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Teachers' Spatial Skills Across Disciplines and Education Levels: Exploring Nationally Representative Data

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ABSTRACT

Efforts to improve U.S. students' educational outcomes have often focused on improving their engagement, performance, and retention in science, technology, engineering, and math (STEM) fields. Spatial skills, which enable us to visualize and manipulate objects in real and imagined spaces, are important for student learning in STEM. Additionally, student learning may depend on teachers' skills and attitudes. This study used nationally representative data to examine the spatial skills of high school students who later became precollege teachers. Results showed that secondary STEM teachers had substantially stronger spatial skills than secondary non-STEM teachers and preschool/primary teachers. Compared to the general population, 79% of secondary STEM teachers had above average spatial skills versus 61% of secondary non-STEM teachers and 47% of preschool/primary teachers. The weaker spatial skills of preschool and primary teachers are concerning because spatial skills are key to STEM learning beginning at early ages. These results suggest future research is needed to investigate how teachers' spatial skills influence student learning.

SCIENTIFIC ABSTRACT

Teachers' skills and attitudes in a specific domain can influence students' learning in that domain. Here we focused on spatial skills, which are important for learning in science, technology, engineering, and math (STEM) fields. Fostering students' spatial skills may rely on teachers' comfort in implementing spatially demanding activities in the classroom. This study used nationally representative data from Project TALENT to examine the spatial skills of high school students who later became preschool to high school teachers (n = 4,428 teachers). Results showed that secondary STEM teachers had

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Researchers interested in reproducing or extending this analyses should contact the American Institutes of Research directly to obtain the Project TALENT dataset (see https://www.projecttalent.org/contact/).

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stronger spatial skills than secondary non-STEM teachers (by 0.5 standard deviations) and preschool and primary teachers (by 0.8 standard deviations). These differences remained substantial even after accounting for differences in general intelligence and gender distributions. These results suggest the need for research on how teachers' spatial skills impact students' spatial skills and STEM learning.

Keywords: spatial skills, STEM, teacher education, grade school education, early childhood education
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Efforts to improve U.S. students' educational outcomes have often focused on improving their engagement, performance, and retention in science, technology, engineering, and math (STEM) fields (e.g., Graham, Frederick, Byars-Winston, Hunter, & Handelsman, 2013; Hayden, Ouyang, & Scinski, 2011). An important factor in learning STEM topics is spatial skills, which enable us to manipulate and make sense of spatial relations in real and imagined spaces. Prior studies have shown that spatial skills are important to STEM learning at all educational levels. For instance, spatial skills have predicted math understanding among preschool and primary students (Gunderson, Ramirez, Beilock, & Levine, 2012; Verdine, Golinkoff, Hirsh-Pasek, & Newcombe, 2017). Among secondary students, these skills have been related to performance in science and technology (e.g., Ganley, Vasilyeva, & Dulaney, 2014), as well as mathematics (Stavridou & Kakana, 2008). Spatial skills have also predicted students' pursuit of STEM degrees and occupations later in life. For instance, spatial skills measured in middle school (Shea, Lubinski, & Benbow, 2001) and high school (Wai, Lubinski, & Benbow, 2009) predicted STEM degree attainment and STEM employment more than a decade later. These educational and occupational choices are attributed to many factors such as relative performance in math versus verbal domains (Park, Lubinski, & Benbow, 2007; Riegle-Crumb, King, Grodsky, & Muller, 2012; Wang, Eccles, & Kenny, 2013). However, spatial skills have also predicted STEM degree attainment and employment even after controlling for mathematics and verbal skills (Wai et al., 2009; see Wai & Kell, 2017 for a review). In summary, past studies have found that spatial skills measured from preschool to high school predict later STEM outcomes, suggesting that spatial skills are critical to students' learning at all educational levels.

Students' learning in a specific domain may depend on teachers' skills and affect toward that domain. For instance, in one large longitudinal study, first- and third-grade teachers' pedagogical content knowledge of mathematics predicted students' gains in mathematical achievement (Hill, Rowan, & Ball, 2005; for a review of more recent studies, see Gess-Newsome, 2015). In another study, first- and second-grade girls improved less in mathematics to the extent that their female teachers were anxious about doing mathematics problems (Beilock, Gunderson, Ramirez, & Levine, 2010). Teachers' skills and attitudes may also affect student learning in areas that are not formally taught, including spatial skills. For instance, spatial anxiety (i.e., anxiety about completing spatial tasks such as navigating in an unfamiliar mall) in first and second grade teachers predicted their students' mental rotation skills at the end of the school year, even after controlling for teachers' math anxiety and students' mental rotation skills at the beginning of the school year (Gunderson, Ramirez, Beilock, & Levine, 2013). However, Gunderson et al. (2013) did not measure teachers' spatial skills, leaving open questions about how they relate to anxiety and influence students' spatial skills.

To characterize teachers' spatial skills, this present study analyzed the nationally representative Project TALENT dataset, which sampled nearly 400,000 high school students in 1960 and followed them for over 1 decade (Wise, McLaughlin, & Steel, 1979). We examined spatial skills in three different categories of teachers: preschool and primary teachers, secondary STEM teachers, and secondary non-STEM teachers. We tested for differences between categories (e.g., preschool/primary vs. secondary STEM teachers) and within each category (e.g., secondary English vs. social studies teachers). In contrast, prior studies of teachers' spatial skills have used convenience samples of preservice teachers (e.g., Lord & Holland, 1997; Marchis, 2017) or grouped all teachers into one aggregate category (Wai et al., 2009), leaving open questions about how teachers' spatial skills vary across educational levels and subject areas. We also compared teachers' spatial skills to the population means of (a) all high school students sampled in Project TALENT and (b) college graduates in Project TALENT. Early childhood advocates have recently called for all preschool teachers to have at least a bachelor's degree (Barnett, 2003; National Research Council, 2001), and many public preschool programs are now following this recommendation (C. C. Miller, 2017). College graduates were therefore an important reference population in addition to the general high school population sampled in Project TALENT.

Method

Data Sources

Longitudinal dataset. Project TALENT was a nationally representative longitudinal study of roughly 400,000 participants who were high school students (Grades 9–12) when first sampled in the spring of 1960. During this first wave of data collection, participants completed several survey questionnaires and cognitive tests including measures of spatial, mathematical, and verbal skills (see Wai et al., 2009, e.g., items from the cognitive measures). Follow-up questionnaires were administered 1, 5, and 11 years after participants' expected high school graduation year. For instance, the 11-year follow-up was conducted in 1974 for the 9th grade cohort (i.e., students who were ninth graders when first tested in 1960), 1973 for the 10th grade cohort, 1972 for the 11th grade cohort, and 1971 for the 12th grade. The follow-up questionnaires asked about participants' educational attainment, occupation, personal health, and other topics. Cognitive tests were administered only in the first wave of data collection when participants were high school students, and not in the follow-up waves (see also Wise et al., 1979, for a full description of the measures and questionnaires administered).

We obtained this longitudinal dataset by completing a restricted use data agreement with the American Institutes of Research (AIR). AIR gave us version 0e of the Project TALENT dataset, which had 377,016 participants and 2,102 variables. The file was named "all_master0e_rel.sas7bdat," last modified October 9th, 2013, and sized 1.15 gigabytes. Supplemental appendixes S1 and S2 contain the R and Stata scripts used to process and analyze this data file for our research. However, the data use agreement we signed prohibits sharing this data file with other researchers. Researchers interested in reproducing or extending our analyses should instead contact AIR

Table 1
Sample Size and Percent Male by Teacher Type

Teacher type	n	Percent male (weighted)
Preschool/primary	2,032	15%
Elementary school	1,786	17%
Nursery school or kindergarten	246	.4%
Secondary non-STEM	1,455	52%
Commercial education	142	62%
English	455	45%
Foreign language	149	40%
Home economics	98	0%
Physical education	254	50%
Social studies	357	76%
Secondary STEM	941	80%
Mathematics	344	74%
Science	379	76%
Trade/industrial/vocational education	218	90%

Note. Teachers specializing in art, music, special education, or speech were excluded because Project TALENT's occupational categorization did not distinguish between primary versus secondary teachers for those teacher types. These data were based on the primary occupations that participants reported at the 11-year follow-up.

directly to obtain the Project TALENT dataset (see https://www.projecttalent.org/contact/).

Participants selected for analysis. Our analyses focused on teachers who taught at the preschool to secondary school level at the 11-year follow-up (n = 4,478). From these 4,478 teachers, 50 were excluded from analyses because they had missing data for all four spatial tests (i.e., they had no spatial test data), resulting in a final analytic sample size of n = 4,428. Based on the categorization scheme detailed in Table 1, we grouped these teachers into three categories: preschool/primary (n = 2,032), secondary non-STEM (n = 1,455), and secondary STEM (n = 941). For instance, the secondary STEM category included teachers who taught mathematics (n = 344), science (n = 379), and trade/industrial/vocational education (n = 218); see Table 1 for more information on teacher categorization and sample sizes. Teachers who taught art, music, special education, or speech were excluded from our analyses because Project TALENT's coding of occupations did not distinguish between primary versus secondary teachers for those subjects.

Data Analytic Procedures

Standardized cognitive composite scores. Consistent with Wai et al.'s (2009) analyses, scores on individual cognitive tests were combined to create composite scores for spatial, mathematical, and verbal skills (see Table 2 for description of these individual tests). For instance, the spatial composite was based on four tests measuring three-dimensional (3D) spatial visualization, two-dimensional (2D) spatial visualization, mechanical reasoning, and abstract reasoning skills. Raw scores were summed using weights provided in Wai et al. (2009); estimated reliabilities for these composites were approximately 0.90 (see Humphreys, Lubinski, & Yao, 1993 for psychometric details).

Among the n = 4428 teachers included in analyses, a small percentage (3.6%) had missing data for at least one cognitive test. Multiple imputation was used to impute missing values for the 11 individual cognitive tests before their scores were summed to compute composite scores. The imputation model was an additive regression model based on the full Project TALENT sample of n = 377,016 participants. Five imputed data sets were created using the aregImpute() function in the Hmisc R package (Analytics Vidhya Content Team, 2016; see Appendix S1 for additional details). Each dataset was analyzed separately using the procedures described below, and the results from the five data sets were pooled. All standard errors and significance tests reported in the Results section took into account both the within- and between-imputation variances (White, Royston, & Wood, 2011). Results were similar when using listwise deletion (i.e., exclude participants with any missing data on the cognitive tests), but multiple imputation is widely considered a superior method (White et al., 2011).

To compare teachers to population means, cognitive composite scores were standardized (i.e., converted to z scores) using the full Project TALENT sample. Scores were standardized within each grade level to account for cohort effects (e.g., twelfth graders outperforming ninth graders). For instance, a ninth grader's standardized spatial score was calculated using the overall ninth grade mean and standard deviation for the composite spatial score. We also computed another set of standardized scores using only participants who had completed college by the 11-year follow-up survey. Analyses using scores standardized relative to the college graduate population included only college-educated teachers (n = 3,841) and excluded teachers who had not earned a college degree by the 11-year follow-up (n = 247) or had missing data for their highest level of education (n = 340); see Table 3. These standardized scores therefore compared teachers to two reference populations: (a) all high school students in Project TALENT's first wave of data collection and (b) college graduates. We tested for differences from these population means using two-tailed, one-sample t tests that compared sample means with 0 (i.e., the reference population mean).

Table 2
Descriptions of Tests Used for Cognitive Ability Composites

Composite	Test	Description
Spatial	3D Spatial Visualization	Visualizing 2D figures after they have been folded into 3D figures
	2D Spatial Visualization	Visualizing 2D figures when they were rotated or flipped in a plane
	Mechanical Reasoning	Deducing relationships between gears, pulleys, and springs as well as knowledge of the effects of basic physical forces, such as gravity
	Abstract Reasoning	A nonverbal measure of finding logical relationships in sophisticated figure patterns
Math	Mathematics Information	Knowledge of math definitions and notation
	Arithmetic Reasoning	Reasoning ability needed to solve basic arithmetic items
	Introductory Mathematics	All forms of math knowledge taught through the ninth grade
	Advanced Mathematics	Knowledge in algebra, plane and solid geometry, probability, logic, logarithms, and basic calculus
Verbal	Vocabulary	The general knowledge of words
	English Composite	Capitalization, punctuation, spelling, usage, and effective expression
	Reading Comprehension	The comprehension of written text covering a broad range of topics

Note. See Wai, Lubinski, and Benbow (2009) for details on how individual test scores were combined to compute ability composite scores.

Table 3
Highest Degree Earned by Teacher Type (Sample Sizes)

Highest degree earned	Teacher type: Preschool/primary	Secondary non-STEM	Secondary STEM
No response	170	109	61
High school diploma or lower	150	49	48
Bachelor's degree	1,203	765	476
Graduate or professional degree	509	532	356

Regression analyses. Multiple regression models compared spatial skills across teacher types and controlled for covariates such as mathematical and verbal skills. Teacher type was entered into regression models using two dummy codes that compared secondary STEM and non-STEM teachers with preschool/primary teachers. Postestimation commands were used to compare secondary non-STEM and STEM teachers to each other (see Appendix S2 for the Stata code used to run these regression models and postestimation commands). The shared variance between spatial, mathematical, and verbal skills accounts for general intelligence (Wai et al., 2009). Controlling for mathematical and verbal skills therefore tested whether differences in teachers' spatial skills were driven by differences in general intelligence. Additionally, we controlled for gender because men typically outperform women on several spatial tasks (D. I. Miller & Halpern, 2014), and gender ratios varied widely across teacher types. For instance, women were 85% of preschool/primary teachers but only 20% of secondary STEM teachers (see Table 1). Table 4 displays the correlations between the cognitive composites and gender.

Probability survey weights. To ensure our estimates were nationally representative, inverse probability survey weights were used in all analyses to account for unequal sampling probabilities during the 1960 testing. These weights also helped address potential bias introduced by participants who did not respond to the standard mail-in surveys at the 11-year follow-up (see Wise et al., 1979 for response rates). To estimate characteristics of these initial nonrespondents, Project TALENT researchers assiduously tracked down randomly selected subsamples of them using phone interviews and other methods. Researchers obtained response rates ranging from 60% to 84% for these participants who did not respond to the initial mail-in surveys (Wise et al., 1979, Table 2.3). These special respondents were given higher weights in longitudinal analyses, as explained in Chapter 4 of the Project TALENT Data Bank Handbook (Wise et al., 1979). We used the Follow-up Special Sample Weights (*B*) described in Table 4.1 of that handbook (Wise et al., 1979) and used a linearized variance estimator to compute standard errors using Stata's *svy* commands (Wolter, 2007).

Table 4
Correlation Matrix for Cognitive Composites and Gender

Variable	Spatial	Math	Verbal	Male
Spatial	—			
Math	.55	—		
Verbal	.50	.71	—	
Male	.25	.11	−.13	—

Note. These correlations were based on the full sample of teachers' scores ($n = 4{,}428$) standardized relative to the general high school population. All correlations had $ps < .0001$.

Results

Comparing to Population Means

Figure 1a shows teachers' weighted mean cognitive composite scores standardized relative to the general high school population in Project TALENT. Among the three teacher types, secondary STEM teachers had the highest mean spatial skills ($M = 0.73$), which were significantly higher than the general population mean, based on a one-sample *t* test comparing the standardized mean with 0 ($p < .001$). Secondary non-STEM teachers ($M = 0.28$) also had higher spatial skills than the population mean ($p < .001$). Preschool/primary teachers had the lowest spatial skills ($M = -0.04$), which did not significantly differ from the population mean ($p = .54$). Figure 2 shows the distributions of teachers' spatial composite scores. Compared to the general population, 79% of secondary STEM teachers had above average spatial skills versus 61% of secondary non-STEM teachers and 47% of preschool/primary teachers (see Figure 2a).

As another descriptive comparison, we also compared college-educated teachers to the population mean of college graduates. Using college graduates as a reference population made teachers appear worse in comparison because the college graduate population performed better than the general high school population (e.g., by 0.5 SDs on the spatial composite). Figure 1b shows this effect by graphing college-educated teachers' performance standardized relative to college graduates. For instance, both college-educated preschool/primary ($M = -0.55$) and secondary non-STEM teachers ($M = -0.32$) had lower spatial skills than the college graduate population mean ($ps <$ .001). However, college-educated secondary STEM teachers had higher spatial skills than the college graduate population mean ($M =$ 0.25; $p = .036$). Compared to the college graduate population, 60% of secondary STEM teachers had above average spatial skills versus 40% of secondary non-STEM teachers and 30% of preschool/primary teachers (see Figure 2b). Secondary STEM teachers therefore had above average spatial skills, regardless of the reference population. In contrast, secondary non-STEM teachers were above average and preschool/primary teachers were average only when compared to the general population; these other two teacher types were below average compared to college graduates.

Comparing Figure 1a and Figure 1b shows that choice of the reference population made a large difference on interpreting whether teachers had above or below average spatial skills. However, choice of the reference population had little impact on interpreting the relative performance of the three teacher types compared to each other. For instance, secondary STEM teachers performed better than preschool/primary teachers by roughly 0.8 SDs, regardless of the reference population. The next set of analyses used multiple regression to more formally test for differences across teacher types and control for differences in general intelligence and gender ratios.

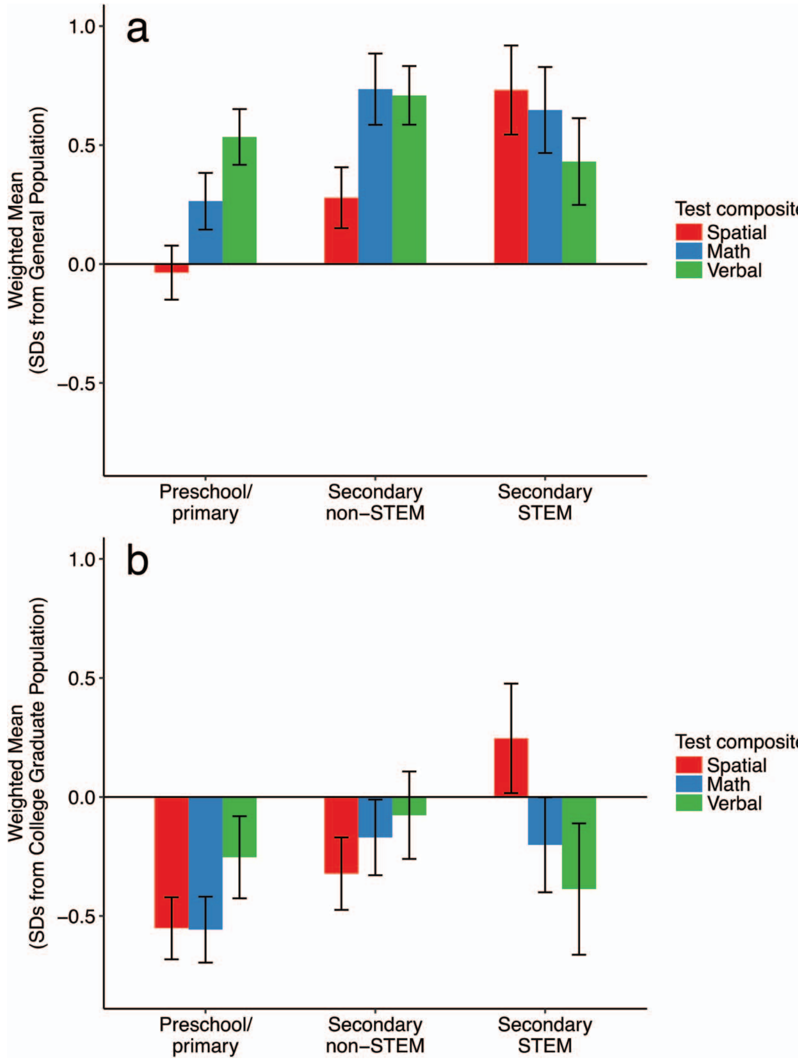

Figure 1. Weighted mean cognitive performance by teacher type. The top panel includes data from all teachers ($n = 4{,}428$) and the bottom panel includes data from only teachers who reported having completed a college degree ($n = 3{,}841$). Error bars denote 95% confidence intervals.

Comparing Across Teacher Types

Table 5 shows results from regression models predicting all teachers' scores standardized relative to the general high school population (see left side of the table) and college-educated teachers' scores standardized relative to the college graduate population (see right side of the table). Results were highly consistent across these two types of regression models. We therefore focus here on describing results for the full sample of teachers' scores standardized relative to the general high school population (but see Table 5 for complete results).

For the full sample of teachers, regression analyses confirmed that all pairwise comparisons between the three teacher types were statistically significant on the spatial composite ($ps < .001$; see Model 1 in Table 5). The difference between preschool/primary versus secondary STEM teachers was particularly large ($b = 0.77$) and remained after controlling for the mathematics composite, verbal composite, and gender ($ps < .001$; see Models 2 and 3). The difference between secondary non-STEM versus STEM teachers ($b = 0.45$) also remained after controlling for these other covariates ($ps < .001$). However, the difference between preschool/primary versus secondary non-STEM teachers ($b = 0.31$) was nonsignificant after controlling for these covariates ($ps > .10$). Secondary STEM teachers therefore had the highest spatial skills compared to the other two teacher types, even after controlling for general intelligence and gender. Preschool and primary teachers had the lowest spatial skills, but they did not significantly differ from secondary non-STEM teachers after controlling for general intelligence and gender.

Categorizing teachers into three groups may mask important differences within those groups (e.g., math vs. science teachers). We therefore conducted omnibus tests for differences within each teacher group. Spatial skills did not significantly vary within the preschool/primary teacher group, $F(1, 2031) = 1.28$, $p = .26$, or the secondary STEM teacher group, $F(2, 939) = 0.91$, $p = .40$, but did vary within the secondary non-STEM teacher group, $F(5, 1450) = 2.89$, $p = .013$. However, among secondary non-STEM teachers, no pairwise difference between any two teacher types (e.g., English vs. social studies teachers) was significant when using Bonferroni corrections for multiple comparisons (but see Table 6 for the disaggregated means). More focused studies are therefore needed to more precisely estimate differences within these aggregate teacher categories.

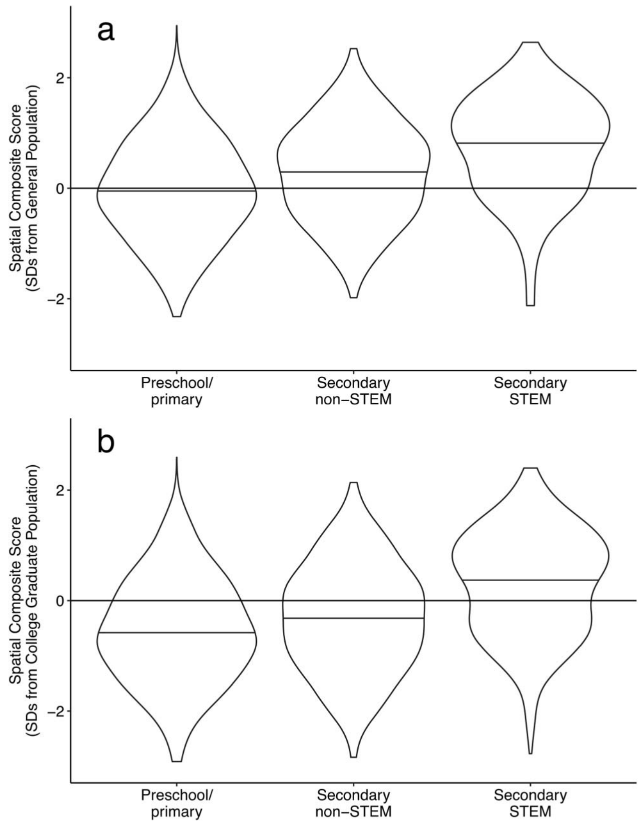

Figure 2. Distributions of composite spatial performance by teacher type. The top panel includes data from all teachers (n = 4,428) and the bottom panel includes data from only teachers who reported having completed a college degree (n = 3,841). The solid black lines within each distribution indicate median values.

Table 6
Spatial Composite Scores by Field for Secondary Non-STEM Teachers

Teacher field	n	M	SE
Commercial education	142	−.19	.22
English	455	.47	.10
Foreign language	149	.63	.25
Home economics	98	.21	.30
Physical education	254	.28	.12
Social studies	357	.03	.13

Note. Means were based on teachers' scores standardized relative to the general high school population in Project TALENT. This table displays disaggregated means for the secondary non-STEM teachers because spatial skills significantly varied by field within this teacher group (p = .013), but not within the preschool/primary or secondary STEM teacher groups (ps > .25).

Discussion

Teachers play an important role in shaping students' educational outcomes and experiences (e.g., Ball, Hill, & Bass, 2005; Baumert et al., 2010; Baylor & Ritchie, 2002). Using nationally representative data, this study investigated teachers' spatial skills because spatial skills are critical to learning in STEM fields. Results showed that secondary STEM teachers had stronger spatial skills than the general population, college graduate population, and other teachers. The difference between secondary STEM teachers and preschool and primary teachers was particularly large (0.8 standard deviations). Preschool and primary teachers' spatial skills were average compared to the general population, but below average by almost 0.6 standard deviations compared to the college graduate population. Secondary non-STEM teachers had stronger spatial skills than the general population but weaker spatial skills than the college graduate population.

Secondary STEM teachers had substantially higher spatial skills than other teachers even after controlling for general intelligence and gender; these other factors therefore cannot alone account for STEM teachers' especially high spatial skills. These results align with other studies showing the unique role of spatial skills in predicting students' decisions to later pursue STEM education and employment (see Wai & Kell, 2017 for a review). For instance, another way to view our results is that spatial skills measured in high school predicted later STEM employment among precollege teachers, even after controlling for general intelligence. In other words, individuals with teaching interests and strong spatial skills may be more attracted to teaching STEM subjects than other subjects.

Preschool and primary teachers, in contrast, may have chosen their profession based on other motivations such as a desire to interact with and care for young children (Croft, Schmader, & Block, 2015). Nevertheless, preschool and primary teachers are often required to

Table 5
Unstandardized Coefficients in Regression Models Predicting Teachers' Spatial Skills

	All teachers			College graduates only		
Predictor	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Secondary non-STEM vs. preschool/primary	.31***	.12	−.002	.23*	.07	−.07
Secondary STEM vs. preschool/primary	.77***	.69***	.49***	.80***	.72***	.50***
Secondary STEM vs. secondary non-STEM	.45***	.57***	.49***	.57***	.66***	.57***
Math		.29***	.26***		.30***	.27***
Verbal		.33***	.39***		.25***	.30***
Male			.34***			.37***
R^2	.10	.40	.43	.09	.37	.39

Note. The left side displays results for all teachers' spatial skills (n = 4428) standardized relative to the general high school population, and the right side displays results for college-educated teachers' spatial skills (n = 3841) standardized relative to the college graduate population. The reference group for dummy coding was preschool and primary teachers. The comparison between secondary non-STEM versus STEM teachers was based on postestimation commands.
* $p < .05$. *** $p < .001$.

teach STEM topics and may do so reluctantly (e.g., National Research Council, 2012; Tu, 2006). In our analyses, these teachers had substantially weaker spatial skills than secondary STEM teachers, despite having somewhat (though nonsignificantly) higher verbal skills (see Figure 1). Future research should investigate the motivational and cognitive factors that may account for these large differences in teachers' spatial skills. Such research would be important because spatial skills are fundamental for students' STEM learning even at these early educational levels (e.g., Battista & Clements, 1996; Guay & McDaniel, 1977; Gunderson et al., 2012).

These results collectively highlight the need for research on how teachers' spatial skills influence teachers' practice and students' learning. Students develop spatial skills in part through environmental factors such as spatially demanding activities in the classroom and everyday life (see Uttal et al., 2013, for a meta-analysis). However, students may have fewer learning opportunities if their teachers are reluctant about including spatial activities in the curriculum or are ineffective at teaching such activities. Consistent with this hypothesis, Otumfuor and Carr (2017) found that middle school teachers' spatial skills were related to their use of representational gestures and pedagogical content knowledge during geometry instruction, a spatially demanding STEM subject. Furthermore, one prior longitudinal study found that first- and second-grade children improved less in their mental rotation skills if their teachers had higher spatial anxiety (Gunderson et al., 2013), although this study's claims are limited by its nonexperimental design.

Research centered on teachers' skills and attitudes could identify ways to help teachers overcome obstacles in implementing spatial activities in the classroom. For instance, one longitudinal study found that primary school teachers' spatial anxiety decreased after teachers attended a professional development workshop focused on approaches for teaching spatial skills (Ping et al., 2011). In this workshop, teachers learned about laboratory research on spatial development and collaborated with researchers to design spatial classroom activities appropriate for primary schoolchildren. Teachers' spatial anxiety, but not reading or mathematics anxiety, decreased one year after attending this workshop. Future experimental research should investigate whether such workshops and other related interventions (e.g., Sorby, 2009) could improve teachers' spatial skills and, by extension, also improve students' spatial skills and STEM learning.

Limitations

Because our study represents data from the 1960s and 1970s, our findings might not generalize to current teachers. Although some teachers in Project TALENT may still be teaching in classrooms today, changes in contextual factors such as teacher education requirements may have caused teachers' cognitive profiles to change over time. Another limitation in our research was that spatial skills were only measured when participants were high school students. This longitudinal design allowed us to investigate if spatial skills predicted later occupational choices. However, further education or other experiences might have caused the cognitive profiles of these individuals to change from high school to the time of their employment as teachers. To address these limitations, future research should directly assess the spatial skills of practicing teachers who more recently completed their teaching certifications.

Implications

Our findings highlight the need to examine how teachers' spatial skills influence the development of students' spatial skills. Although required to teach STEM content (National Research Council, 2012; Tu, 2006), preschool and primary teachers have relatively weak spatial skills compared to college graduates and other teachers. Teachers with weaker spatial skills may be more reluctant or find it more challenging to implement spatial tasks in their classrooms, depriving their students of valuable learning opportunities (Otumfuor & Carr, 2017). This possibility would be problematic because spatial skills are teachable (Uttal et al., 2013) and are crucial to learning and future success in STEM disciplines (e.g., Casey, Nuttal, Pezariz, & Benbow, 1995; Shea et al., 2001). If teachers' spatial skills affect students' learning, investigating how to improve teachers' skills may provide novel ways to boost students' performance in STEM disciplines.

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