Journal for the Education of the Gifted
2020, Vol. 43(4) 370–404

DOI: 10.1177/0162353220955225
journals.sagepub.com/home/jeg
SAGE

Proficiency and Giftedness: The Role of Language Comprehension in Gifted Identification and Achievement

Rashea Hamilton[1], Daniel Long[2], D. Betsy McCoach[2], Vonna Hemmler[3], Del Siegle[2], Sarah D. Newton[2], E. Jean Gubbins[2], and Carolyn M. Callahan[3]

Abstract

English learners (ELs) are the fastest growing population of students in the United States and currently represent nearly 10% of public school enrollment; however, they also constitute less than 3% of gifted program enrollment in these schools. Although an increasing number of studies explore this underrepresentation, research that specifically examines the role of language proficiency in gifted identification is limited. This study explored the role of several factors on ELs' time to reclassification (the point at which students are considered to have reached language proficiency and are no longer classified as ELs) and, in turn, being identified for gifted services. The findings suggested notable demographic and socioeconomic influences on the time to reclassification of ELs. Students who were reclassified earlier tended to be enrolled in schools with more gifted students and had a greater probability of being identified as gifted.

Keywords

English learners, reclassification, gifted identification

[1]Washington Student Achievement Council, Olympia, USA
[2]University of Connecticut, Storrs, USA
[3]University of Virginia, Charlottesville, USA

Corresponding Author:
D. Betsy McCoach, University of Connecticut, 249 Glenbrook Road Unit 3064, Storrs, CT 06269, USA.
Email: betsy.mccoach@uconn.edu

Between 1995 and 2005, the population of English learners (ELs) in American public schools doubled in at least 23 states (Payán & Nettles, 2008).[1] Currently, the U.S. Department of Education (USDOE) estimates that ELs represent approximately 10.1% of public K–12 enrollment, and it is expected that ELs will make up 40% of the total public school population by 2050 (Goldenberg, 2008; USDOE, 2018a). Despite this rapid growth, ELs represent less than 3% of gifted program enrollment in these schools (USDOE, 2018b). Part of this disproportionality might be related to the lower achievement on standardized tests that ELs may display when compared to never- or non-ELs (i.e., students whose home language is English or who speak a non-English home language but were never classified as EL; Murphey, 2014). However, standardized tests administered in English may underestimate what ELs actually know, especially for those with strong skills in their home languages (Ardasheva et al., 2012). Some of the disproportionality may also be a direct result of EL classification itself. Schools and districts may have explicit policies that systemically restrict students classified as EL from participating in certain classes (Kanno & Kangas, 2014). Furthermore, gifted programs may have screening procedures not appropriate for identifying ELs. The inability of educators to appropriately respond to the unique needs of their ELs may also contribute to the lack of ELs in gifted programs and their overrepresentation in special education programs (e.g., Harris et al., 2009).

Background

Factors Related to EL Outcomes

Student factors. Research suggests that the majority of ELs in public schools are from low-income families (Estrada & Wang, 2018). As is the case with other student populations, limited income is associated with poor academic outcomes for ELs. Researchers have found that ELs from low-income backgrounds may gain English proficiency more slowly than their higher income EL peers (Burke et al., 2016; Carhill et al., 2008; Hakuta et al., 2000).

School factors. School- and district-level factors also seem to play a role in Els' achievement. School poverty, for example, is correlated with EL student outcomes. Using multilevel structural equation- and hierarchical linear modeling, Miura (2006) examined the role of student- and school-level variables in high-stakes test performance for a sample of 4,529 fourth- and sixth-grade ELs in Ohio. Student-level variables included time spent in U.S. schools, home language, gender, race/ethnicity, socioeconomic status (SES), migrant status, and English language proficiency; school-level variables included school percentages of student mobility and student's eligibility for free or reduced-price lunch (FRPL). School poverty was correlated with EL student performance on the fourth- and sixth-grade state assessments (Miura, 2006).

In another study, Hakuta and colleagues (2000) analyzed data from four school districts, two in Canada and two in the United States, to examine factors related to students' time to English proficiency. Predictors included student/family and school poverty, as measured by parental education and eligibility for FRPL, respectively. Hakuta et al. measured English proficiency with various assessments including the Woodcock Language Proficiency Battery, MacMillan Informal Reading Inventory, and the Idea Proficiency Test. Reclassification, the point at which students were considered to have reached language proficiency and were no longer classified as ELs, occurred more slowly in schools in which at least 70% of students qualified for FRPL, as compared with lower poverty schools (Hakuta et al., 2000). In addition, ELs whose parents had more than a high school diploma displayed higher English proficiency scores than other students in the sample.

More recently, Carhill and colleagues (2008) used multilevel modeling to examine various factors related to English proficiency, as measured by the Bilingual Verbal Abilities Test (BVAT), in a sample of 273 adolescent ELs. Although student-level characteristics such as maternal education predicted English proficiency, scores on the school factors such as school level of English proficiency and school level of English usage were also related to individual English proficiency. School poverty did not predict student-level English proficiency, after controlling for student, family, community, and school factors, but did correlate with student BVAT scores.

Program factors. In addition to school demographics, the way in which schools approach the education of ELs may also influence student outcomes. For example, bilingual education programs are associated with improved EL outcomes. Umansky and Reardon (2014) examined nine cohorts of ELs who entered a district in kindergarten between fall 2000 and spring 2009 and were enrolled in one of the district's four EL programs. They found that students enrolled in dual-language programs tended to have higher rates of reclassification by the end of high school than those in English immersion programs, although the dual-language-enrolled students demonstrated slower reclassification rates in elementary school. In addition, several scholars have argued that school-level failure to meet the needs of ELs is associated with students' continued classification as EL. These authors have advanced the notion that some ELs are continually classified as such, not because of an inability to attain language proficiency, but due to subpar instruction, enrollment in inconsistent learning environments, and/or exposure to learning environments in which their diverse backgrounds were not valued, which may be the case in English-only classrooms (Kibler et al., 2018; Menken & Kleyn, 2010). Thus, several demographic and programmatic factors may affect ELs' likelihood of achieving favorable academic outcomes and reclassification.

Time to Reclassification

Although a standard time to EL reclassification does not exist, the Every Student Succeeds Act (ESSA) mandates that schools keep track of and report ELs who have not been reclassified after 5 years of initial classification and enrollment in schools (U.S. Department of Education, 2016). This timeline roughly aligns with recommendations from scholars, who suggest that the process of becoming "English proficient" and attaining reclassification may take somewhere between 2 and 7 years. For instance, Conger (2009) found that ELs in a New York City school district took approximately 3 years to achieve English proficiency, whereas Thompson (2017) concluded that participants in her longitudinal study in Los Angeles took between 4 and 7 years. Similarly, Umansky and Reardon (2014) found that ELs in California had a median time to reclassification of approximately 6 to 7 years.

Moreover, Hakuta and colleagues (2000) distinguished expectations for reclassification by oral and academic proficiency: Skills such as sound discrimination, oral expression, vocabulary comprehension, production, and listening comprehension—considered to be components of oral proficiency—generally develop within 3 and 5 years, whereas academic English proficiency requires 4 to 7 years to attain (Hakuta et al., 2000).

Given differences in the types of language used and promoted in and outside the classroom, it may seem sensible to divide English language skills into social and academic abilities (Hakuta et al., 2000). Similarly, Cummins (1979, 1994, 2000) juxtaposed *basic interpersonal communication skills* (BICS), more informal language, and *cognitive academic language proficiency* (CALP), language students are expected to use in academic tasks. However, parts of the language education community have criticized this division, fearing that this distinction may stigmatize ELs as “unready to learn” if they come into the classroom with a perceived advantage in BICS but a lack of, or reduced ability to develop, CALP (Aukerman, 2007, p. 626).

Such a critique is pertinent to the current study, which uses standardized tests to measure language proficiency. As language proficiency tests can vary in terms of whether they measure one type of language proficiency more than the other and how they assess skills within each type, their use can lead to variation in the inferences made about ELs’ performance on the assessments and, thus, readiness for reclassification (Wolf & Faulkner-Bond, 2016). We acknowledge that language proficiency tests as they are currently used might not capture *all* of an EL’s linguistic abilities or readiness for reclassification. However, that does not detract from the practical significance of the current study. It is imperative to consider the relationship between time to reclassification, or time classified as EL, and an EL’s prospects for gifted education, not only because these standardized assessments currently play a central role in identifying students for gifted education, but also because there is yet-to-be-understood variation in how long it takes students to become reclassified and in the factors that might affect this timetable. Understanding this variation may facilitate accurate and proportional identification of EL students as gifted, particularly in the context of the ever-EL framework in which ELs receive this label regardless of whether or when they reclassify (Umansky et al., 2017).

Reclassification and Student Outcomes

Time to reclassification can vary considerably, and we have limited understanding about how this influences ELs’ outcomes. Research suggests that being reclassified does indeed relate to student outcomes (Ardasheva et al., 2012; Carlson & Knowles, 2016; Kim & Herman, 2009). In particular, Carlson and Knowles (2016) studied ELs in Wisconsin, a state that requires schools to automatically reclassify students after they reach a certain score on the state English proficiency exam. The authors used a regression discontinuity design (RDD) to examine the impact of reclassification on various outcomes. Their findings suggested reclassification had a positive effect on students' academic outcomes. Specifically, students who scored right above the English proficiency exam cutoff score and were thus reclassified demonstrated higher ACT-taking rates, higher ACT scores, higher high school graduation rates, and higher postsecondary enrollment rates than ELs right below the cutoff score (Carlson & Knowles, 2016).

Related research by Kim and Herman (2009) exploring the language-based achievement gap in three states also demonstrated an association between reclassification and student outcomes. Their sample included students between fourth and eighth grade who were non-EL and ever-EL (i.e., students who were formerly and currently classified as EL) at the time of data collection. The authors examined students' scores on state reading, math, and science assessments to measure achievement; they utilized scores from the state's English language proficiency exam to assess ELs' skills in reading, writing, listening, and speaking. The authors estimated multilevel models to assess differences in achievement. First, they observed achievement gaps between current ELs and non-ELs in all subjects across all three subjects, with non-ELs outperforming their EL counterparts. They also uncovered achievement gaps between former ELs and non-ELs—after controlling for students' eligibility for FRPL, former EL students reclassified at least 2 years prior to data collection generally outperformed their non-EL peers across all three states in all subjects (with the exception of eighth-grade science scores in one state where former ELs performed on par with non-ELs). However, mixed results appeared for recently reclassified students (those reclassified within 2 years of data collection). In one state, recently reclassified ELs demonstrated lower performance when compared with non-ELs, whereas in another state, recently reclassified ELs outperformed non-ELs. In the third state, recently reclassified ELs outperformed non-ELs in fourth but not eighth grade (Kim & Herman, 2009).

In a similar study, Ardasheva and colleagues (2012) also used multilevel modeling to explore the relationship between reclassification and student outcomes. They utilized the Language Assessment Scales in reading/writing and oral language as the measure of English proficiency and the math and reading components of the Kentucky Core Content Test as the measure of achievement. Results indicated that reclassified ELs significantly outperformed non-ELs by just under 10 points and also outperformed current ELs by just under 20 points. Furthermore, reclassified/former ELs in low-SES schools still outperformed their non-EL and current EL peers (Ardasheva et al., 2012).

These studies make an important contribution by employing an ever-EL framework to demonstrate the association between reclassification and student outcomes. This approach—the inclusion not just of current ELs but also of former ELs—is part of an innovative turn in the literature and has been recommended as a necessary next step for this body of work to obtain a more nuanced understanding of how EL classification influences achievement-related processes and vice versa. There is considerable variation across schools, districts, and states in the criteria ELs must meet to be reclassified (e.g., de Jong, 2004; Estrada & Wang, 2018; Linquanti et al., 2016; Saunders & Marcelletti, 2013). An EL might qualify for reclassification in one state but miss the cutoff for it in others (meaning that what is viewed and analyzed as progress or proficiency in one instance does not hold in others), which may alter the types of conclusions drawn about this population.

Furthermore, schools and districts regularly engage in reclassification processes for their ELs, therefore turnover from EL to reclassified as non-EL (i.e., former EL) is common. Even so, most of the literature related to this population tends to focus only on students currently classified as EL and not on those that have been reclassified, partially because in most states, former ELs' progress and performance are no longer monitored after reclassification. Researchers like Estrada and Wang (2018) and Saunders and Marcelletti (2013) have blamed this exclusion of reclassified students from previous analyses for falsely categorized, and perhaps oversimplified, claims about the achievement gap between current ELs and former- or non-ELs.

Although the accurate identification of such a gap is not the focus of this study, a parallel argument may stand to bear on our conclusions: Excluding former ELs from our analysis could potentially mischaracterize the relationship between reclassification and identification for gifted education, just as these authors argue has occurred for the association between reclassification and achievement. Therefore, we employed the ever-EL framework in our study to consider the performance of both current and former ELs (e.g., Linquanti et al., 2016; Umansky et al., 2017) and to investigate the relationship between time to reclassification to gifted identification.

The Current Study

Despite what we know about processes for reclassifying ELs and their presence in gifted education programs, no research has specifically linked the two and examined the role of reclassification in gifted identification. The current study aimed to address this gap. Using extant data from one full cohort of students in one state, we explored the following research questions:

Research Question 1: What was the average time to reclassification for ELs and how did this outcome relate to race/ethnicity and income level?
Research Question 2: How did time to reclassification predict ELs' likelihood for identification for gifted programming? How did race/ethnicity, income, and achievement affect gifted identification?

Method

Data

In this study, we used longitudinal data from the department of education in a large southern state. The identification policies used by districts in this state varied notably, but most school districts used multiple measures for identification of gifted students including ability tests, achievement tests, and other measures. The state provided gifted identification status but was not able to provide the IQ tests and/or other evaluation data used to identify students as gifted. The state data also included demographics, achievement test scores, and EL status for all fifth-grade students in the 2013–2014 academic year. A total of 212,018 students were enrolled in fifth grade in this state in 2013–2014. The data included three waves of student-level demographic, EL and gifted status indicators, and achievement data from this cohort, from third grade through fifth grade as well as dates of entry into, and reclassification from, EL programs between kindergarten and fifth grade (K–5) for this cohort of students. School- and district-level data included individual-level variables aggregated by the school and district in which students were enrolled at third grade.

Sample

To facilitate this investigation of time to EL exit, we restricted our analysis to students who had data on all variables of interest and completed a traditional academic progression from K to 5, without repeating or skipping a grade. This restricted our analysis to administrative records to students who were enrolled in kindergarten within the state in 2008–2009, first grade in 2009–2010, second in 2010–2011, third in 2011–2012, fourth in 2012–2013, and fifth in 2013–2014. Therefore, when we only examined students with available K–5 enrollment data and students who followed a traditional K–5 progression, our sample decreased by 35% (from 212,018 to 136,956) due to student mobility and as 22% of schools with fifth-grade students in 2013–2014 did not report kindergarten enrollment data. After listwise deletion of missing data on achievement scores, EL status, time in EL programs, gifted status, and demographic data, our sample for all students consisted of 127,617 students. As presented in Table 1, approximately 12% of the full sample were identified as gifted, 65% qualified for FRPL, and 20% were classified as EL at some point between kindergarten and fifth grade (i.e., ever-ELs). In addition, approximately 43% were non-Hispanic White, 30% of the sample were Hispanic, 20% were African American/Black, and 3% were Asian.

The analytic sample for this study included only those students who were classified as EL at any point between kindergarten and fifth grade. After listwise deletion, the final sample size was 24,892 ELs, in 1,710 schools, in 65 districts. In our analytic sample of ever-ELs, approximately 9% of the sample were identified as gifted, and 87% were FRPL eligible. In addition, 79% of the EL sample were Hispanic, 10% were African American/Black, 5.5% were non-Hispanic White, and 4.5% were Asian.

Measures

English learner status. In the state administrative data, students classified as having limited English proficiency were coded as ELs. At the individual/student level, EL was a dichotomous variable, coded "0" for students never classified as ELs and "1" for students classified as ELs at any point between kindergarten and fifth grade. At the

Table 1. Descriptive Statistics—Demographics.

	All students (N = 127,617)		Non-ELs (N = 102,725)		ELs (N = 24,892)		Early-exit ELs (N = 2,004)		Late-exit ELs (N = 22,888)	
Variables	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Student-level variables										
Time in EL (days)	232	553	0	0	1,192	654	734	331	1,876	349
Gifted	0.12	0.33	0.13	0.34	0.09	0.28	0.14	0.35	0.08	0.28
Free or reduced-price lunch (FRPL)	0.65	0.48	0.59	0.49	0.87	0.33	0.80	0.40	0.88	0.32
English learner (EL)	0.20	0.40	1.00		1.00		1.00		1.00	
Hispanic	0.30	0.46	0.18	0.39	0.79	0.40	0.73	0.45	0.80	0.40
Black	0.20	0.40	0.23	0.42	0.10	0.30	0.11	0.31	0.10	0.30
Asian	0.03	0.16	0.02	0.15	0.05	0.21	0.05	0.23	0.04	0.21
Other, non-White race	0.04	0.20	0.05	0.21	0.01	0.10	0.02	0.14	0.01	0.09
School-level variables										
Gifted, school prop.	0.11	0.11	0.11	0.11	0.11	0.10	0.11	0.09	0.11	0.10
FRPL, school prop.	0.66	0.25	0.63	0.25	0.79	0.20	0.72	0.23	0.79	0.20
EL, school prop.	0.21	0.21	0.15	0.16	0.43	0.24	0.33	0.20	0.44	0.24
Hispanic, school prop.	0.30	0.25	0.25	0.21	0.54	0.29	0.44	0.24	0.55	0.29
Black, school prop.	0.21	0.23	0.22	0.23	0.20	0.22	0.20	0.21	0.19	0.22
Asian, school prop.	0.03	0.03	0.03	0.03	0.02	0.03	0.03	0.03	0.02	0.03
Other, non-White race, school prop.	0.04	0.03	0.04	0.03	0.03	0.03	0.03	0.03	0.03	0.03
District-level variables										
Gifted, district prop.	0.10	0.04	0.09	0.04	0.11	0.04	0.10	0.04	0.11	0.04
FRPL, district prop.	0.70	0.09	0.69	0.09	0.74	0.07	0.71	0.07	0.74	0.07
EL, district prop.	0.20	0.14	0.17	0.13	0.31	0.14	0.27	0.12	0.31	0.14
Hispanic, district prop.	0.29	0.17	0.26	0.15	0.41	0.17	0.37	0.15	0.42	0.18
Black, district prop.	0.26	0.13	0.25	0.13	0.27	0.10	0.25	0.11	0.27	0.10
Asian, district prop.	0.02	0.01	0.02	0.01	0.02	0.01	0.03	0.01	0.02	0.01
Other, non-White race, district prop.	0.04	0.02	0.04	0.02	0.03	0.02	0.03	0.01	0.03	0.02

Note. Early-exit ELs were students whose time in EL was less than or equal to the mean for ELs (1,192); late-exit students were students whose time in EL was greater than the mean. All School and District variables are from students' third-grade classes unless otherwise noted. These descriptive statistics were computed after listwise deletion of missing data.

school and district levels, continuous EL variables reflected the proportions of students in each school/district with this EL classification (aggregated from the full student cohort data set).

Race/ethnicity. State data also included students' race/ethnicity. Our analyses included dichotomous indicators for African American/Black, Hispanic, Asian, White, or an "other" race (representing students who did not fall into any of the four aforementioned groups). White was the reference group for our analyses. At the school and district levels, two continuous race variables (aggregated from the full student cohort data) reflected the proportion of students in each school/district that were Black or Hispanic, respectively.

Free or reduced-price lunch. The dichotomous FRPL variable served as a proxy for income, students who were FRPL eligible at any point between third and fifth grade were coded "1"; all other students were coded "0." At the school and district levels, FRPL was a continuous variable that reflected the proportion of students in the school/district eligible for FRPL (aggregated from the full student cohort data).

Time in EL. We measured time in EL, or time to reclassification, in years, from 0 to 5. To create this variable, we first calculated the number of days in which students were classified as EL between kindergarten and fifth grade, based on administrative records of the date of classification as EL and the date of exit from EL (reclassification). The histogram in Figure 1 demonstrates the stochastic and multimodal nature of the EL variable when measured in days. We compared model fit measuring time in EL discretely (in years) and continuously (in days; see Figures 1 and 2). The continuous version of time in EL was measured as total days/365. In the discrete version of time in EL, "0" represented students in EL less than 365 days, "1" represented students in EL between 365 and 729 days, and so on. Testing the relative fit of each of the multilevel models we estimated in this study, with EL time measured continuously (days) versus discretely (years), employing the discrete EL time variable produced better fit across all models. For example, in the baseline model of time in EL on the odds of being identified as gifted, the model with EL measured discretely had a better fit: The Akaike information criterion (AIC) was 78,818 for time measured continuously and 78,498 for time measured discretely. (Lower AIC values indicate better model-data fit.)

There was also notable non-linearity in the relationship between time in EL (no matter how we measured it) and the percentage of ELs identified as gifted (see Table 2). Therefore, we examined a series of models to identify the best way to represent the non-linear influence of time to EL exit on the proportion of ELs identified as gifted. We compared a linear model (AIC = 78,498), a quadratic model (time and time squared; AIC = 77,922), and a linear spline model (with a linear time variable and a spline variable defined as "0" for year 0, "1" for year 1, and "0" for years 2 to 5; AIC = 77,036). The AIC fit statistics showed that a linear trend plus a spline at Time 2 fit the data best.[2]

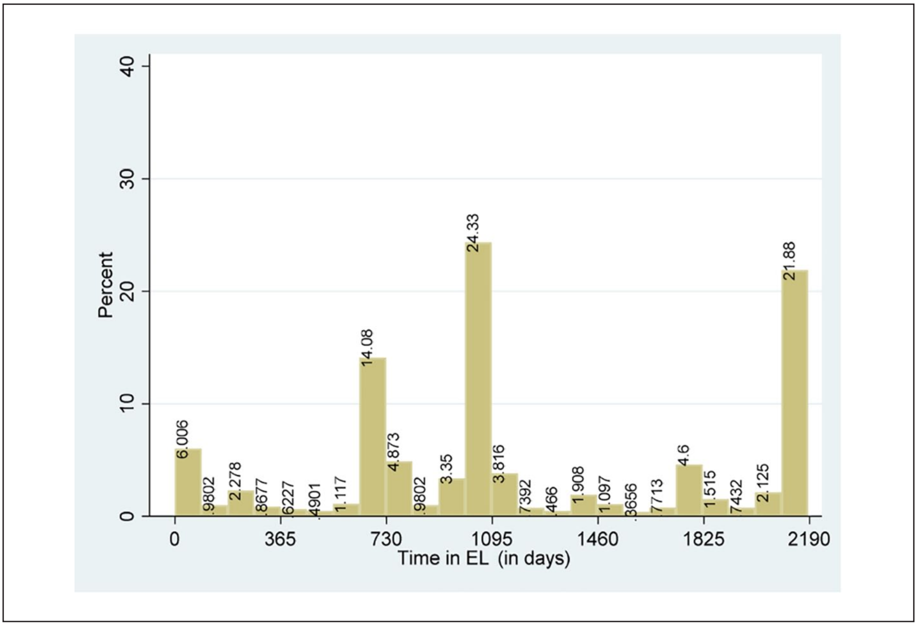

Figure 1. Time to EL exit (in days).
Note. Each bar in this histogram represents 3 months. The last bar represents students still in EL at the end of fifth grade. EL = English learner.

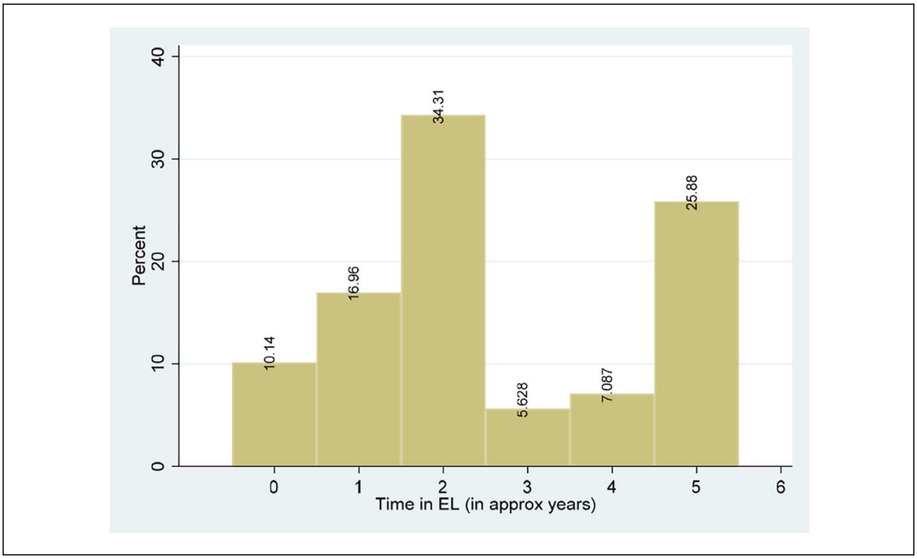

Figure 2. Time to EL exit (in years).
Note. EL = English learner.

Table 2. Percent Gifted and Math and Reading Achievement by Time to EL Exit.

Time in EL	% Identified as gifted	Math third grade	Reading third grade
0	13.7	207.7	207.0
1	22.6	214.0	211.7
2	8.5	204.8	203.3
3	5.6	201.9	201.8
4	2.9	199.3	198.1
5	0.6	190.8	188.2
Total	8.8	202.5	200.7

Note. Time in EL measured discretely. EL = English learner.

Gifted identification. At the student level, gifted identification was a dichotomous variable (coded "0" or "1") in which "1" indicated the student was identified as gifted by fifth grade. At the school and district levels, gifted identification was a continuous variable that represented the school or district proportion of students identified as gifted by fifth grade (aggregated from the full student cohort).

Achievement. The state administrative data included continuous, student-level achievement scores on the state's math and reading tests in third, fourth, and fifth grade. To predict students' gifted identification status by the fall of fifth grade, we utilized students' end of third-grade reading and math scores to represent achievement. At the school and district levels, achievement scores were aggregated from the student level by school or district, respectively. Tables 1 and 3 report the descriptive statistics for each of the variables in this study.

Analysis

To examine student-, school- and district-level influences on students' time in EL as well as a student's probability of being identified as gifted, we estimated a series of three-level hierarchical linear models (HLMs). We used this analytical framework because multilevel analyses account for the clustered nature of the data and result in more accurate standard error estimates (McCoach, 2010; McCoach & Adelson, 2010; Raudenbush & Bryk, 2002; Raudenbush et al., 2011).

Research Question 1

For Research Question 1 (time to reclassification), we examined student-level variables as predictors of time in EL, including student race/ethnicity, FRPL eligibility, and achievement scores. We also modeled school- and district-level variables, including the proportion of students eligible for FRPL, proportion of ELs, proportion of gifted students, proportion of African American students, proportion of Hispanic students, proportion of Asian students, and proportion of other non-White

Table 3. Descriptive Statistics—Achievement.

Variables	All students		Non-ELs		ELs		Early-exit ELs		Late-exit ELs	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Student-level variables										
Math ach. (third grade)	206.21	20.30	207.11	20.42	202.48	19.37	207.65	20.07	202.03	19.24
Math ach. (fourth grade)	218.77	20.83	219.42	20.90	216.07	20.33	220.05	21.43	215.72	20.19
Math ach. (fifth grade)	224.64	20.24	225.25	20.31	222.12	19.75	226.42	19.86	221.75	19.69
Reading ach. (third grade)	206.06	19.01	207.35	19.10	200.74	17.68	207.12	18.99	200.18	17.46
Reading ach. (fourth grade)	215.80	19.53	216.86	19.81	211.39	17.68	216.97	18.76	210.90	17.50
Reading ach. (fifth grade)	224.38	19.55	225.39	19.68	220.21	18.46	225.70	18.85	219.73	18.35
School-level variables										
Avg. reading ach. (third grade)	204.58	8.08	204.98	8.11	202.95	7.75	203.75	7.82	202.88	7.74
Avg. math ach. (third grade)	203.98	7.79	204.62	7.77	201.34	7.29	203.15	7.14	201.18	7.29
District-level variables										
Avg. reading ach. (third grade)	202.34	2.88	202.32	3.03	202.46	2.16	202.40	2.35	202.46	2.14
Avg. math ach. (third grade)	202.37	2.58	202.55	2.71	201.63	1.78	202.36	1.92	201.57	1.76
Sample size	127,617		102,725		24,892		2,004		20,888	

Note. Early-exit ELs were students whose time in EL was less than or equal to the mean for ELs (1,192); late-exit students were students whose time in EL was greater than the mean. All School and District variables are from students' third-grade classes unless otherwise noted. These descriptive statistics were computed after listwise deletion of missing data. EL = English learner.

students at the district and school levels. We also included school and district mean reading and math achievement. We group mean-centered continuous student-level variables around their school means and continuous school-level variables around their district means; we centered all district-level variables around the grand mean. For models with no school- or district-level variables, we centered continuous student-level variables around their grand means. This strategy allowed us to interpret the model intercept as the average time in EL for White (reference) students, in an average school.

With these variables, we estimated five random intercept models (Models 1a through 1e), each of which featured time in EL as the outcome variable of interest (Y_{ijk}). Model 1a incorporated four student-level, dichotomous, race/ethnicity indicators at Level 1, which represented whether each student was Black, Hispanic, Asian, or other (see Table 4). Model 1b added a dichotomous indicator for FRPL to the student level of Model 1a. Model 1c added the third-grade math and third-grade reading achievement variables to the student level of Model 1b.

Model 1d incorporated school-level and district-level covariates into our prior model (1c). In other words, Model 1d featured time in EL (Y_{ijk}) as the outcome variable, the seven student-level variables previously modeled, and six school-level variables (i.e., proportion of Black and Hispanic in each school; proportion of FRPL in each school; proportion of EL in each school; and school-level average third-grade math and reading achievement). Model 1d also included six district-level variables (i.e., proportion of Black and Hispanic in each district; proportion of FRPL in each district; proportion of EL in each district; and district-level average third-grade math and reading achievement). The final model (Model 1e) expanded Model 1d to include the proportion gifted in each school at Level 2 and the proportion gifted in each district at Level 3.

Research Question 2

For Research Question 2 (investigating the relationship between EL reclassification in gifted identification), we first modeled the relationship between time to reclassification and the probability of being identified as gifted by fifth grade. We utilized a parametric spline model to estimate the non-linear trend seen in Table 2. This spline term was “0” for EL exit in less than 1 year and more than 2 years, and “1” for EL exit between 1 and 2 years. As such, it provided an estimate of the increase in probability of identification that occurred for students who exited in more than 1 but less than 2 years. With estimates of the intercept, the year slope, and the 0–1 year 1–2 spline, we can predict the log-odds of being identified as gifted. For instance, at Year 0, the log-odds of being gifted was the intercept. The log-odds of being identified as gifted for students who exited EL within 1 year was the intercept. The log-odds of being identified as gifted for students who exited EL in more than 1 but less than 2 years was the intercept plus the spline coefficient, plus the year slope $\times$ 1. Afterward, the log-odds of being identified as gifted at year in more than n but less than $n + 1$ years was the intercept plus the year slope $\times (n)$.

Table 4. Multilevel Modeling Equations: Predicting English Learner Reclassification.

Model	Model equations, by level	
1a	Level 1:	
	$Y_{ijk} = \pi_{0jk} + \pi_{1jk}(Black_{ijk}) + \pi_{2jk}(Hispanic_{ijk}) + \pi_{3jk}(Asian_{ijk}) + \pi_{4jk}(Other_{ijk}) + e_{ijk}$	
	Level 2:	Level 3:
	$\pi_{0jk} = \beta_{00k} + r_{0jk}$	$\beta_{00k} = \gamma_{000} + u_{00k}$
	$\pi_{1jk} = \beta_{10k}$	$\beta_{10k} = \gamma_{100}$
	$\pi_{2jk} = \beta_{20k}$	$\beta_{20k} = \gamma_{200}$
	$\pi_{3jk} = \beta_{30k}$	$\beta_{30k} = \gamma_{300}$
	$\pi_{4jk} = \beta_{40k}$	$\beta_{40k} = \gamma_{400}$
1b	Level 1:	
	$Y_{ijk} = \pi_{0jk} + \pi_{1jk}(Black_{ijk}) + \pi_{2jk}(Hispanic_{ijk}) + \pi_{3jk}(Asian_{ijk}) + \pi_{4jk}(Other_{ijk}) + \pi_{5jk}(FRPL_{ijk}) + e_{ijk}$	
	Level 2:	Level 3:
	$\pi_{0jk} = \beta_{00k} + r_{0jk}$	$\beta_{00k} = \gamma_{000} + u_{00k}$
	$\pi_{1jk} = \beta_{10k}$	$\beta_{10k} = \gamma_{100}$
	$\pi_{2jk} = \beta_{20k}$	$\beta_{20k} = \gamma_{200}$
	$\pi_{3jk} = \beta_{30k}$	$\beta_{30k} = \gamma_{300}$
	$\pi_{4jk} = \beta_{40k}$	$\beta_{40k} = \gamma_{400}$
	$\pi_{5jk} = \beta_{50k}$	$\beta_{50k} = \gamma_{500}$
1c	Level 1:	
	$Y_{ijk} = \pi_{0jk} + \pi_{1jk}(Black_{ijk}) + \pi_{2jk}(Hispanic_{ijk}) + \pi_{3jk}(Asian_{ijk}) + \pi_{4jk}(Other_{ijk}) + \pi_{5jk}(FRPL_{ijk}) + \pi_{6jk}(Math_{ijk}) + \pi_{7jk}(Read_{ijk}) + e_{ijk}$	
	Level 2:	Level 3:
	$\pi_{0jk} = \beta_{00k} + r_{0jk}$	$\beta_{00k} = \gamma_{000} + u_{00k}$
	$\pi_{1jk} = \beta_{10k}$	$\beta_{10k} = \gamma_{100}$
	$\pi_{2jk} = \beta_{20k}$	$\beta_{20k} = \gamma_{200}$
	$\pi_{3jk} = \beta_{30k}$	$\beta_{30k} = \gamma_{300}$
	$\pi_{4jk} = \beta_{40k}$	$\beta_{40k} = \gamma_{400}$
	$\pi_{5jk} = \beta_{50k}$	$\beta_{50k} = \gamma_{500}$
	$\pi_{6jk} = \beta_{60k}$	$\beta_{60k} = \gamma_{600}$
	$\pi_{7jk} = \beta_{70k}$	$\beta_{70k} = \gamma_{700}$

(continued)

Table 4. (continued)

Model	Model equations, by level
1d	Level 1: $Y_{ijk} = \pi_{0jk} + \pi_{1jk}(Black_{ijk}) + \pi_{2jk}(Hispanic_{ijk}) + \pi_{3jk}(Asian_{ijk}) + \pi_{4jk}(Other_{ijk}) + \pi_{5jk}(FRPL_{ijk}) + \pi_{6jk}(Math_{ijk}) + \pi_{7jk}(Read_{ijk}) + e_{ijk}$
	Level 2: $\pi_{0jk} = \beta_{00k} + \beta_{01k}(SBlack_{jk}) + \beta_{02k}(SHispanic_{jk}) + \beta_{03k}(SFRPL_{jk}) + \beta_{04k}(SEL_{jk}) + \beta_{05k}(SMath_{jk}) + \beta_{06k}(SRead_{jk}) + r_{0jk}$
	$\pi_{1jk} = \beta_{10k}$; $\pi_{2jk} = \beta_{20k}$; $\pi_{3jk} = \beta_{30k}$; $\pi_{4jk} = \beta_{40k}$; $\pi_{5jk} = \beta_{50k}$; $\pi_{6jk} = \beta_{60k}$; $\pi_{7jk} = \beta_{70k}$
	Level 3: $\beta_{00k} = \gamma_{000} + \gamma_{001}(DBlack_k) + \gamma_{002}(DHispanic_k) + \gamma_{003}(DFRPL_k) + \gamma_{004}(DEL_k) + \gamma_{005}(DMath_k) + 6(DRead_k) + u_{00k}$
	$\beta_{01k} = \gamma_{010}$; $\beta_{02k} = \gamma_{020}$; $\beta_{03k} = \gamma_{030}$; $\beta_{04k} = \gamma_{040}$; $\beta_{05k} = \gamma_{050}$; $\beta_{06k} = \gamma_{060}$
	$\beta_{10k} = \gamma_{100}$; $\beta_{20k} = \gamma_{200}$; $\beta_{30k} = \gamma_{300}$; $\beta_{40k} = \gamma_{400}$; $\beta_{50k} = \gamma_{500}$; $\beta_{60k} = \gamma_{600}$; $\beta_{70k} = \gamma_{700}$
1e	Level 1: $Y_{ijk} = \pi_{0jk} + \pi_{1jk}(Black_{ijk}) + \pi_{2jk}(Hispanic_{ijk}) + \pi_{3jk}(Asian_{ijk}) + \pi_{4jk}(Other_{ijk}) + \pi_{5jk}(FRPL_{ijk}) + \pi_{6jk}(Math_{ijk}) + \pi_{7jk}(Read_{ijk}) + e_{ijk}$
	Level 2: $\pi_{0jk} = \beta_{00k} + \beta_{01k}(SBlack_{jk}) + \beta_{02k}(SHispanic_{jk}) + \beta_{03k}(SFRPL_{jk})\beta_{04k}(SEL_{jk}) + \beta_{05k}(SMath_{jk}) + \beta_{06k}(SRead_{jk}) + \beta_{07k}(SGifted_{jk}) + r_{0jk}$
	$\pi_{1jk} = \beta_{10k}$; $\pi_{2jk} = \beta_{20k}$; $\pi_{3jk} = \beta_{30k}$; $\pi_{4jk} = \beta_{40k}$; $\pi_{5jk} = \beta_{50k}$; $\pi_{6jk} = \beta_{60k}$; $\pi_{7jk} = \beta_{70k}$
	Level 3: $\beta_{00k} = \gamma_{000} + \gamma_{001}(DBlack_k) + \gamma_{002}(DHispanic_k) + \gamma_{003}(DFRPL_k) + \gamma_{004}(DEL_k) + 5(DMath_k) + \gamma_{006}(DRead_k) + \gamma_{007}(DGifted_k) + u_{00k}$
	$\beta_{01k} = \gamma_{010}$; $\beta_{02k} = \gamma_{020}$; $\beta_{03k} = \gamma_{030}$; $\beta_{04k} = \gamma_{040}$; $\beta_{05k} = \gamma_{050}$; $\beta_{06k} = \gamma_{060}$; $\beta_{07k} = \gamma_{070}$
	$\beta_{10k} = \gamma_{100}$; $\beta_{20k} = \gamma_{200}$; $\beta_{30k} = \gamma_{300}$; $\beta_{40k} = \gamma_{400}$; $\beta_{50k} = \gamma_{500}$; $\beta_{60k} = \gamma_{600}$; $\beta_{70k} = \gamma_{700}$

Note. i = individual; j = school; k = district.

Table 5. Percent Gifted by Time to EL Exit in Largest School District Versus All Other Districts.

	All EL students	ELs in largest school district	ELs in all other school districts
Time (years)	% Identified as gifted	% Identified as gifted	% Identified as gifted
0	13.7	28.3	11.6
1	22.6	33.4	8.7
2	8.5	13.9	5.5
3	5.6	7.1	5.3
4	2.9	4.6	2.3
5	0.6	0.9	0.4
Total	8.8	15.7	0.5

Note. Relative frequencies based on 24,892 total EL students; 8,660 ELs in the largest school district; and 16,232 ELs in all remaining school districts (excluding the largest district). Time in EL measured discretely. EL = English learner.

We estimated these spline models with and without random effects. When we added the random effects for the spline variable, the coefficients changed notably and the random effects were statistically significant—this raised concerns that certain schools or districts were driving the non-linearity observed in the descriptive statistics in Table 2. Examining the residuals from the random-effect spline models, we found that one of the largest school districts in the state (which accounted for 1/3 of the EL students in the region) was, indeed, driving the observed non-linearity. Table 5 shows that this district exhibited a non-linear trend, whereas all other districts displayed monotonic, decreasing trends. To account for the dramatic influence of this district, we included a dummy variable for the school district at Level 3. The district dummy predicted the intercept and interacted with the linear and spline slope parameters (see equation for Model 2a, in Table 6, for the full model). Comparing the three-level models with a linear time trend, a quadratic time trend, and the spline model (with and without dummy variables for the largest district), the spline model with the large district indicator fit best.

In addition to the linear time slope and time spline, we incorporated five student-level variables in Model 2b: four dummy variables for race (Hispanic, Black, Asian, Other race) and a dichotomous indicator for FRPL eligibility. At Level 2, we added four school-level variables: proportions of Black and Hispanic students; proportion of FRPL-eligible students; the proportion of ELs in each school. At Level 3, we included a dummy variable for the largest district and four additional district-level variables: proportions of Black and Hispanic students; proportion of FRPL-eligible students; and proportion of ELs in each district. We group-mean centered all Level-1 and Level-2 continuous variables and grand-mean centered the continuous district-level variables (see Model 2b, in Table 6). Dummy coded dichotomous variables at Level 1 were not centered.

Table 6. Multilevel Modeling Equations: Predicting Log-Odds of Gifted Identification.

Model	Model equations, by level
2a	Level 1: $\eta_{ijk} = \pi_{0jk} + \pi_{1jk}(ELTime_{ijk}) + \pi_{2jk}(TimeSpline_{ijk})$
	Level 2: $\pi_{0jk} = \beta_{00k} + r_{0jk}$; $\pi_{1jk} = \beta_{10k} + r_{1jk}$; $\pi_{2jk} = \beta_{20k}$
	Level 3: $\beta_{00k} = \gamma_{000} + \gamma_{001}(LargeDistrict_k) + u_{00k}$; $\beta_{10k} = \gamma_{100} + \gamma_{101}(LargeDistrict_k) + u_{10k}$; $\beta_{20k} = \gamma_{200} + \gamma_{201}(LargeDistrict_k)$
2b	Level 1: $\eta_{ijk} = \pi_{0jk} + \pi_{1jk}(ELTime_{ijk}) + \pi_{2jk}(TimeSpline_{ijk}) + \pi_{3jk}(Black_{ijk}) + \pi_{4jk}(Hispanic_{ijk}) + \pi_{5jk}(Asian_{ijk}) + \pi_{6jk}(Other_{ijk}) + \pi_{7jk}(FRPL_{ijk})$
	Level 2: $\pi_{0jk} = \beta_{00k} + \beta_{01k}(SBlack_{jk}) + \beta_{02k}(SHispanic_{jk}) + \beta_{03k}(SFRPL_{jk}) + \beta_{04k}(SEL_{jk}) + r_{0jk}$; $\pi_{1jk} = \beta_{10k} + r_{1jk}$; $\pi_{2jk} = \beta_{20k}$; $\pi_{3jk} = \beta_{30k}$; $\pi_{4jk} = \beta_{40k}$; $\pi_{5jk} = \beta_{50k}$; $\pi_{6jk} = \beta_{60k}$; $\pi_{7jk} = \beta_{70k}$
	Level 3: $\beta_{00k} = \gamma_{000} + \gamma_{001}(LargeDistrict_k) + \gamma_{002}(DBlack_k) + \gamma_{003}(DHispanic_k) + \gamma_{004}(DFRPL_k) + \gamma_{005}(DEL_k) + u_{00k}$; $\beta_{01k} = \gamma_{010}$; $\beta_{04k} = \gamma_{040}$; $\beta_{02k} = \gamma_{020}$; $\beta_{03k} = \gamma_{030}$; $\beta_{10k} = \gamma_{100} + \gamma_{101}(LargeDistrict_k) + u_{10k}$; $\beta_{20k} = \gamma_{200} + \gamma_{201}(LargeDistrict_k)$; $\beta_{30k} = \gamma_{300}$; $\beta_{60k} = \gamma_{600}$; $\beta_{40k} = \gamma_{400}$; $\beta_{70k} = \gamma_{700}$; $\beta_{50k} = \gamma_{500}$

(continued)

Table 6. (continued)

Model	Model equations, by level
2c	Level 1:

$$\eta_{ijk} = \pi_{0jk} + \pi_{1jk}\left(ELTime_{ijk}\right) + \pi_{2jk}\left(TimeSpline_{ijk}\right) + \pi_{3jk}\left(Black_{ijk}\right) + \pi_{4jk}\left(Hispanic_{ijk}\right) + \pi_{5jk}\left(Asian_{ijk}\right) + \pi_{6jk}\left(Other_{ijk}\right) + \pi_{7jk}\left(FRPL_{ijk}\right)$$

Level 2:

$$\pi_{0jk} = \beta_{00k} + \beta_{01k}\left(SBlack_{jk}\right) + \beta_{02k}\left(SHispanic_{jk}\right) + \beta_{03k}\left(SFRPL_{jk}\right) + \beta_{04k}\left(SEL_{jk}\right) + \beta_{05k}\left(SGifted_{jk}\right) + r_{0jk}$$

$$\pi_{1jk} = \beta_{10k} + r_{1jk}$$

$$\pi_{2jk} = \beta_{20k} \quad \pi_{5jk} = \beta_{50k}$$
$$\pi_{3jk} = \beta_{30k} \quad \pi_{6jk} = \beta_{60k}$$
$$\pi_{4jk} = \beta_{40k} \quad \pi_{7jk} = \beta_{70k}$$

Level 3:

$$\beta_{00k} = \gamma_{000} + \gamma_{001}\left(LargeDistrict_k\right) + \gamma_{002}\left(DBlack_k\right) + \gamma_{003}\left(DHispanic_k\right) + \gamma_{004}\left(DFRPL_k\right) + \gamma_{005}\left(DEL_k\right) + \gamma_{006}\left(DGifted_k\right) + u_{00k}$$

$$\beta_{01k} = \gamma_{010} \quad \beta_{05k} = \gamma_{050}$$
$$\beta_{02k} = \gamma_{020}$$
$$\beta_{03k} = \gamma_{030}$$
$$\beta_{04k} = \gamma_{040}$$

$$\beta_{10k} = \gamma_{100} + \gamma_{101}\left(LargeDistrict_k\right) + u_{10k}$$
$$\beta_{20k} = \gamma_{200} + \gamma_{201}\left(LargeDistrict_k\right)$$

$$\beta_{30k} = \gamma_{300} \quad \beta_{60k} = \gamma_{600}$$
$$\beta_{40k} = \gamma_{400} \quad \beta_{70k} = \gamma_{700}$$
$$\beta_{50k} = \gamma_{500}$$

(continued)

Table 6. (continued)

Model	Model equations, by level
2d	Level 1:

$$\eta_{ijk} = \pi_{0jk} + \pi_{1jk}\left(ELTime_{ijk}\right) + \pi_{2jk}\left(TimeSpline_{ijk}\right) + \pi_{3jk}\left(Black_{ijk}\right) + \pi_{4jk}\left(Hispanic_{ijk}\right) + \pi_{5jk}\left(Asian_{ijk}\right) + \pi_{6jk}\left(Other_{ijk}\right)$$
$$+ \pi_{7jk}\left(FRPL_{ijk}\right) + \pi_{8jk}\left(Math_{ijk}\right) + \pi_{9jk}\left(Read_{ijk}\right)$$

Level 2:

$$\pi_{0jk} = \beta_{00k} + \beta_{01k}\left(SBlack_{jk}\right) + \beta_{02k}\left(SHispanic_{jk}\right) + \beta_{03k}\left(SFRPL_{jk}\right)$$
$$+ \beta_{04k}\left(SEL_{jk}\right) + \beta_{05k}\left(SGifted_{jk}\right) + \beta_{06k}\left(SMath_{jk}\right)$$
$$+ \beta_{07k}\left(SRead_{jk}\right) + r_{0jk}$$

$$\pi_{1jk} = \beta_{10k} + r_{1jk}$$

$\pi_{2jk} = \beta_{20k}$ $\quad \pi_{6jk} = \beta_{60k}$
$\pi_{3jk} = \beta_{30k}$ $\quad \pi_{7jk} = \beta_{70k}$
$\pi_{4jk} = \beta_{40k}$ $\quad \pi_{8jk} = \beta_{80k}$
$\pi_{5jk} = \beta_{50k}$ $\quad \pi_{9jk} = \beta_{90k}$

Level 3:

$$\beta_{00k} = \gamma_{000} + \gamma_{001}\left(LargeDistrict_{k}\right) + \gamma_{002}\left(DBlack_{k}\right)$$
$$+ \gamma_{003}\left(DHispanic_{k}\right) + \gamma_{004}\left(DFRPL_{k}\right) + \gamma_{005}\left(DEL_{k}\right)$$
$$+ \gamma_{006}\left(DGifted_{k}\right) + \gamma_{007}\left(DMath_{k}\right)$$
$$+ \gamma_{009}\left(DRead_{k}\right) + u_{00k}$$

$\beta_{01k} = \gamma_{010}$ $\quad \beta_{06k} = \gamma_{060}$
$\beta_{02k} = \gamma_{020}$ $\quad \beta_{07k} = \gamma_{070}$
$\beta_{03k} = \gamma_{030}$
$\beta_{04k} = \gamma_{040}$
$\beta_{05k} = \gamma_{050}$

$$\beta_{10k} = \gamma_{100} + \gamma_{101}\left(LargeDistrict_{k}\right) + u_{10k}$$

$$\beta_{20k} = \gamma_{200} + \gamma_{201}\left(LargeDistrict_{k}\right)$$

$\beta_{30k} = \gamma_{300}$ $\quad \beta_{70k} = \gamma_{700}$
$\beta_{40k} = \gamma_{400}$ $\quad \beta_{80k} = \gamma_{800}$
$\beta_{50k} = \gamma_{500}$ $\quad \beta_{90k} = \gamma_{900}$
$\beta_{60k} = \gamma_{600}$

Note. EL Time, at Level 1, refers to the discretely measured version of this variable. $P((EverGifted) = 1 | \pi_{jk}) = \phi_{ijk}.Log(\phi_{ijk} / (1 - \phi_{ijk}) = \eta_{ijk}$.
i = individual; j = school; k = district; EL = English learner.

Next, to create Model 2c, we incorporated the proportion of gifted students at the school and district levels into Model 2b. Finally, in Model 2d, we added third-grade math and third-grade reading achievement to the student level, group-mean centered third-grade math and reading achievement to the school level, and grand-mean centered third-grade math and reading achievement to the district level. (See Table 6 for the set of equations corresponding to each of the models described above.)

Results

Descriptive Statistics

Examining the distribution of exit from EL programs for K–5 students (see Figure 1) revealed a multimodal pattern, with a notable exit rate at the end of second grade (about 24% of ELs exited in the last 3 months of the second-grade year). The next highest rate of exit was 14% for the 3 months at the end of first grade. Nearly one quarter of students were still in EL programs by the end of fifth grade: 22% of students were in EL programs more than 2,100 days. When examining the ordinal time in EL variable, we found a steadily increasing rate of exit from EL up to the third year—10% of students exited before the first year, 17% between the first and second year, and 34% between the second and third year, followed by a dramatic decline from the third to the fourth year, with 6% of students exiting between Years 3 and 4 and 7% exiting between Years 4 and 5 of EL programming (see Figure 2). Right censoring was evident in the EL variable, with nearly one quarter of the students still classified as EL by the end of the fifth year.

Early-exit EL students, those reclassified before completing 1,192 days of EL programming (the average number of days to reclassification for ELs), exhibited mean mathematics and reading scores that were above the sample average. Mean third-grade achievement scores in math and reading were 206 and 206, respectively, across all students in the state, and mean math and reading scores were 202 and 201, respectively, across all EL students. However, early-exit ELs earned scores of 208 and 207 on these subject-specific achievement tests (see Table 3). Further underscoring this difference between early- and late-exit ELs (late-exit ELs were reclassified after 1,192 days of EL programming): EL students reclassified after completing between 1 and 2 years of EL programming demonstrated mean third-grade math and reading scores of 214 and 212, whereas ELs reclassified between Years 4 and 5 of programming earned scores of 199 and 198 in these subjects (see Table 2). In addition, 23% of EL students completing between 1 and 2 years of EL programming were identified as gifted. In contrast, students who exited EL after more than 4 years had substantially lower identification rates, between 0.5% and 3% (see Table 2).

Table 2 also shows dramatic non-linearity in the proportion of EL students identified as gifted, by time to EL exit. Specifically, the highest gifted identification rates were for ELs who were reclassified in less than 2 (more than 1) years: identification rates decreased as time to EL exit increased for ELs reclassified after the 2-year mark. As discussed in the "Method" section, one large district, which had about one third of the EL students, did appear to drive this specific non-linear trend in gifted identification rates. In contrast, all the other districts (taken together) exhibited a monotonically declining rate of gifted identification as time to EL exit increased (see Table 5).

Average Time to Reclassification and Its Association With Race/Ethnicity and Income

In Table 1, approximately 20% of the full sample included students classified as EL at some point between kindergarten and fifth grade. Within this population, students took an average of 1,192 days to be reclassified, about 3.2 years, and an average of 2.6 years when time was recoded into whole years (e.g., “0” if days to reclassify was less than 365, “1” if days to reclassify was greater than 365 and less than 730). The median number of days until reclassification, however, was 1,010. Students who were reclassified earlier (i.e., less than the mean, 1,192 days or less) were more likely to be identified as gifted, less likely to be FRPL eligible, and less likely to be Hispanic. However, early- and late-exit ELs featured similar proportions of Asian and Black students (see Table 1).

In addition, Table 7 shows the correlations between time to EL exit and other covariates. The negative correlation between time to EL exit and gifted identification ($r = -.22$) indicated that ELs who were reclassified more quickly were more likely to be identified as gifted. Time to reclassification and third-grade academic achievement were also negatively related ($r = -.38$ for math and $-.44$ for reading), indicating that students who exited EL earlier tended to score higher on state achievement tests. Time to exit was positively correlated with FRPL status ($r = .16$), indicating that FRPL-eligible students tended to exit EL more slowly than non-FRPL students (Cohen’s $d = -.48$).

The multilevel regression analyses examined the independent contributions of each of these variables in explaining time to EL exit (see Table 8). Model 1c, the model containing all student-level covariates, exhibited the best fit. Notice that in Models 1d and 1e, which include the full set of school and district covariates, only one of the school covariates was statistically significant (group-mean centered school reading achievement). However, the third-grade math and reading achievement variables were grand-mean centered in Model 1c; therefore, the student grand-mean centered reading achievement variable accounted for the both within and between school variance in mathematics and reading achievement.

In Model 1c, after controlling for FRPL status and race/ethnicity, students with higher math ($\gamma_{600} = -0.016$) and reading achievement ($\gamma_{700} = -0.031$) tended to exit EL more quickly. After controlling for third-grade mathematics and reading achievement, race/ethnicity (Black, $\gamma_{100} = 0.14$; Hispanic, $\gamma_{200} = 0.19$; Asian, $\gamma_{300} = 0.44$) and FRPL status ($\gamma_{500} = 0.22$) positively predicted students’ time to reclassification ($p < .001$). In other words, Asian, Hispanic, Black and FRPL students were slower to exit EL programs than reference students of equal academic ability. However, on average, Asians had higher average math and reading scores than students from all other racial/

Table 7. Correlations Between Time to EL Exit and Other Covariates.

Variables	EL time	Gifted	FRPL eligible	Hispanic	Black	Asian	Other race	Third math ach.	Third read ach.
EL time	1.00								
Gifted	−.22	1.00							
FRPL	.16	−.11	1.00						
Hispanic	.02	−.02	.12	1.00					
Black	.06	−.03	.09	−.65	1.00				
Asian	−.05	.07	−.19	−.43	−.07	1.00			
Other	−.02	.0005	−.05	−.19	−.03	−.02	1.00		
Third math	−.38	.36	−.20	−.03	−.09	.14	.02	1.00	
Third read	−.44	.37	−.20	−.03	−.08	.11	.02	.65	1.00

Note. N = 24,892. Time in EL measured discretely. EL = English learner; FRPL = free or reduced-price lunch.

ethnic groups. In the models without academic achievement, Asians left EL programs at equal rates, as compared with White students (γ_{300} = 0.10, p = .289 in Model 1b). After controlling for academic achievement, Asian students exited EL more slowly (γ_{300} = 0.437, p < .001 in Model 1c).

In Model 1e, after controlling for other variables in the model, higher within-school math (γ_{600} = −0.016) and reading (γ_{700} = −0.031) achievement predicted faster time to reclassification. At Level 2, higher between-school, within-district reading achievement also predicted earlier EL reclassification (γ_{060} = −0.028, p < .001; see Table 8, Model 1e). After controlling for all other variables in the model, students whose state math and reading achievement scores were both 1 standard deviation (about 20 points) above the mean exited EL programs 1 year more quickly. Finally, in Model 1e, after controlling for other variables in the model, students in schools with higher percentages of ELs tended to remain in EL programs longer (γ_{030} = 0.68, p = .04).

Time to Reclassification and Identification for Gifted Programming

Table 9 contains the series of multilevel models that predicted students' likelihood of being identified as gifted, as a function of time to reclassification and student, school, and district demographics. Figure 3 shows the predicted probability of gifted identification by time to EL exit for the largest school district and all the other districts, based on our first non-linear model (Model 2a). This pattern is similar to the descriptive statistics presented in Table 5.

In Model 2c, after controlling for demographic variables at all levels and accounting for the percentage of identified gifted students at the school and district levels, in most districts, as time to reclassification increased, the probability of being identified as gifted decreased. In the one large district, for students who were in EL for at least 2 years, time in EL negatively predicted students' likelihood of gifted identification; however, students who exited EL in 1 to 2 years were actually slightly more likely to be identified as gifted than students who exited in less than 1 year. Even after controlling for mathematics and reading achievement (Model 2d) and demographics at the student, school, and district levels, EL students who were reclassified more quickly were more likely to be identified as gifted; those who were reclassified more slowly were less likely to be identified as gifted.

In Model 2d, after controlling for all other variables in the model, students with higher third-grade math and reading achievement were more likely to be identified as gifted. In addition, controlling for time to reclassification, achievement, and demographics at all three levels, the odds of being identified as gifted were 39% higher for Asian EL students (γ_{700} = 0.327; $e^{0.327}$ = 1.39). On the contrary, the odds of being identified as gifted were approximately 50% higher for White students than they were for Black (γ_{500} = −0.393; (1/[$e^{0.393}$] = 1.48) or Hispanic (γ_{600} = −0.412; (1/[$e^{0.412}$] = 1.51) EL students. In addition, student poverty had a negative effect on the likelihood of gifted identification. Holding everything else constant, the odds of being identified as gifted were 23% higher for EL students who were not FRPL (γ_{900} = −0.209; (1/[$e^{0.209}$] = 1.23).

Table 8. Role of Poverty and Race/Ethnicity on Time to EL Exit.

	Model 1a			Model 1b			Model 1c			Model 1d			Model 1e		
Variables	Coef.	*SE*	*p*	Coef.	*SE*	*p*	Coef.	*SE*	*p*	Coef.	*SE*	*p*	Coef.	*SE*	*p*
Level 1															
Intercept	2.904	0.114	<.001	2.502	0.109	<.001	2.762	0.107	<.001	2.914	0.107	<.001	2.903	0.105	<.001
Black	0.492	0.071	<.001	0.374	0.069	<.001	0.138	0.064	.032	0.083	0.071	.242	0.083	0.071	.242
Hispanic	0.385	0.087	<.001	0.293	0.079	<.001	0.191	0.058	<.001	0.184	0.057	.001	0.184	0.057	.001
Asian	0.050	0.093	.591	0.100	0.094	.289	0.437	0.070	<.001	0.419	0.069	<.001	0.417	0.069	<.001
Other	−0.090	0.137	.514	−0.094	0.139	.496	−0.047	0.118	.691	−0.059	0.112	.601	−0.059	0.112	.600
FRPL				0.548	0.036	<.001	0.216	0.042	<.001	0.189	0.041	<.001	0.189	0.041	<.001
Third math ach.							−0.016	0.002	<.001	−0.017	0.002	<.001	−0.016	0.002	<.001
Third read ach.							−0.031	0.002	<.001	−0.031	0.002	<.001	−0.031	0.002	<.001
Level 2															
Black, prop.										0.039	0.216	.858	0.041	0.216	.848
Hispanic, prop.										−0.357	0.192	.063	−0.377	0.197	.055
EL, prop.										0.666	0.318	.036	0.684	0.325	.036
FRPL, prop.										0.065	0.159	.681	0.051	0.164	.759
Math, avg.										−0.008	0.005	.139	−0.007	0.005	.166
Read, avg.										−0.029	0.005	<.001	−0.028	0.006	<.001
Gifted, prop.													−0.240	0.201	.233
Level 3															
Black, prop.										−0.719	0.528	.178	−0.767	0.537	.158
Hispanic, prop.										−1.868	0.901	.043	−1.922	0.885	.034
EL, prop.										0.453	0.793	.570	0.447	0.741	.548
FRPL, prop.										1.764	1.187	.145	1.907	1.196	.116
Math, avg.										−0.025	0.027	.347	−0.028	0.026	.290
Read, avg.										−0.017	0.041	.678	−0.016	0.040	.697
Gifted, prop.													1.572	1.986	.432

(continued)

Table 8. (continued)

	Model 1a			Model 1b			Model 1c			Model 1d			Model 1e		
Variables	Coef.	*SE*	*p*	Coef.	*SE*	*p*	Coef.	*SE*	*p*	Coef.	*SE*	*p*	Coef.	*SE*	*p*
Intercept variance															
Level 1	2.680			2.667			2.132			2.134			2.134		
Level 2	0.313			0.277			0.237			0.255			0.255		
Level 3	0.375			0.366			0.368			0.306			0.306		
LL		–48,344.00			–48,224.02			–45,467.19			–45,510.80			–45,510.02	
Deviance		96,688.20			96,448.04			90,934.37			91,021.59			91,020.04	
N		24,892			24,892			24,892			24,892			24,892	
Parameters		8			9			11			23			25	
AIC		96,704.20			96,466.04			90,956.37			91,074.63			91,077.01	
BIC		96,769.18			96,539.14			91,045.72			91,293.93			91,312.55	
Pseudo-R^2 (ratio of log–likelihoods)	.001			.004			.061			.060			.060		

Note. Model 1c was the best fitting model. Sample of 24,892 ELs, in 1,710 schools, in 65 districts. For all Level-2 variables, *prop.* represented the proportions of students in each school with the specified characteristic. For all Level-3 variables, *prop.* represented the proportions of students in each district with the specified characteristic (e.g., the *Black, prop.* variable at Level 2 represented the proportions of Black students in each school, whereas the *Black, prop.* variable at Level 3 denoted the proportions of Black students in each district). Similarly, for the achievement variables, *avg.* indicated the average achievement at a given level (e.g., at Level 2, *Math avg.* represented the average math achievement in each school, whereas at Level 3, *Math avg.* represented the average math achievement in each district). For Models 1b and 1c, all achievement variables were grand-mean centered. For Models 1d and 1e, Level-1 achievement variables were group-mean centered, all school variables were group-mean centered, and district variables were grand-mean centered. White was the omitted/reference category for the Level-1 race/ethnicity variables. EL = English learner; FRPL = free or reduced-price lunch; LL = log–likelihood; AIC = Akaike information criterion; BIC = Bayesian information criterion (calculated with the total number of Level-1 units).

Table 9. Role of Time to EL Exit on Log-Odds of Being Identified as Gifted.

	Model 2a				Model 2b				Model 2c				Model 2d			
Fixed effects	Coef.	*SE*	*t*	*p*	Coef.	*SE*	*t*	*p*	Coef.	*SE*	*t*	*p*	Coef.	*SE*	*t*	*p*
Level 1																
Intercept	−2.455	0.132	−18.624	<.001	−2.066	0.169	−12.193	<.001	−2.289	0.161	−14.219	<.001	−4.384	0.197	−22.294	<.001
EL time	−0.630	0.041	−15.518	<.001	−0.584	0.040	−14.442	<.001	−0.576	0.039	−14.884	<.001	−0.337	0.044	−7.701	<.001
EL time × large district	−0.103	0.128	−0.804	.424	−0.126	0.119	−1.065	.291	−0.143	0.113	−1.261	.212	−0.124	0.106	−1.167	.247
EL time spline, 0 to 1	0.380	0.085	4.456	<.001	0.313	0.087	3.612	<.001	0.316	0.086	3.654	<.001	0.199	0.093	2.132	.033
EL time spline × large district	0.372	0.106	3.504	<.001	0.441	0.108	4.095	<.001	0.444	0.109	4.087	<.001	0.152	0.115	1.320	.187
Black					−0.551	0.127	−4.350	<.001	−0.538	0.129	−4.182	<.001	−0.393	0.132	−2.968	.003
Hispanic					−0.404	0.085	−4.777	<.001	−0.394	0.087	−4.517	<.001	−0.412	0.089	−4.629	<.001
Asian					0.901	0.109	8.299	<.001	0.906	0.111	8.140	<.001	0.327	0.115	2.838	.005
Other					−0.102	0.215	−0.472	.637	−0.072	0.220	−0.329	.742	−0.181	0.224	−0.808	.419
FRPL					−0.487	0.055	−8.855	<.001	−0.504	0.057	−8.872	<.001	−0.209	0.058	−3.621	<.001
Third math ach.													0.053	0.001	36.270	<.001
Third read ach.													0.054	0.002	35.364	<.001
Level 2																
Black, school prop.					−0.054	0.397	−0.135	.892	0.362	0.336	1.078	.281	0.228	0.455	0.502	.616
Hispanic, school prop.					−1.332	0.449	−2.967	.003	−0.635	0.371	−1.712	.087	−0.546	0.506	−1.078	.281
FRPL, school prop.					−0.493	0.343	−1.436	.151	1.756	0.303	5.788	<.001	0.895	0.477	1.876	.061
EL, school prop.					1.165	0.428	2.723	.007	1.062	0.342	3.103	.002	0.755	0.482	1.567	.117
Gifted, school prop.									8.981	0.407	22.070	<.001	12.286	0.608	20.196	<.001
Third math, school avg.													0.016	0.014	1.163	.245
Third read, school avg.													−0.038	0.017	−2.228	.026
Level 3																
Large district	1.696	0.593	2.861	.006	1.018	0.589	1.727	.089	−0.336	0.432	−0.776	.441	−0.326	0.553	−0.590	.558
Black, district prop.					−0.641	1.045	−0.614	.542	−0.407	0.776	−0.525	.602	−1.517	1.094	−1.387	.171
Hispanic, district prop.					1.163	1.629	0.714	.478	0.427	1.408	0.304	.763	−0.565	1.908	−0.296	.768
FRPL, district prop.					−2.920	1.324	−2.204	.031	−0.358	1.178	−0.304	.762	−3.659	2.039	−1.794	.078
EL, district prop.					2.807	1.710	1.642	.106	3.210	1.487	2.159	.035	4.335	2.084	2.080	.042
Gifted, district prop.									14.487	2.548	5.685	<.001	20.149	3.193	6.311	<.001
Math, district avg.													0.079	0.057	1.400	.167
Read, district avg.													−0.184	0.089	−2.077	.042

(continued)

Table 9. (continued)

Variance components	*SD*	Var. comp.	χ^2	*p*	*SD*	Var. comp.	χ^2	*p*	*SD*	Var. comp.	χ^2	*p*	*SD*	Var. comp.	χ^2	*p*
Level 1																
Intercept, *e*	0.750	0.563			0.747	0.557			0.775	0.601			0.646	0.417		
Level 2																
Intercept, r_0	1.235	1.524	2,201.978	<.001	1.292	1.669	2,273.121	<.001	0.840	0.706	1,656.848	<.001	1.610	2.593	2,396.719	<.001
EL time slope, r_1	0.278	0.077	1,078.124	>.500	0.294	0.086	1,083.310	>.500	0.256	0.066	1,109.260	>.500	0.546	0.298	1,475.239	.029
Level 3																
Intercept, u_{00}	0.567	0.321	137.978	<.001	0.453	0.205	94.433	<.001	0.251	0.063	62.944	.189	0.290	0.084	45.491	>.500
EL time slope, u_{10}	0.115	0.013	58.685	>.500	0.105	0.011	51.168	>.500	0.099	0.010	53.256	>.500	0.079	0.006	34.977	>.500

Note. Model 2d was the best fitting model. Sample of 24,892 ELs, in 1,710 schools, in 65 districts. Time in EL measured discretely. For all Level-2 variables, *prop.* represented the proportions of students in each school with the specified characteristic. For all Level-3 variables, *prop.* represented the proportions of students in each district with the specified characteristic (e.g., the *Black, prop.* variable at Level 2 represented the proportion of Black students in each school, whereas the *Black, prop.* variable at Level 3 denoted the proportion of Black students in each district). Similarly, for the achievement variables, *avg.* indicated the average achievement at a given level (e.g., at Level 2, *Math avg.* represented the average math achievement in each school, whereas at Level 3, *Math avg.* represented the average math achievement in each district). For Models 2 and 3, FRPL and achievement variables at all levels were grand-mean centered. For Models 4 and 5, Level-1 FRPL and achievement variables were group-mean centered, all school variables were group-mean centered, and district variables were grand-mean centered. White was the omitted/reference category for the Level-1 race/ethnicity variables. All intercepts can be interpreted as the log-odds of being identified as gifted for an average, White, EL student. Unit-specific model results reported. No model fit indices appear in this table because the penalized quasi-likelihood (PQL) estimation method (for multilevel logistic regression models) does not yield log–likelihood or deviance values. EL = English learner; FRPL = free or reduced-price lunch.

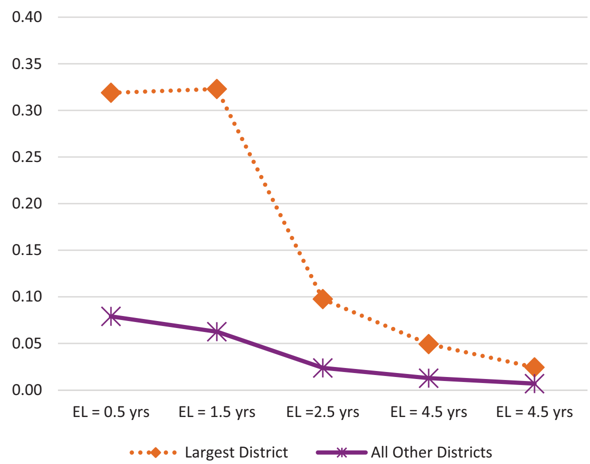

Figure 3. Role of time to EL exit on gifted identification.
Note. EL = English learner.

Finally, as expected, the proportion of gifted students in the school and district had very large positive effects on students' probabilities of being identified as gifted, controlling for the influence of achievement, demographics, poverty, and the largest school district. A 1% increase in the percentage of gifted students in a *school* increased the likelihood of gifted identification by 13%, $e^{(0.01\ 12.286)} - 1 = 0.13$, and a 1% increase in a district's percentage of identified students increased the likelihood identification by 22%, $e^{(0.01\ 20.15)} - 1 = 0.22$.

Comparing Models 2c and 2d, controlling for academic achievement reduced the effect of time to exit on the likelihood of being identified as gifted. More notably, though, the effect of time to reclassification predicted the probability of being identified as gifted, *even after controlling* for academic ability. Figure 4 demonstrates this finding, presenting the predicted probabilities of gifted identification for students at, and up to 3 standard deviations above, the mean level of academic achievement (for students not in the largest district). Figure 4 graphs the predicted probabilities of gifted identification for a student in the reference group who: (a) exited EL in less than 1 year; (b) who exited EL in 1–2 years; and (c) who exited EL in 4–5 years and compares those three trajectories to the predicted probability of being identified as gifted for non-ELs with similar demographic characteristics. Across the achievement continuum (x-axis), students with similar achievement levels who exited from EL programs earlier were more likely to be identified as gifted. The probability of being identified as gifted was lower for students who exited EL more slowly, even after controlling for third-grade mathematics and reading achievement. Holding time in

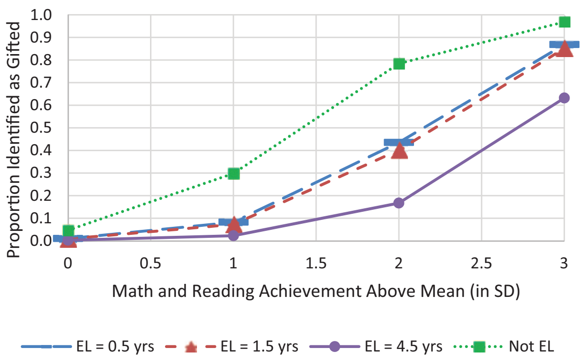

Figure 4. Role of time to EL exit on identification by students' academic ability (for EL students not in the largest district).
Note. EL = English learner.

EL constant, students with higher achievement were more likely to be identified as gifted. Furthermore, students 3 standard deviations above the mean on achievement, who exited EL in less than 2 years, were nearly as likely as non-EL students to be identified as gifted.

Discussion

This study explored the impact of EL language comprehension skills, as indicated by reclassification or time in EL, on gifted identification and achievement. We found notable demographic and socioeconomic influences on the time to reclassification of ELs. Students who were reclassified earlier tended to have higher achievement, were less likely to be FRPL eligible, and less likely to be Black or Hispanic. In addition, ELs who were reclassified earlier were more likely to be identified as gifted than other ELs, even after controlling for third-grade mathematics and reading achievement.

The relationship between early EL exit and gifted identification could be due to unmeasured higher levels of student ability. If true, then early EL exit may be a useful proxy for ability that is not captured by achievement tests. Therefore, it could be useful to include early EL exit, in addition to the achievement and other multiple measures already used to identify gifted students.

In the current study, students' average time to reclassification was around 3.2 years. This falls squarely within the timeframes presented in the literature (Conger, 2009; Hakuta et al., 2000). Conger (2009) suggested that younger students tend to learn more quickly than older students. In the current study, the early-exit ELs reclassified in an average of 2 years and the late-exit ELs required more than 4 years to reclassify.

This current study also found that FRPL-eligible students spent more time in EL, even after controlling for achievement. This finding is consistent with Hakuta and colleagues (2000) findings that demographic factors, such as SES, can influence EL time to reclassification. Also consistent with Carhill et al. (2008) but inconsistent with Hakuta et al. (2000), we did not find evidence of an effect of school poverty on time spent in EL.

Reclassification on Gifted Identification

Although research that makes a direct connection between EL status and gifted identification is limited, the literature suggests that reclassification is positively associated with various achievement-related outcomes. Therefore, we hypothesized that ELs who were reclassified more quickly would more likely be identified as gifted. We also expected students who were reclassified more quickly to exhibit higher third-grade achievement scores, especially in reading. However, we were less certain about whether time to reclassification would make an independent contribution to predicting students' probabilities of being identified as gifted, particularly after controlling for mathematics and reading achievement.

Given that achievement tests are typically administered in English, one might expect ELs to have lower rates of achievement, as compared with non-ELs (Kim & Herman, 2009). However, an increasing number of studies examining the outcomes of current and former ELs have observed that former ELs often outperform their non-EL peers. Kim and Herman (2009) found that, although there were achievement gaps between current ELs and non-ELs across state achievement tests, there were also gaps between former ELs and non-ELs, with former ELs frequently outperforming their non-EL peers across multiple states and subjects. Similarly, Ardasheva and colleagues (2012) found that reclassified EL students significantly outperformed non-ELs students and current ELs on standardized reading and math tests. Results from the current study also support these findings. Although the average third-grade achievement score for non-ELs was 207 in both reading and math, early-exit ELs had an average math score of 210 and reading score of 208 in third grade. In fact, students who spent 2 years with the EL classification averaged scores of 214 and 211 in third-grade math and reading, respectively.

As faster reclassifications were associated with higher achievement, we would expect faster reclassification to also be associated with higher gifted-identification rates, which was the case in the current study. ELs who were reclassified more quickly were more likely to be identified as gifted. More noteworthy was the finding that even after controlling for third-grade mathematics and reading achievement and demographics, students who exited EL more quickly were more likely to be identified as gifted by the end of fifth grade. However, further research should investigate what other factors might influence this reclassification–identification relationship.

Implications

The current study elucidates the importance of context when attempting to understand the educational experiences of ELs. It is not enough to simply look at those students who have yet to attain proficiency as an indication of how dual- and multilingual students are doing in schools. The most successful ELs may no longer be classified as such. This study supports the current literature, which calls for schools and districts to continue tracking the outcomes of former ELs to better evaluate the educational outcomes of dual-language learners. Tracking former ELs may also help educators to better serve current ELs and determine what continuing supports and opportunities reclassified students may need.

Furthermore, a variety of studies critique the assumption that *reclassified* students are a monolithic group (e.g., Linquanti et al., 2016; Umansky et al., 2017). The current research supports this contention—students who recently reclassified may have different needs than those with more time since reclassification—which underscores the need to individualize services to the unique needs of each student. Our results also suggest that school context matters for the outcomes of EL students. School and district factors seemed to have varying associations on EL outcomes.

Limitations

There are several limitations to the current study. First, we had access to data for only one cohort of students, those who were fifth graders in 2013–2014. In addition, we only examined a cohort in one state. Therefore, we do not know how the results might differ for other cohorts or for students in other states. Also, some of our measures were limited. For instance, the only available measure of poverty in our data set was FRPL eligibility. A measure that is more finely attuned to the financial limitations that families, schools, and districts experience, while preferable, was not available in the current dataset. Finally, we were limited in our ability to comprehensively compare EL reclassification with gifted identification. Although we had specific entry and exit dates for ELs, we only had binary (yes/no) data available for students' gifted status. This limited our ability to make clear connections between the role of EL reclassification and gifted identification.

Future Research

Future research should continue the growing trend of utilizing an ever-EL framework when evaluating student outcomes, especially when making comparisons to students for whom English is the home language (and other non- or never-ELs). Researchers might also consider other school-level factors when examining EL classification and gifted identification. Evidence that professional development, for example, can help enhance identification rates of traditionally underrepresented populations (Esquierdo & Arreguin-Anderson, 2012); future research should examine the effects of professional development on the identification of EL students. Finally, the most intriguing finding from our study was that time to reclassification independently predicts a student's probability of being identified as gifted, even after controlling for third-grade mathematics and reading achievement. This relationship deserves further attention and exploration. Our results suggest that time to reclassification may provide a way to screen former ELs for gifted programs. Alternatively, perhaps it already is.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The authors disclosed receipt of the following financial support for the research and/or authorship of this article: This research from the National Center for Research on Gifted Education (NCRGE; http://ncrge.uconn.edu; http://ncrge.uconn.edu) was funded by the Institute of Education Sciences, U.S. Department of Education (PR/Award # R305C140018).

ORCID iDs

Rashea Hamilton https://orcid.org/0000-0002-7591-1410
Daniel Long https://orcid.org/0000-0003-1887-2993
Vonna Hemmler https://orcid.org/0000-0002-4550-8356
Del Siegle https://orcid.org/0000-0001-5579-9217

Notes

1. For this article, we operate under the federal definition of an *EL* as a student who (a) speaks a home language other than English and/or (b) grew up in an environment in which a language other than English was dominant and/or (c) whose "difficulties in speaking, reading, writing, or understanding the English language" may prohibit the student from achieving in classrooms in which the language of instruction is English (U.S. Department of Education, 2016, p. 43).
2. Hierarchical linear model (HLM) uses penalized quasi-likelihood (PQL) to generate quasi-likelihood rather than maximum likelihood estimates, therefore the authors' calculations of AIC fit statistics based on quasi-likelihood estimates should be interpreted with caution.

References

Ardasheva, Y., Tretter, T. R., & Kinny, M. (2012). English language learners and academic achievement: Revisiting the threshold hypothesis. *Language Learning*, *62*(3), 769–812. https://doi.org/10.1111/j.1467-9922.2011.00652.x

Aukerman, M. (2007). A culpable CALP: Rethinking the conversational/academic language proficiency distinction in early literacy instruction. *The Reading Teacher*, *60*(7), 626–635. https://doi.org/10.1598/RT.60.7.3

Burke, A. M., Morita-Mullaney, T., & Singh, M. (2016). Indiana emergent bilingual student time to reclassification: A survival analysis. *American Educational Research Journal*, *53*(5), 1310–1342. https://doi.org/10.3102/0002831216667481

Carhill, A., Suárez-Orozco, C., & Páez, M. (2008). Explaining English language proficiency among adolescent immigrant students. *American Educational Research Journal*, *45*(4), 1155–1179. https://doi.org/10.3102/0002831208321443

Carlson, D., & Knowles, J. E. (2016). The effect of English language learner reclassification on student ACT scores, high school graduation, and postsecondary enrollment: Regression discontinuity evidence from Wisconsin. *Journal of Policy Analysis and Management*, *35*(3), 559–586. https://doi.org/10.1002/pam.21908

Conger, D. (2009). Testing, time limits, and English learners: Does age of school entry affect how quickly students can learn English? *Social Science Research*, *38*(2), 383–396. https://doi.org/10.1016/j.ssresearch.2008.08.002

Cummins, J. (1979). *Cognitive/academic language proficiency, linguistic interdependence, the optimum age question and some other matters* (Working Papers on Bilingualism No. 19] (pp. 121–129). Ontario Institute for Studies in Education.

Cummins, J. (1994). The acquisition of English as a second language. In K. Spangenberg-Urbschat & R. Pritchard (Eds.), *Kids come in all languages: Reading instruction for ESL students* (pp. 36–62). International Reading Association.

Cummins, J. (2000). *Language, power and pedagogy: Bilingual children in the crossfire*. Multilingual Matters.

de Jong, E. J. (2004). After exit: Academic achievement patterns of former English language learners. *Education Policy Analysis Archives*, *12*(50), 1–20. https://doi.org/10.14507/epaa.v12n50.2004

Esquierdo, J. J., & Arreguin-Anderson, M. (2012). The "invisible" gifted and talented bilingual students: A current report on enrollment in GT programs. *Journal for the Education of the Gifted*, *35*(1), 35–47. https://doi.org/10.1177/0162353211432041

Estrada, P., & Wang, H. (2018). Making English learner reclassification to fluent English proficient attainable or elusive: When meeting criteria is and is not enough. *American Educational Research Journal*, *55*(2), 207–242. https://doi.org/10.3102/0002831217733543

Goldenberg, C. (2008, Summer). Teaching English language learners: What the research does—and does not—say. *American Educator*, 8–44. https://tinyurl.com/y6bbhklf

Hakuta, K., Butler, Y. G., & Witt, D. (2000). *How long does it take English learners to attain proficiency?* (Report No. 2000-1). The University of California Linguistic Minority Research Institute. https://eric.ed.gov/?id=ED443275

Harris, B., Plucker, J. A., Rapp, K. E., & Martínez, R. S. (2009). Identifying gifted and talented English language learners: A case study. *Journal for the Education of the Gifted*, *32*(3), 368–393. https://doi.org/10.4219/jeg-2009-858

Kanno, Y., & Kangas, S. (2014). "I'm not going to be, like, for the AP": English language learners' limited access to advanced college-preparatory courses in high school. *American Educational Research Journal*, *51*(5), 848–878. https://doi.org/10.3102/0002831214544716

Kibler, A. K., Karam, F. J., Futch Ehrlich, V., Bergey, R., Wang, C., & Molloy Elreda, L. (2018). Who are "long-term English learners"? Using classroom interactions to deconstruct a manufactured learner label. *Applied Linguistics*, *39*(5), 741–765. https://doi.org/10.1093/applin/amw039

Kim, J., & Herman, J. L. (2009). A three-state study of English learner progress. *Educational Assessment*, *14*(3–4), 212–231. https://doi.org/10.1080/10627190903422831

Linquanti, R., Cook, H. G., Bailey, A. L., & MacDonald, R. (2016). *Moving toward a more common definition of English learner: Collected guidance for states and multi-state assessment consortia*. Council of Chief State School Officers. https://tinyurl.com/y6x2o6o7

McCoach, D. B. (2010). Dealing with dependence (Part II): A gentle introduction to Hierarchical Linear Modeling. *Gifted Child Quarterly*, *54*(3), 252–256. https://doi.org/10.1177/0016986210373475

McCoach, D. B., & Adelson, J. (2010). Dealing with dependence (Part I): Understanding the effects of clustered data. *Gifted Child Quarterly*, *54*(2), 152–155. https://doi.org/10.1177/0016986210363076

Menken, K., & Kleyn, T. (2010). The long-term impact of subtractive schooling in the educational experiences of secondary English language learners. *International Journal of Bilingual Education and Bilingualism*, *13*(4), 399–417. https://doi.org/10.1080/13670050903370143

Miura, Y. (2006). *High-stakes test performance of limited English proficient students in Ohio* (Document No. ucin1163696263) [Doctoral Dissertation]. University of Cincinnati. OhioLINK. https://tinyurl.com/yyjpn7qw

Murphey, D. (2014). *The academic achievement of English language learners: Data for the U.S. and each of the states* (Research Brief Publication No. 2014-62). Child Trends. https://tinyurl.com/lyoja8c

Payán, R. M., & Nettles, M. T. (2008). *Current state of English-language learners in the U.S.: K–12 student population*. Educational Testing Service.

Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical linear models* (2nd ed.). Sage.

Raudenbush, S. W., Bryk, A. S., Cheong, Y. F., Congdon, R. T., & Du Toit, M. (2011). *HLM 7: Hierarchical linear and nonlinear modeling*. Scientific Software International.

Saunders, W. M., & Marcelletti, D. J. (2013). The gap that can't go away: The Catch-22 of reclassification in monitoring the progress of English learners. *Educational Evaluation and Policy Analysis*, *35*(2), 139–156. https://doi.org/10.3102/0162373712461849

Thompson, K. D. (2017). English learners' time to reclassification: An analysis. *Educational Policy*, *31*(3), 330–363. https://doi.org/10.1177/0895904815598394

Umansky, I. M., & Reardon, S. F. (2014). Reclassification patterns among Latino English learner students in bilingual, dual immersion, and English immersion classrooms. *American Educational Research Journal*, *51*(5), 879–912. https://doi.org/10.3102/0002831214545110

Umansky, I. M., Thompson, K. D., & Díaz, G. (2017). Using an ever–English learner framework to examine disproportionality in special education. *Exceptional Children*, *84*(1), 76–96. https://doi.org/10.1177/0014402917707470

U.S. Department of Education. (2016). *Non-regulatory guidance: English learners and Title III of the Elementary and Secondary Education Act (ESEA), as amended by the Every Student Succeeds Act (ESSA)*. https://tinyurl.com/yah87yr9

U.S. Department of Education. (2018a). *2015–16 Estimations for enrollment* [Data file]. https://ocrdata.ed.gov/downloads/projections/2015-16/Enrollment-Overall.xlsx

U.S. Department of Education. (2018b). *2015–16 Gifted and talented enrollment estimations* [Data file]. https://ocrdata.ed.gov/downloads/projections/2015-16/Gifted-Talented-Enrollment.xlsx

Wolf, M. K., & Faulkner-Bond, M. (2016). Validating English language proficiency assessment uses for English learners: Academic language proficiency and content assessment performance. *Educational Measurement: Issues and Practice*, *35*(2), 6–18. https://doi.org/10.1111/emip.12105

Author Biographies

Rashea Hamilton, PhD, is a former research scientist and current affiliate at the University of Connecticut. Her primary areas of expertise include social inequality, family engagement, and quantitative methodology.

Daniel Long, PhD, is a research scientist at the University of Connecticut. He received his BA in Economics from Swarthmore College, his MS in Sociology from the University of Wisconsin–Madison, and his PhD in Sociology of Education from the University of Wisconsin–Madison.

D. Betsy McCoach, PhD, is a professor in the Measurement, Evaluation, and Assessment program at the University of Connecticut. She has extensive experience in structural equation modeling, longitudinal data analysis, hierarchical linear modeling, instrument design, and factor analysis.

Vonna Hemmler, PhD, is a postdoctoral researcher at the University of Virginia. Her research interests pertain broadly to the equitable education of culturally and linguistically diverse students, particularly English learners in K–12 schools.

Del Siegle, PhD, is director of the National Center for Research on Gifted Education (NCRGE) and holds the Lynn and Ray Neag Endowed Chair for Talent Development in the Neag School of Education at the University of Connecticut. He is a past president of the National Association for Gifted Children (NAGC) and past co-editor of the *Journal of Advanced Academics* and *Gifted Child Quarterly*. He received both the Distinguished Scholar Award and the Distinguished Service Award from NAGC. His research interests include underachievement and issue related to underserved populations.

Sarah D. Newton is an advanced doctoral student of Measurement, Evaluation, and Assessment program at the University of Connecticut. She holds a BA in Criminology/Psychology and an MS in Criminal Justice from Central Connecticut State University. Her research interests include program evaluation/needs assessment; instrument development, reliability, and validity; statistical modeling in a latent variable framework; and the performance of information criteria in multilevel modeling contexts.

E. Jean Gubbins, PhD, is a professor of Educational Psychology at the University of Connecticut and associate director of the National Center for Research on Gifted Education. In addition to her teaching experiences with elementary and secondary students, she has been an instructor at the college level, a consultant on gifted and talented education throughout the country, and an evaluator for the state department.

Carolyn M. Callahan, PhD, is a Commonwealth Professor of Education at the University of Virginia. Dr. Callahan served as Site Director of the National Research Center on Gifted and Talented and, in this role, as PI of more than 10 large-scale studies over the past 23 years.