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Factors Influencing College Readiness: A Multilevel Study to Measure School Effects

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Abstract. This paper explored the significant student and school level predictors of college readiness in reading and the mathematics employing a two-level hierarchical generalized linear model (HGLM). The proportions of variance explained and effect sizes at the school level were determined to measure school effects. The study included 12,554 students and 51 high schools from one of the largest school districts in the United States. At the student level, reading and mathematics achievement including several disciplinary and demographic factors were significant whereas at the school level, average school achievement, percent retention and school poverty were significant in predicting college readiness. The effect sizes, which ranged from .39 to .42, were determined to be medium representing the moderate strength of school effects.

Keywords: Multilevel modeling, college readiness, significant predictors, effect sizes, school effects

Introduction

College readiness for students has become more important than ever in K-12 education system. It is essential for high school students to be college ready before their graduation. College readiness for high school students is the knowledge, skills, and ability a student should possess to be ready to succeed in entry-level college courses. Past research shows that more than one quarter of the high school graduates in the United States did not enrol in postsecondary institutions during the fall semester immediately after high school graduation. During 2013, only 70% of the high school graduates in the United States enrolled in colleges in the fall immediately after high school completion (NCES, 2015). This paper is based on the research conducted in the School District of Palm Beach County (SDPBC), Florida. The SDPBC is the fifth largest district in Florida and the twelfth largest district in the United Sates.

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In the State of Florida, the Florida Department of Education (FDOE) provides the criteria for determining college readiness in reading and mathematics for all students based on ACT (American College Test), SAT (Scholastic Aptitude Test), PERT (Postsecondary Education Reading Test), and CPT (Common Placement Test). The cut-off scores in each of these tests for determining college readiness in reading and mathematics were provided by the FDOE. During 2014, the percentage of students in the United States who were college ready in ACT reading and ACT mathematics were 44% and 43%, respectively (ACT, 2014b). There have been limited studies in predicting college readiness in reading and mathematics despite the importance of the research topic. This research explores significant student and school level predictors of college readiness so that concerned educators and administrators can control such factors for increasing college success rates of graduating high school students. In order to turn college aspirations into college attainment, high schools need clear indicators of college readiness and clear performance standards which must allow schools and districts to assess where their students currently stand and to measure their progress (Roderick, Nagaoka & Coca; 2009).

The purpose of this article is twofold: exploring the significant predictors of college readiness in reading and mathematics and determining the effect sizes at school level models. We predicted college readiness, a dichotomous outcome, employing a two-level Hierarchical Generalized Linear Model (HGLM). This research will benefit the school districts and high schools in the United States and other countries in terms of preparing the students for the entry level college courses by controlling the significant predictors in students' favor.

Literature Review

Selecting Relevant *Predictors in the Models*

This study used academic achievement, grade retention as well as demographic and disciplinary factors at student and school levels to predict college readiness. Previous studies found that college readiness is positively impacted due to student achievement (ACT, 2008; Atkinson & Geiser, 2009), and dual (college) credit enrolments (Allen, 2010; Kim & Bragg, 2008).

Based on the grade retention research, Bowman (2005) reported that retention does not typically increase student performance and Reynolds (1992) found a negative effect of retention on academic achievement and other educational outcomes. Shepard and Smith (1990) argued that the retained children may appear to do better in the short term, but they are at much greater risk for future failure than their equally achieving, non-retained peers. Jacob and Lefgren (2009) found a modest effect of grade retention on preventing high school completion given by dropout.

The findings of past studies substantiate the negative effect of student's ESE (disabilities) status on academic performance and postsecondary education. Trainin and Swanson (2005) found that the students with learning disabilities scored significantly lower than students without learning disabilities in word reading, processing speed, semantic processing, and short-term memory. Among students with disabilities who graduate from high school and attend a postsecondary education program, completion rates are low (Brand, Valent, & Danielson; 2013) and the majority of students with disabilities failed to graduate or to receive a degree from their program up to eight years after high school (Newman et al., 2011).

Perry and Morris (2014) found that higher levels of exclusionary discipline within schools over time generate collateral damage, negatively affecting the academic achievement of non-suspended students in punitive contexts. Past research explored the negative effect of suspension and expulsion on academic achievement independent of socio-demographic influences, and this could have caused students to fall behind on classroom assignments and instruction (Rausch & Skiba, 2005).

A research by ACT (2014b) found that most Hispanic students are not academically ready for college since 2010 regardless of subjects and readiness rates for them remain low regardless of core course taking. Greene & Forster (2003) found that nationally, only 32% of students in the Class of 2001 were found to be college ready, with significantly lower rates for Black and Hispanic students. Study shows that only 53 percent of Latinos who attempt credit-bearing math courses complete those courses with a grade of C or better. Meanwhile, the rates for Whites (63 percent) and Asians (66 percent) were found higher (Malcom-Piqueux, Bensimon, Suro, Fischer, Bartle, Loudenback, & Rivas; 2012). In reading, the college readiness benchmark scores for Hispanic (29%) students are found lower than those for White (54%) and all (44%) students (ACT, 2014b). Further, the same report reveals that the college readiness benchmark scores in mathematics for Hispanic (29%) students are found lower than those for White (52%) and all (43%) students. Nationally, only 32% of students in the Class of 2001 were found to be college ready, with significantly lower rates for Black and Hispanic students (Greene & Forster, 2003).

Research shows that students from low-income families lag behind their peers in meeting college and career readiness benchmarks (ACT, 2014a). Many people argue that a large pool of students who are qualified to attend college are prevented from enrolling by a lack of adequate income or other social or demographic hurdles (Greene & Winters, 2005).

Modeling Perspective

In order to determine the effect sizes for school level models, we need to estimate the variances at student and school levels. Many studies in past used the estimation of level-1 variance components in binary response model (Bryk and Thum, 1989; Finn and Rock, 1997; Goldstein, 1991; Guo & Zhao, 2000; Longford, 1994; McCulloch, 1994). For example, Bryk and Thum (1989) predicted dropout as a binary outcome and estimated variance associated with dropout and Goldstein (1991) adopted a general approach for the estimation of variance (at level-1 model) in multilevel nonlinear model using a linearization. Earlier works also demonstrated the use of multilevel binary models with student and school level data employing a two-level HGLM (Goldschmidt & Wang, 1999; Rumberger, 1995; Subedi & Howard, 2013).

Researchers in past determined school effects or effect sizes for higher level group employing multilevel models (Goldstein, 1997; Rowan, Correnti, & Miller, 2002; Subedi & Howard, 2013; Thomas, Sammons, Mortimore, & Smees, 1997). They determined effectiveness based on effect sizes which were computed using variance of school level model. Subedi and Howard (2013) predicted binary response outcome that involved students' graduation and dropout status employing a two-level HGLM technique. The current study explores unanswered research questions associated with college readiness in order to improve student performance targeted to postsecondary education.

Research Questions

This paper aims to answer the following research questions.

1. What are the significant student and school level predictors of college readiness in reading and mathematics for high school students?
2. What are the proportions of variance explained and effect sizes at school level for predicting college readiness in reading and mathematics?

Methods

Data

This study included 12,554 students and 51 high schools from the School District of Palm Beach County (SDPBC), Florida, USA. The two major college placement tests that measure the college readiness in the SDPBC are SAT and ACT. In addition to these assessments, PERT and CPT are also used as measures of college readiness of SDPBC (and Florida) students. Based on the 2014 test results of these assessments, the college readiness flags were created based on the benchmarks provided by the State of Florida. In this study, approximately 95% of the students were twelfth graders with college readiness flags based on SAT, ACT, PERT, or CPT cut scores. The ACT is tested in Reading, English, Mathematics, and Science. The SAT and PERT are given in Reading, Mathematics, and Writing. The CPT is given in Algebra, Reading and Sentence Skills.

During 2014, the scale scores for SAT ranged from 200 to 800 (College Board, 2014) and that for ACT ranged from 1 to 36 (ACT, 2014b). According to FDOE (2016), the PERT scale scores ranged from 50 to 150. FDOE (2014) provides the cut-off scores for college readiness measures in reading and mathematics as follows based on the scale scores of ACT, SAT, PERT, and CPT examinations.

- ACT: 19 for both reading and mathematics
- SAT: 440 for both reading and mathematics
- PERT: 106 for reading and 114 for mathematics

The data in this study included high school graduates with 51%, 60%, and 20% college ready in Reading in ACT, SAT, and PERT tests, respectively. Similarly, 35%, 58%, and 16% of the students were college ready in Mathematics in ACT, SAT, and PERT tests, respectively. Many of the students took more than one (of these) tests. Only 0.2% or less students were college ready in CPT Reading and Elementary Algebra (with cut-off scores of 83 and 72, respectively).

The reliability coefficients for ACT Reading and Mathematics assessments were .88 and .91, respectively (ACT, 2014b). Similarly, the reliability estimates for SAT Reading and Mathematics tests were .93 and .92, respectively (Ewing, Huff, Andrews, & King, 2005).

Variables

Student Level Predictors

Reading achievement. This is a continuous variable with Florida Comprehensive Assessment Test (FCAT) scores ranging from 178 to 1537.
Algebra achievement. This is a continuous variable with End-Of-Course (EOC) algebra scores ranging from 26 to 471.
Retention. This is a dichotomous variable with 1 for student's (high school) grade retention status and 0 for non-retention status.
Exceptional student education (ESE). This is a dichotomous variable with 1 for student's ESE status and 0 for non-ESE status.
Free or reduced price lunch (FRL). This is a dichotomous variable with 1 for student's FRL (participation) status and 0 for non-FRL status.
Hispanic. This is a dichotomous variable with 1 for Hispanic status and 0 for non-Hispanic status of a student.
Average suspension. This is a continuous variable for a student with the average of in-school and out-of-school suspension events from grades 9 through 12. This variable ranged from 0 to 23.

School Level Predictors

Average Algebra achievement. This is a continuous variable with school average of Algebra EOC scores that ranged from 311 to 419.
School percent retention. This is a continuous variable with school percent retention that ranged from 1% to 11.4%.
School percent FRL. This is a continuous variable with school percent of FRL students that ranged from 16% to 70%.

Determining d-Type Effect Sizes

The proportion of variance for school level model is calculated and reported as the ratio of school variance to total (school plus student) variance. As suggested by Rowan et al. (2002), d-type effect sizes at school level are calculated as the square root of the ratio of school level variance to the total (student plus school level) variance, and the effect sizes are classified as small, medium and large depending on the magnitude of effects as given below.

- Below .39 -- Small
- 0.39 – 0.45 -- Medium
- 0.46 or higher -- Large

In results section, we compute and report the effect sizes for school level models to determine school effects while predicting student's college readiness.

Model Development

A two-level HGLM was employed where two separate models were developed and analyzed to predict student's college readiness in reading and mathematics. The final models incorporated only significant predictors at level-1 and level-2 (i.e., student and school levels). Such models are known as conditional models which include selected predictors in level-1 and level-2 equations. Research question 1 is answered by estimating the slopes associated with level-1 and level-2 predictors. Research question 2 is answered by estimating the proportions of variance explained at school-level models, and effect sizes d based on these variance components. The level-2 variance terms were deleted from the models if they were not significant as suggested by Subedi (2005).

Although the college readiness status is a dichotomous outcome, it can be treated as if it were continuous. For example, Bryk, & Thum (1989) and Goldstein (1991) have treated binary outcomes as continuous by incorporating the random term in level-1 model. Due to their computational efficiency over alternate techniques such as logit and probit, Amemiya (1985) has incorporated random term in level-1 model. Assuming that Y_{ij} is the student's status in College Readiness in Reading (CRR), the log of probability of CRR can be predicted by the level-1 conditional model for i^{th} student nested in j^{th} school as given by Equation (1a).

$$\log(P(Y_{ij}=1)/(1-P(Y_{ij}=1))) = \beta_{0j} + \beta_{1j}(\text{READACH})_{ij} + \beta_{2j}(\text{AVGSUSP})_{ij} + \beta_{3j}(\text{RETENTION})_{ij} + \beta_{4j}(\text{ESE})_{ij} + \beta_{5j}(\text{HISPANIC})_{ij} + e_{ij} \quad (1a)$$

In Equation (1a), β_{0j} is the intercept. The coefficients β_{1j}, β_{2j}, β_{3j}, β_{4j}, and β_{5j} are student level slopes or effects for reading achievement (READACH), average suspensions (AVGSUSPS), retention (RETENTION), student's ESE status (ESE), and student's Hispanic status (HISPANIC), respectively. Further, e_{ij} is student level random term distributed normally with mean zero and constant variance.

The level-2 conditional model can be formulated as follows in Equation (1b) by incorporating significant school level predictors to predict the coefficients of level-1 model, from in Equation (1a), as outcomes.

$$\begin{aligned}
\beta_{0j} &= \gamma_{00} + \gamma_{01}(\text{SCHLPCTRET})_j + u_{0j} \\
\beta_{1j} &= \gamma_{10} + \gamma_{11}(\text{SCHLPCTRET})_j \\
\beta_{2j} &= \gamma_{20} \\
\beta_{3j} &= \gamma_{30} \qquad (1b) \\
\beta_{4j} &= \gamma_{40} \\
\beta_{5j} &= \gamma_{50}
\end{aligned}$$

Equations (1b) consists of fixed portion (γ terms) and random portion (u terms) of effects where the term γ_{00} represents the average college readiness rate in reading for all schools and u_{0j} represents the random effects at school level with multivariate normal distribution. The coefficient γ_{01} represents the effect of school percent retention on average college readiness rate in reading and γ_{11} represents the interaction effect of school percent retention and student reading achievement. The following coefficients represent their effects on the predicted probability of college readiness in reading:

- γ_{10} represents the effect of average reading achievement,
- γ_{20} represents the effect of average suspension,
- γ_{30} represents the effect of students with retention status relative to the effect of promoted students,
- γ_{40} represents the effect of ESE students relative to the effect of non-ESE students,
- γ_{50} represents the effect of Hispanic students relative to the effect of non-Hispanic students.

Assuming that Y_{ij} is the student's status in College Readiness in Mathematics (CRM), the log of probability of CRM can be predicted by the level-1 conditional model for i^{th} student nested in j^{th} school as given by Equation (2a).

$$\log(P(Y_{ij}=1)/(1-P(Y_{ij}=1))) = \beta_{0j} + \beta_{1j}(\text{ALGACH})_{ij} + \beta_{2j}(\text{RETENTION})_{ij} + \beta_{3j}(\text{ESE})_{ij} + e_{ij} \qquad (2a)$$

In Equation (2a), β_{0j} is the intercept. The coefficients β_{1j}, β_{2j}, and β_{3j} are the effects of student's algebra achievement (ALGACH), retention (RETENTION) status, and ESE (ESE) status, respectively. Further, e_{ij} is student level random term distributed normally with mean zero and constant variance.

Similarly, the level-2 model, in order to predict the coefficients in Equation (2a), can be formulated as below in Equation (2b).

$$\begin{aligned}
\beta_{0j} &= \gamma_{00} + \gamma_{01}(\text{SCHLAVGALGACH})_j + \gamma_{02}(\text{SCHLPCTFRL})_j + u_{0j}\\
\beta_{1j} &= \gamma_{10} + \gamma_{11}(\text{SCHLPCTFRL})_j\\
\beta_{2j} &= \gamma_{20} \qquad (2b)\\
\beta_{3j} &= \gamma_{30}
\end{aligned}$$

In Equation (2b), γ_{00} represents the average college readiness rate in mathematics for all schools and u_{0j} represents the random effects at school level with multivariate normal distribution. The coefficient γ_{01} represents the effect of school average algebra achievement and γ_{02} represents the effect of school percent FRL on college readiness in mathematics. The term γ_{11} represents the interaction effect of school percent of FRL and student algebra achievement. Further, the following coefficients represent their effects on the predicted probability of college readiness in mathematics:

- γ_{10} represents the effect of average algebra achievement,
- γ_{20} represents the effect of students with retention status relative to the effect of promoted students,
- γ_{30} represents the effect of ESE students relative to that of of non-ESE students.

Note that the single-equation can also be formulated by substituting Equation (1b) in Equation (1a) and Equation (2b) in Equation (2a) in order to demonstrate the interaction effects of level-1 and level-2 predictors. However, the formulation of the single-equation model is beyond the scope of this paper.

The fixed effects (intercepts and slopes) and random effects (variance components) at student and school levels are estimated using PROC GLIMMIX procedure in SAS program (Kim, Preisser, Rozier, & Valiyaparambil, 2006; Little, Milliken, Stroup, & Wolfinger, 1996; SAS Institute, 2006).

The research question 1 is answered by estimating fixed effects, γs, and p-values associated with these effects in Equations (1b) and (2b). The research question 2 is answered by estimating the school level variance term, u_{0j}, and calculating effect sizes using the following formula as provided by Rowan et al. (2002).

$$d = \sqrt{(\text{Variance in achievement lying among school})} \,/\, \sqrt{(\text{Total student} + \text{school variance in student achievement})} \quad (4)$$

The large sample size of the SDBPC, quality data used from authentic sources, high ACT and SAT test reliabilities, and the use of sophisticated statistical modeling technique ensured the validity and reliability of the results of this study. The findings of the study can be generalized to the population with similar demographic composition in the United States and other countries.

Results

Table 1 provides the analysis results with significant effects of several student and school level predictors on college readiness in reading. At student level, the effects of reading achievement ($p<.0001$), average suspension ($p<.001$), student's status of retention ($p<.0001$), ESE ($p<.0001$), and Hispanic ($p<.01$) are found significant. At school level, the effects of school percent of retention ($p<.0001$) and its interaction effect with reading achievement ($p<.0001$) are found significant.

Table 1. Estimation of predictors' effects for predicting college readiness in reading

Effect	Estimate	Std. Error	p-value
Reading achievement	0.011	0.001	<.0001
Average suspension	-0.014	0.003	<.0001
Retention	-0.194	0.019	<.0001
ESE	-0.220	0.023	<.0001
Hispanic	-0.043	0.014	<.01
School percent retention	-4.254	0.261	<.0001
Reading ach.* School pct. ret.	-0.020	0.001	<.0001

The results in Table 2 show the significant effects of several student and school level predictors on college readiness in mathematics. At student level, the effects of algebra achievement ($p<.0001$), student's status of retention ($p<.001$) and ESE ($p =.027$) are found significant. At school level, school average algebra achievement ($p<.0001$), school percent of FRL or school poverty ($p<.01$) and its interaction effect with algebra achievement ($p<.01$) are found significant.

The results showed positive effects of reading as well as algebra achievements, and school average algebra achievement. The results showed negative effects of average suspension, student's statuses of retention, ESE, and Hispanic, and school percentages of retention as well as FRL students. In addition, the interaction effects of school percent of retention with reading achievement and the school percent of FRL with algebra achievement were found negative.

Table 2. Estimation of predictors' effects for predicting college readiness in mathematics

Effect	Estimate	Error	p-value
Algebra achievement	0.007	0.001	<.0001
Retention	-2.162	0.577	<.001
ESE	-1.225	0.554	0.027
School average Alg. achievement	0.006	0.001	<.0001
School percent FRL (school poverty)	-1.149	0.389	<.01
Algebra ach. * School percent FRL	-0.003	0.001	<.01

Table 3. Estimations of variance explained, p-values, and effect sizes at school level for predicting college readiness in reading and mathematics

Outcome measure	Variance explained	p-value	Effect size (d-type)
College readiness in reading	18%	<.0001	0.42
College readiness in mathematics	15%	<.0001	0.39

Table 3 shows the variances explained, p-values (associated with school level variances), and d-type effect sizes for two separate school level models while predicting college readiness in reading and mathematics. The proportion of variance explained and effect size for predicting college readiness in reading are found 18% and 0.42, respectively. The proportion of variance explained and effect size for predicting college readiness in mathematics are found 15% and 0.39, respectively. Both of these effect sizes are 'medium' representing the moderate strength of school effects while predicting college readiness.

Discussion

What the Significant Predictors Tell Us?

The study found significant effects of academic, disciplinary, and demographic factors on college readiness in reading and mathematics. The results with significant positive effect of student achievement on college readiness is analogous to the previous findings reported by ACT (2008) and the findings of Atkinson and Geiser (2009). With an intuitive implication, the findings implied that the college-bound students will have higher probability of success in entry-level college courses only if the better students are prepared in high school reading and algebra courses. Further, the study showed a negative effect of (grade) retention on college readiness in reading and mathematics. This result is analogous to the findings provided by Bowman (2005) and Reynolds (1992) that found the negative effect of retention on academic achievement and educational outcomes.

Student's status of being Hispanic exerted significant negative effect on college readiness in reading. This result resembles the research findings for Latino students who (successfully) completed credit-bearing math courses at rates below their White and Asian classmates (Malcom-Piqueux, 2012). Hispanic students were found to be college ready with significantly lower rates (ACT, 2014b; Greene & Forster, 2003). Further, a student with ESE (disabilities) status impacted negatively on college readiness in reading and mathematics. The results were similar to the findings of Brand et al. (2013), Newman et al. (2011) as well as by Trainin and Swanson (2005) which revealed that the students with disabilities who graduated from high school and attended a postsecondary education program, had low completion rates.

The average suspension (combined in-school and out-of-school suspensions) showed significantly negative effect on college readiness in reading. This result is analogous to the findings of Perry and Morris (2014) as well as Rausch and Skiba (2005) that revealed a decreased student achievement due to the effect of suspension and expulsion independent of socio-demographic influences. Further, the negative effect of free or reduced price lunch on college readiness is supported by previous studies of Greene and Winters (2005) and the fact that students from low-income families lag behind their peers in meeting college and career readiness benchmarks (ACT, 2014a).

It is worth to argue that the school percent of retention and school poverty (i.e., school percent FRL), through the interaction with student achievement in reading and algebra, respectively, have caused to generate negative effects even though student achievements (in reading and algebra as well) showed positive effects on college readiness. To elaborate, the higher percentages of retained or FRL students in a school will lower the chance of a student to be college ready (in reading or mathematics) despite good academic performance in reading or algebra.

School Effects

School effect in this study is determined by the effect sizes at school level models for predicting college readiness in reading and mathematics which were 0.42 and 0.39, respectively. Both of these effect sizes are found to be in a category of 'medium' as per Rowan et al. (2002). These findings represent the moderate strength of school effects to predict college readiness incorporating student and school level predictors in the models.

This paper harnessed a technique for computing effect sizes for dichotomous outcomes due to variation among schools in college readiness. This study extended the method of Rowan et al. (2002) computing effect sizes for level-2 model in binary response models. For this purpose, we assumed the level-1 outcome to be approximately normal (Warn, Thompson, & Spiegelhalter, 2002) and computation of level-1 variance in generalized linear model (Goldstein, 1991; Kim et al., 2006). The computation of effect sizes at level-2 model employing two-level HGLM demonstrated in this paper would provide a technique to measure school effects in educational research.

Conclusions

This paper predicted college readiness in reading and mathematics, employing a multilevel models, incorporating significant predictors at student and school levels in one of the largest school districts in the United States. The effect sizes for school level models were determined using the amount of variances accounted for student and school levels. Several technical aspects are discussed in terms of computing effect sizes.

This research has several implications. Considering significant predictors of college readiness identified in this study, an intervention is recommended for controlling such factors. Such an intervention process would help the school districts and schools improve the college readiness rates of graduating students. The effect sizes of "medium" strengths that produced moderate school effects due to school-to-school variation in college readiness rates for both reading and mathematics substantiate the importance of the predictors used in the models. This study systematically demonstrated a valid method for computing effect size for binary response models that could be replicated by educational researchers and evaluators. Such a theoretically based and empirically evidenced model would be beneficial for other school districts in the national and international contexts to measure school effects.

Several limitations can be documented based on this study. First, few student and school level predictors are missing in this study due to the data unavailability. The examples of such predictors are students' home environment, parent involvement, extracurricular activities at student level and principal's leadership as well as the percent of teachers with different types of certifications. It is recommended the future studies use such predictors in level-1 and level-2 models. The researchers in future may use a more complex model for exploring significant predictors of college readiness employing a three-level HGLM using student, teacher, and school predictors at level-1, level-2, and level-3 models, respectively.

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