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RESEARCH ARTICLE

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Using eye gaze to reveal cognitive processes and strategies of engineering students when solving spatial rotation and mental cutting tasks

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Abstract

Background: Spatial problem-solving is an essential skill for success in many engineering disciplines; thus, understanding the cognitive processes involved could help inform the design of training interventions for students trying to improve this skill. Prior research has yet to investigate the differences in cognitive processes between spatial tasks in problem-solving to offer learners timely feedback.

Purpose/Hypothesis: In this study, we investigated how different spatial tasks change the cognitive processes and problem-solving strategies used by engineering students with low spatial ability.

Design/Method: Study participants completed mental rotation and mental cutting tasks of high and low difficulty. Eye-tracking data were collected and categorized as encoding, transformation, and confirmation cognitive processes. The adoption of either a holistic or piecemeal strategy and response accuracy were also measured.

Results: Mental rotation was found to have a higher number of fixations for each cognitive process than the mental cutting task. The holistic strategy was used in both difficulty levels of the mental cutting task, while the piecemeal strategy was adopted for the mental rotation task at a high difficulty level. Only encoding fixations were significantly correlated with accuracy and most strongly correlated with strategy.

Conclusion: Encoding is an important cognitive process that could affect subsequent cognitive processes and strategies and could, thus, play an important role in performance. Future development in spatial training should consider how to enhance encoding to aid students with low spatial ability. Educators can utilize gaze metrics and empirical research to provide tailored and timely feedback to learners.

KEYWORDS

cognitive processes, eye-tracking, first-year engineering students, spatial ability

1 | INTRODUCTION

Spatial ability is an important area for engineering education because of its strong connections to both academic and professional performance in the science, technology, engineering, and math (STEM) fields (Wai et al., 2009). Spatial ability refers to "the ability to generate, retain, retrieve and transform well-structured visual images" (Lohman, 1996, p. 112) that enable effective learning and problem-solving in STEM. For example, chemistry requires rotating 3D models of molecules to determine the polarity (H. K. Wu & Shah, 2004) as well as to comprehend models (e.g., ball-and-stick models and structural formulas; Dickmann et al., 2019), and astronomy requires imagining the movements of celestial bodies, such as the phases of the moon (Cole et al., 2018). Spatial ability relevant to computer programming (Jones & Burnett, 2008) includes visualizing processes and data flows (Cheah, 2020), while surgery and geology require visualizing cross sections of anatomical structures and geological sites, respectively (Kali & Orion, 1996; Orion et al., 1997; Rochford, 1985). There are abundant examples illustrating how STEM education requires students to engage in such different types or categories of spatial thinking as mental rotation, perspective taking, and navigation (Atit et al., 2020; Cheng, 2017), and substantial research has indicated that spatial skills predict outcomes not only in education but also in careers (Buckley et al., 2018; Wai et al., 2009).

Spatial ability plays an important role in engineering education in areas pertaining to communication and visualization (Bertoline & Wiebe, 2005) as can be seen by the emphasis on engineering graphics in the first-year engineering curriculum. With three-dimensional computer-aided design programs replacing traditional two-dimensional drawings, educational materials for engineering graphics have to be updated to include spatial reasoning of 3D geometrical modeling (Lieu & Sorby, 2015; Lockhart & Johnson, 2000). However, the inclusion of this 3D educational material has potentially raised the expected spatial ability of engineering students, with the result that students who do not exhibit high spatial ability may be discouraged (Marunić & Glazar, 2014) and consider leaving the program.

With retention rates remaining problematic in engineering disciplines (Desai & Stefanek, 2017; Paura & Arhipova, 2016; Tayebi et al., 2021), engineering education must prioritize developing students' skills in spatial problem-solving, particularly for those identified as having low spatial ability. As Wai et al. (2009, 2010) argued, students' need for the spatial ability to succeed in STEM education has been a contributing factor to the shortage of the engineering workforce in the US. Thus, training to promote spatial ability has become an important area of research, leading to a wide range of training methods, including dedicated practice (pen-and-paper) exercises (e.g., Sorby et al., 2003) and computer training programs (e.g., augmented reality systems; Carbonell Carrera & Bermejo Asensio, 2017). In the last decade, universities and colleges have demonstrated improvement in student outcomes by offering short spatial training courses incorporating the training methods from research (e.g., Miller & Halpern, 2013; Sorby et al., 2018). In general, spatial training has been found to be effective at elevating scores in spatial ability tests; however, the transfer of this training to other tasks and the causal benefits to STEM education outcomes require further research (Stieff & Uttal, 2015; Uttal et al., 2013; Wai et al., 2009).

Current spatial training interventions are learner-focused, requiring students to practice various exercises without being easily adaptable to their needs in terms of both instruction and learning. These interventions can be enhanced by unobtrusive, immediate feedback on how students are solving spatial problems. Specifically, spatial training could leverage the relationship between spatial problem-solving performance, cognitive processes, and problem-solving strategy (Bochynska et al., 2021; Cooper & Podgorny, 1976; Cooper & Shepard, 1973; Nazareth et al., 2019; Schultz, 1991). For example, training students to gain collection and awareness of problem-solving strategies has been demonstrated to close the performance gap in spatial problem-solving (Brown et al., 2019; Hsi et al., 1997; Lin, 2016; Moè, 2016). Both instructors and students can leverage the feedback given to focus the training on the specific cognitive processes or strategies where the students need improvement.

The most common and intuitive approach for identifying the cognitive processes involved in spatial thinking is through self-reporting or interviews (LeCompte et al., 1993; Mintzes et al., 2005). However, both approaches can be intrusive in accessing student cognitive processes and problem-solving strategies, unless self-reflection is part of the instructional method. Further, as cognitive processes may be hard to explain, self-reporting has been found to be difficult for students and sometimes unreliable (Schwarz, 1999). Thus, complementary assessment methods of cognitive processes are invaluable in selective environments or for triangulating findings in engineering education.

Past research has investigated the use of eye-tracking to indicate cognitive processes (Just & Carpenter, 1976, 1985; Toth & Campbell, 2019; Xue et al., 2017) and strategies (Khooshabeh & Hegarty, 2010; Nazareth et al., 2019) in spatial problem-solving. Despite extensive recent eye-tracking studies on other topics in engineering education (e.g., Was et al., 2017), eye-tracking investigations on cognitive processes and strategies have primarily focused on mental rotation tasks (Chen & Yang, 2014; Khooshabeh & Hegarty, 2010; Nazareth et al., 2019; Xue et al., 2017). Given the differences across the various types of spatial tasks (Hegarty & Waller, 2004; Kozhevnikov & Hegarty, 2001), research results on the cognitive processes, strategies, and performance for one type of spatial task may not generalize to others, potentially leading to the misapplication of research by both educators and students in providing and understanding the feedback. In summary, research examining the interactions among cognitive processes, problem-solving strategies, and types of spatial thinking together with feedback from eye-tracking should be provided to educators and students for personalizing or adapting spatial training.

The purpose of this research is to advance our understanding of eye gaze in providing feedback to educators and students for adapting spatial training. Specifically, this research aims to answer the following two research questions:

- R1: How do gaze metrics of cognitive processes vary across the various types of spatial tasks and difficulty levels in relation to performance?
- R2: How do gaze metrics of cognitive processes reflect the problem-solving strategies being adopted across the two spatial tasks investigated here?

This study contributes to engineering education by providing (1) empirical evidence on how cognitive processes may vary across various types of spatial tasks and on how difficulty can inform the future development of spatial training methods and programs; (2) empirical evidence on the gaze metrics of cognitive processes and spatial strategies that can be used by educators, students, and adaptive learning systems to personalize training. The collective research results explicitly aim to advance engineering assessment in providing unobtrusive assessments of cognitive processes in spatial problem-solving that could be more conducive to learning in some education environments or for some student groups.

2 | LITERATURE REVIEW

2.1 | Cognitive processes and strategies in spatial task problem-solving

Understanding cognitive processes are crucial for the engineering education field to help instructors support students by creating a well-adapted learning environment that facilitates how to "learn to learn" (De Graaff & Christensen, 2004, p. 461). The ability to reflect on one's reasoning (i.e., cognitive processes), otherwise known as metacognition (Flavell, 1979; Marra et al., 2022; Wengrowicz et al., 2018), allows students to learn how to approach problems and monitor their progress. Both of these abilities are the key to becoming a competent professional engineer (Wengrowicz et al., 2018). For example, incorporating think-aloud protocols in engineering design problems can lead to improved self-evaluation/monitoring and attention to strategy and domain knowledge (Marra et al., 2022). This type of feedback can benefit both educators and students as it can help direct instruction and learn appropriately by reflecting on students' cognitive processes and strategies.

The literature provides a strong research foundation on cognitive processes in spatial ability and thinking. Initial research conducted by Cooper and Shepard (1973) conceptualized three sequential cognitive processes for a mental rotation that still dominate current research today (Hegarty & Waller, 2004; Nolte et al., 2022; Xue et al., 2017):

1. The *encoding* of the stimuli as an internal representation in working memory. This internal representation must include the essential structure or features of the stimulus to be effective for subsequent cognitive processing.
2. The *transformation* of the mental representation in correspondence with the real-world stimuli. For example, individuals need to mentally rotate the initial representation to some target rotation in physical reality.
3. The *confirmation* of whether the transformation (i.e., rotated internal representation) is correct with respect to the physical object's target orientation.

Subsequent research into these cognitive processes of spatial ability has revealed that familiarity with the objects decreases the processing time for encoding (Cooper & Shepard, 1973), while disparity between the initial and target object representation increases the processing time for transformation (Heil et al., 1998; Terlecki et al., 2008), and any mismatch between transformed and target mental representations increases processing time for confirmation (Just & Carpenter, 1976). Recently, researchers have found no distinguishing factors in the ability to mentally rotate along a cardinal axis or a completely skewed axis (Nolte et al., 2022), suggesting that rotation along a skewed axis can be broken down into multiple rotations along a cardinal axis for easier transformation. These findings directed the development of spatial training methods to "strengthen" these cognitive processes or simply spatial ability, particularly through training exercises (e.g., Leone et al., 1993; Munoz-Rubke et al., 2021; also refer to reviews by Drauden, 1980 and Wauck, 2020).

Cognitive processes are intertwined with spatial problem-solving strategies, which are another significant predictor of performance. The literature commonly discusses task-independent, spatial problem-solving strategies in terms of the dichotomy of holistic and analytical/piecemeal strategies that originated from research in mental rotation (Khooshabeh et al., 2013; Nazareth et al., 2019; Schultz, 1991; Stieff et al., 2014; Yuille & Steiger, 1982; Zhao & Sala, 2018). Some studies include task-dependent spatial thinking strategies, such as cube counting (refer to Hsi et al., 1997), that are only applicable to specific spatial tests or tasks. The holistic strategy transforms a full internal representation with one sweeping mental operation, whereas the piecemeal strategy decomposes the internal representation into subcomponents for simpler but multiple transformations from the initial to the target representation of subcomponents (i.e., transformation subgoals). The key distinction between the two strategies is that the piecemeal strategy has simpler but more mental operations to execute, making it susceptible to more errors and a longer processing time.

Research has found that individuals employing the holistic strategy more often had higher mental rotation test scores than those employing the piecemeal strategy (Bethell-Fox & Shepard, 1988; Linn & Petersen, 1985; Logie et al., 2011). The piecemeal strategy is typically applied to mental rotation tasks involving complex and unfamiliar spatial tasks (Yuille & Steiger, 1982; Zhao & Sala, 2018). Males apply the holistic strategy more often than the piecemeal and tend to outperform females who prefer the piecemeal strategy (Hegarty, 2018; Heil & Jansen-Osmann, 2008; Linn & Petersen, 1985); however, spatial strategy training, including being cognizant of available strategies and suggesting an effective strategy, has been found to eliminate the performance difference between the two sexes (Boone & Hegarty, 2017; Hsi et al., 1997).

The literature also includes an analysis of the interactions between cognitive processes and strategies in spatial thinking. For example, Just and Carpenter (1985) argued that the transformation process is inherently piecemeal based on the correlation of transformation processing time with the degree of disparity between initial and target object representation, with several studies supporting their conclusion that the transformation process is inherently piecemeal (Nolte et al., 2022; Xue et al., 2017). Recent research has explored the potential of encoding as a strategy for solving spatial problems. For example, Margulieux (2020) proposed the spatial encoding strategy (SpES), a theory that postulates encoding essential features (i.e., landmarks) into the mental representation that could dictate the nature of subsequent cognitive processing. In earlier research, Zhao and Sala (2018) suggested that the holistic strategy demands the encoding of more spatial details based on their finding that people with good spatial memory exhibited longer response time with respect to angular disparity for standard objects than non-standard objects (also refer to Yuille & Steiger, 1982). Instruction on visual chunking, that is, encoding multiple pieces of visual information as a single representation (rather than multiple) to improve processing efficiency, has been found to improve performance in identifying matches or mismatches of 3D representations of hypothetical molecules (Stieff et al., 2020). These studies suggest potential interactions between cognitive processes and spatial strategies. However, such interactions have not been explicitly investigated, particularly in terms of how encoding and perhaps confirmation processes reflect the strategies being adopted by the problem-solver.

2.2 | Eye-tracking in engineering education and spatial problem-solving

Engineering education research has employed eye-tracking to study and assess cognitive processes during problem-solving and learning (Lai et al., 2013; Rodrigues & Rosa, 2019), primarily because eye gaze behavior or metrics can be used to infer cognitive processes as posited by the eye-mind hypothesis, which argues that where the eyes look reflects the processes in or states of the mind to a degree (Just & Carpenter, 1980; Schindler & Lilienthal, 2019; C. J. Wu & Liu, 2022). Specifically, gazes are tracked continuously to determine fixation, the cluster of gazes proximate in time and location, to indicate what visual information is being encoded. To gather information elsewhere, a saccade, a relatively large and rapid movement between fixations, would be made for gazes to fixate or cluster at a different location. Research has investigated various gaze metrics to infer cognitive states and performance, such as longer fixations typically suggesting more extensive cognitive processing and larger saccade amplitudes suggesting expertise (Brams et al., 2019; Jacob & Karn, 2003; Joseph & Murugesh, 2020; Just & Carpenter, 1980). Eye-tracking has been implemented with the use of multimedia instructional materials on computers, with O'Keefe et al. (2014) demonstrating that students with more fixation transitions between the sliders and graph components simulating the Ideal Gas Laws showed better comprehension based on test results. Eye-trackers have also been used by pre-service teachers to obtain a heatmap of the visual attention on their multimedia contents (e.g., slides) to guide them in redesigning these teaching materials to be more effective (Langner et al., 2022).

Specifically related to spatial ability, Just and Carpenter (1976) conducted the initial eye-tracking study on the cognitive processes of encoding, transformation, and confirmation for the Shepard Metzler rotation task (Shepard & Metzler, 1971), operationalizing encoding as fixations traversing back and forth repeatedly between any segments of two objects, transformation as fixation traversing between corresponding segments of two objects, and confirmation as a short sequence of fixation traversing between corresponding parts of the two objects other than the transformed segments. In further research, Just and Carpenter (1985) found that all fixation metrics measuring the three processes increased with rotation angle and longer transformation processing time for individuals with low spatial ability. Subsequent research produced similar supporting findings that fixations and fixation transitions are more frequent for more complex mental rotation tasks (e.g., angular disparity) and individuals with lower spatial ability (Chen & Yang, 2014; Xue et al., 2017).

To operationalize a spatial strategy for solving the Shepard Metzler rotation task, Khooshabeh and Hegarty (2010) used the ratio of the consecutive fixation frequency within each object to the saccade frequency between the two objects. A strategy ratio close to one indicates the use of the holistic strategy, and a ratio greater than one indicates the piecemeal strategy. Individuals with high spatial ability tended to exhibit a ratio closer to one for this task (Khooshabeh & Hegarty, 2010). In a recent mental rotation task study, Nazareth et al. (2019) applied latent profile analysis to fixation metrics, including the strategy ratio, to determine the performance benefits of employing the holistic strategy and the difference in the adoption rate of the holistic strategy between males and females. Toth and Campbell (2019) found higher fixation duration for the types of mental rotation problems (i.e., structural foil) that cannot be solved by the holistic strategy than for the types that can (i.e., mirror).

Current research indicates that eye-tracking can support the quantitative investigation of the relationship between cognitive processes and spatial strategies. Further, eye-tracking presents a promising unintrusive means to provide feedback on cognitive processes and spatial strategies to both educators and students for personalized learning. For these reasons, our study employed eye-tracking to investigate the interactions between cognitive processes and spatial strategies for both mental rotation and mental cutting tasks of different levels of difficulty. We hypothesized that the difficulty level of the tasks would lead to an increase in encoding eye fixations for both mental rotation and mental cutting due to the increased demand for the formation of a mental representation in working memory (Cohen & Hegarty, 2007, 2012; Miyake et al., 2001), which has been found to correlate with encoding fixations (Gould, 1973; Joseph & Murugesh, 2020; Just & Carpenter, 1976; Xue et al., 2017). In addition, we hypothesized that fixations during the encoding and transformation processes would correlate positively with the strategy ratio because piecemeal strategy is usually associated with more difficult items that require more mental operations for both encoding and transformation.

3 | METHOD

3.1 | Participants and recruitment

This study recruited 44 men and 44 women first-year engineering students from a remedial course at a major university in the US. Following the recommendations of the 2017 Trans and Gender Non-Confirming Task Force (Booth et al., 2017) to not perpetuate a sex binary and/or a gender binary of "male" and "female," this demographic information was collected with a trans-inclusive "Gender Identity" question using the following wording: Gender Identity (select all that apply): (1) Woman, (2) Man, (3) Transgender, (4) Non-binary/non-conforming, (5) Prefer not to respond. The participants in this study self-identified with the "Man" and "Woman" binary. The overall gender distribution of the first-year engineering students' enrollment at the study institution in the year of the study was 78% men and 22% women, and the gender representation of the course used in this study matches the overall first-year engineering cohort. Nationally, according to the ASEE "By the Numbers" 2019 report, the undergraduate enrollment awarded by gender (the report indicates that year, not many institutions reported any individuals who were non-binary gendered or other gendered) was 76.2% male and 23.8% female (American Society for Engineering Education, 2020).

Our participants were recruited from a remedial course offered to students with below-average mental rotation ability as determined by scoring fewer than 17 out of 30 correct responses on the Purdue Spatial Visualization Test: Rotations (PSVT:R), which was given at the beginning of the academic year to all first-year engineering students. The course, which was offered in the fall semester, provided training on how to visualize and virtually represent simple solids, manipulate the same objects, combine an object with other objects into a complex assembly, and use additive manufacturing equipment, specifically a 3D printer, to produce the object. While the students enrolled in the course also took the Santa Barbara Solids Test (SBST) at the beginning of the fall semester, these scores were omitted as part of the screening criteria. Rather the PSVT:R was used to screen participants because of the desirable psychometric properties (refer to details in Section 3.3 Spatial Task Type). Study recruitment began early in the fall semester, and data collection started mid-semester. Participants self-reported normal or corrected-to-normal vision. All participants signed a consent form for this study, which was approved by the Institutional Review Board (IRB) of the university.

3.2 | Experimental conditions

This study employed a 2×2 within-subject design that included the treatment of spatial task types at two levels (i.e., the PSVT:R/mental rotation and the SBST/mental cutting), and the treatment of difficulty at two levels (Low and High).

3.2.1 | Spatial task types/categories

The study included two spatial ability tests. The first test was the revised PSVT:R, which assessed the ability to perform 3D mental rotations (Guay, 1976). For each PSVT:R item (left side of Figure 1), the participants were given a pair of objects, one in the reference position (A1) and another in a rotated target position (A2). The participants were also given an object (B1) in a reference position and were asked to select among five options as the target object (B2) that was rotated in the same fashion as the pair of objects (A1, A2). The PSVT:R was selected as the mental rotation task because of its strong psychometric properties: internal consistency (Cronbach's $\alpha = .862$, $N = 1022$), construct validity (mean tetrachoric correlations $= 0.29$), and item discrimination (only two items have a point-biserial correlation between item score and total score under 0.30) based on a study by Yoon (2011). The study conducted by Maeda et al. (2013) produced similar findings (Cronbach's $\alpha = .839$, $N = 2469$; mean point-biserial correlations of 0.35 with seven items having an item discrimination index under 0.3). In addition, Yoon (2011) identified difficult and easy items that are relevant for the treatment of difficulty (refer to Section 3.2.2 difficulty).

The second test was the SBST, which assessed the ability to identify the two-dimensional cross-section of a three-dimensional geometric solid (Cohen & Hegarty, 2012). For each SBST item (right side of Figure 1), the participants were presented with an object intersected by a cutting plane and asked to select from four options, the correct

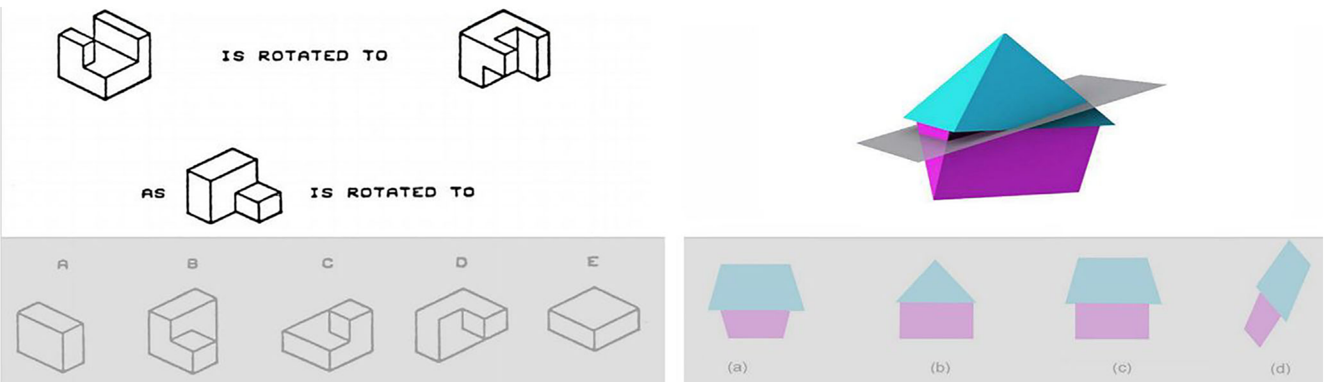

FIGURE 1 A sample tasks of Purdue Spatial Visualization Test: Rotations (PSVT:R) (left; Yoon, 2011) and Santa Barbara Solids Test (SBST) (right; Cohen & Hegarty, 2012). The top area (unshaded) defines the question section, whereas the bottom area shaded in gray defines the response section for the two types of spatial ability tests.

two-dimensional representation of the cross-section. The SBST was selected for measuring mental cutting ability because of its high internal consistency (Cronbach's α of .910, $N = 223$; Cohen & Hegarty, 2012). Further, the SBST showed a moderate correlation with the Vandenburg Mental Rotation test ($r(221) = .57$; Cohen & Hegarty, 2007), suggesting that the PSVT:R score should be a sufficient screening criterion for participants with low spatial ability in both mental rotation and cutting. The SBST also has well-defined difficulty dimensions—the geometric complexity and the orientation of the cutting plane—that are useful for selecting items for difficult experimental manipulation. In addition, it is the most common test for measuring mental cutting ability (Ashour et al., 2022; Cohen & Bairaktarova, 2018; Uygan & Kurtuluş, 2016).

For the purpose of gaze analysis, each PSVT:R and SBST test item was divided into a question section (top half of Figure 1) and a response section (bottom half of Figure 1 shaded gray). The two sections were created to mirror the side-by-side judgment in the Shepard Metzler rotation task so that the fixation metrics formulated by Just and Carpenter (1976) and Khooshabeh and Hegarty (2010) would be applicable to this study (refer to Section 3.4 Measures).

3.2.2 | Difficulty

The items in the two spatial ability tests were classified as having either a high or low difficulty level. For the revised PSVT:R, this study included Items 1, 7, 29, and 30. Based on the results from the study conducted by Yoon (2011), Questions 1 and 7 were considered low difficulty, with an accuracy of 82.8% and 75.6%, respectively, while Questions 29 and 30 were considered high difficulty, having 39.5% and 20.7% accuracy, respectively.

Since there were no prior performance data for the SBST tasks, the levels of difficulty were set based on the orientation of the cutting plane, which has been suggested to define item difficulty (Cohen & Hegarty, 2012). The SBST task difficulty is low for orthogonal (horizontal or vertical) but high for oblique cutting planes. In this study, both the high and low levels of the difficult treatment include one of each type of the following solids: simple solids (cones, cubes, cylinders, prisms, or pyramids), joined solids (two simple solids attached at their edge), and embedded solids (one simple solid enmeshed within another). The study included SBST Items 4, 11, and 24 with orthogonal cutting planes for low difficulty and 15, 22, and 23 with nonorthogonal cutting planes for high difficulty.

3.3 | Procedure

After completing the informed consent, the participants were seated in a quiet room and asked to place their chins on an adjustable chinrest approximately 60 cm from a laptop screen. The participants made minor position adjustments as needed. When they felt comfortable, the eye-tracker was calibrated until the accuracy was above 90%. The Mangold Vision Eye-Tracker (*Eye Tracking Software Mangold Vision*, n.d.), which collected gaze data as participants responded to the spatial task questions, included a mini eye-tracker with an accuracy of approximately 0.5-degree visual angle and utilized dark pupil binocular or monocular tracking (*Eye Tracking Software Mangold Vision*, n.d.). The eye tracker recorded the participant's gaze in the X-Y coordinates of the computer screen at 60 Hz. Post calibration, three instruction slides on the PSVT:R and SBST tests were presented to the participant. For each test item, the participants were given 20 s to answer, a time limit derived based on the average completion time of a test item or proposed time limit in prior work (Cohen & Hegarty, 2014; Guay, 1980). The participants proceeded to the next test item before the time limit once they wrote down their answers to ensure scoring accuracy. Before presenting an item, a focus slide appeared for 5 s to help standardize the starting fixation position and mental focus on the upcoming item.

3.4 | Measures

Table 1 summarizes the performance and four gaze metrics used here to address the research questions. The performance metric was accuracy computed as the proportion of correct answers to the spatial task questions for each experimental condition. Each question/trial was marked as either correct or incorrect.

In this study, the four gaze metrics were derived from different categories of fixations computed with X-Y gaze coordinates based on the work conducted by Just and Carpenter (1976) and Khooshabeh and Hegarty (2010): encoding fixations, transformation fixations, confirmation fixations, and strategy ratio. Fixations were computed using the

TABLE 1 Performance and gaze metrics

Metrics	Description
Accuracy	Proportion of correctly answered questions
Encoding fixations	Encoding fixations totaled beginning from the first fixation in the question or the response section of any figure segment. The accumulation ends once the fixation moves to the other section.
Transformation fixations	Transformation fixations are tallied from the first consecutive fixations that move between the question and the response sections.
Confirmation fixations	First consecutive fixations in either the response or the question section after transformation fixations
Strategy ratio	The ratio of the number of consecutive fixations in each figure to the number of eye movements or fixation changes between the two figures.

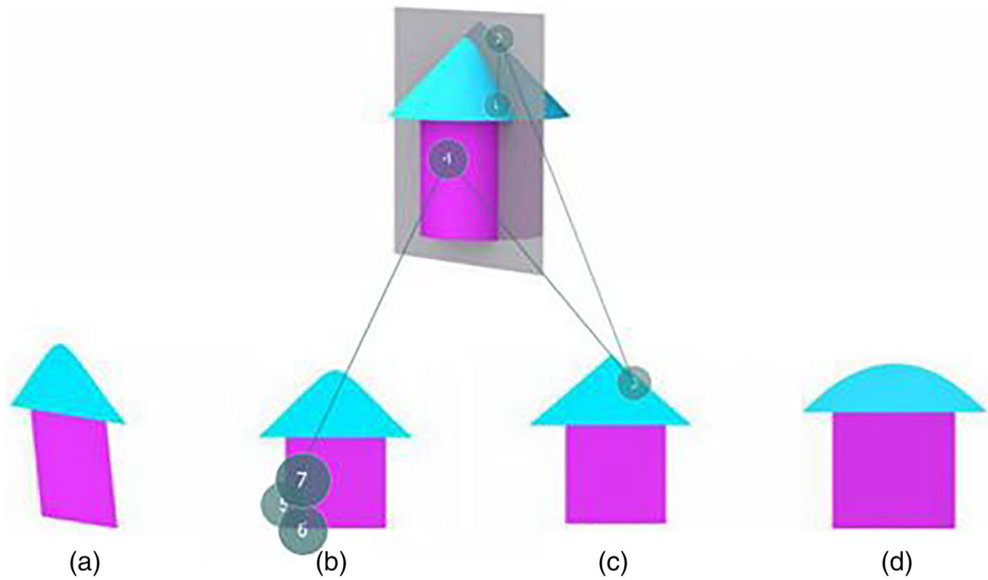

FIGURE 2 Sequence of fixations when a participant engages in an Santa Barbara Solids Test (SBST) task. The numbered and shaded circles represent fixations. Fixations 1 and 2 are categorized as encoding fixations, while Fixations 3, 4, and 5 are categorized as transformation fixations, and Fixations 6 and 7 are confirmation fixations.

dispersion-based algorithm in the Mangold software (Mangold Vision ver 3. 16. 0. 21) by clustering sequential gazes close to one another within the 200 ms threshold.

Encoding fixations were tallied from the first fixation in the question section or the response section of a figure segment until a fixation moved to the other section. Based on this definition of encoding fixations, it is possible that participants could begin the encoding process in the response section and the transformation process in the question section; however, none of the participants in this study began encoding in the response section. Figure 2 presents an example illustrating the fixations computed for a participant solving an SBST question. Fixations 1 and 2 (depicted as shaded and numbered circles in Figure 2) were classified as encoding because these were the first fixations on the question section before a fixation moved to the response section.

Transformation fixations were tallied from the consecutive fixations moving between the question section and the response section from the last encoding fixation. In Figure 2, Fixations 3, 4, and 5 were considered transformations because they occurred after the encoding fixations and traversed repeatedly between the question section and the response section.

Confirmation fixations were tallied from the first consecutive fixations either in the response section or the question section after the transformation fixations. In Figure 2, Fixations 6 and 7 were considered confirmation because Fixation 6 marked the first consecutive fixations in the response section, and Fixation 7 represented all subsequent fixations.

The strategy ratio was calculated as the ratio of consecutive fixations made within each figure to the number of fixation changes between the two figures. Figure 2 illustrates five consecutive fixations within a figure (Fixations 1, 2, 5, 6, 7) and three eye movements changing between figures (from Fixations 2 to 3, 3 to 4, and 4 to 5). Therefore, the strategy ratio is five divided by three, equaling one and two-thirds.

3.5 | Analysis

The data analysis was conducted in three steps. First, descriptive statistics were computed after checking for missing values. Second, to address the first research question, a Shapiro–Wilk test of normality and two-way repeated measure ANOVAs (Analysis of Variance) were performed for assessing the main and interaction effects of spatial task type and difficulty on the gaze metrics, strategy ratio, and accuracy. Third, to address the second research question, Pearson's correlation statistics with bias-corrected and accelerated bootstrap (BCa) confidence intervals were computed to analyze the association between strategy ratio, fixation-based metrics of cognitive processes, and accuracy.

4 | RESULTS

A total of 880 trials were administered across 88 participants, each completing 10 (4 PSVT:R and 6 SBST) spatial ability test items, that is, trials. Data from five participants were dropped as the information provided was incomplete: no fixations were recorded or no fixations were included in the response section. Thus, the final dataset contains 830 trials from 83 participants (39 males and 44 females). The accuracy and gaze metrics were aggregated and averaged for each trial. Table 2 presents the mean and standard deviation for each experimental condition.

4.1 | Effects of spatial task types and difficulty

The Shapiro–Wilk test of normality showed that only four measures were normally distributed at each treatment level (Table 3). In most cases, violation of normality has a limited impact on the significance levels of the *F*-test (Blanca Mena et al., 2017; Cochran, 1947; Pearson, 1931). Furthermore, the assumption of sphericity was a non-issue given only two levels for each treatment (i.e., PSVT:R and SBST spatial task types, and high and low difficulty levels).

The results from the five ANOVAs found in Table 4 present the significant main and interaction effects on the five measures. We further describe these effects by individual measures, omitting the main effects when interaction effects are present.

TABLE 2 Mean (*M*) and standard deviation (SD) for gaze measures and accuracy

		Difficulty level	
Metrics (n = 83)	**Spatial task types**	**Low mean (SD)**	**High mean (SD)**
Encode fixations	PSVT:R	6.09 (3.169)	9.90 (3.712)
	SBST	1.85 (0.727)	2.30 (0.953)
Transformation fixations	PSVT:R	5.84 (2.518)	5.58 (3.056)
	SBST	1.74 (0.608)	1.59 (0.652)
Confirmation fixations	PSVT:R	3.55 (3.980)	2.55 (3.048)
	SBST	10.65 (4.291)	13.11 (4.220)
Strategy ratio	PSVT:R	3.93 (2.088)	5.58 (4.208)
	SBST	1.21 (0.675)	1.16 (0.479)
Accuracy (proportion correct)	PSVT:R	0.82 (0.288)	0.28 (0.314)
	SBST	0.62 (0.361)	0.51 (0.358)

Abbreviations: PSVT:R, Purdue Spatial Visualization Test: Rotations; SBST, Santa Barbara Solids Test.

TABLE 3 Test of normality assumption

Measure	Spatial task types	Difficulty	Shapiro–Wilk		
			Statistic	**df**	**Sig.**
Encode	PSVT:R	Low	0.919	83	0.000
Transformation	PSVT:R	Low	0.984	83	0.396
Confirmation	PSVT:R	Low	0.838	83	0.000
Strategy	PSVT:R	Low	0.895	83	0.000
Accuracy	PSVT:R	Low	0.632	83	0.000
Encode	PSVT:R	High	0.978	83	0.156
Transformation	PSVT:R	High	0.964	83	0.020
Confirmation	PSVT:R	High	0.814	83	0.000
Strategy	PSVT:R	High	0.802	83	0.000
Accuracy	PSVT:R	High	0.738	83	0.000
Encode	SBST	Low	0.885	83	0.000
Transformation	SBST	Low	0.913	83	0.000
Confirmation	SBST	Low	0.975	83	0.105
Strategy	SBST	Low	0.797	83	0.000
Accuracy	SBST	Low	0.831	83	0.000
Encode	SBST	High	0.936	83	0.000
Transformation	SBST	High	0.827	83	0.000
Confirmation	SBST	High	0.976	83	0.124
Strategy	SBST	High	0.882	83	0.000
Accuracy	SBST	High	0.868	83	0.000

Abbreviations: PSVT:R, Purdue Spatial Visualization Test: Rotations; SBST, Santa Barbara Solids Test; df, degrees of freedom; Sig, significance.

TABLE 4 Two-way repeated measure Analysis of Variance (ANOVA) results for gaze metrics and accuracy

Factors	Metrics	Degrees of freedom	df error	Mean square	Mean square error	*F*	Significance	Partial eta squared
Spatial task type	Encode	1	82	2908.535	7.159	406.280	0.000*	0.832
	Transformation	1	82	1356.148	5.005	270.951	0.000*	0.768
	Confirmation	1	82	6464.533	19.551	330.643	0.000*	0.801
	Strategy	1	82	1056.940	6.085	173.682	0.000*	0.679
	Accuracy	1	82	0.010	0.145	0.070	0.793	0.001
Difficulty	Encode	1	82	375.328	4.231	88.711	0.000*	0.520
	Transformation	1	82	3.347	3.537	0.946	0.334	0.011
	Confirmation	1	82	44.587	8.320	5.359	0.023*	0.061
	Strategy	1	82	53.453	5.275	10.132	0.002*	0.110
	Accuracy	1	82	8.729	0.056	156.639	0.000*	0.656
Spatial task type * Difficulty	Encode	1	82	234.461	3.717	63.076	0.000*	0.435
	Transformation	1	82	0.226	3.317	0.068	0.795	0.001
	Confirmation	1	82	247.523	8.386	29.515	0.000*	0.265
	Strategy	1	82	59.997	5.617	10.681	0.002*	0.115
	Accuracy	1	82	3.725	0.052	72.035	0.000*	0.468

$^{*}p < .05$.

4.1.1 | Encoding fixations

The interaction effect between spatial task type and difficulty was significant on encoding fixations ($F(1,82) = 63.076$, $p < .001$). As Figure 3 illustrates, PSVT:R recorded substantially more encoding fixations than SBST irrespective of difficulty; however, difficulty level had greater effect on encoding for PSVT:R than for SBST. As the descriptive statistics (Table 2) indicated, the difference in encoding fixation was much greater between PSVT:R low ($M = 6.09$, SD = 3.169) and high difficulty ($M = 9.90$, SD = 3.712) than between SBST low ($M = 1.85$, SD = 0.727) and high difficulty ($M = 2.30$, SD = 0.953).

4.1.2 | Transformation fixations

The main effect of spatial task type was significant on transformation fixations.

($F(1,82) = 270.951$, $p < .001$), with these being higher when solving PSVT:R.

($M = 5.711$, SD = 2.142) compared to SBST ($M = 1.67$, SD = 0.474). Figure 4 presents parallel lines illustrating the main effect of spatial task type (and the non-significance of the interaction effect) on transformation fixations.

4.1.3 | Confirmation fixations

The interaction effect between spatial task type and difficulty was significant on encoding fixations for confirmation fixations ($F(1,82) = 29.515$, $p < .001$). As Figure 5 illustrates, PSVT:R induced more confirmation fixations than SBST. Further, SBST recorded fewer confirmation fixations at low ($M = 10.65$, SD = 4.291) than at high difficulty ($M = 13.11$, SD = 4.220), exhibiting the opposite trend of PSVT:R, which had higher confirmation fixations at low ($M = 3.55$, SD = 3.980) than at high difficulty ($M = 2.55$, SD = 3.048).

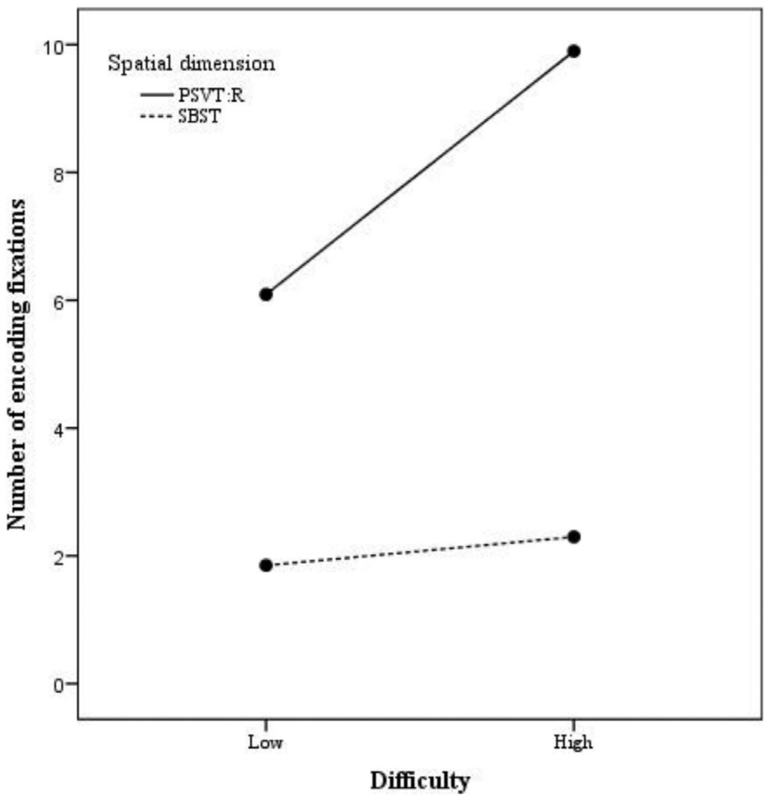

FIGURE 3 The interaction effect between spatial task type and difficulty in encoding fixations. The solid line represents the Purdue Spatial Visualization Test: Rotations (PSVT:R) and the dotted line represents the Santa Barbara Solids Test (SBST).

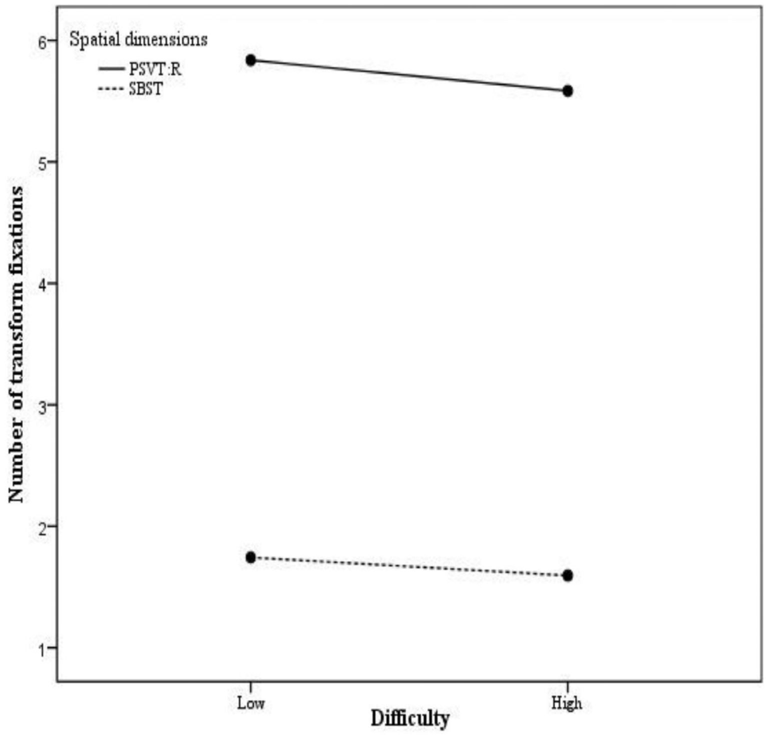

FIGURE 4 The interaction effect between spatial task type and difficulty on transformation fixations. The solid line represents the Purdue Spatial Visualization Test: Rotations (PSVT:R) and the dotted line represents the Santa Barbara Solids Test (SBST).

4.1.4 | Strategy ratios

The interaction effect between spatial task type and difficulty was significant on strategy ratios (F(1,82) = 10.681, p = .002). As illustrated in Figure 6, PSVT:R had lower strategy ratios at low difficulty (M = 3.93, SD = 2.088) than at high difficulty (M = 5.58, SD = 4.208); however, SBST strategy ratios for low (M = 1.21, SD = 0.675) and high difficulty (M = 1.16, SD = 0.479) were similar.

4.2 | Participant accuracy during spatial problem-solving

The interaction effect between spatial task type and difficulty was significant n accuracy (F(1,82) = 72.035, $p < .001$). As Figure 7 illustrates, the difference in accuracy was much greater for PSVT:R between low (M = 0.82, SD = 0.288) and high difficulty (M = 0.28, SD = 0.314) levels than for SBST between low (M = 0.62, SD = 0.361) and high difficulty (M = 0.51, SD = 0.358) levels.

4.3 | Relationship between cognitive processes and strategy use

The Shapiro–Wilk tests indicated that the metrics were not normally distributed: encoding fixations (W(332) = 0.846, $p < .01$); transformation fixations (W(332) = 0.859, $p < .01$); confirmation fixations (W(332) = 0.932, $p < .01$); strategy ratio (W(332) = 0.716, $p < .01$); and accuracy (W(332) = 0.844, $p < .01$). The sample size of 332 for each metric is based on the average values for each experimental condition per participant (i.e., 83 participants * 2 types of spatial task * 2 levels of difficulty). Pearson product–moment correlation coefficients are considered robust to violation of the normality assumption (Bishara & Hittner, 2012; Edgell & Noon, 1984; Havlicek & Peterson, 1977) and were thus computed for the fixation metrics of the cognitive processes, strategy ratio, and accuracy across trials. Given the non-normally distributed data, BCa confidence intervals (Beasley et al., 2007) were computed with 1000 samples to confirm the significance of the Pearson correlation statistics. Specifically, the null hypothesis of zero correlation is rejected if the 2.5th to 97.5th percentile of this bootstrap sampling distribution does not include zero.

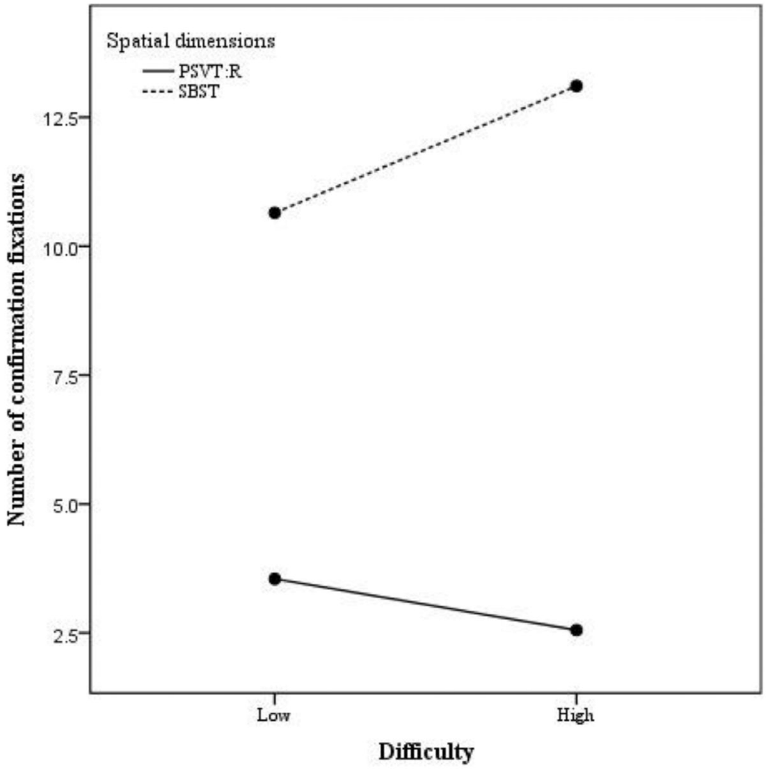

FIGURE 5 The interaction effect between spatial task type and difficulty on confirmation fixations. The solid line represents the Purdue Spatial Visualization Test: Rotations (PSVT:R) and the dotted line represents the Santa Barbara Solids Test (SBST).

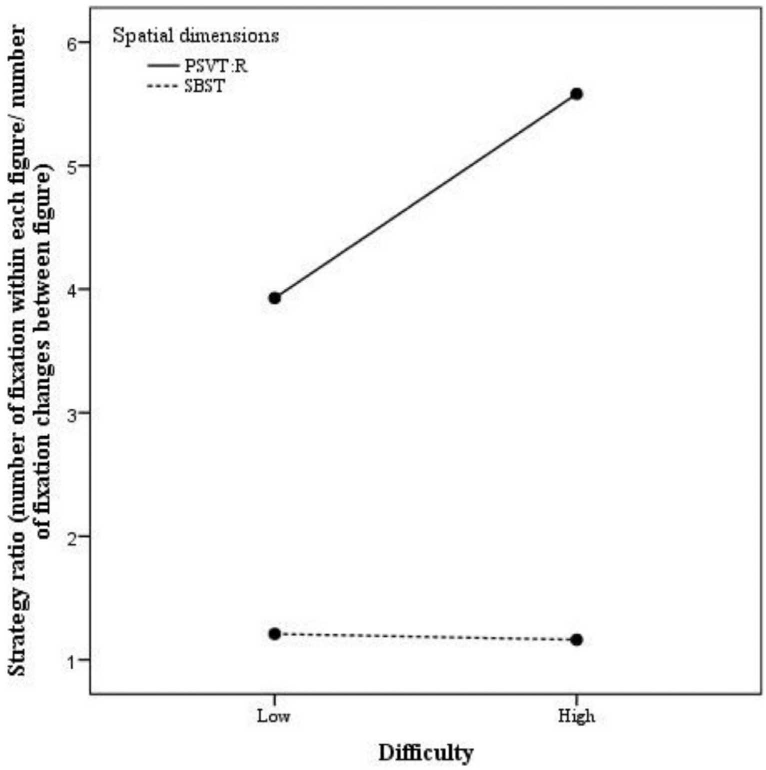

FIGURE 6 The interaction effect between spatial task type and difficulty on strategy ratio. The solid line represents the Purdue Spatial Visualization Test: Rotations (PSVT:R), and the dotted line represents the Santa Barbara Solids Test (SBST). Strategy ratio is the number of consecutive fixations on an object over the number of eye movements between the objects.

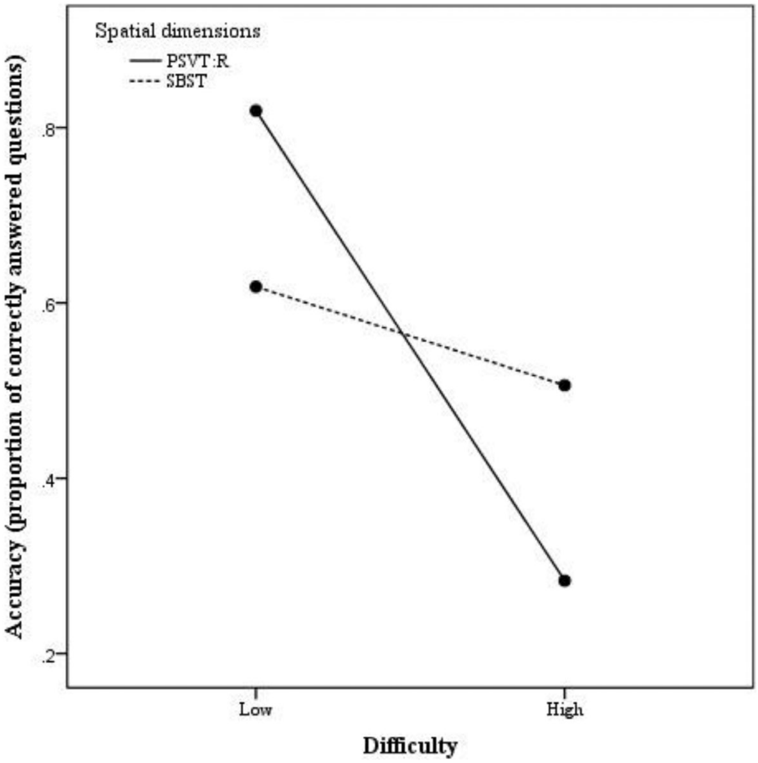

FIGURE 7 The interaction effect between spatial task type and difficulty on accuracy. The solid line represents the Purdue Spatial Visualization Test: Rotations (PSVT:R), and the dotted line represents the Santa Barbara Solids Test (SBST). Accuracy is the proportion of correctly answered questions for each treatment.

TABLE 5 Correlations between strategy, cognitive processes, and accuracy

			Strategy ratio ($N = 332$)	Encode ($N = 332$)	Transformation ($N = 332$)	Confirmation ($N = 332$)	Accuracy ($N = 332$)
Strategy ratio	*r*		1	0.601**	0.309**	−0.482**	−0.056
	BCa 95% CI	Lower		0.509	0.220	−0.545	−0.178
		Upper		0.692	0.431	−0.427	0.064
Encode	*r*		0.601**	1	0.383**	−0.617**	−0.150**
	BCa 95% CI	Lower	0.509		0.285	−0.663	−0.256
		Upper	0.692		0.488	−0.568	−0.039
Transformation	*r*		0.309**	0.383**	1	−0.585**	−0.071
	BCa 95% CI	Lower	0.220	0.285		−0.642	−0.179
		Upper	0.431	0.488		−0.534	0.028
Confirmation	*r*		−0.482**	−0.617**	−0.585**	1	0.039
	BCa 95% CI	Lower	−0.545	−0.663	−0.642		−0.084
		Upper	−0.427	−0.568	−0.534		0.150
Accuracy	*r*		−0.056	−0.150**	−0.071	0.039	1
	BCa 95% CI	Lower	−0.178	−0.256	−0.179	−0.084	
		Upper	0.064	−0.039	0.028	0.150	

Abbreviations: BCa, bias-corrected and accelerated bootstrap; CI, confidence intervals.
**Significant at the .01 level (2-tailed).

Table 5 presents the correlation statistics among the metrics. Strategy ratios were positively and moderately correlated with encoding fixations ($r(332) = .601$, $p < .001$), as well as positively and slightly correlated with transformation fixations ($r(332) = .309$, $p < .001$). However, strategy ratio was negatively and moderately correlated with confirmation fixations ($r(332) = -.482$, $p < .001$). This study did not find a significant correlation between strategy ratios and accuracy ($r(332) = -.056$, $p = .311$). Encoding fixations were positively and slightly correlated with transformation fixations ($r(332) = .383$, $p < .001$), but negatively and moderately correlated with confirmation fixations ($r(332) = -.617$, $p < .001$). The transformation fixations were negatively and moderately associated with confirmation fixations ($r(332) = -.585$, $p < .001$). Accuracy was only negatively and slightly correlated with encoding fixations ($r(332) = -.150$, $p < .001$).

5 | DISCUSSION

This study utilized eye-tracking to investigate the cognitive processes and strategies of students with low spatial ability while solving mental rotation and cutting tasks at two difficulty levels. The gaze data used to compute fixations were categorized and analyzed based on the work of Just and Carpenter (1976) and Khooshabeh and Hegarty (2010) that operationalized three cognitive processes (encoding, transformation, and confirmation) and two strategies (holistic and piecemeal).

The results from this study supported our first hypothesis that difficulty would lead to increased encoding fixations for both mental rotation and mental cutting because difficulty has been associated with the increased demand needed to form mental representation in working memory (Miyake et al., 2001). Our results are consistent with prior studies also finding that more encoding time is required for complex tasks (Cooper & Podgorny, 1976; Heil & Jansen-Osmann, 2008; Lovett & Schultheis, 2021; Zhao, Zhu, & Della Sala, 2019). In addition, we observed an interaction effect of spatial task type and difficulty level of task on encoding fixations. The encoding fixations of students with low spatial ability were significantly higher for mental rotations compared to mental cutting.

Prior research has found no significant difference in the contribution of visuospatial working memory storage to different spatial task types (Miyake et al., 2001; Wang et al., 2021) that would suggest such a significant difference in encoding fixations, indicating that mental cutting and mental rotation exhibit different encoding degradation with difficulty. According to the spatial SpES theory (Margulieux, 2020), the encoding process becomes inadequate due to the inability to identify useful landmarks for internalizing the representation of the appropriate orientation. The lack of chunking or landmarks implies a lack of essential structures stored within visuospatial working memory (Stieff et al., 2020).

The second hypothesis was confirmed as our results found that encoding and transformation eye fixations correlated positively with the strategy ratio (Table 5). The strategy ratio also had a higher correlation with encoding fixation ($r(332) = .601$, $p < .001$) than transformation fixation ($r(332) = .309$, $p < .001$), suggesting that the encoding process may be more indicative of the mental strategy than the transformation process. Prior research may have over-emphasized that strategy reflects the number of steps or increments in the transformation process (Khooshabeh et al., 2013; Yuille & Steiger, 1982; Zhao & Sala, 2018). The encoding process must capture essential structural features to support the subsequent transformation process, and the omission of essential features may lead to degradation and unsuccessful transformation. The evidence for the potentially degraded transformation is the significant, albeit weak, correlation between encoding and transformation fixations ($r(332) = .383$, $p < .001$).

The importance of the encoding process is further confirmed by the only significant, albeit weak, correlation with accuracy ($r(332) = -.150$, $p < .001$). Considered as the first cognitive process in spatial problem-solving (Cooper & Shepard, 1973; Hsing et al., 2022; Shepard & Metzler, 1971; Xue et al., 2017; Zhao, Della Sala, & Gherri, 2019), encoding, which generates the internal representation, might dictate the subsequent cognitive processes and strategy. Difficult tasks can compromise this encoding process, and a compromised encoding process may also mean compromised internal representations, further suggesting transformation would not lead to the correct response except by chance. Hence, the confirmation of the transformed representations would suggest either failed mental manipulation or an incorrect response. We further consider that participants needed to identify hidden parts of three-dimensional objects depending on how these objects were projected onto the two-dimensional plane in the PSVT:R. If participants failed to identify these hidden parts, the internal representation would be incorrect, and rotation of the incorrect internal representation even along the correct axis at the correct angular magnitude would likely yield an incorrect response. The magnitudes of the significant correlation statistics range between moderate and weak, suggesting other factors critical to success in spatial problem-solving. While spatial training should not merely focus on the encoding process, our results signal the need for instructional design to improve teaching on the relatively neglected encoding process for students with low spatial ability.

This eye-tracking study in spatial problem-solving contributes to the knowledge and innovation in engineering assessment. The research indicates that the gaze metrics can be used to understand and assess the cognitive processes of engineering students engaging in spatial tasks without interruptions such as verbal queries during problem-solving (e.g., verbal queries). This form of assessment can be more conducive to learning for some engineering education environments and student groups that prefer quiet deliberations. The gaze metrics can also be used in conjunction with the technology underlying innovative adaptive learning systems as well as in feedback to educators and students to personalize learning (also refer to implications for practice in Section 5.1). Finally, the results indicating the importance of the encoding process in spatial problem-solving shed light on the epistemology of engineering with implications for the practice of engineering education, specifically, the success of interventions to improve spatial problem-solving rests on teaching effective encoding as well as transformation.

5.1 | Implications for practice

There are clear opportunities for utilizing gaze metrics instructional strategies. Educators can leverage the unintrusive nature of eye-tracking and provide almost real-time feedback to students. For example, eye-tracking can alert instructors if a student is having trouble identifying hidden parts of the PSVT:R. They can also demonstrate the encoding process to students, in particular, how the instructors themselves identify the hidden parts of three-dimensional objects in the PSVT:R. Further, self-regulated learning is increasingly becoming part of instructional design (Paris & Paris, 2001) with supporting evidence that it improves achievement (e.g., Jansen et al., 2019; Jansen et al., 2020). Using eye-trackers to demonstrate and assess gaze behaviors of the encoding process represents an extension of the early work conducted by Hsi et al. (1997), who demonstrated that basic instructions on knowing the availability and having the awareness of different spatial strategies could improve spatial thinking performance. Educators can supplement pen-and-paper training with replay videos of individual student's gaze movements to facilitate student reflections on the processing (Penttinen et al., 2013).

In reflecting on their processing behavior, students can self-evaluate/monitor their cognitive process during spatial problem-solving with the support of eye-tracking. An extension to computer software scaffolding (Guzdial, 1994), eye-tracking scaffolding that provides hints to students with respect to their visual attention has been demonstrated to improve the self-efficacy of students in a computer programming class (Sun & Hsu, 2019). A similar approach with an eye-tracker to indicate whether encoding is effective and whether a holistic strategy is used can be invaluable for the interaction between instructors and students in developing more personalized training programs, which may maximize the benefits of students' training time on spatial ability.

One form of personalized training is adaptive learning systems, which have not yet reached a mature state to be widely deployed. Scheiter et al. (2017) mentioned that one challenge of adaptive learning systems is diagnosing the learner state, and eye-tracking presents a potential solution for adapting delivery of contents and methods. Our eye-tracking results provided support for the use of eye-gaze metrics prescribed by Just and Carpenter (1976) and Khooshabeh and Hegarty (2010) for adaptive learning of spatial problem-solving. Specifically, the encoding fixations and strategy ratios in this study can differentiate two spatial tasks and difficulty levels, potentially resulting in adjustments in content and/or delivery for adaptive learning. However, given only a moderate correlation between encoding and performance, our study also suggests that eye gaze metrics need either further advances or complementary metrics to be effective for adaptive learning systems for spatial problem-solving.

5.2 | Limitations and future work

This study administered a speeded test (a combination of both a power test and a speed test) to provide equal footing for the PSVT:R and SBST tests. Traditionally, the PSVT:R is administered with a time limit of 20 min (Guay, 1980). However, Yoon (2011) argued that it should have no time limit. The literature does not include studies administering SBST with a time limit (Cohen & Hegarty, 2012). To address that issue, our participants were instructed to finish the test within 12 min, the midrange of the average completion time of 10–15 min for the SBST (Cohen & Hegarty, 2014).

Given our methodological decision of a speeded test, interpretations of the psychometric properties with respect to extant research should be considered in light of this difference (Lu & Sireci, 2007).

Another limitation is that our screening for spatial ability was entirely based on PSVT:R rather than a range of spatial ability tests that would produce a more valid and reliable study sample. Furthermore, there is a concern for a potential confounding effect between the two types of spatial tests and levels of difficulty. Equating any one dimension for two types of tests is always a challenge. Our results did not reveal a significant main effect of spatial tasks on accuracy, addressing some of the concerns about this issue. However, researchers should be aware of this limitation.

Eye gaze data or metrics are not unambiguously inferable, often reflecting a wide range of human responses such as emotions as well as cognitive processes (Lim et al., 2020; Zheng et al., 2014). Researchers have interpreted fixations as a degree of information extraction (Jacob & Karn, 2003), attention (Rehder & Hoffman, 2005; Wang et al., 2021), cognitive load (Joseph & Murugesh, 2020; Yamada & Kobayashi, 2018), and confusion (Pachman et al., 2016; Salminen et al., 2018). A recent study on geometric problem-solving highlighted that fixations and saccades, on occasion, do not reflect cognitive attention as suggested by the eye-mind hypothesis (Schindler & Lilienthal, 2019). Further, the correlations between cognitive processes and accuracy found in our study are in the moderate and weak range, limiting the strength of our prescription for educational instruction. Therefore, triangulation of eye-tracking metrics with other measurement methods and adaptation of eye-gaze metrics specific to the study domains are important considerations for future research in and advancement of adaptive learning systems.

Researchers have mentioned that PSVT:R is prevalent in STEM education (Maeda et al., 2013; Yoon, 2011). Therefore, participants are likely to have prior exposure to it, thus affecting our sampling. Further, this research focused exclusively on students with low spatial ability, meaning the results should be interpreted accordingly. Future research should incorporate additional spatial ability tests for screening participants and studying students with different spatial abilities.

Future research could investigate the relationship between the transformation process and accuracy. The lack of a significant correlation between the two suggests that the outcome of the transformation process and the adoption of a holistic strategy would be moot if the internal representation formulated by the encoding process was faulty. Therefore, at least for the population with low spatial ability, investigating if the encoding process should be viewed as the primary challenge merits further investigation.

Future work should also use eye-tracking to examine the characteristics of essential structures for encoding so that educators can augment spatial training or educational materials with visual cues or guidance on the encoding process. Eye-tracking has been effective in evaluating the impact of visual cues in multimedia learning (Boucheix & Lowe, 2010; de Koning et al., 2010). For example, eye-tracking indicates that color coding can improve learning effectiveness (Ozcelik et al., 2009, 2010). Given that color coding also enhances the ability to remember the subcomponents used during the piecemeal strategy in mental rotation tasks (Khooshabeh & Hegarty, 2010), educators can use the encoding fixations of effective problem-solvers to locate and then visualize landmarks for improving the encoding process in spatial problem-solving.

6 | CONCLUSIONS

We conducted an eye-tracking study investigating cognitive processes and strategies adopted by engineering students to solve mental rotation and mental cutting spatial problems. The results indicated that the type and difficulty of spatial problems led to differences in the cognitive processes and strategies being adopted. We found a higher number of encoding fixations in mental rotation tasks and spatial tasks of high difficulty. Furthermore, the number of encoding fixations correlated with the strategy used. These findings collectively indicate that mental cutting tasks appear to involve easier encoding than mental rotation tasks, and the encoding process may be more indicative of the strategy used than the transformation process.

The study findings suggest that eye-tracking technology and gaze metrics can substantially benefit both instructors and learners in spatial problem-solving, essential for success in many engineering disciplines. Instructors can monitor and identify deficiencies in cognitive processes or strategies of learners in real-time. Furthermore, eye-tracking also allows learners to engage in self-evaluation/monitoring of their learning behavior to produce improved learning outcomes.

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