enrolled in a post-secondary institution. Of the students whose educational expectation was "don't know", 55.4% were enrolled in a post-secondary institution [2]. A cursory examination of these percentages reveals a jump in post-secondary enrollment when the students 10th grade EXP were bachelor's degree or higher. At first glance, these percentages seem to indicate that raising EXP will raise post-secondary enrollment. However, the assessment of multiple factors goes into the creation of EXP, and many of these factors (e.g., SES) have effects independent of EXP.

In the present study, because over 50% of the students who indicated "don't know" are enrolled in a post-secondary institution, the expectation variable was recoded: 1 = "Less than high school graduation", 2 = "GED or other equivalency only", 3 = "High school graduation only", 4 = "Don't know", 5 = "Attend or complete 2-year college/school", 6 = "Attend college, 4-year degree incomplete", 7 = "Graduate from college", 8 = "Obtain Master's degree or equivalent", and 9 = "Obtain PhD, MD, or other advanced degree".

2.7. Research Questions

The research questions of the present study were a) to what degree do models with and without the ACT and GPA explain IC?; b) to what degree do GPA, the ACT, SES, EM, IM, SE, and EXP affect IC directly or indirectly?; and c) do the results above hold true across gender and race?

3. METHOD

3.1. Data

The data for this research is from the nationally representative Education Longitudinal Study: 2002 (ELS: 2002), conducted by the National Center for Education Statistics (NCES) with a Restricted Data Use License. The Institutes for Education Statistics (IES), Data Security Office granted the license based upon the proposal for this study. The sampling design of the ELS: 2002 involved a multistage, stratified cluster sample of students including 752 public, Catholic, and other private schools. There are four major data components of ELS: 2002: base-year, first follow-up, high school transcript data, and second follow-up. In the spring of 2002, 15,362 high school sophomores completed the base-year questionnaire. The first follow-up took place in the spring of 2004, when most sample members were seniors in high school, and 15,000 participated. One year after most sample members had graduated high school; transcripts were requested for all sample members who participated in at least one of the first two phases. At least one transcript was collected from 14,900 students. The second follow-up took place in 2006, approximately two years after most sample members had graduated from high school, and 14,200 participated in the second follow-up [84]. Of those, 10,534 reported that they had attended a post-secondary institution within two years of graduation, and these students are the focus of the current investigation. There were missing values before the analyses; all cases with missing values were deleted listwise resulting in 4,210 participants in this study. The final sample has 56.1% female students and 43.9% male students. Race categories were recoded from the original data to merge the following groups "Hispanic, race specified" with "Hispanic, race not specified" to create a single Hispanic category. There were 7.8% African American, 0.3% American Indian/Alaskan Native, 10.4% Asian, 69.6% Caucasian, 7.6% Hispanic, 4.0% more than one race specified, and 0.3% Native Hawaiian/Pacific Islander students in the sample.

3.2. Data Analysis

3.2.1. Structural Equation Modeling

Structural equation modeling (SEM) was conducted using AMOS (version 17) software [85]. SEM was selected as a statistical methodology for this study because of its several advantages over regression modeling. It allows: for complex theoretical structures that include multiple constructs to be tested; for studying multiple independent and mediator variables by examining both their direct and indirect effects; for modeling of error terms; for the reduction of measurement error by having multiple indicators per latent variable; for testing models overall rather than coefficients individually, and testing coefficients across

multiple between-subjects groups; for providing more robust estimates by comparing alternative models to evaluate relative model fit, rather than being susceptible to error of interpretation by misspecification as in regression; and for better model visualization through its graphical modeling interface [86-88]. Therefore, given these benefits, SEM was used to test the measurement models and the structural models, as well as to conduct multiple group analyses in this study.

3.2.2. Assumptions and Estimation Method

Multivariate normality is a common assumption in SEM [86]. The values of univariate and multivariate skewness and kurtosis were examined in order to determine whether each variable was approximately normally distributed. No values of the skewness and kurtosis were greater than |2.0|. Additionally, data was screened for outliers; there were two outliers, but no corrective action was taken because there were no differences in results when the outliers were removed. When the multivariate normality assumption is met, the maximum likelihood (ML) parameter estimates are asymptotically efficient, and the associated ML test statistic is asymptotically chi-square distributed, and converges to its chi-square distribution quickly so that a chi-square approximation works well starting at medium sample sizes [89]. Therefore, because the data met the multivariate normality assumption and there is a large sample size (N = 4210), ML estimation was used for all of the analyses.

3.2.3. Fit Indices

Chi-square tests can be influenced by large sample sizes [90,91]. Because of the large sample size in this study, the χ^2 test may indicate statistical significance for trivial differences between the sample and the reproduced covariance matrices, which results in an erroneous rejection of the model. Therefore, fit indices were also used to evaluate model fit. In evaluating model fit, Hu and Bentler [92,93] suggested the two-index strategy. This includes reporting the Root Mean Square Error of Approximation (RMSEA) [94] or the Standardized Root Mean Square Residual (SRMR) [95], and supplementing it with one of the following: Bentler's Comparative Fit Index (CFI), Tucker-Lewis Fit Index (TLI, Non-Normed Fit Index), Bollen's Incremental Fit Index (IFI) [96], or Relative Non-centrality Index (RNI). Augmenting Hu and Bentler's two-index strategy, a three-index strategy was used in this study: RMSEA, CFI, and TLI. The RMSEA provides a measure of model misspecification, and it is a measure of discrepancy between the sample and the reproduced covariance matrices per degree of freedom. RMSEA values of less than .05 are conventionally considered to indicate an excellent fit, and values up to about .08 are considered an acceptable fit [88], while Hu and Bentler [93] recommended a cutoff close to .06. The CFI compares the covariance matrix predicted by the model to the observed covariance matrix, and compares the null model with the observed covariance matrix. The TLI provides a measure of incremental fit when compared to a null model. CFI and TLI values vary between 0 and 1.0, and values of .95 and above are considered a good model fit [93]. Further, when a comparison between models was made, in addition to χ^2 difference tests, Cheung and Rensvold's suggestion [97] that a difference in CFI of less than or equal to .01 as an indication of invariance was followed.

3.2.4. Two-Step Approach

Kline [88] urged researchers to follow a two-step approach, which is to test the pure measurement model that underlies a full structural equation model first, and if the fit of the measurement model is acceptable, then proceed to the second step of testing the model by comparing its fit with that of different structural models. Following this approach, measurement models were validated first, and structural models were fit later. The former was accomplished through confirmatory factor analysis (CFA), whereas the latter was accomplished through path analysis with latent variables as well as through model comparisons.

3.2.4.1. Measurement Models

The first part of this study was to validate the measurement models. A CFA of the measurement model allows researchers to evaluate whether all items on a particular scale represent the same latent construct [87]. CFAs were conducted to test the fit of the proposed measurement models.

Twenty-six ELS items were entered into the measurement models as multiple indicators to estimate the latent constructs. Items were recoded to ensure a common directionality. Three measurement models were hypothesized: EM was represented by one latent construct with five items. IM was represented by two latent constructs of MIM and RIM with three items per construct, and GIM represented by a single observed item from the data set. SE was represented by three latent constructs of MSE, ESE, and GSE with five items per construct. The factor loadings from EM to "learns skills for job in school"; from MIM to "math is fun"; from RIM to "reads in spare time"; from GSE to "can learn something well if wants to"; from MSE to "can

understand difficult math texts"; and from ESE to "can do an excellent job on English tests" were set to 1.0 to scale each of the latent

3.2.4.2. Structural Models

The second part of this study was to fit structural models. A structural model provides maximum likelyhood estimates of all identified model parameters, and evaluates the degree to which the model reproduces the observed variance–covariance matrix based on a chi-square goodness of fit statistic [98]. Two hypothesized full models that included structural and measurement models were evaluated. The first full model that included the ACT and GPA (Full Model 1) suggested that the latent variables of EM and IM, SE, and SES directly influence EXP, GPA, and the ACT and also directly and indirectly influence institutional choice. Additionally, EXP directly influences GPA and the ACT and directly and indirectly influences IS. GPA directly influences ACT scores and directly and indirectly influences IS. Finally, ACT scores directly influences IS.

Further, in order to examine the unique contribution of EM and IM, SE, and EXP to IC, compared to SES, a second model (Full Model 2) that does not include ACT and GPA was proposed. According to this model, EM and IM, SE, and SES directly influence EXP and directly and indirectly influence IS.

Direct and Indirect Effects. Standardized indirect effects are determined by multiplying the pair of structural paths from independent variables to dependent variables. Bootstrapping is used to test the significance of the indirect effects [99]. Bootstrapping is a preferred method for testing indirect effects in mediation analyses because it provides asymmetric confidence intervals around the estimate [100]. For this study, 10,000 samples were bootstrapped to generate empirically based 95% bias-corrected confidence intervals for the unstandardized indirect effects. Using bias-corrected confidence intervals is preferred to percentile confidence intervals because bias-corrected confidence intervals produce more accurate values [101]. For statistical significance tests, considering the large sample size and multiple tests of statistical significance on the same data of the present study, a conservative statistical criterion ($p < .001$) was used to protect against Type I error.

Multiple Group Analyses Across Gender and Race. The third part of this study was to examine whether the measurement and structural relationships are invariant across gender as well as race. Measurement invariance across gender and race was assessed using multiple-group procedures in which sets of parameter were constrained sequentially in a series of hierarchically nested models. A statistically significant increase in χ^2 values between adjacent models indicates that the cross-group invariance constraints result in a statistically significantly worse fit. This is taken as an indication that the constrained parameters are invariant. However, when a comparison between models was made, in addition to χ^2 difference tests, Cheung and Rensvold's suggestion [35] that a difference of CFI of less than or equal to .01 is an indication of invariance was also followed. A series of nested models were analyzed and compared by examining the differences in CFI values, in addition to changes in model χ^2 values. The first model in this sequence was one in which all model parameters were varied across groups. In the second model, factor loadings were constrained to be equal across groups; in the third model, factor variances and covariance were constrained to be equal; in the forth model, β were constrained to be equal across groups; in the fifth model, structural means were constrained to be equal across groups; and in the final model, structural variances and covariance were constrained to be equal across groups.

4. RESULTS

4.1. Measurement Models

The three measurement models were tested: Model EM with a latent variable, Model IM with the two latent variables of MIM and RIM and the observed variable GIM, and Model SE with the three latent variables of GSE, MSE, and ESE. As Table **1** shows, the results indicated that all of the three models fit the data well:

In Model EM, as Table **1** shows, based on the large sample size, χ^2 (20.80; df = 4) was statistically significant, possibly suggesting a poor fit. However, the low RMSEA (.03) and high CFI (1.00) and TLI (.99) indicated a good fit with the data. The standardized factor loadings ranged from .37 to .86 and were statistically significant, suggesting the items are highly related to their factor.

In Model IM, as Table **1** shows, χ^2 (56.79; df = 5) was also statistically significant, possibly suggesting a poor fit. However, the low RMSEA (.05) and high CFI (1.00) and TLI (.99) indicated a good fit with the data. The standardized factor loadings ranged from .61 to .89 for MIM and from .77 to .88 for RIM, and all were

statistically significant, suggesting the items are highly related to their factors.

In Model SE, as Table **1** shows, χ^2 (704.92; *df* = 80) was also statistically significant, possibly suggesting a poor fit. However, the low RMSEA (.04) and high CFI (.99) and TLI (.98) indicated a good fit with the data. The standardized factor loadings ranged from .80 to .87 for GSE, from .67 to .81 for MSE, and from .77 to .88 for ESE, and all were statistically significant, suggesting the items are highly related to their factors.

Therefore, CFA supported that each model fit the data well, and that the hypothesized constructs measure discrete, single latent variables. Further, the results also provided support for subsequent SEM [88].

4.2. Structural Models

The two hypothesized structural models, a model with ACT and GPA (Full Model 1) and a model without ACT and GPA (Full Model 2), were tested. χ^2 statistics were statistically significant for both of the models (χ^2 = 3470.45; *df* = 410 for Full Model 1; χ^2 = 3106.64.45; *df* = 370 for Full Model 2), possibly suggesting poor fits. However, the low values of RMSEA (.04 for both) and high values of CFI (.96 for both) and TLI (.95 for both) indicated both models fit well with the data.

A χ^2 difference was computed to test the difference in fit between the two models. Table **2** shows fit indices for each model as well as differences in χ^2 and CFI between the two models. The χ^2 difference was statistically significant, suggesting that the Full Model 2 is a better fit than the Full Model 1. However, because χ^2 difference tests could be influenced by the large sample size, a difference of CFI was considered. The difference in CFI between the two models was .001, indicating that both of the models fit well with the data. However, as Table **3** shows, the R^2 indicated that 32% of the IC variances were explained by Full Model 1, whereas 16% of the variances were explained by the Full Model 2, which suggests that Full Model 1 is a better model. Although Full Model 2 did not represent the data as complete as Full Model 2 did, it still explained a considerable amount of the IC variances (16%).

4.2.1. ACT's Direct Effects on IC

As Table **4** and Figure **1** show, ACT significantly (ACT total effect= direct effect, β = .37) influenced IC more than any other variables, and it influenced only directly. ACT was significantly influenced by all of GPA, SES, SE, IM, EM, and EXP: GPA (β = .50), SES (β = .30), SE (MSE [β = .11] & GSE [β = .10]), IM (RIM [β = .15] & GIM [β = -.07]), EM (β = -.14), and EXP (β = .04). As Table **3** shows, 51% of the ACT variances were explained by Full Model 1.

Table 3: R^2 values of Expectation, SAT, GPA, and IC for Full Models 1 and 2

Criterion	Full Model 1	Full Model 2
	With ACT & GPA	Without ACT & GPA
EXP	.09*	.09*
ACT	.51**	--
GPA	.18**	--
IC	.32**	.16*

Note: *p < .01, **p < .001; EXP = Educational expectations; IC = Institutional choice.

Table 1: Fit Indices for the Hypothesized Measurement Models

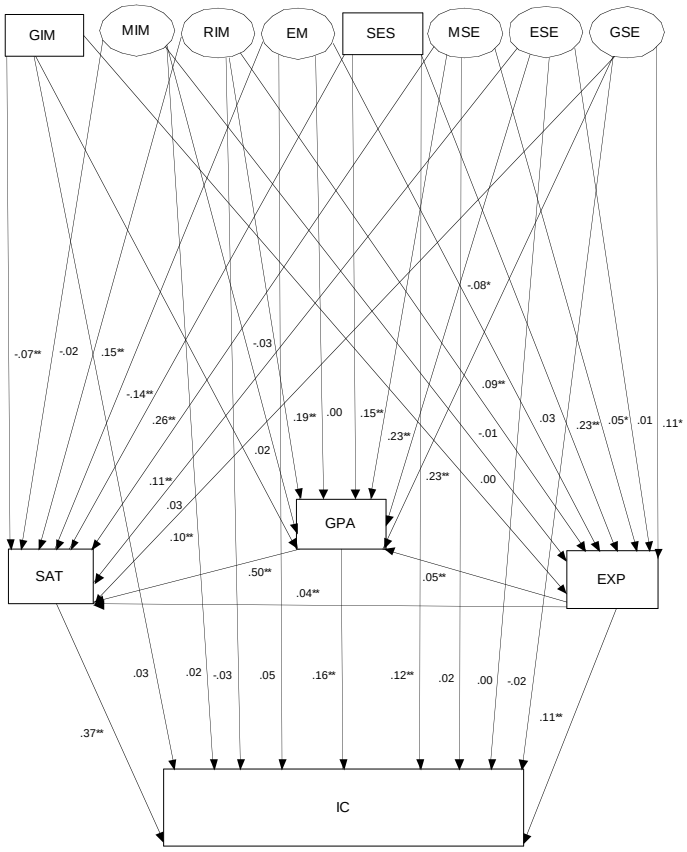
Model	χ^2	*df*	*RMSEA*	*CFI*	*TLI*
EM	20.80**	4	.032	.998	.994
IM	56.79**	5	.050	.996	.986
SE	704.92**	80	.043	.986	.981
Recommended cutoffs [93]			≤ .06	≥.95	≥.95

Note: RMSEA = Root Mean Square Error of Approximation; CFI = Comparative Fit Index; TLI = Tucker-Lewis Fit Index (Non-Normed Fit Index); **p < .001; EM = Extrinsic motivation; IM = Intrinsic motivation; SE= Self-efficacy.

Table 2: Fit Indices for the Hypothesized Structural Models and Model Comparison

Full Model	χ^2	*df*	*RMSEA*	*CFI*	*TLI*	$\Delta\chi^2$	*Δdf*	*ΔCFI*†
1. w/ ACT & GPA	3470.45**	410	.042	.959	.950	363.81**	40	.001
2. w/o ACT & GPA	3106.64**	370	.042	.960	.953	Cutoff [97] ΔCFI ≤ .01		
Cutoffs [91]			≤ .06	≥.95	≥.95			

Note: RMSEA = Root Mean Square Error of Approximation; CFI = Comparative Fit Index; TLI = Tucker-Lewis Fit Index (Non-Normed Fit Index); *p < .001; † indicates comparisons between the two models.



Note: IC = Institutional choice; EM = Extrinsic motivation; IM = Intrinsic motivation; GIM = General intrinsic motivation; RIM = Reading intrinsic motivation; MIM= Math intrinsic motivation; SE= Self-efficacy; GSE = General academic self-efficacy; MSE = Math self-efficacy; ESE = English self-efficacy; EXP = Educational expectations.

Figure 1: Relationships among motivation factors (EM, IM, SE, EXP), GPA, ACT, and SES and *β* values for predicting IC.

4.2.2. GPA's Direct and Indirect Effects on IC

As Table **4** and Figure **1** show, GPA (total effect, *β* =.34) significantly influenced IC next after ACT, and it influenced significantly directly (*β* =.16) as well as indirectly (*β* =.18). It influenced IC significantly indirectly through ACT (*β* =.50.). It was influenced by SE, SES, IM, and EXP: SE (MSE [*β* = .23] & GSE [*β* = .23]), IM (RIM [*β* = .19]), SES (*β* = .15), and EXP (*β* = .05). As Table **3** shows, 18 % of the GPA variances were explained by Full Model 1.

4.2.3. SES's Direct and Indirect Effects on IC

As Table **4** and Figure **1** show, SES (total effect, *β* =.30) significantly influenced IC next after ACT and GPA, and it influenced significantly directly (*β* =.12) as well as indirectly (*β* =.18). It influenced IC significantly indirectly through ACT (*β* = .26), EXP (*β* = .23), and GPA (*β* = .15).

4.2.4. SE's Indirect Effects on IC

As Table **4** and Figure **1** show, SE significantly (SE total effect = MSE total effect + GSE total effect, *β* =.27)

Table 4: Standardized Direct, Indirect, and Total Effects of Motivation Factors on Institutional Choice (IC)

Predictor		Effects (β) on IC		
		Direct	Indirect	Total
EM		.05	-.05*	≈ 0
IM	GIM	.03	-.02	.01
	MIM	.02	-.02	≈ 0
	RIM	-.03	.13**	.10**
SE	GSE	-.02	.13**	.12*
	MSE	.02	.13**	.15**
	ESE	≈ 0	-.02	-.02
EXP		.11**	.03**	.14**
SES		.12**	.18**	.30**
ACT		.37**	≈ 0	.37**
GPA		.16***	.18**	.34**

Note: [a] Totals may not add properly due to rounding;*p < .01, **p < .001; EM = Extrinsic motivation; IM = Intrinsic motivation; GIM = General intrinsic motivation; RIM = Reading intrinsic motivation; MIM= Math intrinsic motivation; SE= Self-efficacy; GSE = General academic self-efficacy; MSE = Math self-efficacy; ESE = English self-efficacy; EXP = Educational expectations.

influenced IC next after ACT, GPA, and SES, and it influenced IC significantly only indirectly (MSE [β = .13] & GSE [β = .13]) through GPA (β = .23) and ACT (β = .10) for GSE and through GPA (β = .23) and ACT (β = .11) for MSE.

4.2.5. EXP's Direct and Indirect Effects on IS

As Table **4** and Figure **1** show, EXP significantly (EXP total effect, β =.14) influenced IC, and it influenced significantly directly (β =.11) as well as indirectly (β =.03). It influenced IC significantly indirectly through GPA (β = .05), and ACT (β = .04, p = .001). It was influenced by SES (β = .23) and IM (RIM [β = .09). As Table **3** shows, 9% of the EXP variances were explained by Full Model 1.

4.2.6. EM and IM's Indirect Effects on IC

As Table **4** and Figure **1** show, IM significantly (IM total effect, β =.10) influenced IC, and it influenced significantly (RIM [β =.13) only indirectly through GPA (β = .19), ACT (β = .15), and EXP (β = .09). However, EM significantly influenced IC negatively (β = -.05) at α level of .01 only indirectly through ACT.

4.2.7. Multiple Group Analyses Across Gender

Separate covariance matrices for boys (n = 1849) and girls (n = 2361) were used as input for the multiple group analyses across gender. χ^2 values and difference tests, and values of other fit indices for the series of analyses are shown in Table **5**. The model comparisons resulted in statistically significant χ^2 differences for the analyses in which the factor loadings, factor variances and covariance, β, structural means, and structural variances and covariance were constrained to be equal across groups. This indicated that factor variances and covariance ($\Delta\chi^2$ [30] = 541.87), β ($\Delta\chi^2$ [14] = 421.16), structural means ($\Delta\chi^2$ [2] = 39.47), and structural variances and covariance ($\Delta\chi^2$ [20] = 63.49, p < .001) were statistically significantly different across gender, except the differences in the factor loadings ($\Delta\chi^2$ [44]) = 67.07, p > .001).

Although statistically significant increases in χ^2 were found, however, the various fit indices still showed good fits with the data with the constraint of invariant factor loadings, factor variances and covariance, β, structural means, and structural variances and covariance. Further, these differences across gender did not appear to be substantial when the actual parameter values were examined. The standardized total effects were slightly different across gender. For boys, the standardized total effect of GPA (β = .36) was greater than that of ACT (β = .30) on IC, whereas for girls, the standardized total effect of ACT (β = .42) was greater than that of GPA (β = .35). This indicated that GPA influenced boys more than ACT, whereas ACT influenced girls more than GPA when they made an IS. Further, modification indexes (MIs) were examined to determine whether parameter values differed across two groups. In multiple group analyses, values of the MIs for parameters held invariant represent the amount that the overall χ^2 value would decrease if the parameter values were allowed to differ. These examinations revealed that most of the MIs for the parameters were small and negligible except those for two parameters: the intercepts of the scores on the ACT (scores for boys = 596.31 & for girls = 490.34) and GPA (for boys = 2.71 & for girls = 3.04) as well as the β from EXP to ACT (β for boys = .06 & for girls = .03) and GPA (boys = .04 & girls = .05). This indicated that the intercept for ACT was higher for boys, whereas the intercept for GPA was higher for girls. This also indicated that EXP influenced ACT more than GPA for boys, whereas EXP influenced GPA more than ACT for girls. However, despite these MIs, none of the differences in the CFI values were greater than .01, as shown Table **5**, which indicated that Full Model 1 was sufficiently useful to describe the data for both boys and girls.

Table 5: Model Comparison across Gender (Boys [n = 1849] & Girls [n = 2361])

Model	χ^2	*df*	*RMSEA*	*CFI*	*TLI*	$\Delta\chi^2$†	*Δdf*†	*ΔCFI*†
1. Unconstrained	3909.49**	820	.030	.958	.958	-	-	-
2. Factor loading	3976.56**	864	.030	.958	.952	67.07	44	≈ 0
3. Model 2 + factor variance & covariance	4518.43**	894	.031	.951	.945	541.87**	30	.007
4. Models 2-3 + regression weight	4939.59**	908	.033	.945	.940	421.16**	14	.006
5. Models 2-4+ structural mean	4979.06**	910	.033	.945	.940	39.47**	2	.001
6. Models 2-5+ structural variance & covariance	5042.55**	930	.033	.944	.940	63.49**	20	.001

Note: † indicates comparisons are to the previous model, 1 with 2, 2 with 3, and so on; *p < .01, **p < .001.

4.2.8. Multiple Group Analyses Across Race

Due to the small number of American Indian/ Alaskan Native (n = 12) and Native Hawaiian/Pacific Islander (n = 11) students, these groups were not included in the multiple group analysis across race. Separate covariance matrices for African American (n = 328), Asian (n = 438), Caucasian (n = 2930), Hispanic (n = 322), and more than one race (n = 169) were inputted. χ^2 values and difference tests, and values of other fit indices for the series of analyses are shown in Table **6**. The model comparisons resulted in statistically significant χ^2 differences for the analyses in which the factor loadings, factor variances and covariance, β, structural means, and structural variances and covariance were constrained to be equal across groups. This indicated that factor variances and covariance, $\Delta\ \chi^2$ (56) = 617.01, β, $\Delta\ \chi^2$ (8) = 147.00, structural means, $\Delta\ \chi^2$ (2) = 39.47, and structural variances and covariance, $\Delta\ \chi^2$ (80) = 244.72, were statistically significantly different across race, except the differences in the factor loadings, $\Delta\ \chi^2$ (120) = 322.52, $p > .001$.

Although statistically significant increases in χ^2 were found, however, the various fit indices still showed good fits with the data with the constraint of invariant factor loadings, factor variances and covariance, β, structural means, and structural variances and covariance. Further, these differences across race did not appear to be substantial when the actual parameter values were examined. The standardized total effects were slightly different across race. The standardized total effects of GPA were greater than those of ACT on IC for African American (ACT = .39 & GPA = .52), Hispanic (ACT = .30 & GPA = .35), and more than one race (ACT = .29 & GPA = .37) students, whereas those of ACT were greater than those of GPA for Asian (ACT = .50 & GPA = .23) and Caucasian (ACT = .37 & GPA = .31) students. This indicated that GPA influenced African American, Hispanic, and more than one race students more than ACT, whereas ACT influenced Asian and Caucasian students more than GPA when they made an IS. Further, the MIs were examined to determine whether parameter values differed across groups. These examinations revealed that most of the MIs for the parameters were small and negligible. MIs for African American students indicated that EXP influenced ACT and GPA, and further GPA influenced ACT less for African American students than other students. Additionally, the intercept values of African American students' ACT and GPA were smaller than other students'. Further, MIs indicated that the mean values of African American and Hispanic students were smaller than those of the other students'. The MIs for Asian students indicated that the variances of Asian students' SES were larger than those for other students'. However, despite these MIs, none of the differences in the CFI values were greater than .01, as shown Table **6**, which indicated that Full Model 1 was sufficiently useful to describe the data for all of the students regardless of racial categorization.

5. DISCUSSION

The model with GPA and ACT predicts IC more completely than the model without GPA and ACT. The model without GPA and ACT, however, still explains the variances of IC considerably, which indicates that there are other variables, including SES and other motivation variables, that explain IC besides GPA and ACT.

5.1. ACT: The Biggest Effects on IC

Students' ACT scores directly influence IC more than any other factors in this study. This is similar to previous studies in that test scores are more heavily weighted at more selective institutions [40]. This is,

Table 6: Model Comparisons across Race (Asian [n = 438], African [n = 328], Hispanic [n = 322], More Than One Race [n = 169], & Caucasian [2930])

Model	χ^2	*df*
1. Unconstrained	5260.77**	2050
2. Factor loading	5497.45**	2226
3. Model 2 + factorvariance & covariance	5819.96**	2346
4. Models 2-3 + regression weight	6436.97**	2402
5. Models 2-4+ structural mean	6583.97**	2410
6. Models 2-5+ structural variance & covariance	6828.68**	2490

Note: † indicates comparisons are to the previous model, 1 with 2, 2 with 3, and so on; *$p < .01$, **$p < .001$.

partly, inconsistent with previous studies because students' ACT scores are more influential than their GPA on IC in the present study, whereas test scores are second to GPA in admission decision in other studies [39,40].

More than half of the variances of ACT scores are explained by the model with GPS and ACT, which indicates that the variables included in this study explain students' ACT scores well. When looking at what influences students' ACT scores, it is found that their GPA is the strongest predictor of their ACT scores. The next predictor of their ACT scores is their SES background, which is consistent with previous studies [44,102] in that they found a positive relationship between ACT and SES. This might be because students with higher SES background take the ACT more frequently than those with lower SES background do, or because students with higher SES background have better support when preparing for the ACT. Additionally, students' motivations factors including SE (specifically by MSE & GSE), IM (specifically by RIM & GIM), EM, and EXP, in this order, also significantly influence their ACT scores. This indicates that students' SE on general academic achievement and on mathematics is a very important predictor of their ACT scores. The results also indicate that students' love of reading as well as their expectations on future education are very important predictors of their ACT scores. It should also be noted that students' GIM significantly influence their ACT scores negatively, which might be because GIM in this study only includes one ELS item, "classes are interesting and challenging," it does not represent intrinsic motivation well. Additionally, students' EM significantly influences their ACT scores negatively, which is consistent with previous studies in that EM is negatively related to students' achievement [57,58].

5.2. GPA: The Second Biggest Effects on IC

Students' GPA is the second most influential variable for IC directly and indirectly. It influences IC indirectly through their ACT scores, and it is influenced by SE (specifically by MSE and GSE), SES, IM (specifically by RIM), and EXP. The result indicates that students' SE on general academic achievement and on mathematics are more influential than their SES background on GPA. This is consistent with previous studies in that students' SE on specific tasks is a useful predictor of academic achievement [53,54,103-106]. The result also indicates that students' love of reading as well as their expectations on future education are very important predictors of their GPA as well as of their ACT scores above. A student who is intrinsically motivated to read is likely to read more and may acquire more vocabulary, which reflects itself in higher GPA and better preparedness for the ACT. It should be noted that the model with GPS and ACT indicates that the variables included in this study explain students' GPA not as well as their ACT scores. Thus, there may be other variables that can explain students' GPA.

5.3. SES: The Third Biggest Effects on IC

The third most influential variable for IC is students' SES background. These findings support the previous findings that indicate a relative decrease in the importance of SES [37]. It influences IC directly as well as indirectly, next after ACT and GPA, and more indirectly than directly, mostly through ACT, EXP, and GPA. This indicates that SES influences students' ACT scores the most, their expectations for their future educational plan second, and their GPA next.

5.4. SE: The Fourth Biggest Effects on IC

After ACT, GPA, and SES in this study, SE (specifically by MSE and GSE) significantly influences IC the most and only indirectly. This is consistent with previous studies in that students with high SE set higher goals than students with low SE do [70-73]. The results indicates that students' SE on general academic achievement and on mathematics indirectly influences on IC through their GPA and ACT scores, more GPA than ACT. This is consistent with previous studies in that SE is positively related to academic performance [65-67]. Of the motivation variables, SE influences more than the other variables in this study.

5.5. EXP: The Fifth Biggest Effects on IC

EXP significantly influences IC, which is consistent with previous studies in that not only are students with higher EXP more likely to enroll in post-secondary education [2], but their level of EXP serves as a useful predictor of the selectivity of their chosen institution [27, 81,82]. EXP influences significantly IC directly as well as indirectly, but mostly indirectly through students' GPA and ACT scores. As EXP of how far the students expect to get in school increases, their GPA and ACT scores increase directly. EXP is influenced by students' SES background and IM (specifically RIM), which indicates that not only students' SES background but also their love of reading directly influence their EXP.

5.6. EM and IM: The Last Effects on IC

IM (specifically RIM) significantly influences IC only indirectly through GPA, ACT, and EXP. This indicates that students' love of reading is an influential factor for IC, as it directly influences their GPA the most, ACT the second most, and EXP next. However, EM significantly negatively influences IC only indirectly through their ACT scores, as noted earlier, which is consistent with previous studies in that EM is negatively related to students' achievement [57,58].

5.7. Effect of Gender and Race on IC

The results of the multiple group analyses across gender as well as across race indicate that the model of the present study is useful to predict IC regardless of students' gender or race. Thus, the interpretations of the results of the present study, including those of the results for the direct and indirect effects of the variables on IC, are valid for boys and girls as well as for African American, Asian, Caucasian Hispanic, and more than one race students.

5.8. Limitations of the Present Study and Suggestions for Future Studies

There are some limitations in the current study. The first limitation comes from one of the drawbacks inherent in this software package that does not allow for the application of sampling weights to the data. ELS: 2002 data collection involved a multistage stratified cluster sampling system that involved the oversampling certain types of schools and groups of students—i.e. private schools and Asian students [84]. Therefore, the generalizability of the results of the present study might be limited.

Another limitation of the study is that it does not take into account other variables that appear to be salient to the criterion variable, choice of first institution attended. One such variable is the geographic proximity of the student with the first attended institution [2]. The location of the post-secondary institution relative to the students' home likely influences a student's IS. Additionally, the only variable in this study referencing financial considerations is SES. The addition of other financial variables such as institution cost of attendance, the availability of financial aid, and other forms of financial support would present a more accurate depiction of the phenomenon of IS. Accounting for financial considerations should provide a clearer picture of the influence of motivation on IS.

6. CONCLUSIONS

IC is positively influenced by SE on general academic achievement and mathematics, EXP, and reading IM, in addition to ACT, GPA, and SES, and negatively influenced by EM. The results also indicated that these effects hold true regardless of students' gender and race. Reading IM, SE on general academic achievement and mathematics, and EXP influence IC indirectly through influencing GPA and ACT. Especially, the finding that SE (GSE & MSE) has a greater influence than SES on GPA, although SES has a greater influence than SE on ACT, suggests the importance of SE on students' GPA.

The ability of these motivation variables to predict IC suggests that a greater emphasis should be placed on enhancing these motivation variables in students. Extra support with students' developing SE on mathematics and academic achievement in general will be beneficial to increasing their ACT and GPA, eventually IC. Extra emphasis on understanding the value of and importance of reading for themselves, but not frequently for recognition or good grades, would also be beneficial. Encouraging students to set intrinsic goals than extrinsic motivation for IC and to value and appreciate their personal growth and enrichment for IC, but not focusing on external rewards, would also be beneficial. Giving opportunities for college visits might help with their EXP to access to more selective colleges.

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