Predictors of English Learner Graduation Rates in Georgia

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Using publicly available data, the researchers examined variables that may predict English learner graduation rates (ELGR) at the school and school-system levels to determine whether the school average per pupil expenditure (PPE), the school mobility rate (MOB), the percentage of teachers out of field (TOF), and the percentage of inexperienced teachers and/or school leaders (INEX) are significant school- and system-level predictors of ELGR. Researchers estimated five multilevel linear models examining within- and between-group relationships. Analyses of 2019–2020 academic year data for 117 high schools from 42 school systems in the state of Georgia showed that student mobility rates (MOB) and teacher quality (TOF) were significant predictors of ELGR. Paradoxically, increased school spending (PPE) did not predict higher ELGR. These findings help address the lack of research on ELGR and help practitioners identify the school indicators that may be related to this important student outcome.

Keywords: graduation rate, English learners, district factors, school factors, multilevel modeling

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Graduating from high school has long been considered a mark of accomplishment for teenagers as well as a cause of celebration and a source of pride for their families. The correlation between high school graduation and long-term positive outcomes, such as better employment prospects, higher lifelong earning potential, increased satisfaction with life, fewer chronic health conditions, and longer life expectancy, is well documented (e.g., Hahn & Truman, 2015; Krueger et al., 2015; Oreopoulos, 2007; Vaughn et al., 2014). High school graduation rates also figure prominently in school evaluation rubrics. The national graduation rate has steadily increased from 79% in 2011 to 86% in 2019, a 7-point increase (Irwin et al., 2021), while Georgia's graduation rate has seen a doubly steep 14-point increase from 69.7% in 2012 to 83.7% in 2021 (Georgia Department of Education [GaDOE], 2021). At the same time, graduation rates among English learners (ELs), who comprised 10% of all U.S. school-aged children in 2020, have also fared well. From 57% in 2011 to 68% in 2018, EL graduation rates nationwide have risen 11 percentage points (Office of English Language Acquisition [OELA], 2020). This statistic gives hope, but the graduation rate gap between ELs and all students in 2018 was 17 percentage points. From 2011 to 2022, the EL graduation rate in Georgia, the state in which this study was conducted, increased by approximately 34 percentage points. Despite this positive trajectory, Georgia remains among the states with the lowest EL graduation rates nationwide (OELA, 2020), with 66.2% of ELs in Georgia schools graduating in 2022 (GaDOE, 2022).

Studies examining EL graduation rates are scarce; however, research investigating factors impacting high school graduation rates for the general student population is more prevalent. Much research has explored student-centered factors such as motivation, school engagement, and family support (Zaff et al., 2017). Factors within the school and/or district's locus of control are within the purview of this study. School- and district-related factors that have been shown consistently to influence high school completion include school spending, teacher quality, and student attendance and mobility rates (e.g., Jackson, 2020; Wood et al., 2017; Zaff et al., 2017). Examples of other diverse school- and district-related factors impacting high school graduation for students generally include school size, schoolwide socioeconomic status, school start times, positive student-teacher relationships, and school-sponsored extracurricular opportunities (McKeever & Clark, 2017; Wood et al., 2017; Zaff et al., 2017).

The paucity of research on EL graduation rates is likely because EL graduation rates have not always been reported consistently (Kanno & Cromley, 2013). Though the No Child Left Behind Act of 2001 (NCLB, 2002) required EL graduation data to be reported, many states and school systems continued to underreport the data. Since the advent of the Every Child Succeeds Act (ECSA, 2015), EL graduation rates have been reported more consistently, but minimal studies have examined these rates. The few studies in this area have shown that ELs fare less well than their English-dominant counterparts, being less likely to graduate from high school (Deussen et al., 2017; Gwynne et al., 2012; Kieffer & Parker, 2017) or pursue postsecondary educational opportunities (Johnson, 2019).

Even fewer studies have examined the variables that may influence EL graduation rates or strategies schools may employ to increase EL graduation rates. More recently, Mindrila (2021) found EL graduation rates in the state of Georgia were consistently lower than the overall graduation rates of all students. Analyses of EL graduation rates for 51 school systems within Georgia showed non-significant variations in EL graduation rates over a four-year period between 2017 and 2020. In addition, Mindrila (2021) found school systems located in rural parts of the state had significantly higher 2020 EL graduation rates than school systems located in cities and suburban areas. Mindrila (2021) concluded that ELs in suburban and city districts were less likely to earn high school diplomas than their counterparts in less-populated rural parts of Georgia. The current study continues this line of research by examining publicly reported variables that may predict EL graduation rates (ELGR) at the school and school-system levels. Researchers aimed to determine whether the school average per pupil expenditure (PPE), the school mobility rate (MOB), the percentage of teachers out of field (TOF), and the percentage of inexperienced teachers and/or school leaders (INEX) are significant school- and system-level predictors of ELGR.

Specifically, the study addressed the following research questions:

1. Are school average per pupil expenditure (PPE), the school mobility rate (MOB), the percentage of teachers out of field (TOF), and the percentage of inexperienced teachers and/or school leaders (INEX) significant school-level predictors of ELGR?
2. Are school average per pupil expenditure (PPE), the school mobility rate (MOB), the percentage of teachers out of field (TOF), and the percentage of inexperienced teachers and/or school leaders (INEX) significant system-level predictors of ELGR?

The study's first null hypothesis (H_{01}) was that PPE, MOB, TOF, and INEX were not significant school-level predictors of ELGR. The second null hypothesis (H_{02}) was that PPE, MOB, TOF, and INEX were not significant system-level predictors of ELGR. In contrast, the first alternative hypothesis (H_{a1}) stated that PPE, MOB, TOF, and INEX were significant school-level predictors of ELGR. The second alternative hypothesis (H_{a2}) stated that PPE, MOB, TOF, and INEX were significant system-level predictors of ELGR.

Operational Definitions

Georgia complies with the No Child Left Behind Act of 2001 (NCLB) by defining a graduate as a student who leaves high school with a Regular Diploma (this does not include Certificates of Attendance or Special Education Diplomas) in the standard time (i.e., 4 years). The graduation rate calculation represents the number of graduates divided by the number of students who attended the school. The number of students attending the school includes any student reported in the Student Record and excludes no-shows (GOSA, 2022). The current study used the 4-year graduation rates of students classified as ELs (ELGR).

In Georgia, the Georgia Professional Standards Commission (GaPSC) establishes the certification requirements under the Official Code of Georgia Annotated (O.C.G.A.). However, Georgia law also allows administrators to waive certification requirements in Title 20 with an approved Charter or Strategic Waiver Application. Indices of teacher professional qualifications in the state, schools, and school systems include the percentage of inexperienced teachers and/or school leaders (INEX) and teachers out of field (TOF; GOSA, 2022).

O.C.G.A. §20-14-3 requires GOSA, in coordination with the Georgia Department of Education (GaDOE), to create a financial efficiency rating. The law requires that GOSA and the GaDOE collaborate to "adopt and annually review, and revise as necessary, indicators of the quality of learning by students, financial efficiency, and school climate for individual schools and for school systems." The PPE calculation is typically used to determine the Financial Efficiency Star Rating (FESR) and represents the average amount of money that a school or school system allocates per student (GOSA, 2021). The MOB indicator, also known as the churn rate, represents the ratio of the total number of student entries and withdrawals between October

1 and May 1 and the total number of students enrolled on the first Tuesday in October (GOSA, 2022; APSInsights, 2018).

Methods

Data Sources

Data consisted of 117 high schools from 42 school systems in the state of Georgia. Out of the 446 schools reporting graduation rates for all students, only 117 reported EL graduation rates for the 2019–2020 academic year. Data for the study were compiled from public records provided by the Governor's Office of Student Achievement (GOSA, 2022). For each school, researchers used the ELGR, PPE, MOB, TOF, and INEX. The PPE variable indicates the average amount that school systems and/or schools allocate per student. Student mobility rates (MOB) represent the proportion of students enrolling or withdrawing from a school throughout the academic year. The TOF and INEX variables indicate the proportion of teachers within a school who were hired without meeting certification requirements. The state's certification requirements are specified by the Professional Standards Commission. Nevertheless, school officials have the authority to waive certification requirements and hire out-of-field teachers and inexperienced teachers and/or leaders.

Data Analysis

Before analyzing the data, researchers examined the distribution of missing values. All schools included in the study had valid EL graduation rates; however, some schools had missing values on the other variables. Missing values ranged between 0% and 2.6% and had a completely random distribution (Little MCAR's $\chi^2_{(15)} = 15.893$, $p = .389$). To avoid losing data, missing values were imputed using the expectation maximization algorithm. Researchers further examined the distribution of the variables by calculating descriptive statistics and indices of skewness and kurtosis.

Multilevel Linear Modeling

The sample consisted of schools in the state, which are clustered under school systems (average cluster size = 2.786). Multilevel or hierarchical regression models account for the clustered nature of the data and estimate a hierarchical system of regression equations (Raudenbush & Byrk, 1986, 1988). Specifically, they estimate the relationships between predictors, which can be at various levels of the data, and a single outcome measured at the lowest level (Hox, 2010). The researchers employed two-level linear modeling to predict ELGR based on PPE, MOB, TOF, and INEX. All predictors were measured at the school level and were converted into z scores for regression analyses.

The researchers explored the structure of the data by estimating (a) an unconditional, intercept-only, two-level model (Model 1), (b) a within-group conditional model with random intercepts (Model 2), (c) a between-group model with means as outcomes (Model 3), (d) a within- and between-group model (Model 4), and (e) a between-group random slopes model (Model 5). The estimation of the null model (Model 1) yielded sample statistics for both the within-group and between-group level. This preliminary information allowed researchers to explore relationships among variables within and across school systems and, therefore, addressed both research questions. Model 1 also provided a baseline for assessing model fit. In contrast to the intercepts-only or unconditional model that did not incorporate predictors, Model 2 allowed researchers to begin the examination of predictive relationships. This conditional model specified random intercepts and used predictors at the within-group level thus addressing the first research question. Nevertheless, this model did not inform researchers on between-group relationships between predictors and ELGR. Therefore, researchers examined variations across groups by estimating between-group predictors without the within-group predictors (Model 3). This type of model aims to predict between-group differences and is, therefore, referred to as “means as outcomes’’ (Kelloway, 2014, p. 195). Model 3 addressed the second research question. Model 4 simultaneously estimated the relationships of interest at the within-group and between-group levels. Model 4 provided information both on the within-group and between-group level thus addressing both research questions. Model 5 aimed to determine whether regression slopes varied significantly across groups and provided supplementary information addressing the second research question. In contrast to Model 3, which predicted intercept differences across groups, Model 5 was similar to a moderation hypothesis, and specified that the relationships of interest differed between groups (Kelloway, 2014).

Researchers used the following criteria to assess model fit (a) -2 log likelihood, (b) Akaike Information Criterion (AIC), (c) Bayesian Information Criterion (BIC), (d) Sample-Size Adjusted BIC, (e) the χ^2 test of model fit, (f) Root Mean Square Error of Approximation (RMSEA), (g) Standardized Root Mean Square Residual (SRMR), (h) Comparative Fit Index (CFI), and (i) Tucker-Lewis Index (TLI). Parameters were calculated using grand mean centering and the robust maximum likelihood (MLR) estimation method with the M*plus* 8.4 statistical software. The MLR estimation method provides accurate results with continuous variables that do not necessarily have normal distribution (Muthén & Muthén, 2017). In addition to model parameter estimates and goodness of fit indices, the within- and between-group correlations and covariances and the intraclass correlation coefficients (ICCs) for all variables are reported. ICCs represent the percentage of variance that exists at the group level (Kelloway, 2014).

Results

Descriptive Analyses

Descriptive analyses showed that the average 2020 EL graduation rate for the schools included in the study was 66.44% (*SD* = 20.246). The average school PPE was $9,223.37 (*SD* = $2,026.28) and the average MOB was 18.39% (*SD* = 23.98). The average TOF was 9.86% (*SD* = 6.10) and the average INEX was 42.36% (*SD* = 14.80). Variables ELGR and TOF had relatively normal distributions, whereas the other variables had higher indices of skewness and kurtosis. Interestingly, MOB rates had a maximum value of 130.8%. This is possible because MOB is a function of the number of student moves (entries and withdrawals), which can exceed the number of students enrolled at the beginning of the school year. The school with the maximum MOB value is a high school located in a suburban school system with a high density of students from immigrant families. Table 1 reports descriptive statistics and skewness and kurtosis coefficients for all variables.

Table 1

Descriptive Statistics

Statistic	ELGR (%)	PPE	MOB (%)	TOF (%)	INEX (%)
Min	0	6976.67	2.4	0	17
Max	100	21665.12	130.8	38	99
M	66.44	9223.37	18.393	9.86	42.36
SD	20.25	2026.28	23.98	6.10	14.80
Skewness	-1.166	2.798	3.248	1.174	2.126
Kurtosis	1.463	11.082	9.888	2.917	6.112

Multilevel Linear Modeling

Model 1 results showed that, within school systems, the strongest covariances were ELGR–MOB, PPE–MOB, and ELGR–PPE. While PPE–MOB was a positive relationship, ELGR–MOB and ELGR–PPE were negative. The weakest relationships were ELGR–TOF and PPE–TOF. Between school systems, the strongest covariance was TOF–PPE followed by TOF–INEX. PPE–TOF was a negative relationship, whereas TOF–INEX was positive. TOF had the highest ICC, indicating that approximately 33.4% of the TOF variance is between-group variance. Variables MOB and INEX had the lowest ICCs, indicating that the between-group variance of these variables was only 8.0% and 2.7% respectively. Table 2 reports the within- and between-group covariances, correlations, and ICCs for all variables. Table 3 lists Model 1–Model 5 estimates of model fit. Grand means of the study variables are included in Table 4, which reports the standardized model results for all estimated models.

Table 2

Sample Statistics

	ELGR	PPE	MOB	TOF	INEX
Within:					
Covariances					
ELGR	0.898				
PPE	-0.497	0.795			
MOB	-0.669	0.655	0.969		
TOF	-0.007	0.009	-0.203	0.685	
INEX	-0.215	0.213	0.251	0.098	0.925
Correlations					
PPE	-0.588				
MOB	-0.717	0.746			
TOF	-0.009	0.013	-0.249		
INEX	-0.236	0.248	0.265	0.124	
Between:					
Means	0.017	0.075	-0.018	-0.093	-0.025
Covariances					
ELGR	0.115				
PPE	-0.081	0.191			
MOB	-0.033	0.005	0.027		
TOF	0.060	-0.182	0.049	0.344	
INEX	0.007	-0.044	0.034	0.148	0.080
Correlations					
PPE	-0.546				
MOB	-0.595	0.064			
TOF	0.304	-0.711	0.511		
INEX	0.077	-0.355	0.735	0.890	
Intraclass Correlations	0.113	0.193	0.027	0.334	0.080

Table 3

Model Fit Estimates

	Model 1	Model 2	Model 3	Model 4	Model 5
Loglikelihood					
H_0 Value	-817.584	-122.042	-748.614	-711.823	-789.800
H_0 Scaling Correction Factor for MLR	1.947	1.110	0.755	0.921	1.653
H_1 Value	-711.733	-122.043	-711.733	-711.733	-
H_1 Scaling Correction Factor for MLR	1.501	1.110	0.854	0.921	-
Information Criteria					
Akaike (AIC)	1665.168	258.084	1511.227	1445.647	1621.600
Bayesian (BIC)	1706.600	277.420	1530.563	1476.031	1679.606
Sample-Size Adjusted BIC ($n^* = (n + 2) / 24$)	1659.184	255.292	1508.435	1441.259	1613.223
χ^2 *Test of Model Fit*					
χ^2	181.453	0.000	71.749	0.181	-
df	20	0	4	0	-
p-value	0.000	1.000	0.000	0.000	-
Goodness of Fit Indices					
RMSEA (Root Mean Square Error of Approximation)	0.263	0.000	0.380	0.000	-
CFI (Comparative Fit Index)	0.000	1.000	0.367	0.998	-
TLI (Tucker Lewis Index)	0.000	1.000	0.000	1.000	-
SRMR (Standardized Root Mean Square Residual)					
Within	0.335	0.001	0.440	0.001	-
Between	0.453	0.038	0.281	0.035	-

Table 4

Standardized Model Results

	Estimate	S.E.	Est./S.E.	Two-tailed *p*
Model 1 (Intercept Only – Unconditional Model)				
Between:				
Means				
ELGR	0.065	0.422	0.153	0.878
PPE	0.133	0.268	0.496	0.620
MOB	0.019	0.923	0.020	0.984
TOF	-0.189	0.250	-0.754	0.451
INEX	0.093	0.652	0.143	0.886
Model 2 (Random Intercepts – Conditional Model)				
Within				
PPE → ELGR	-0.188	0.124	-1.525	0.127
MOB → ELGR	-0.606	0.087	-7.005	0.000
TOF → ELGR	-0.103	0.073	-1.409	0.159
INEX → ELGR	0.003	0.053	0.054	0.957
Residual Variances				
ELGR	0.464	0.099	4.697	0.000
R^2				
ELGR	0.536	0.099	5.436	0.000
Between				
Means				
ELGR	0.123	0.373	0.329	0.742
Model 3 (Means as Outcomes)				
Between Level				
PPE → ELGR	-0.102	0.523	-0.195	0.845
MOB → ELGR	-1.127	2.020	-0.558	0.577
TOF → ELGR	0.012	0.421	0.028	0.978
INEX → ELGR	0.249	1.493	0.167	0.868
Intercepts				
ELGR	0.009	0.314	0.028	0.977
Residual Variances				
ELGR	0.012	0.719	0.016	0.987
Model 4 (Within and Between)				
Within (School Level):				
PPE → ELGR	-0.032	0.182	-0.177	0.859
MOB → ELGR	-0.740	0.114	-6.466	0.000
TOF → ELGR	-0.192	0.044	-4.369	0.000
INEX → ELGR	-0.008	0.050	-0.156	0.876
Residual Variances				
ELGR	0.446	0.085	5.270	0.000
R^2				
ELGR	0.554	0.085	6.552	0.000

Between (School System Level):				
PPE → ELGR	-0.058	1.065	-0.055	0.956
MOB → ELGR	-1.208	1.386	-0.871	0.384
TOF → ELGR	0.300	1.949	0.154	0.878
INEX → ELGR	0.707	2.240	0.315	0.752
Intercepts				
ELGR	0.062	0.306	0.202	0.840
Residual Variances				
ELGR	0.228	0.961	0.237	0.813
R^2				
ELGR	0.772	0.961	0.803	0.422
Model 5 (Random Slopes)				
Within (School Level):				
Variances				
PPE	0.758	0.312	2.429	0.015
MOB	0.985	0.226	4.365	0.000
TOF	0.712	0.140	5.100	0.000
INEX	0.956	0.244	3.921	0.000
Residual Variances				
ELGR	0.550	0.086	6.364	0.000
Between (School System Level)				
Random Slopes				
PPE → random slope	0.035	0.047	0.741	0.458
MOB → random slope	0.003	0.073	0.035	0.972
TOF → random slope	0.007	0.058	0.116	0.908
INEX → random slope	0.004	0.049	0.080	0.936
Means				
ELGR	0.086	0.133	0.648	0.517
PPE	0.077	0.122	0.630	0.529
MOB	0.003	0.087	0.036	0.971
TOF	-0.102	0.132	-0.771	0.441
INEX	0.020	0.162	0.125	0.901
Random Slope	-0.214	0.047	-4.571	0.000
Variances				
ELGR	0.058	0.047	1.233	0.218
PPE	0.277	0.108	2.557	0.011
MOB	0.011	0.108	0.098	0.922
TOF	0.300	0.147	2.045	0.041
INEX	0.039	0.221	0.177	0.859
Random Slope	0.006	0.015	0.407	0.684

Model 2 parameter estimates showed that MOB (estimate = -0.606, $p < .001$) was a significant within-group predictor of ELGR and the within-group regression model explained 53.6% of the variance ($p < .001$; Table 4). As indicated in Table 4, Model 2 had the best fit to the data. Results from Model 3 showed that at the between-group level none of the study variables were significant predictors of ELGR group means (Table 4). Compared to the other models, this model had a moderate fit to the data (Table 4). Consistent with Model 3, Model 4 yielded non-significant between-group estimates for all predictors. Similar to Model 2, Model 4 yielded MOB as a significant within-group predictor of ELGR (estimate = -0.740, $p < .001$). Additionally, in Model 4 the TOF estimate was statistically significant (estimate = -0.192, $p < .001$). Within groups, predictors explained 55.4% of the variance ($p < .001$). Model 4 had the second best fit to the data (Table 4) but was more informative than Model 2, which had the best fit. Although between-group relationships were not statistically significant, taking them into account yielded TOF as an additional significant within-group predictor of ELGR in conjunction with MOB. Model 5 results showed that slopes did not vary significantly (Table 4); therefore, relationships did not differ at the school system level.

Discussion

Paradoxically, the current study showed that increased spending does not predict higher EL graduation rates. This finding may suggest that there are better solutions than indiscriminately throwing money at the problem. More targeted interventions for issues related to the specific needs of ELs are needed to address the problem of low ELGR directly. For example, school-level leaders should implement professional learning focused on ELs and find ways to incentivize completing English to Speakers of Other Languages (ESOL) endorsements or similar certifications. Even moderate training in ESOL teaching methods can positively impact student outcomes (Lavery et al., 2019). Moreover, schools and districts could purposefully allocate funds to recruit high-quality ESOL teachers and support specialists, sponsor after-school tutoring and extracurricular activities for ELs, etc. Schools confronted with issues such as low student performance, high mobility rates, etc., may be allocating more money per student (e.g., Title 1 schools) but to little avail (Jackson, 2020; Roza, 2010). Mindrila (2021) found that these schools are located mostly in urban and suburban areas. Purposeful allocation of funds, or lack thereof, may be an issue here.

Over a decade ago, Roza (2010) revealed that education dollars are allocated in ways that often are sharply at odds with the stated priorities of public school systems. Public school systems often profess a commitment to equitable outcomes for all students, yet cases of districts pushing more funding to wealthier schools are well attested (Knight et al., 2022; Roza, 2010). More recently, Knight et al. (2022) found inequitable spending patterns, racial and income-based spending gaps, and resource disparities across multiple California school districts, thus underscoring the need for fully transparent information on how districts and schools allocate their funds nationwide. Unfortunately, publicly available school expenditure data by student subgroup or student support programs are unavailable in Georgia.

The negative relationship between ELGR and MOB is consistent with previous research showing that ELs who remain settled in a particular school tend to graduate eventually (Cashiola et al., 2022). MOB was a strong school-level predictor of ELGR (Model 2 and Model 4), and the relationship between MOB and ELGR was negative. That is, as school mobility rates—the percentage of students entering and exiting a school—increased, EL graduation rates decreased. The implication is immediately clear: students who are settled in a single school tend to perform better and eventually graduate compared to those who are mobile.

Researchers have known for some time that student mobility affects graduation rates, or "that student mobility is both a symptom of disengagement and an important risk factor for high school dropout" (Rumberger & Larson, 1998, p. 1). ELs, especially those from economically disadvantaged home environments, are particularly prone to change schools for various reasons, such as seeking better economic outcomes or escaping poor neighborhoods (Beaudette, 2015; Calibuso & Winsler, 2021; Welsh, 2017). Moreover, transferring schools disrupts student learning, including the time it takes for ELs to become proficient in English (Mitchell et al., 1997). Students who change schools frequently must adjust to new teachers, curricula, and classmates (Beaudette, 2014), which can lead to emotional problems and lower academic performance (Dinnen et al., 2020).

Many suggestions have been made for lessening school mobility. For example, Dinnen et al. (2020) found that fostering school connectedness, generally understood as students believing that the adults in a school care about them as individuals and as learners, inhibits mobility. Other researchers have shown building positive relationships and rapport with students may limit the negative effects of mobility (e.g., Schmitt et al., 2018). Likewise, student participation in clubs and afterschool programs has been found to moderate negative effects associated with mobility (Voight et al., 2017). These findings suggest there are numerous actions school leaders can take to mitigate the effects of school mobility on ELs, but these school reforms should begin with building positive school cultures and environments where all students, including culturally and linguistically diverse students, feel welcomed, safe, and valued for their unique contributions to the school community.

When relationships were estimated at both the school and the system level, TOF was also a significant school-level predictor of ELGR (Model 4), and like with MOB, the relationship was again negative. In other words, the EL graduation rate declined as the number of teachers hired out of field increased. The implications of this finding are many and suggest preparing teachers to support ELs "must become a mainstream concern" for school leaders (Bunch, 2013, p. 301).

Employing highly qualified teachers certified in their respective fields is important to student success, particularly for ELs who are in need of specialized support by trained educators certified to provide language support services (Ruiz de Castilla, 2018). Moreover, specialized pedagogical knowledge is necessary to help ELs master rigorous high school curricular standards while learning English as an additional language (Ollerhead, 2018).

Limitations and Further Research

By examining data that are publicly available through Georgia's school accountability online database, this study elucidates which school- and district-related variables may or may not promote EL graduation rates in Georgia public high schools. The limited information about the participating schools (such as the number of ELs in each school), the sample size, and location of this study (117 high schools from 42 school systems in the state of Georgia) necessarily limit the generalizability of the findings, though the current study's results are consistent with previous studies that have demonstrated strong correlations among limited student mobility, recruitment of highly qualified teachers, and measures of student achievement, including high school graduation rates (e.g., Dinnen et al., 2020; Jackson, 2020; McKeever & Clark, 2017; Rumberger & Larson, 1998; Voight et al., 2017; Wood et al., 2017; Zaff et al., 2017). Future research should continue this focus by examining the variables analyzed in this study (and others) longitudinally over several years. Additional school- and/or district-related variables to explore—some publicly available, others not—include attendance rates, school SES levels, school size, school climate, the prevalence of extracurricular activities, etc. (McKeever & Clark, 2017; Wood et al., 2017; Zaff et al., 2017). In addition, employing mixed-methods research by conducting focus groups and interviews with ELs, parents, teachers, and school leaders to determine what stakeholders perceive as variables influencing EL graduation rates may further elucidate these findings and offer additional avenues of inquiry for increasing EL graduation rates and bridging other achievement gaps between ELs and their English-dominant peers.

Conclusion

This study is an important starting point for exploring variables influencing EL graduation rates (ELGR) in Georgia and other states. The results of this study revealed significant relationships between ELGR and school mobility rates, per-pupil expenditures, and percentages of out-of-field teachers, respectively. The inverse relationship between student mobility and ELGR underscores the need for school leaders to find ways to keep students, especially culturally and linguistically diverse learners, settled in a supportive school for as long as possible. The inverse relationship between ELGR and per-pupil expenditures seems counterintuitive, though the publicly available data for this study did not specify how school funds were allocated. A key implication here is that schools should allocate funds in a targeted manner to address the unique learning and social needs of ELs. Lastly, teacher quality, represented by the number of out-of-field teachers, is an important factor to consider when seeking to create a supportive learning environment for ELs. Teachers of ELs should be experts in their respective fields and familiar with best practices for supporting ELs. The findings and implications of this study should serve as important points of consideration for school leaders and policymakers and prompt further research exploring other variables likely to affect ELGR.

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