Student Achievement and Performance Between Specialized and Non-Specialized Teacher Groups in Elementary Schools

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Abstract

Teachers matter with respect to student achievement and performance. Teacher specialization is one of the education reforms to enhance teacher effectiveness and promote student achievement. However, the study of teacher specialization in elementary schools is limited, making it challenging to understand better when and under which conditions teacher specialization impacts student achievement. Such an issue may raise challenges to advancing teacher specialization, promoting the teacher workforce, and increasing education reform efficiency. This study explored the association between elementary teacher specialization and student achievement and performance. The results reveal a negative association between the growth of student test scores and elementary teacher specialization in ELA and STEM in a large school district in a southeastern state. Also, the results illustrate that student score differences between their teachers' specialization types depend on grade levels. Student attendance rates in science classes are correlated with their STEM teachers' specialization types. We discuss several possible factors that influenced the findings, providing suggestions to researchers and policymakers regarding the implementation of teacher specialization in elementary schools.

Keywords: teacher specialization; elementary school; teacher quality; multilevel model

Introduction

Teachers play an important role in developing student achievement and performance, often serving as the critical link between educational policies and student outcomes in the classroom (Chetty et al., 2014; Hattie, 2003). Hattie (2003) highlighted that teacher influence accounts for 30% of the variance in student achievement, second only to students' individual abilities. With this significant role, the potential impact of specialized teachers—those with deep content knowledge and pedagogical skills in a specific subject—on student outcomes becomes a crucial focus. As schools and policymakers continually seek strategies to enhance student learning, understanding how specialized teachers contribute to improving student performance could provide actionable insights for improving teaching practices and educational systems (Bastian & Fortner, 2020).

Teacher specialization, also termed "departmentalization" or "platooning" in prior studies (e.g., Chan & Jarman, 2004; Chang et al., 2008; Hood, 2010), is one teacher-focused structural reform used in elementary schools to enhance student achievement and performance. In contrast to non-specialized teachers who teach all four major subject areas to a fixed group of students in one self-contained classroom, specialized teachers teach a specific subject to students from various classrooms in one, or multiple, grade levels. This approach has been adopted broadly in elementary schools throughout the United States in response to the passage of the No Child Left Behind Act of 2002 (Hood, 2010). Policymakers who adopted the teacher specialization model expected that this organizational strategy could lessen teachers' accountability pressures, improve teacher retention, increase student exposure to a wider scope of experience, and enhance student achievement in elementary schools (Chan & Jarman, 2004; Delviscio & Muffs, 2007). Specifically, in the scenario that school districts are racing to improve student outcomes on standardized tests and their teachers are under pressure to improve the scores of students (Chang et al., 2008; Hood, 2010), teacher specialization is considered a feasible and affordable reform in elementary schools.

However, there is limited and conflicting research evidence for the notion that teacher specialization can benefit student achievement and performance in elementary schools, making it difficult for educators to decide whether to adopt or dismantle teacher specialization and whether their decisions affect student achievement and performance. While Condie et al. (2014) and Goldhaber et al. (2013) found that teacher specialization was beneficial for elementary teachers' professional development in their subject area expertise and improving student achievement, other researchers did not find advantages of enhancing student achievement when implementing teacher specialization in elementary schools (e.g., Bastian & Fortner, 2020; Fryer, 2018; Hwang & Kisida, 2022). These inconsistent conclusions about the relationship between teacher specialization and student achievement highlight the need for more evidence to inform decisions on implementing teacher specialization in elementary schools.

As shown in the Common Guidelines for Education and Development (Institute of Education Sciences & National Science Foundation, 2013), an early step in research on the effectiveness of educational interventions is exploring extant data to understand if there are at least associations between the intervention and the intended outcome. Therefore, it is important to investigate the association between teacher specialization and student achievement and performance to enrich the evidence regarding the implementation of teacher specialization in elementary schools. Exploration of existing data could inform the design of future experimental studies to examine causal relationships between specialization and student achievement.

Research Purpose and Research Questions

This study explored the relationship between teacher specialization status (specialized teachers versus non-specialized teachers) and student achievement and performance in elementary schools in a school district with the goal of enriching the existing body of evidence that can aid educational stakeholders when considering the implementation of teacher specialization in elementary schools. We explored three research questions in the context of elementary schools within a single, large school district in a southeastern state:

1. To what extent do elementary students in the district with non-specialized teachers show growth differences in language arts, math, and science test scores compared to students with subject-specialized teachers or to students with both specialized and non-specialized teachers?
2. To what extent does the result of Research Question 1 vary by grade level in each subject?
3. To what extent does the attendance rate differ between students with and without subject-specialized teachers in the district? Does this difference vary by grade level?

Literature Review

Teacher specialization is a common organizational strategy in middle and high schools in which students take different subjects from different teachers across various classrooms (Hood, 2010). In contrast, elementary schools typically organize classrooms with non-specialized teachers who teach all four major subject areas: language arts, mathematics, science, and social studies (Hood, 2010). In the following sections, we will review the reasons for implementing teacher specialization in elementary schools, the correlational relationship between teacher specialization and student achievement, the correlational relationship between teacher specialization and student performance, and the potential issues behind inconsistent conclusions on teacher specialization among previous research.

Teacher Specialization in Elementary Schools

In response to the passage of the No Child Left Behind Act of 2002, some elementary schools implemented teacher specialization for student growth (Hood, 2010). These schools assign specialized teachers with a smaller number of subjects to teach, departmentalizing the same subject-specific specialized teachers in a team to collaborate on improving their teaching strategies, consequently improving student growth (Bastian & Fortner, 2018; Chan & Jarman, 2004; Minott, 2016).

Additionally, teacher specialization can maximize the advantages and expertise of teachers whose proficiency is teaching a specific subject rather than another subject in elementary schools. Such implementation may enhance student achievement and performance (Condie et al., 2014).

Teacher Specialization and Student Achievement

Practitioners and policymakers have discussed whether implementing the strategy of teacher specialization is beneficial to elementary school students for more than ten years. Researchers have explored the correlational relationship of teacher specialization with student achievement in elementary schools. For example, Williams (2009) compared the difference in fifth-grade students' mathematics achievement between math-specialized teachers and non-specialized teachers, for a sample consisting of 180 teachers and 9,386 students from the State of Georgia, demonstrating that students' passing rates on a mathematics criterion-referenced competency test in the teacher specialization group was higher than students with non-specialized teachers.

However, findings in the literature are inconsistent regarding the correlational relationship between teacher specialization and student achievement. Hwang and Kisida (2022) found that Grades 3–5 students in Indiana taught by specialized teachers had lower math and reading scores than students taught by non-specialized teachers.

Teacher Specialization and Student Performance

Fryer (2018) found that the strategy of teacher specialization was not only associated with student achievement but also related to student performance (i.e., attendance rates) in the school-level comparison. Fryer (2018) evaluated the correlational relationship between student attendance rates and teacher specialization, finding a year-on-year decline in student attendance rates in the Houston Independent School District with elementary teacher specialization. Furthermore, Chang et al. (2008) investigated the difference in students' connectedness to schools between students taught by specialized and non-specialized elementary teachers from a school district in Kentucky. They did not find a significant correlation between teacher specialization and student connectedness.

Potential Issues Behind Inconsistent Conclusions on Teacher Specialization

When contrasting data characteristics and methodologies in previous studies, we find that inconsistent conclusions likely stem from whether the study accounted for school impact, grade level differences, the nature of student assignment to specialized teachers, or other confounding variables. Prior studies using *t*-tests and regression analyses (e.g., Chang et al., 2008; Williams, 2009) did not consider school impacts on student achievement, leading to estimated bias. Hwang and Kisida (2022) used a multilevel model to account for school impacts but analyzed seven years of data with a fixed intercept for student achievement, without considering grade-level variations. The varying impacts across elementary schools and grade levels (Brobst et al., 2017; Cook & Mansfield, 2016; Fryer, 2018; Kisa, 2014; Wayne & Youngs, 2003) may lead to inconsistent conclusions, blocking the comprehensive understanding of associations between teacher specialization and student achievement. Between these findings, and simply the possibility of other confounding variables in correlational findings, studies investigating this relationship remain incomplete.

Methods

This section presents the sample and outlines the data analysis procedure used to address the research questions.

Sample

We obtained data from the records of a large school district in Florida, including teacher- and student-level demographic and achievement data for Grades 3 through 5 during the 2021–2022 school year. The data set for this research included 49 schools, of which 27 employed subject-specialized teachers and 22 did not have any subject-specialized teachers.

Teacher Data

Within the data collected for analysis, 458 teachers taught English language arts (ELA), and 429 teachers taught math and science in the 2021–2022 school year. Eighty-seven teachers specialized in ELA, and 73 teachers specialized in STEM. Tables 1 and 2 show the teacher characteristics between the groups with and without subject-specific specialization in ELA and STEM, respectively. Most teachers were White women with bachelor’s degrees, regardless of whether they were specialized teachers or non-specialized teachers.

Student Data

Student achievement data were comprised of Northwest Evaluation Association (NWEA) test scores for ELA, math, and science in Grades 3–5. The dataset contained NWEA ELA scores for 3,697 students in Grade 3, 3,427 students in Grade 4, and 4,045 students in Grade 5. The ELA dataset contained missing data with proportions of 0.07, 0.04, and 0.02 corresponding to the fall, winter, and spring quarter exams, respectively.

We received NWEA math test scores for 3,720 students in Grade 3, 3,220 students in Grade 4, and 3,657 students in Grade 5. The math dataset contained missing data with proportions of 0.11, 0.06, and 0.03 corresponding to the fall, winter, and spring quarter exams, respectively.

The dataset contained NWEA Science test scores for 3,869 students in Grade 3, 3,330 students in Grade 4, and 3,865 students in Grade 5. The Science dataset contained missing data with the proportions of 0.12, 0.05, and 0.03 corresponding to the fall, winter, and spring quarter exams, respectively.

Table 1. *ELA Teacher Demographic Data*

Grade Level	Demographic		Specialized Teacher Num (%)	Non-Specialized Teacher Num (%)
Grade 3	Total number of teachers		18	167
	Gender	Female	18 (100)	156 (93)
		Male	0 (0)	11 (7)
	Ethnicity	Asian	0 (0)	0 (0)
		Black	0 (0)	3 (2)
		White	18 (100)	153 (92)
		Hispanic	0 (0)	7 (4)
		Multiple	0 (0)	1 (1)
		Others	0 (0)	2 (1)
	Highest Degree of Education	High School Diploma	0 (0)	1 (1)
		Associate degree	0 (0)	3 (2)
		Bachelor's degree	11 (61)	103 (62)
		Master's degree	3 (17)	23 (14)
Grade 4	Total number of teachers		21	112
	Gender	Female	21 (100)	105 (94)
		Male	0 (0)	7 (6)
	Ethnicity	Asian	0 (0)	1 (1)
		Black	0 (0)	2 (2)
		White	19 (90)	99 (88)
		Hispanic	1 (5)	4 (4)
		Multiple	1 (5)	5 (4)
		Others	0 (0)	1 (1)
	Highest Degree of Education	Bachelor's degree	13 (62)	74 (66)
		Master's degree	4 (19)	21 (19)
Grade 5	Total number of teachers		30	110
	Gender	Female	25 (83)	96 (87)
		Male	5 (17)	14 (13)
	Ethnicity	Asian	0 (0)	0 (0)
		Black	1 (3)	2 (2)
		White	25 (83)	98 (89)
		Hispanic	2 (7)	5 (5)
		Multiple	2 (7)	3 (3)
		Others	0 (0)	0 (0)
	Highest Degree of Education	Bachelor's degree	22 (73)	66 (60)
		Master's degree	4 (13)	23 (21)

Table 2. *STEM Teacher Demographic Data*

Grade Level	Demographic		Specialized Teacher Num (%)	Non-specialized Teacher Num (%)
Grade 3	Total number of teachers		12	160
	Gender	Female	11 (92)	151 (94)
		Male	1 (8)	9 (6)
	Ethnicity	Asian	0 (0)	0 (0)
		Black	0 (0)	3 (2)
		White	11 (92)	146 (92)
		Hispanic	1 (8)	7 (4)
		Multiple	0 (0)	1 (1)
		Others	0 (0)	2 (1)
	Highest Degree of Education	High School Diploma	0 (0)	1 (1)
		Associate degree	0 (0)	2 (1)
		Bachelor’s degree	8 (67)	98 (61)
		Master’s degree	2 (16)	23 (14)
Grade 4	Total number of teachers		22	105
	Gender	Female	21 (95)	99 (94)
		Male	1 (5)	6 (6)
	Ethnicity	American Indian	1 (5)	0 (0)
		Asian	0 (0)	1 (1)
		Black	0 (0)	2 (2)
		White	19 (85)	93 (88)
		Hispanic	1 (5)	4 (4)
		Multiple	1 (5)	4 (4)
		Others	0 (0)	1 (1)
	Highest Degree of Education	Bachelor’s degree	68 (65)	13 (59)
		Master’s degree	22 (21)	3 (14)
Grade 5	Total number of teachers		30	100
	Gender	Female	24 (80)	87 (87)
		Male	6 (20)	13 (13)
	Ethnicity	Asian	0 (0)	0 (0)
		Black	0 (0)	2 (2)
		White	28 (93)	90 (90)
		Hispanic	2 (7)	3 (3)
		Multiple	0 (0)	3 (3)
		Others	0 (0)	0 (0)
	Highest Degree of Education	Bachelor’s degree	19 (64)	61 (61)
		Master’s degree	4 (13)	21 (21)

We also obtained student attendance rates for the 2021–2022 school year, computed by the recorded number of present days divided by 180 total days.

Data Analysis Procedure

To address the research questions, we included two independent variables in the model: teacher specialization and grade level. Teacher specialization, the primary focus of this research, was dummy-coded into two variables to enhance interpretability. Additionally, we hypothesized that the association between teacher specialization and elementary student achievement varies by grade level, as prior research has reported differing results across grade levels (e.g., Hwang & Kisida, 2022; Williams, 2009).

The following sections are structured in three parts: (a) Data Preprocessing, which details the variables used and methods for handling missing data; (b) Multilevel Modeling for Longitudinal Data, which outlines the model structure for addressing Research Questions 1 and 2; and (c) Two-Level Model for Student Attendance Rate Data, which describes the model structure for addressing Research Question 3.

Data Preprocessing

The dependent variable is students' NWEA test scores in the fall, winter, and spring exams in the year 2021–2022 in one subject. The independent variables are the time variable representing the assessment time point in fall, winter, or spring, teacher types in specialization, grade, and school. This study contains three groups of the teachers' type of specialization, which are (a) student solely with non-specialized teachers, (b) student solely with specialized teachers, and (c) student with both specialized and non-specialized teachers when studying one subject. Tables 3 to 5 show the balanced student characteristics between different teacher types. Two dummy coding variables (Code = 0 or 1) were created for the three teacher types to improve the interpretability of the variable. Meanwhile, we selected the variable of grade based on the literature review of inconsistent conclusions among Grades 3 to 5. We selected the variable of school to consider the variety of school impacts on student achievement and performance.

Additionally, we replaced the missing data by running multiple imputations by chained equations (MICE) in R 4.2.1 with the "mice" R package (van Buuren & Groothuis-Oudshoorn, 2011). We set the imputation method to predictive mean matching and the number to be five imputations for each data set. As a result, we obtained a completed dataset by averaging parameter estimates from the multilevel model across the five imputed datasets. This method can reduce estimation bias due to missing data (Enders, 2010). More discussion and implementation of MICE can be found in Enders (2010).

Multilevel Modeling for Longitudinal Data

We structured three multilevel models for the longitudinal data, separately analyzing students' NWEA ELA, math, and science test scores with different teacher types. The structure of each subject test score model was the same, which contained three levels. Level 1 was within-student measures of each student's NWEA fall, winter, and spring test scores, each quarter exam denoted by t. Level 2 was the student level, which allowed differences in students' initial scores and considered the covariates of teacher types and grade levels. Level 3 was the school level, which captured the average score differences between schools. Note that in the data, teacher and school levels were largely confounded (e.g., having very few specialized teachers in any given school). Hence, Level 3 can be seen as controlling simultaneously for the teacher and school factors. The model for analyzing test scores in each subject was defined as follows.

$$\begin{aligned} Y_{itk} = \delta_{000} &+ \delta_{010}Specialize_{ik} + \delta_{020}BothType_{ik} + \delta_{030}Grade_{ik} \\ &+ \delta_{040}Specialize_{ik}Grade_{ik} + \delta_{050}BothType_{ik}Grade_{ik} + \delta_{100}a_{itk} \\ &+ \delta_{110}Specialize_{ik}a_{itk} + \delta_{120}BothType_{ik}a_{itk} + e_{01k}Specialize_{ik} \\ &+ e_{02k}BothType_{ik} + e_{00k} + \mu_{0ik} + \varepsilon_{itk}, \end{aligned} \tag{1}$$

where Y_{itk} refers to Student i's score in Quarter exam t at School k. a_{itk} is the time parameter. δ_{000} is the overall average score of students with non-specialized teachers in Grade 3. δ_{010} is the association between test scores of students with and without specialized teacher. δ_{020} is the association between test scores of students with both-type teachers and students with non-specialized teachers. δ_{030} is the average score difference between grade levels. δ_{100} is the average student growth slope across exam times. δ_{040}, and δ_{050} are the average score differences between teacher types conditioning on the same grade level. δ_{110}, and δ_{120} are the average student growth slope conditioning on the same teacher type. $e_{00k}, e_{01k}, e_{02k}, \mu_{0ik}$, and ε_{itk} are the random effects, which followed the normal distributions. When modeling, we attempted to allow growth slopes δ_{100} among all students to vary across time. Nevertheless, this attempt caused a convergence issue due to the model's complexity. Therefore, we fixed the effect of student growth slope δ_{100}, which indicated all students obtained the identical average growth slope from fall to winter exams and the identical average growth slope from winter to Spring exams among all students.

Two-Level Model for Modeling Student Attendance Rate Data

To explore the association between student attendance rates and subject-specialized teachers, a two-level model was structured in which Level 1 contained student attendance rates with the covariates of their teacher types and student grade levels, and Level 2 was the variation between schools. The model was defined as follows.

$$\begin{aligned} Attend_{ik} = \gamma_{00} &+ \gamma_{10}Specialize_{ik} + \gamma_{20}BothType_{ik} + \gamma_{30}Grade_{ik} \\ &+ \gamma_{40}Specialize_{ik}Grade_{ik} + \gamma_{50}BothType_{ik}Grade_{ik} + e_{0k} \\ &+ e_{1k}Specialize_{ik} + e_{2k}BothType_{ik} + \mu_{ik}, \end{aligned} \tag{2}$$

where $Attend_{ik}$ is Student i's attendance rate at School k. γ_{00} is the overall average of attendance rates in students with non-specialized teachers in Grade 3. γ_{10} is the average student attendance rate difference between students with and without specialized teachers. γ_{20} is the average student attendance rate difference between students with both-type teachers and students with non-specialized teachers. γ_{30} refers to the magnitude of average student attendance rate changes as one-unit grade level increases their grade levels. γ_{40} and γ_{50} are the average student attendance rate differences between teacher types conditioning on the same grade level. e_{0k}, e_{1k}, e_{2k} and μ_{ik} are the random effects, which followed normal distributions.

All data analyses were implemented in R (R Core Team, 2022).

Table 3. *Characteristics of Students Who Took ELA Course*

Grade Level	Demographic		With Specialized Teacher Num (%)	Without Specialized Teacher Num (%)	With Both Specialized and Non-specialized Teacher Num (%)
Grade 3	Gender	Female	297 (51.92)	1,542 (50.34)	34 (54.84)
		Male	275 (48.08)	1,521 (49.66)	28 (45.16)
	Ethnicity	American Indian	3 (0.52)	15 (0.49)	0 (0)
		Asian	19 (3.32)	111 (3.62)	2 (3.23)
		Black	46 (8.04)	239 (7.80)	7 (1.13)
		Hispanic	167 (29.20)	732 (23.90)	17 (27.42)
		Multiple	32 (5.59)	196 (6.40)	4 (6.45)
		White	305 (53.32)	1,770 (57.79)	32 (51.61)
	Transfer Schools During 2021–2022		1 (0.17)	76 (2.48)	26 (4.19)
Grade 4	Gender	Female	471 (50.97)	1,210 (49.63)	40 (61.54)
		Male	443 (47.94)	1,197 (49.10)	25 (38.46)
	Ethnicity	American Indian	3 (0.32)	9 (0.37)	0 (0)
		Asian	37 (4.00)	96 (3.94)	1 (1.54)
		Black	65 (7.03)	191 (7.83)	11 (16.92)
		Hispanic	220 (23.81)	585 (24.00)	14 (21.54)
		Multiple	59 (6.39)	155 (6.36)	3 (4.62)
		White	530 (57.36)	1,371 (56.23)	36 (55.38)
	Transfer Schools During 2021–2022		10 (1.08)	34 (1.39)	22 (33.85)
Grade 5	Gender	Female	657 (47.99)	1,240 (47.95)	44 (46.32)
		Male	700 (51.13)	1,330 (51.43)	47 (49.47)
	Ethnicity	American Indian	0 (0)	8 (0.31)	0 (0)
		Asian	31 (2.26)	91 (3.52)	4 (4.21)
		Black	130 (9.50)	198 (7.66)	10 (10.53)
		Hispanic	366 (26.73)	620 (23.98)	25 (26.32)
		Multiple	73 (5.33)	165 (6.38)	7 (7.37)
		White	757 (55.30)	1,488 (57.54)	45 (47.37)
	Transfer Schools During 2021–2022		6 (0.44)	49 (1.89)	44 (46.32)

Table 4. *Characteristics of Students Who Took Math Course*

Grade Level	Demographic		With Specialized Teacher Num (%)	Without Specialized Teacher Num (%)	With Both Specialized and Non-specialized Teacher Num (%)
Grade 3	Gender	Female	223 (48.37)	1,623 (50.25)	20 (51.28)
		Male	233 (50.54)	1,564 (48.42)	17 (43.59)
	Ethnicity	American Indian	2 (0.43)	15 (0.46)	0 (0)
		Asian	13 (2.82)	119 (3.68)	3 (7.69)
		Black	43 (9.32)	262 (8.11)	2 (5.13)
		Hispanic	138 (29.93)	803 (24.86)	9 (23.08)
		Multiple	30 (6.51)	198 (6.13)	5 (12.82)
		White	230 (49.89)	1,790 (55.42)	18 (46.15)
	Transfer Schools During 2021–2022		2 (0.43)	83 (2.57)	23 (58.97)
Grade 4	Gender	Female	407 (46.94)	1,143 (49.98)	33 (50.00)
		Male	448 (51.67)	1,116 (48.80)	33 (50.00)
	Ethnicity	American Indian	3 (0.35)	8 (0.35)	0 (0)
		Asian	24 (2.77)	89 (3.89)	1 (1.52)
		Black	76 (8.77)	177 (7.74)	11 (16.67)
		Hispanic	221 (25.49)	552 (24.14)	21 (31.82)
		Multiple	60 (6.92)	142 (6.21)	7 (10.61)
		White	471 (54.33)	1,291 (56.45)	26 (39.39)
	Transfer Schools During 2021–2022		7 (0.81)	35 (1.53)	25 (37.88)
Grade 5	Gender	Female	615 (48.77)	1,122 (48.36)	33 (43.42)
		Male	631 (50.04)	1,181 (50.91)	41 (53.95)
	Ethnicity	American Indian	2 (0.16)	7 (0.30)	0 (0)
		Asian	36 (2.85)	83 (3.58)	3 (3.95)
		Black	117 (9.28)	188 (8.10)	7 (9.21)
		Hispanic	338 (26.80)	554 (23.88)	17 (22.37)
		Multiple	76 (6.03)	149 (6.42)	7 (9.21)
		White	677 (53.69)	1,322 (56.98)	40 (52.63)
	Transfer Schools During 2021–2022		7 (0.56)	41 (1.77)	33 (43.42)

Table 5. *Characteristics of Students Who Took Science Course*

Grade Level	Demographic		With Specialized Teacher Num (%)	Without Specialized Teacher Num (%)	With Both Specialized and Non-specialized Teacher Num (%)
Grade 3	Gender	Female	227 (48.30)	1,682 (49.97)	17 (51.52)
		Male	238 (50.64)	1,641 (48.75)	14 (42.42)
	Ethnicity	American Indian	2 (0.43)	15 (0.45)	0 (0)
		Asian	14 (2.98)	125 (3.71)	3 (9.09)
		Black	44 (9.36)	268 (7.96)	2 (6.06)
		Hispanic	142 (30.21)	814 (24.18)	5 (15.15)
		Multiple	31 (6.60)	209 (6.21)	4 (12.12)
		White	232 (49.36)	1,892 (56.21)	17 (51.52)
	Transfer Schools During 2021–2022		2 (0.43)	84 (2.50)	23 (69.70)
Grade 4	Gender	Female	422 (47.52)	1,191 (50.13)	33 (50.00)
		Male	454 (51.13)	1,157 (48.70)	33 (50.00)
	Ethnicity	American Indian	3 (0.34)	8 (0.34)	0 (0)
		Asian	26 (2.93)	97 (4.08)	1 (1.52)
		Black	76 (8.56)	185 (7.79)	11 (16.67)
		Hispanic	226 (25.45)	564 (23.74)	21 (31.82)
		Multiple	62 (6.98)	147 (6.19)	7 (10.61)
		White	483 (54.39)	1,347 (56.69)	26 (39.39)
	Transfer Schools During 2021–2022		7 (0.79)	33 (1.39)	25 (37.88)
Grade 5	Gender	Female	668 (48.72)	1,169 (48.17)	30 (44.78)
		Male	687 (50.11)	1,243 (51.22)	35 (52.24)
	Ethnicity	American Indian	2 (0.15)	7 (0.29)	0 (0)
		Asian	37 (2.70)	90 (3.71)	4 (5.97)
		Black	126 (9.19)	194 (7.99)	7 (10.45)
		Hispanic	364 (26.55)	579 (23.86)	17 (25.37)
		Multiple	81 (5.91)	154 (6.35)	6 (8.96)
		White	745 (54.34)	1,388 (57.19)	31 (46.27)
	Transfer Schools During 2021–2022		7 (0.51)	43 (1.77)	38 (56.72)

Results

Our data meet the assumptions of linearity and homoscedasticity, as the residuals were distributed randomly across observed scores and their estimated values. The linear QQ plots without tails and the residual histograms that followed normal distributions confirm the normality assumption.

The model structure of student scores clustering in their schools is necessary for analyzing each data set, and the intra class correlation (ICC) provides an estimate of the amount of variance that is attributed to school clusters. The intra class correlation (ICC) of the school level was 0.191 in the ELA dataset, which indicated that 19.1% of the total variance in student ELA scores could be explained by the variation in school averages. The ICC of the school level was 0.174 in the math dataset, which indicated that 17.4% of the total variance in student math scores could be explained by the variation in school averages. The ICC of the school level was 0.162 in the science dataset, which indicated that 16.2% of the total variance in student science scores could be explained by the variation in school averages.

Multilevel Modeling for Longitudinal Data in Student NWEA ELA Scores

Table 6 demonstrates the differences in average student growth in ELA between those taught only by ELA-specialized teachers and those taught only by non-specialized teachers. For students taught only by ELA-specialized teachers, the average Winter test score increased by 3.96 points from the fall, and the spring test score increased by 6.71 points from fall. In contrast, for students taught only by non-specialized teachers, the average winter test score increased by 4.38 points from the fall, and the spring test score increased by 7.66 points from the fall (Figure 1). Additionally, there is no significant difference in ELA growth between students taught by both types of teachers (BTT) and those taught only by non-specialized teachers.

To answer Research Question 2, Table 6 indicates that differences in ELA scores between the groups of specialized and non-specialized teachers vary by grade level. We found no difference in average ELA scores between students taught only by ELA-specialized teachers and those taught only by non-specialized teachers in Grades 3 and 4. However, in Grade 5, students taught only by ELA-specialized teachers scored, on average, 2.01 fewer points on the NWEA ELA test than students taught only by non-specialized teachers.

Likewise, Table 6 shows differences in ELA scores between students taught by BTT and those students taught only by non-specialized teachers vary by grade level. We did not find test score differences in Grades 4 and 5, whereas Grade 3 students taught by BTT scored, on average, 7.16 lower points on the fall NWEA ELA test than those taught only by non-specialized teachers.

Multilevel Modeling for Longitudinal Data in Student NWEA Math Scores

Table 7 demonstrates that students with various types of teachers grow differently in math across three time points of NWEA assessment compared to students with non-specialized teachers. For students taught by BTT, their NWEA math scores increased by 9.32 points on average. For students taught only by STEM-specialized teachers, their math scores increased by 9.87 points on average. For students taught only by non-specialized teachers, their math scores increased by 10.74 points on average. Figure 2 visualizes these changes. Thus, students taught only by non-specialized teachers achieved a greater increase in NWEA math test scores than students with other types of teachers.

Additionally, Table 7 shows that the grade level is not associated with the differences in NWEA math scores between students taught by BTT and those taught only by non-specialized teachers. However, the differences in math scores between students taught only by STEM-specialized teachers and students taught only by non-specialized teachers vary by grade level (Table 7). We found no average difference in math scores between students with and without specialized teachers in Grades 3 and 4. In Grade 5, however, students taught only by STEM-specialized teachers scored, on average, 2.07 points lower on the NWEA math test than those taught only by non-specialized teachers.

Figure 1. *The Statistically Significant Difference in NWEA ELA Test Scores Between Students Taught Only by Specialized Teachers and Students Taught Only by Non-specialized Teachers*

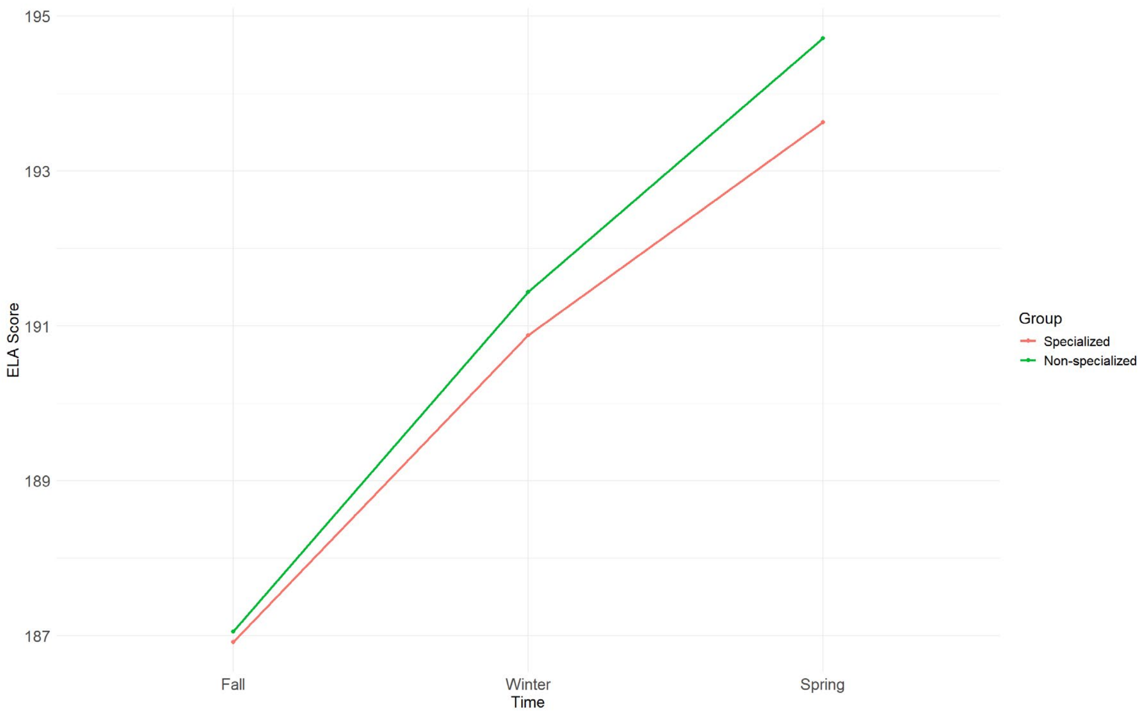

Table 6. *The Associations Between Student NWEA ELA Test Scores and Students' Teacher Types*

Random Effects					
Groups	Name	Variance	*SD*		
Student: School	Intercept	153.938	12.407		
School	Intercept	27.738	5.267		
	Specialized	11.190	3.345		
	Both	8.358	2.891		
Residual		46.347	6.808		
Fixed Effects					
	Estimated (*SD*)	*SE*	*df*	*t*	*p*
Intercept	187.055 (–0.780)	0.812	51.36	230.262	<.001***
Specialized	–0.136 (–0.008)	1.028	61.36	–0.133	0.895
Both	–7.155 (–0.429)	1.961	71.25	–3.648	0.001***
Time Winter	4.375 (0.262)	0.107	22341.99	40.863	<.001***
Time Spring	7.657 (0.459)	0.107	22341.99	71.515	<.001***
Grade 4	10.204 (0.612)	0.373	10299.68	27.387	<.001***
Grade 5	15.663 (0.939)	0.369	10718.22	42.441	<.001***
Specialized: Grade 4	–1.111 (–0.067)	0.930	5400.21	–1.195	0.232
Specialized: Grade 5	–1.870 (–0.112)	0.821	7903.66	–2.278	0.023*
Both: Grade 4	1.511 (0.091)	2.626	112.39	0.575	0.566
Both: Grade 5	0.415 (0.025)	2.310	271.22	0.180	0.858
Specialized: Time Winter	–0.414 (–0.025)	0.209	22341.99	–1.977	0.048*
Specialized: Time Spring	–0.945 (–0.057)	0.209	22341.99	–4.516	<.001***
Both: Time Winter	–0.591 (–0.035)	0.655	22341.99	–0.902	0.367
Both: Time Spring	–0.215 (–0.013)	0.655	22341.99	–0.328	0.743

* $p < .05$. *** $p<.001$.

Figure 2. *The Statistically Significant Difference in NWEA Math Test Scores Among Students With and Without Specialized Teachers*

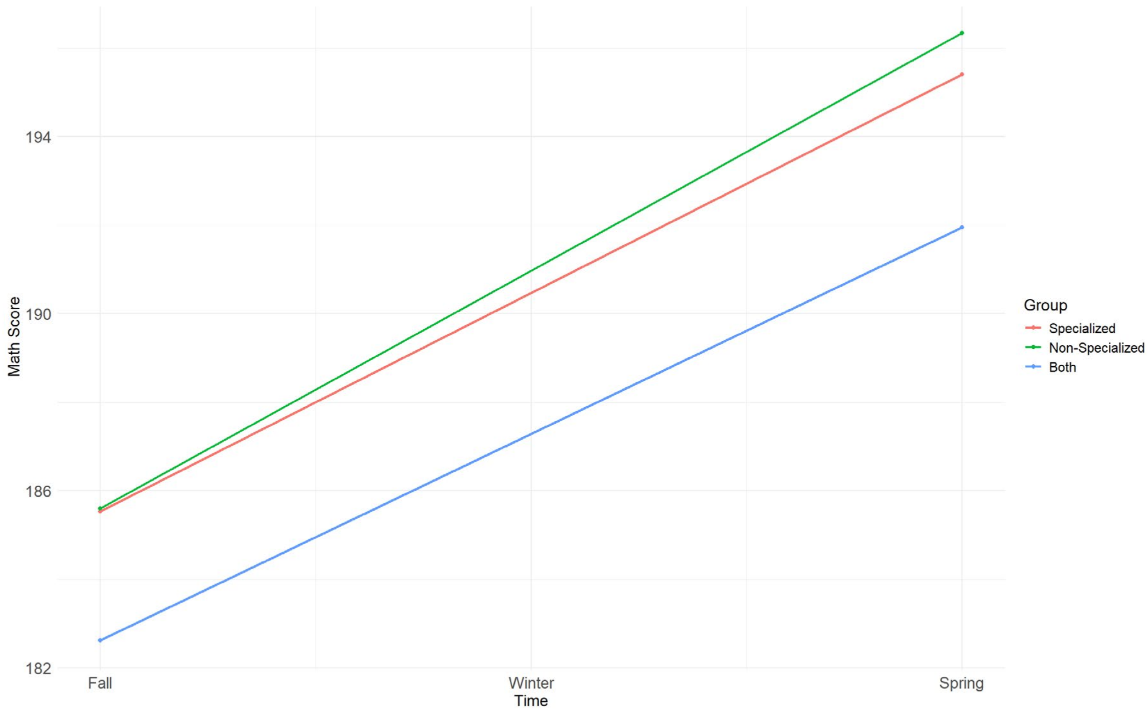

Table 7. *The Associations Between Student NWEA Math Test Scores and Students' Teacher Types*

	Random Effects				
Groups	Name	Variance	*SD*		
Student: School	Intercept	134.762	11.609		
School	Intercept	21.848	4.674		
	Specialized	7.306	2.703		
	Both	6.771	2.602		
Residual		35.495	5.958		
	Fixed Effects				
	Estimated (*SD*)	*SE*	*df*	*t*	*p*
Intercept	185.600 (–0.970)	0.728	50.12	254.860	<.001***
Specialized	–0.062 (–0.004)	0.984	64.71	–0.064	0.950
Both	–2.973 (–0.179)	2.099	498.30	–1.417	0.157
Time Winter	5.765 (0.347)	0.095	21210	60.573	<.001***
Time Spring	10.740 (0.646)	0.095	21210	112.881	<.001***
Grade 4	11.700 (0.703)	0.351	9166	33.300	<.001***
Grade 5	19.860 (1.194)	0.355	10210	56.004	<.001***
Specialized: Grade 4	–0.695 (–0.042)	0.873	8051	–0.796	0.426
Specialized: Grade 5	–2.011 (–0.121)	0.816	9119	–2.465	0.014*
Both: Grade 4	4.213 (0.253)	2.526	3017	1.668	0.095
Both: Grade 5	–0.990 (–0.060)	2.464	3219	–0.402	0.688
Specialized: Time Winter	–0.372 (–0.022)	0.191	21210	–1.948	0.051
Specialized: Time Spring	–0.866 (–0.052)	0.191	21210	–4.532	<.001***
Both: Time Winter	–0.981 (–0.059)	0.634	21210	–1.548	0.122
Both: Time Spring	–1.420 (–0.085)	0.634	21210	–2.241	0.025*

* $p < .05$. *** $p < .001$.

Multilevel Modeling for Longitudinal Data in Student NWEA Science Scores

Table 8 illustrates no growth differences in science among students with various types of teachers. Likewise, the differences in science scores between students with various types of teachers do not vary by grade level.

Two-level Model for Analyzing Student Attendance Rate

To answer RQ3, Table 9 demonstrates no difference in the average attendance rates between students with different types of teachers. However, Table 10 shows that the average attendance rate in science classes for students taught by BTT is 3.74 units lower than for those taught only by non-specialized teachers. Furthermore, Table 10 illustrates that this association varies by grade level. In Grade 4, students taught by BTT in science classes showed an average attendance rate that was 1.03 units less than those taught only by non-specialized teachers. In Grade 5, students who were taught by BTT showed an average attendance rate that was 6.35 units less than those students taught only by non-specialized teachers in science classes.

Discussion

This study explored the relationship between teacher specialization and elementary students' achievement and attendance rates in a large school district. The findings provide insight into the association between teacher specialization and student outcomes, paving the way for future research in causal studies. Results revealed a negative relationship between student test score growth and teacher specialization in ELA and STEM subjects, with differences varying by grade level. Notably, Grade 5 students taught by specialized teachers had lower average scores in ELA or math than those taught by non-specialized teachers. Additionally, student attendance rates in science courses were correlated with teacher specialization but not in ELA courses.

In contrast to Williams (2009) and Fryer (2018), who found a positive relationship between teacher specialization and student achievement and attendance rates, this study aligns with Hwang and Kisida (2022) in finding a negative relationship. Williams (2009) and Fryer (2018) did not account for school-level variability, whereas both this study and Hwang and Kisida (2022) used multilevel models to control for the variety of school impacts. This methodological approach likely improves the understanding of how teacher specialization functions within different school contexts. Furthermore, our results highlight the crucial role of grade level in the association between student growth and teacher specialization status. To our knowledge, this study is the first to investigate these correlations in elementary schools using longitudinal data, considering various school impacts and grade levels.

The various impacts of school contexts can help to explain why students with specialized teachers are not outperforming students taught only by non-specialized teachers in the district. Aside from teacher demographic characteristics, five possible conditions need to be considered. The first one is about specialized teachers' teaching loads. Previous studies defined subject-specialized teachers as the ones who taught no more than three courses in one academic year (e.g., Hwang & Kisida, 2022). Compared to that definition, the specialized teachers in our empirical data taught no less than four courses in an academic year, and some specialized teachers taught cross-subjects regardless of whether their specialization was cross-subject or not.

Table 8. *The Associations Between Student NWEA Science Test Scores and Students' Teacher Types*

Random Effects					
Groups	Name	Variance	*SD*		
Student: School	Intercept	77.182	8.785		
School	Intercept	11.747	3.427		
	Specialized	6.365	2.523		
	Both	2.698	1.643		
Residual		30.781	5.548		
Fixed Effects					
	Estimated	*SE*	*df*	*t*	*p*
Intercept	189.365 (–0.819)	0.541	51	350.308	<.001***
Specialized	–1.188 (–0.096)	0.821	54	–1.447	0.154
Both	–2.990 (–0.241)	1.728	105	–1.730	0.087
Time Winter	3.235 (0.260)	0.087	22120	37.265	<.001***
Time Spring	6.239 (0.502)	0.087	22120	71.863	<.001***
Grade 4	7.777 (0.625)	0.266	10120	29.256	<.001***
Grade 5	13.171 (1.059)	0.268	10760	49.196	<.001***
Specialized: Grade 4	–0.226 (–0.018)	0.664	8871	–0.341	0.734
Specialized: Grade 5	–0.741 (–0.060)	0.622	9788	–1.191	0.234
Both: Grade 4	1.644 (0.132)	2.045	146	0.804	0.423
Both: Grade 5	–0.166 (–0.013)	2.030	198	–0.082	0.935
Specialized: Time Winter	0.150 (0.012)	0.174	22120	0.865	0.387
Specialized: Time Spring	–0.256 (–0.021)	0.174	22120	–1.477	0.140
Both: Time Winter	0.387 (0.031)	0.615	22120	0.629	0.530
Both: Time Spring	–0.971 (–0.078)	0.615	22120	–1.579	0.114

*** $p < .001$.

Table 9. *Association Between Student Attendance Rates and Their Teacher Types in ELA*

Random Effects					
Groups	Name	Variance	*SD*		
School	Intercept	3.864	1.966		
	Specialized	1.089	1.044		
	Both	39.323	6.271		
Residual		36.494	6.041		
Fixed Effects					
	Estimated	*SE*	*df*	*t*	*p*
Intercept	93.040	0.293	50.00	317.091	<.001***
Specialized	–0.103	0.299	30.20	–0.344	0.733
Both	–2.265	1.231	39.89	–1.840	0.073
Grade 4	–0.480	0.100	24530	–4.807	<.001***
Grade 5	–0.605	0.098	28390	–6.116	<.001***
Specialized: Grade4	–0.425	0.251	11400	–1.691	0.091
Specialized: Grade5	–0.047	0.221	17980	–0.212	0.832
Both: Grade4	0.277	0.869	5137	0.318	0.750
Both: Grade5	–2.782	0.738	6748	–3.772	0.000***

*** $p <.001$.

Table 10. *Association Between Student Attendance Rates and Their Teacher Types in Science*

Random Effects					
Groups	Name	Variance	*SD*		
School	Intercept	3.716	1.928		
	Specialized	0.719	0.848		
	Both	33.412	5.780		
Residual		36.638	6.053		
Fixed Effects					
	Estimated	*SE*	*df*	*t*	*p*
Intercept	92.840	0.289	49.99	321.787	<.001***
Specialized	–0.341	0.298	44.36	–1.143	0.259
Both	–3.740	1.217	59.09	–3.072	0.003**
Grade 4	–0.092	0.099	17600	–0.929	0.353
Grade 5	–0.320	0.100	29560	–3.195	0.000***
Specialized: Grade 4	–0.159	0.249	25610	–0.639	0.523
Specialized: Grade 5	0.151	0.233	26700	0.648	0.517
Both: Grade 4	2.715	0.928	6098	2.926	0.003**
Both: Grade 5	–2.609	0.896	7851	–2.913	0.004**

** $p<0.01$. *** $p < .001$.

The second consideration is regarding teachers' motivations in teaching. It is possible that teachers are struggling to be effective as non-specialized teachers, and this led, in part, to their assignment to be specialized teachers. Struggling teachers are sometimes assigned to specialize as a strategy to help them focus on one academic area (Loeb et al., 2012). This would impact the correlation as the teacher's teaching performance may have caused the classification into specialization, rather than the specialization having a causal effect on their teaching performances. This is also related to the possibility that students themselves are assigned to specialized teachers through some systematic decisions that can explain the correlation. For example, if struggling students were more often assigned to specialized teachers in this district, that may explain some of the correlation results we found.

The third consideration is the interaction between specialized teachers and their students. Unlike non-specialized teachers, who spend more time with their students, specialized teachers have fewer opportunities to cultivate their relationships with students (Raphael & Burke, 2012). Although teacher specialization can expose students to a wider range of experiences with different teachers (Chan & Jarman, 2004; Delviscio & Muffs, 2007), specialized teachers may be limited in their ability to address students' needs, as students are less willing to share personal thoughts and needs with specialized teachers compared to non-specialized teachers due to their relationships (Raphael & Burke, 2012).

The fourth consideration is related to teaching strategies. Specialized teachers with or without appropriate knowledge of teaching strategies may impact their student achievement, especially when they work independently without collaborative efforts in an instructional team (Lee et al., 2016). If subject-specialized teachers work independently without engaging in collaborative efforts to prepare for their classes, they encounter the same challenge in identifying issues related to their teaching strategies as non-specialized teachers do. This diminishes the potential advantages of teacher specialization, leading to a small or even negative correlation of specialized teachers with student achievement and performance.

Lastly, students who are struggling in a subject may be assigned to a subject-specialized teacher, leading to a possibility of a negative correlation between teacher specialization and student achievement (Grissom et al., 2021; Kalogrides et al., 2012). Students struggling with a subject may take time to develop their ability in more than a single school year, which cannot be instantly reflected in the data from the three examinations to show the benefits of learning with specialized teachers.

Limitations and Future Research

Limitations and Delimitations

Given these potential factors, our study is limited to considering various school impacts and grade levels, but this scope could be expanded to consider additional factors. We suggest future studies collect more information in the teacher dataset and student dataset, such as teaching motivations, the years of experience in specialized teachers, the consecutive years of teaching in the specific subject, the time length of interaction between teacher and student in classroom hours, and the reasons for students learning with specialized teachers. They may help further insight into the benefits of teacher specialization in elementary schools, and from a research standpoint, knowing the mechanism of how students and teachers are assigned to classrooms with specialized teaching can bring much clarity to understanding the possible causal effects on student outcomes.

Another limitation is the generalizability of this study, as we conducted the research within a single school district. We suggest future studies focusing on different school districts and states to generalize the association between teacher specialization and student achievement and performance.

Future Research

We recommend researchers and policymakers investigate whether the association between teacher specialization and student achievement and attendance rates is relevant to these potential factors. Such future studies can illustrate specific scenarios of adopting teacher specialization in elementary schools.

Conclusion

This study extends the literature on understanding the correlational relationship between elementary teacher specialization and student achievement and performance. We do not assume that teacher specialization directly affected student achievement and attendance rates, nor do we conclude that teacher specialization did not help improve student achievement and attendance rates in the school district. Instead, our results indicate that teacher specialization status is associated with student growth in ELA and math achievement but not in science. Notably, in Grade 5, students taught by specialized teachers showed less growth in ELA, indicating that teacher assignments may need revision to better support upper elementary students in this subject. It is crucial for policymakers to consider more contextual factors to optimize teacher specialization policies, such as reducing ELA-specialized teachers' workload, strengthening relationships between ELA-specialized teachers and students, and providing subject-specific professional development, especially for ELA-specialized teachers in Grades 4 and 5.

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