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Does Spatial Ability Matter More for Low-Achieving Students in Geometry? A Cognitive Load Theory Analysis

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Abstract

Spatial ability is widely regarded as a key cognitive resource for geometric reasoning; however, whether its association with geometry achievement varies across students with different achievement levels remains unclear. Grounded in Cognitive Load Theory, this study examined whether the relationship between spatial ability and geometry achievement is stronger among low-achieving university students than among high-achieving students, considering the potential compensatory role of spatial ability when schema-based knowledge is limited. A correlational design was employed involving 125 university students who completed a 30-item spatial ability test based on the Purdue Spatial Visualization Test format ($\alpha = .97$) and a 5-item geometry achievement test ($\alpha = .94$). Students were classified into low-achieving ($n = 65$) and high-achieving ($n = 60$) groups using a median split. Pearson correlation analysis revealed strong and significant associations in both groups (low-achieving: $r = .76$, $p < .001$; high-achieving: $r = .73$, $p < .001$). However, Fisher's r-to-z comparison indicated no significant difference between the correlations ($z = 0.37$, $p = .71$). Spearman rank correlations further confirmed this pattern (low-achieving: $\rho = .86$; high-achieving: $\rho = .85$; both $p < .001$). These findings indicate that spatial ability is strongly associated with geometry achievement regardless of students' achievement levels. However, it does not appear to serve as a differentially compensatory resource for low-achieving students. The findings highlight the importance of spatial ability in geometry learning across achievement groups and provide implications for instructional design and future research.

1. INTRODUCTION

1.1. Background and Research Gap

Geometry occupies a central place in mathematics education at the higher education level, serving not only as a foundation for advanced mathematical reasoning but also as a critical skill in fields such as engineering, architecture, and computer science. Despite its importance, geometry remains one of the most challenging domains for students, largely because it requires the simultaneous processing of visual, spatial, and logical information, and because designing learning environments that support the development of geometric and spatial understanding remains a persistent challenge for instructors [1].

A substantial body of research has established that spatial ability broadly defined as the capacity to generate, retain, retrieve, and transform visual images plays a critical role in geometric reasoning, with heuristic reviews of the spatial factor literature consistently linking stronger spatial ability to better outcomes across STEM domains [2]. Students with higher spatial ability tend to construct mental representations of geometric figures more efficiently, allowing them to manipulate shapes, infer relationships, and solve problems with less cognitive effort; longitudinal evidence further suggests that these spatial capacities are

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shaped over time by cumulative spatial experience rather than being fixed traits [3], and comparable benefits of well-developed spatial skills for content-specific reasoning have been documented in adjacent STEM domains such as chemistry education [4] and molecular geometry learning supported by three-dimensional virtual representations [5]. However, most existing studies have examined this relationship at the aggregate level, treating student populations as relatively homogeneous, without considering whether the strength of this relationship varies across achievement levels. More broadly, spatial reasoning has been characterized as a foundational cognitive capacity that shapes learning trajectories from early childhood through adulthood, with implications extending well beyond mathematics into science and engineering education [6], and design-based studies of STEAM learning environments similarly show that spatial reasoning is distributed across tools, gestures, and representations during hands-on problem solving [7].

This gap is particularly important when viewed through the lens of Cognitive Load Theory (CLT). CLT posits that working memory has limited capacity, and that learning is optimized when instructional design minimizes extraneous cognitive load while supporting germane load, that is, the load associated with schema construction [8,9]. For low-achieving students, who often possess less-developed prior knowledge and schemas in geometry, the demands of processing spatial information may impose a disproportionately higher cognitive load compared to their high-achieving peers. This raises the possibility that spatial ability functions as a more critical and perhaps compensatory resource for low-achieving students, helping to offset the burden imposed by limited prior knowledge. Consistent with this concern, evidence from introductory physics courses shows that instructional demands from which high-aptitude students benefit can yield no benefit or even negative outcomes—for low-aptitude students, a pattern attributed to excessive cognitive load [10].

Understanding whether spatial ability matters more for low-achieving students has direct implications for instructional design in higher education. If the relationship between spatial ability and geometric performance is indeed stronger among low-achieving students, this would suggest that interventions aimed at strengthening spatial ability could serve as a targeted strategy for reducing achievement gaps in geometry courses, rather than a generic strategy applied uniformly across all students.

Despite the theoretical plausibility of this proposition, empirical evidence directly comparing the strength of the spatial ability–geometry achievement relationship across achievement groups remains limited, particularly within higher education contexts. Most prior studies have focused on school-age populations, leaving a gap in understanding how this relationship manifests among university students, who are expected to engage with more abstract and formalized geometric reasoning.

1.2. Spatial Ability and the Cognitive Demands of Geometry

Spatial ability refers to the cognitive capacity involved in representing, generating, and recalling symbolic, non-linguistic information [11]. Although researchers have proposed various classification schemes, the most widely cited framework distinguishes three components: spatial perception, mental rotation, and spatial visualization [11]. Spatial perception involves determining spatial relationships relative to one's own body orientation despite distracting or misleading cues; mental rotation refers to the rapid and accurate mental rotation of two- or three-dimensional objects; and spatial visualization involves the complex, multi-step processing of spatial information, such as mentally folding or transforming a figure. Some scholars treat mental rotation as a specific sub-process within spatial visualization rather than a fully separate factor, reflecting ongoing debate about the precise boundaries between these components; a comprehensive synthesis of the spatial factor literature similarly notes that the criteria used to classify a skill as "spatial" continue to vary across studies, complicating direct comparisons between instruments [2]. Within the broader Cattell-Horn-Carroll model of intelligence, spatial ability is classified as a distinct broad ability, closely related to but not fully reducible to general intelligence. Longitudinal research also suggests that spatial ability is not purely innate: childhood engagement in spatial activities has been shown to significantly predict spatial performance in adulthood, indicating a developmental and experiential component to this ability [3]. This developmental view is consistent with broader accounts describing spatial intelligence as a capacity that matters across the lifespan rather than being confined to a narrow developmental window [6].

The Purdue Spatial Visualization Test (PSVT), and its revised version PSVT:R, is among the most widely used instruments for measuring spatial visualization, particularly in STEM education research. It has been employed extensively to examine the association between spatial ability and performance in engineering, technology, and mathematics-related domains, with psychometric evaluations supporting its reliability and validity for use with undergraduate populations [12,13]. The rotations-only revised version used in the present study, the Revised PSVT:R, was developed and psychometrically validated by Yoon [16], and has

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since been applied to examine associations between spatial ability and outcomes in domains such as introductory atmospheric science coursework [14] and undergraduate STEM major selection [15].

Geometry learning is widely regarded as one of the more cognitively demanding areas of mathematics because it requires learners to simultaneously coordinate visual, spatial, and logical-deductive processing. Students frequently struggle with visualizing three-dimensional figures, interpreting diagrams accurately, and connecting geometric representations to abstract principles rather than relying on surface appearance. These difficulties are often compounded by inadequate prior knowledge and an incomplete grasp of foundational geometric concepts. Designing instructional environments that adequately support the development of geometric and spatial understanding therefore remains an ongoing challenge, one that requires attention to how learners construct meaning from geometric tools and representations rather than simply transmitting formal content [1]. Because geometric reasoning depends heavily on constructing and manipulating mental representations, learners with weaker spatial processing capacities are particularly susceptible to comprehension breakdowns during problem solving. Empirical evidence with school-aged children supports this link: pupils with stronger visuo-spatial mental imagery tend to display better geometry skills, whereas weaker imagery is associated with poorer geometric performance [17]. Experimental work using an intelligent tutoring system found that split-attention effects—arising when learners must mentally integrate separate diagrammatic and textual sources of geometric information—can meaningfully impair learning outcomes in naturalistic geometry instruction [18], and neurocognitive evidence indicates that translating between graphical and symbolic representations recruits identifiable patterns of brain activity even among mathematically gifted adolescents, underscoring the cognitive demands such translation imposes regardless of overall ability level.

1.3. Cognitive Load Theory and Low-Achieving Students

Cognitive Load Theory (CLT), originally developed by Sweller [22], describes how the limited capacity of working memory constrains learning and problem solving. CLT distinguishes three types of cognitive load. Intrinsic load reflects the inherent complexity of the material being learned and is shaped by both the number of interacting elements and the learner's existing level of expertise; the same content can impose a high intrinsic load on a novice while imposing very little load on an expert. Extraneous load arises from the way information or instructional tasks are presented, and is considered the primary target for instructional design because it consumes working memory resources without contributing to learning. Germane load refers to the working memory resources devoted to constructing and automating schemas in long-term memory; under more recent formulations, germane load is understood not as an independent source of load but as the resources available to manage element interactivity associated with intrinsic load once extraneous load has been minimized [19]. More recent syntheses of CLT continue to reaffirm this basic architecture while extending its application to a wider range of instructional technologies [8], and validated self-report instruments have since been developed to measure intrinsic, extraneous, and germane load separately in empirical studies [9]. Foundational accounts of cognitive architecture further emphasize that instructional procedures succeed or fail depending on how well they align with the way human cognitive structures process and store information [20], a principle that has since been distilled into practical guidance for classroom application of CLT [21].

Within this framework, geometric problem solving can be understood as placing high intrinsic and extraneous demands on working memory, particularly for learners who lack automatized schemas for interpreting spatial information. Direct empirical work applying CLT to geometry instruction supports this view, showing that learners without sufficient prior knowledge benefit from worked-example formats specifically because such formats reduce the extraneous load associated with unguided problem solving on geometric theorems [23]. When learners possess strong spatial processing capacities, part of the burden of forming and manipulating mental representations may be handled more efficiently, effectively freeing working memory resources that would otherwise be consumed by the visuospatial demands of the task. This aligns with broader experimental evidence that deliberately reducing intrinsic cognitive load for instance, by adjusting the ratio of worked solution steps to independent problem-solving opportunities improves learning outcomes in mathematical domains more generally [24,25].

Research comparing high- and low-achieving students in geometric problem solving indicates that the two groups differ not merely in accuracy but in the quality of the schemas they bring to a task. Studies have shown that high-achieving students access a greater number of problem-relevant schemas than low-achieving students, even when both groups perceive similar numbers of geometric elements within a diagram [26]. This suggests that high achievers possess more qualitatively organized prior knowledge, which allows them to construct problem representations more effectively [26].

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A related line of research on schema-based learning suggests that low-aptitude or low-achieving learners typically possess fewer usable schemas from prior instruction, and that a meaningful portion of what schemas they do have may be incomplete or incorrect. As a consequence, these learners are more prone to cognitive overload when working memory demands increase, since they cannot rely on automatized long-term memory structures to offset the load of new information [10]. In contrast, learners with well-developed schemas can supplement limited working memory capacity by retrieving organized knowledge from long-term memory, reducing the effective intrinsic load of a task. This dynamic implies that any additional cognitive resource capable of reducing visuospatial processing demands—such as spatial ability—may hold disproportionate value for learners who lack compensatory schema-based support. Instructional research grounded in this logic has repeatedly shown that worked examples and goal-free problems reduce extraneous load and support schema acquisition across a range of mathematics topics, including trigonometry [27], tangent lines and circles [28], central and inscribed angles [29], and algebraic problem solving [30,31], with collaborative formats offering additional benefits for schema construction [32] and structured task design shown to support even young or anxious learners' mathematical engagement [33,34]. Reviews of this literature conclude that optimizing instructional efficiency through CLT-informed design is central to effective mathematical problem-solving instruction [35].

1.4. Spatial Ability as a Potential Compensatory Resource

A number of studies applying CLT have reported differential effects of instructional design depending on learners' spatial ability. Classic findings from multimedia learning research indicate that certain instructional formats benefit high spatial ability learners considerably more than low spatial ability learners, or conversely that certain design features that create excess extraneous load are more detrimental for those with lower spatial ability; eye-tracking evidence likewise indicates that the effectiveness of instructional formats depends on individual differences such as prior knowledge, working memory capacity, and spatial ability [36]. More recent studies in technology-enhanced environments similarly show that the cognitive load learners experience—and the benefit they derive from visualization-based instruction—varies with their spatial ability and the medium used, whether augmented reality [37] or immersive virtual environments [38]. This body of work implies that spatial ability does not exert a uniform influence across all learners; rather, its role appears to interact with the cognitive demands imposed by the learning task and by the learner's own knowledge base.

Extending this reasoning to achievement grouping, it is plausible that spatial ability functions as a more critical resource specifically for low-achieving students. Because these students are less able to offset visuospatial processing demands through well-organized prior knowledge, their performance in geometry may depend more heavily on their raw capacity to mentally generate, retain, and transform spatial representations. High-achieving students, by contrast, may be able to rely on established schemas to interpret geometric problems even when their spatial ability is comparatively modest, thereby weakening the observed association between spatial ability and performance within this group. This pattern is broadly consistent with findings that instruction explicitly designed around CLT principles produces measurable gains in student achievement in other mathematics domains such as algebra, where reducing unnecessary cognitive load allowed lower-performing learners to benefit disproportionately [39]. More directly, recent work on mathematics teaching innovations has argued that structured spatial ability training can lower the cognitive load associated with managing abstract geometric content, a mechanism that would be expected to matter most for students who otherwise struggle to process such content [40]. Consistent with this broader pattern, spatial visualization training delivered through virtual reality has been shown to transfer to related visuospatial tasks [41], three-dimensional geospatial technology has been linked to gains in spatial thinking alongside changes in learners' cognitive load [42], and computer-aided 3D modeling activities have improved spatial abilities among pre-service teachers [43], lending plausibility to the proposition that spatial-ability-oriented interventions could function as a compensatory resource in geometry learning specifically.

1.5. Present Study and Hypothesis

The present study addresses this gap by examining the correlation between spatial ability measured using a test based on the Purdue Spatial Visualization Test (Revised PSVT:R) [16] and geometry achievement among university students, and by comparing the strength of this correlation between low-achieving and high-achieving groups, categorized based on geometry examination scores. Grounded in Cognitive Load Theory, this study aims to answer the following research question: Does spatial ability show a stronger association with geometry achievement among low-achieving students compared to high-achieving students?

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This study contributes to the literature in two ways. First, it provides empirical evidence on the differential role of spatial ability across achievement levels, extending prior research that has largely treated this relationship as uniform. Second, it offers practical implications for designing differentiated instructional strategies that account for the varying cognitive demands experienced by students with different achievement profiles.

Drawing on the reviewed literature, this study proposes that the relationship between spatial ability and geometry achievement is moderated by achievement level, such that the correlation is stronger among low-achieving students than among high-achieving students. This proposition is grounded in the principle that spatial ability serves a compensatory function under conditions of high cognitive load, a function that becomes more consequential when learners lack the schema-based resources that would otherwise offset that load.

Based on this reasoning, the following hypothesis is proposed:

H1: The correlation between spatial ability (as measured by the Revised PSVT:R) and geometry achievement is significantly stronger among low-achieving university students than among high-achieving university students.

Conceptual framework: Achievement level (high vs. low achievers) moderates the relationship between Spatial ability (30-item test) and Geometry achievement (exam scores); Cognitive Load Theory (intrinsic, extraneous, germane load) provides the theoretical mechanism underlying this relationship.

2. RESEARCH METHOD

2.1. Research Design and Participants

This study employed a correlational, cross-sectional design. The primary variables of interest were spatial ability and geometry achievement, with achievement level (low vs. high) serving as a grouping variable used to test whether the strength of the correlation between spatial ability and geometry achievement differs across achievement groups.

This study was conducted at Universitas Negeri Makassar. The population comprised undergraduate students in the Department of Mathematics, and the sample consisted of 125 students from the Mathematics Education study program within that department, selected as they had all completed foundational geometry coursework relevant to the study's measures. Data were collected as part of a single testing session in which participants completed both the spatial ability test and the geometry achievement test.

2.2. Instruments

Spatial ability was measured using the Revised Purdue Spatial Visualization Test: Visualization of Rotations (Revised PSVT:R) [16], a 30-item instrument assessing mental rotation of three-dimensional figures. Consistent with copyright and ethical considerations regarding proprietary psychometric instruments, individual test items are not reproduced in this manuscript; researchers seeking to use the instrument should contact the original developer [16] or consult the original Purdue Spatial Visualization Test on which the revised rotations-only version is based [44]. Each item was scored dichotomously (1 = correct, 0 = incorrect), yielding a total score ranging from 0 to 30. The psychometric properties of the Revised PSVT:R, including its reliability and factor structure, have been documented extensively in the original validation study [16] and in subsequent psychometric evaluations [13,45]. Internal consistency in the present sample was excellent (Cronbach's $\alpha = .97$).

Geometry achievement was measured using a 5-item test, with each item scored on a 0–20 scale, yielding a total score ranging from 0 to 100. Internal consistency in the present sample was excellent (Cronbach's $\alpha = .94$).

2.3. Procedure, Grouping, and Data Analysis

Both instruments were administered to the same sample of 125 students. Student identifiers were used to match spatial ability scores with geometry achievement scores across the two datasets.

Students were classified into low-achieving and high-achieving groups using a median split on the total geometry achievement score (median = 50). Students scoring at or below the median were classified as low-achieving (n = 65), and students scoring above the median were classified as high-achieving (n = 60).

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Descriptive statistics (mean, standard deviation, minimum, maximum) were computed for spatial ability and geometry achievement scores, both overall and within each achievement group. Normality of both variables was assessed using the Shapiro-Wilk test. Pearson product-moment correlations between spatial ability and geometry achievement were computed separately for the low-achieving and high-achieving groups to test the central hypothesis (H1). Spearman rank correlations were also computed as a robustness check. The strength of the two group-specific correlations was formally compared using Fisher's r-to-z transformation test, which evaluates whether two independent correlation coefficients differ significantly from one another. All analyses were conducted using a significance threshold of $\alpha = .05$.

3. RESULTS AND DISCUSSION

3.1. Descriptive Statistics

Table 1 presents descriptive statistics for spatial ability and geometry achievement, overall and by achievement group. Geometry achievement scores were normally distributed in the overall sample (Shapiro-Wilk, $p = .895$), supporting the use of parametric correlation analysis for this variable. Spatial ability scores, however, departed from normality (Shapiro-Wilk, $p < .001$), reflecting a bimodal distribution in which a substantial number of students scored at or near the floor (0) or ceiling (30) of the test; Spearman rank correlations are therefore reported alongside Pearson correlations as a robustness check.

Table 1. Descriptive statistics for spatial ability and geometry achievement

Variable	Group	n	Mean	SD	Min	Max
Spatial ability (PSVT, 0–30)	Overall	125	14.63	10.79	0	30
Spatial ability (PSVT, 0–30)	Low-achieving	65	5.78	5.33	0	20
Spatial ability (PSVT, 0–30)	High-achieving	60	24.22	5.85	6	30
Geometry achievement (0–100)	Overall	125	49.46	15.38	9	87
Geometry achievement (0–100)	Low-achieving	65	37.62	9.45	9	50
Geometry achievement (0–100)	High-achieving	60	62.30	8.82	51	87

As shown in Table 1, spatial ability scores in the overall sample averaged 14.63 (SD = 10.79) out of a possible 30, while geometry achievement scores averaged 49.46 (SD = 15.38) out of a possible 100. When broken down by achievement group, the two groups differ substantially on both measures: the low-achieving group scored far lower on spatial ability (M = 5.78, SD = 5.33) than the high-achieving group (M = 24.22, SD = 5.85), and the two groups show almost no overlap in their score ranges (0–20 versus 6–30). This pattern, visible directly in the raw descriptive statistics, foreshadows the strong association between the two variables reported in Section 3.2. Students were classified into achievement groups using a median split on geometry achievement scores (median = 50), yielding 65 students in the low-achieving group and 60 students in the high-achieving group. Notably, mean spatial ability scores differed substantially between the two achievement groups (5.78 vs. 24.22), consistent with a strong overall association between spatial ability and geometry achievement in this sample (r = .92).

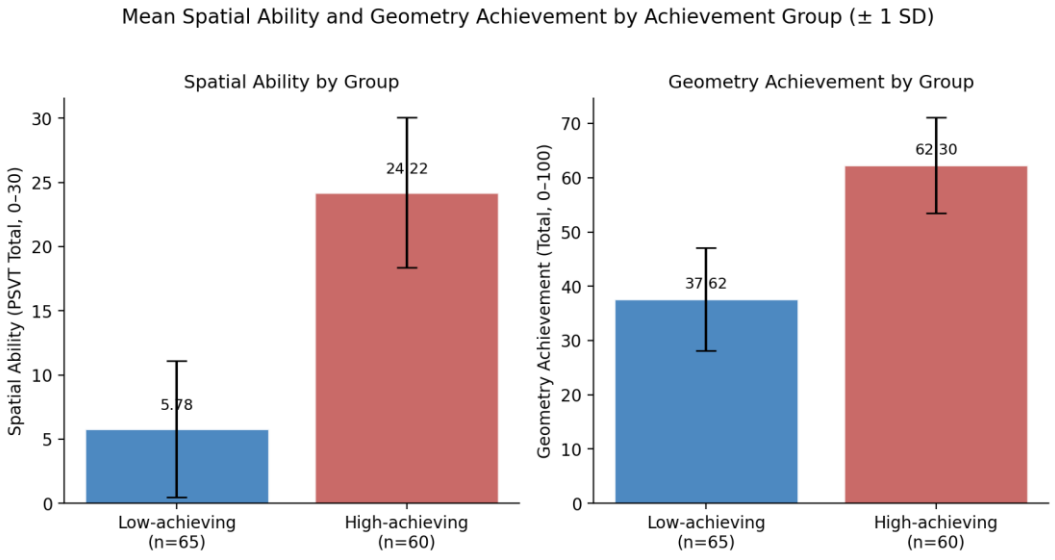


Figure 1. Mean spatial ability and geometry achievement scores by achievement group, with error bars representing ±1 SD.

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Figure 1 illustrates this same group difference graphically. The bar chart shows that mean spatial ability scores are more than four times higher in the high-achieving group than in the low-achieving group, and geometry achievement scores follow a parallel pattern, with the high-achieving group scoring roughly 25 points higher on average. The relatively narrow error bars (representing ±1 SD) around each bar indicate that scores were fairly consistent within each group, particularly for geometry achievement, further supporting the impression of a strong overall relationship between the two variables across the sample.

3.2. Correlation Analysis and Test of the Central Hypothesis (H1)

Contrary to the study's original expectation, the Pearson correlation between spatial ability and geometry achievement was large and highly significant in both achievement groups. Among low-achieving students, the correlation was $r = .76$ ($p < .001$, 95% CI [.64, .85], $r^2 = .58$), and among high-achieving students, the correlation was $r = .73$ ($p < .001$, 95% CI [.59, .83], $r^2 = .54$). The overall sample correlation, collapsing across achievement groups, was $r = .92$ ($p < .001$). Spearman rank correlations produced consistent results (low-achieving: $\rho = .86$, $p < .001$; high-achieving: $\rho = .85$, $p < .001$), confirming that the strong association was not an artifact of the linear correlation method or of the non-normal distribution of spatial ability scores. Item-level analysis, correlating spatial ability with each of the five geometry items individually, showed a consistent pattern of strong, significant associations (r ranging from .81 to .84, all $p < .001$), indicating that the relationship was not driven by any single item.

To formally test whether the spatial ability–geometry achievement correlation differed in strength between the two achievement groups, a Fisher's r-to-z comparison of independent correlations was conducted. The difference between the low-achieving group's correlation ($r = .76$) and the high-achieving group's correlation ($r = .73$) was not statistically significant, $z = 0.37$, $p = .71$.

H1 was not supported. Although spatial ability was strongly and significantly associated with geometry achievement in this sample, the data do not provide evidence that this association is stronger among low-achieving students than among high-achieving students; instead, spatial ability appears to be an equally strong correlate of performance across achievement levels.

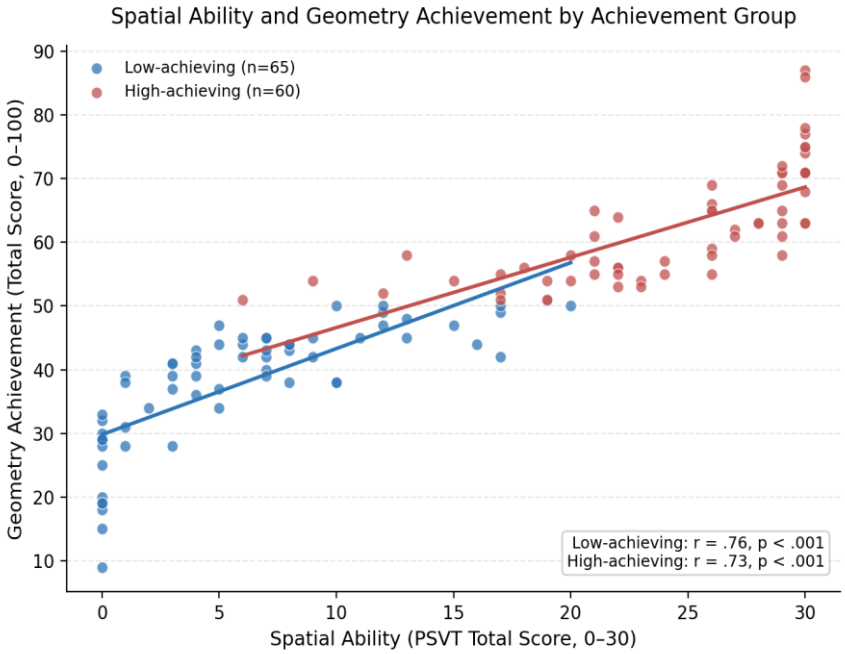


Figure 2. Scatter plot of spatial ability and geometry achievement by achievement group, with group-specific regression lines (both showing a steep positive slope, consistent with the strong correlations reported above).

Figure 2 displays the individual-level data underlying this relationship. Each point represents one student's spatial ability and geometry achievement score, with points colored according to achievement group. Both regression lines rise steeply from left to right, indicating that within each group, students with higher spatial ability tend to also have higher geometry achievement scores. Critically, the two lines have visually similar slopes and are positioned at comparable heights relative to their respective clusters of points, suggesting that the strength of the relationship does not differ markedly between the low-achieving and high-achieving groups—consistent with the formal statistical test reported in Section 3.2.

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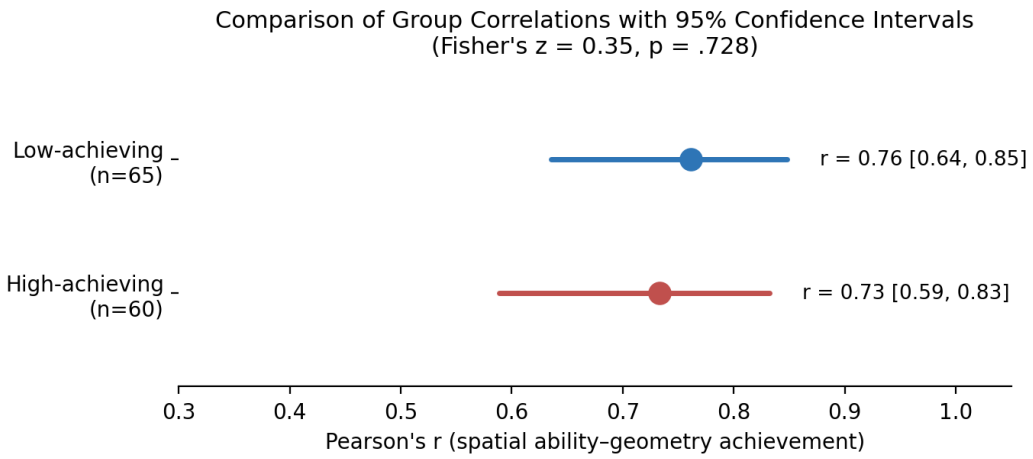


Figure 3. Comparison of Pearson correlations between spatial ability and geometry achievement for the low-achieving and high-achieving groups, with 95% confidence intervals. The overlapping intervals correspond to the non-significant Fisher's r-to-z comparison (z = 0.37, p = .71).

Figure 3 summarizes the key statistical comparison underlying the test of H1. The two horizontal lines represent the 95% confidence intervals around the correlation coefficients for the low-achieving group (r = .76) and the high-achieving group (r = .73), with the dots marking the point estimates. As the figure shows, the two intervals overlap substantially across most of their range, visually confirming that the difference between the two correlations is not statistically significant (Fisher's z = 0.37, p = .71). This overlap indicates that spatial ability is associated with geometry achievement to a similarly strong degree in both groups, rather than being a resource that matters disproportionately for one group over the other.

3.3. Interpreting the Strong, Non-Differential Association through Cognitive Load Theory

This study set out to test whether spatial ability functions as a compensatory cognitive resource that matters more for low-achieving students than for high-achieving students in geometry learning. The data confirmed that spatial ability is strongly related to geometry achievement, but did not support the moderation hypothesis: the correlation was equally strong in both achievement groups, and the two group-specific correlations did not differ from one another. Rather than acting as a resource that is disproportionately important when schema-based knowledge is lacking, spatial ability appears to be a robust, near-uniform predictor of geometric performance across the achievement spectrum in this sample.

Several explanations, each consistent with Cognitive Load Theory, may account for this pattern. First, CLT predicts that a cognitive resource such as spatial ability should matter most when it directly reduces the specific load imposed by a task; if the geometry items used here placed substantial visuospatial demands on all students regardless of prior knowledge, spatial ability could plausibly emerge as an important resource for both low- and high-achieving students rather than for low-achieving students alone. Second, achievement level in this sample, though operationalized as low versus high performance on the geometry test, may not map cleanly onto the schema-availability distinction assumed by the compensatory-resource hypothesis: even the high-achieving group's performance may still have depended heavily on spatial processing rather than on well-automatized schemas that would allow them to bypass visuospatial demands. Third, because spatial ability and geometry achievement were both measured through tasks requiring active mental manipulation of figures, part of the very large shared variance (r = .92 overall) may reflect the two measures tapping a closely overlapping underlying construct, rather than spatial ability acting as a distinct compensatory mechanism separate from geometric reasoning itself.

3.4. Statistical Power and Comparison with Prior Literature

With group sizes of 60 and 65, this study had more than adequate power (> .99) to detect correlations of the magnitude observed (r = .73–.76); indeed, the design was sensitive enough to reliably detect true correlations as small as r ≈ .35 at conventional levels (power = .80, α = .05). The 95% confidence intervals around the observed correlations were correspondingly narrow (low-achieving group: [.64, .85]; high-achieving group: [.59, .83]), and these intervals overlap substantially, reinforcing the Fisher's z result that the two correlations do not differ meaningfully. This precision strengthens confidence that the near-equivalence of the two correlations reflects a genuine pattern in the population from which this sample was drawn, rather than a failure to detect a true difference due to insufficient power.

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The strong, positive spatial ability–geometry achievement correlation observed in this study is well aligned with a broader literature reporting positive associations between spatial ability and STEM performance, including geometry-related tasks [2,4], and with evidence linking stronger visuo-spatial imagery to better geometry performance in school-aged children [17]. What this study adds is evidence that, at least in this university sample, the strength of this association does not depend on students' achievement level: spatial ability was an equally powerful correlate of performance for both low- and high-achieving students. This is more consistent with the view that spatial ability is a broadly important resource for geometric reasoning in general [23] than with the specific proposition that it functions as a compensatory resource unique to learners with weaker schema-based knowledge. It is also consistent with recent evidence that schematic-chunking interventions targeting geometry performance benefit students with geometry learning difficulties without necessarily implying a unique compensatory role for spatial ability among only the lowest-performing learners [46], and with hands-on approaches shown to improve geometry problem-solving broadly across ability levels [47]. More generally, recent accounts of why secondary mathematics remains difficult for many learners continue to emphasize cognitive load as a pervasive factor affecting students across the achievement spectrum, not merely those who struggle most [48], a view reinforced by classroom-based efforts to reduce cognitive load through targeted instructional prompts [49] and by analyses of element interactivity in secondary mathematics content generally [50].

3.5. Instructional Implications, Limitations, and Future Research

If spatial ability is as strongly related to geometry performance among high-achieving students as it is among low-achieving students, instructional interventions aimed at strengthening spatial visualization skills may benefit the student body broadly rather than serving as a targeted, gap-closing strategy for low-achieving students specifically. These findings tentatively point toward incorporating spatial-ability training as a general component of geometry instruction for example, alongside worked examples and scaffolded problem representations [23] rather than reserving such training for students who are struggling. At the same time, given the very strong shared variance between spatial ability and geometry achievement in this sample, instructors may also consider whether current assessment formats disproportionately reward spatial processing over other forms of geometric reasoning, such as verbal-logical proof construction.

This study has several limitations. First, the achievement groups were defined using a median split on a continuous variable, which can obscure more nuanced relationships that might emerge with continuous moderation analysis (e.g., regression-based interaction models); a median-split approach is also less informative when, as here, the association between predictor and outcome is strong across the entire distribution rather than concentrated in one segment of it. Second, spatial ability scores departed from a normal distribution, showing a bimodal pattern with clusters of students near the floor and ceiling of the test; while Spearman correlations confirmed the Pearson results, this distributional feature merits further scrutiny in future data collection to rule out testing-administration artifacts (e.g., disengaged responding among some students). Third, the geometry achievement test comprised only five items, which may not have adequately sampled the range of geometric reasoning skills relevant to spatial processing. Fourth, the cross-sectional, single-sample design cannot rule out contextual factors specific to this cohort of students or this institution. Finally, spatial ability was operationalized using a single instrument; multi-method assessment of spatial ability (e.g., combining visualization, rotation, and perception subtests) might yield different results.

Future research should replicate this design in other samples to confirm whether the strong, non-differential association between spatial ability and geometry achievement observed here generalizes across institutions and populations. Continuous moderation analysis (e.g., hierarchical regression with a spatial ability × achievement-level interaction term) would provide a more sensitive test of whether the strength of this association truly varies across the full range of achievement, rather than relying solely on median-split grouping. Researchers should also investigate the source of the bimodal distribution in spatial ability scores observed in this sample, and extend the geometry achievement measure to include a broader range of item types to clarify whether the strength of the association is specific to highly visuospatial item formats.

4. CONCLUSION

This study examined whether spatial ability is more strongly associated with geometry achievement among low-achieving university students than among high-achieving students, drawing on Cognitive Load Theory to motivate this compensatory-resource hypothesis. Using a correlational design with 125 university students, the study found a strong, highly significant correlation between spatial ability and geometry achievement in both achievement groups (low-achieving: $r = .76$; high-achieving: $r = .73$), with no

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significant difference in correlation strength between groups ($z = 0.37$, $p = .71$). These findings do not support the hypothesis that spatial ability plays a differentially compensatory role for low-achieving students; instead, they suggest that spatial ability is a robust correlate of geometry performance across the full range of achievement levels. Future research employing continuous moderation analysis and more comprehensive geometry assessments is needed to further clarify the conditions under which spatial ability's role in geometric reasoning does or does not vary by achievement level.

DECLARATION ON THE USE OF GENERATIVE AI

During the preparation of this manuscript, the author used a generative artificial intelligence tool (Claude, Anthropic) to assist with language editing, grammar checking, and manuscript formatting. The tool was not used to generate research data, perform the statistical analyses, or produce the scientific content or conclusions of the study. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the accuracy, originality, and integrity of the published article. No generative AI tool is listed as an author, in accordance with COPE guidance on authorship.

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