

Puzzle to progress: relationship between Rubik's Cube solving proficiency, spatial visualization, and anxiety

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SUMMARY

Previous studies have explored puzzle games as tools to enhance spatial abilities and modulate anxiety. However, the Rubik's Cube, a widely recognized cognitive puzzle, has received little attention in relation to spatial abilities and anxiety. This study tested the relationship between Rubik's Cube solving proficiency and spatial visualization, and between proficiency and anxiety (using perceived stress as a proxy). Analyses accounted for demographic and personal covariates, including Rubik's Cube solving experience, age, gender, physical activity, and educational background. We hypothesized that solving proficiency is positively correlated with spatial visualization and negatively correlated with perceived stress. Members of the Rubik's Cube community forums completed an online survey that collected self-reported data on solving proficiency and covariates, alongside an adapted spatial visualization assessment and a perceived stress assessment. Controlling for solving experience, the results indicated a positive correlation between spatial visualization and solving proficiency, but a non-significant correlation between perceived stress and proficiency. Our findings contribute to the literature on cognitive training and clinical interventions. They suggest the Rubik's Cube as a potential tool to enhance spatial visualization or, conversely, visualization training as a possible aid for competitive solvers. Caution is advised in treating the Rubik's Cube as an anxiolytic puzzle, given the potentially limited or nuanced link between Rubik's Cube solving and anxiety. Our results reflect the broader use of tools to support human cognitive and emotional development.

INTRODUCTION

The Rubik's Cube is a three-dimensional puzzle comprised of 26 smaller cubes rotating around a central axis (1). Each of its six faces is divided into nine colored squares. When starting from a "scrambled" state with mixed colors, the challenge is to "solve" the cube, restoring its original state with every face displaying a uniform color (1). Invented by Ernő Rubik in 1974, the Cube quickly gained popularity. The Cube's global revenue has grown consistently since 2021 and will continue to do so (2). In response, advancements have been developed to accommodate new styles of play, including magnetic levitation, corner-cutting, and smart

cubes. Such innovations have also incentivized competitive "speedcubing"—solving a cube as quickly as possible (2). The community has since witnessed remarkable improvements in world records, from Dan Knights' 20-second record in 2003 to Xuanyi Geng's 3.05-second record as of 2025 (3). However, not all solvers participate in speedcubing; many engage in a leisurely manner for enjoyment or relaxation (4).

This breadth of engagement invites questions about the puzzle's psychological implications. The memorization and execution of algorithms by puzzle solvers suggest that cubing (engaging with the Cube) likely relies on spatial memory, pattern recognition, and motor skills. Cubing might also involve mentally envisioning how pieces will move before performing rotations. More subtly, the attentional demand of cubing might provide cognitive diversion, offering stress relief by redirecting focus from external stressors. Despite these plausible connections and the Cube's popularity, little research has probed how individual differences in solving proficiency relate to specific cognitive abilities, such as spatial visualization, or to affective states, such as anxiety.

Spatial visualization is "the skill to mentally manipulate visual images" (5). It is a granular term under the broader framework of "spatial ability," alongside spatial relations, spatial perceptions, mental rotation, and spatial orientation (5). Spatial ability is "the ability to construct, maintain, and transform spatial representations accurately," a constellation of spatial processes foundational to many real-world tasks (6). To recognize the relevance of spatial visualization, we must understand the significance of spatial abilities in realistic contexts.

In academic contexts, spatial abilities are not only linked to academic success in science, technology, engineering, arts, and mathematics (STEAM) fields, but are also integral to the mastery of chemistry, mathematical thinking, computer science, and design technology (7-11). In everyday contexts, spatial ability is also crucial in navigating environments and communicating visually (12). Given this importance, researchers have explored various strategies to enhance spatial abilities; puzzle games are one such strategy. For instance, short-term exposure to puzzle games improved mental rotation accuracy and speed (13). Spatial puzzles, games specifically designed to train spatial abilities, surpassed traditional puzzles in effectiveness when training spatial visualization (13). Among 8-year-olds, both structured block playing and board games enhanced mental rotation, with block playing activating regions associated with spatial working memory and processing (14). Similarly, engagement with the video game *Tetris* produced high initial improvements in mental rotation performance compared to repetitive practice with mental rotation tests (15).

As a popular puzzle game, the Rubik's Cube is highly relevant in its application to spatial abilities. The literature suggests that Cube training enhances mental rotation performance (16). When applying Cube solving as a spatial problem-solving task, the task structure—consistently difficult, variably difficult, or progressively difficult—did not significantly influence the development of near transfer in spatial abilities (17). This suggests that the act of engaging with the puzzle itself, rather than how its difficulty is structured, may be sufficient for spatial ability benefits. Yet, the fundamental connection between existing solving proficiency and spatial visualization specifically, rather than spatial ability as a whole, remains underexplored. The Cube's connection with spatial visualization is particularly significant compared to other spatial abilities. Solving the Cube entails visualizing three-dimensional transformations of colors, a skill paralleling real-world applications of spatial visualization, from visualizing molecules when learning chemistry to everyday activities like packing and arranging furniture (18). How solving proficiency, experience, and engagement with different Cube variants relate to spatial visualization thus also constitutes a set of significant but unanswered questions in the literature. Hence, investigations into the connections between the Cube and spatial visualization are imperative to understand how the Cube might improve performance in academic and everyday tasks.

While research on the Cube has primarily focused on spatial abilities, much less is known about its potential affective links, such as with anxiety. Anxiety is an emotion characterized by anticipatory worry and somatic (physical) symptoms, arising from perceived threats, adverse events, or an expectation thereof (19). Anxiety disorders (e.g., generalized anxiety disorder, panic disorder, and social anxiety disorder) are unanimously recognized as the most prevalent class of psychological disorders (20, 21). For instance, over 60 million people in Europe alone had an anxiety disorder, resulting in total costs exceeding €74 billion (20). These disorders undermine the physical and emotional well-being, social relations, and financial stability of affected individuals and society as a whole (20).

Beyond the widely recognized impacts of anxiety, research has also linked anxiety with weaker cognitive abilities, including processing speed, visuospatial ability, and various forms of memory (21–24). Given the role of puzzle games on cognitive performance, a transitive logic argument suggests that puzzle games might indirectly modulate anxiety by improving cognitive performance (25). This logic has been documented in studies showing that computer games produce anxiolytic effects, significantly lowering cortisol levels (a biomarker of stress) among participants (26, 27). Similarly, puzzle games involving multiple solutions induced stress alleviation and positive emotions among university students, attributable to the cognitive engagement of problem-solving (28). Problem-solving itself is also a therapeutic strategy in anxiety and depression treatment (29, 30). These findings suggest that puzzle games, especially their problem-solving elements, might help manage anxiety disorders and symptoms.

As a cognitively demanding puzzle game that involves problem-solving, the Cube might help regulate emotions and alleviate anxiety. Despite this, the literature remains largely silent on the matter. To date, no known studies have explicitly explored any affective correlate of engagement with the Cube, let alone its relationship with anxiety. Whether a problem-solving task like the Cube can aid emotional regulation remains an important question.

Given these underexplored connections, this study examined the psychology of the Cube by investigating how solving proficiency relates to spatial visualization ability and anxiety level. We hypothesized that solving proficiency would 1) show a positive correlation with spatial visualization and 2) show a negative correlation with perceived stress. Our results support a correlation between spatial visualization and proficiency but not between stress and proficiency. Our findings suggest the Cube's potential application to enhance spatial visualization or, conversely, visualization training as a possible aid for Cube solvers.

RESULTS

Fifty-four participants completed an online survey collecting data on spatial visualization accuracy, visualization

Variable	Variable Name	N	Mean	SD	Min.	Medn.	Max.
X _{1a}	Purdue Spatial Visualization Test (PSVT) correct answers	48	3.58	1.35	1.00	4.00	6.00
X _{1b}	PSVT average time (seconds)	48	22.83	7.87	6.34	22.87	37.55
X ₁	PSVT composite score	48	80.01	33.26	15.50	80.56	166.43
X ₂	Perceived Stress Scale (PSS) 10 score	48	18.58	7.88	0.00	17.50	40.00
X ₃	Cubing experience (months)	48	44.00	33.54	1.00	36.00	145.00
X ₄	Age (years)	48	17.15	3.67	13.00	16.00	32.00
X ₅	Daily sleep (hours)	48	7.65	1.55	4.00	7.50	11.00
X ₆	Physical activity (minutes/day)	48	39.79	28.84	0.00	35.00	120.00
y	Adaptive Average Solving Time (AoN)	48	17.82	9.98	4.49	14.48	44.14

Table 1: Descriptive statistics of numeric variables after outlier exclusion. Shown are spatial visualization test scores (PSVT correct answers, average time, composite score), perceived stress (PSS-10 score), cubing experience (months), demographic covariates (age, daily sleep, physical activity), and solving proficiency (Adaptive Average Solving Time, AoN). Values include mean, standard deviation (SD), minimum (Min.), median (Medn.), and maximum (Max.).

speed, overall visualization ability, perceived stress, alongside demographic and lifestyle covariates (**Table 1**). Solving proficiency was measured by Adaptive Average Solving Time (AoN), a variable designed to capture proficiency with maximum reliability. A lower AoN indicates greater solving proficiency, as it represents a shorter time taken to solve a cube on average.

We measured spatial visualization using an adapted version of the Purdue Spatial Visualization Test (PSVT) and assessed perceived stress using the Perceived Stress Scale (PSS-10). The data informed how spatial visualization and perceived stress correlate with solving proficiency, controlled for significant confounders.

After applying the statistical cleaning procedure described in the Methods—including the listwise deletion of outliers ($n = 6$; 11.11%) and implausible responses ($n = 0$; 0.00%)—the final sample consisted of 48 participants. Sensitivity analyses showed that the significant effects of PSVT correct answers, PSVT composite score, and cubing experience became non-significant (all $p > 0.05$) when including the outliers, and effect sizes attenuated by 54–68%. These sensitivity analyses justified our outlier exclusion.

The final sample consisted mainly of males (93.75%) and high school students (60.42%). Females (6.25%) and participants with middle school (16.67%), undergraduate (18.75%), primary school (2.08%), and postgraduate (2.08%) educational backgrounds comprised smaller proportions of the sample (**Table 1**). Educational backgrounds reflect participants' current or highest level of education completed. We used four multiple linear regression (MLR) models to assess how AoN (y) relates to each of the predictors—PSVT correct answers (x_{1a} , Model 1), PSVT average time (x_{1b} , Model 2), PSVT composite score (x_1 , Model 3), and PSS-10 score (x_2 , Model 4)—controlling for cubing experience in months (x_3). PSVT correct answers indicate visualization accuracy, and PSVT average time represents visualization speed. PSVT composite score corresponds to overall spatial visualization ability, calculated as the sum of time-weighted accuracies (see Methods for details). Despite collecting data on covariates, our models excluded most of them due to their statistical insignificance (all $p > 0.05$) in preliminary multiple linear regression analyses. We aimed to improve model parsimony by retaining statistically significant covariates only, while preserving model fit. The only significant covariate was cubing experience (e.g., in Model 1, $t(45) = -4.264$, $p < 0.001$). All models followed a general form $y = \beta_0 + \beta_1 x_{\text{main}} + \beta_2 x_3 + \epsilon$. We first assessed whether the MLR models met statistical assumptions, including linearity, independence, homoscedasticity, normality, and absence of multicollinearity. All assumptions were satisfied except normality. The Anderson-Darling normality test was significant across all models ($A_1 = 0.814$, $p_1 = 0.033$; $A_2 = 0.787$, $p_2 = 0.038$; $A_3 = 1.429$, $p_3 < 0.001$; $A_4 = 1.415$, $p_4 = 0.001$), suggesting non-normality. Inspection of Quantile-Quantile (Q-Q) plots verified this finding (**Figure 1**). Accordingly, models were estimated using robust standard errors (SEs), which are resilient to heteroscedasticity and reduce reliance on the normality assumption.

Applying robust SEs, models 1 and 3 showed significant negative correlations between AoN (y) and PSVT correct answers ($t(45) = -2.694$, $p = 0.010$) and between AoN and PSVT composite score ($t(45) = -3.362$, $p = 0.002$), with small

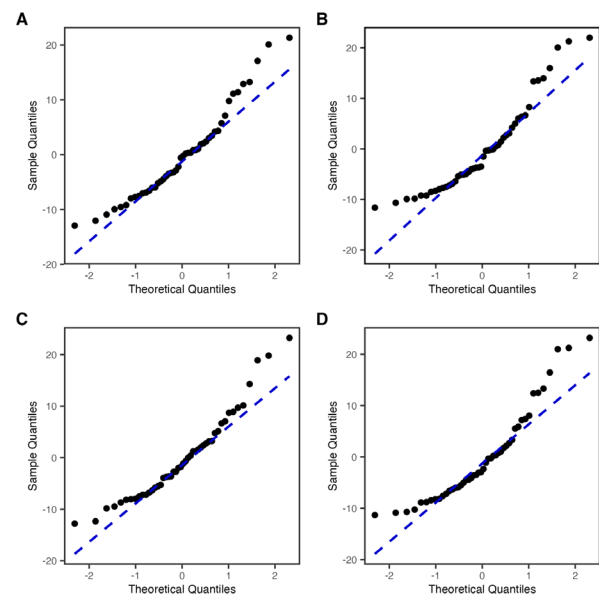


Figure 1: Quantile-Quantile (Q-Q) plots evaluating residual distributions across all multiple linear regression (MLR) models ($N = 48$). Residuals (black) for each model are plotted against theoretical quantiles of a standard normal distribution (dashed blue reference line): (A) Model 1: Adaptive Average Solving Time (AoN) vs. Purdue Spatial Visualization Test (PSVT) Correct Answers; (B) Model 2: AoN vs. PSVT response time; (C) Model 3: AoN vs. PSVT composite score; and (D) Model 4: AoN vs. Perceived Stress Scale (PSS-10) score.

to medium effect sizes ($\eta^2 = 0.050$ and 0.048 , respectively) (**Figure 2**). The results suggested that for two hypothetical individuals one point apart in PSVT correct answers, the individual with the higher accuracy is predicted to solve a cube 2.368 seconds faster ($\beta_1 = -2.368$), regardless of cubing experience. For two differing by 10 points in the PSVT composite score, the one with the higher score is predicted to solve the cube 0.97 seconds faster ($\beta_1 = -0.097$), regardless of experience. The results revealed that proficiency is positively correlated with both spatial visualization accuracy and overall visualization ability.

Meanwhile, the other models showed non-significant correlations between AoN (y) and PSVT average time ($t(45) = -0.641$, $p = 0.525$) or PSS-10 score ($t(45) = -0.226$, $p = 0.823$), suggesting that solving proficiency is not significantly correlated with visualization speed or perceived stress (**Figure 2**).

Together, analyses supported the positive correlation between solving proficiency and spatial visualization, specifically with visualization accuracy but not speed. Meanwhile, the results failed to support a negative correlation between proficiency and perceived stress, as AoN and PSS-10 score showed non-significant correlations.

DISCUSSION

This study tested two hypotheses about Rubik's Cube solving proficiency: 1) solving proficiency is positively correlated with spatial visualization, and 2) solving proficiency is negatively correlated with perceived stress. We assessed the hypotheses with MLR models controlling for cubing experience. Our findings support the first hypothesis, but not the second.

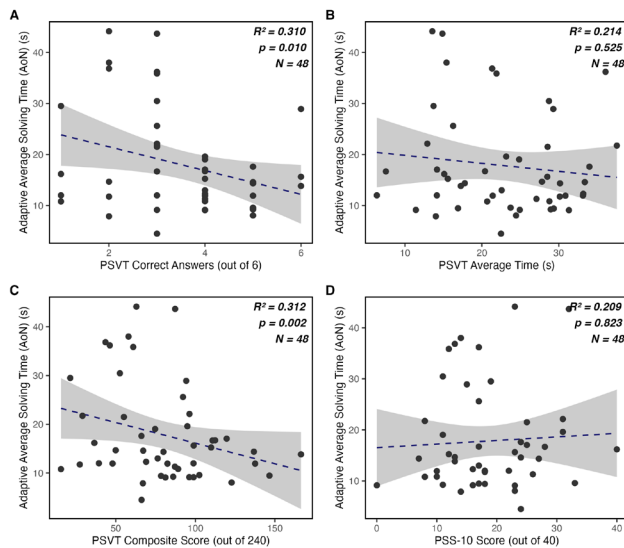


Figure 2: Multiple linear regression (MLR) models predicting Adaptive Average Solving Time (AoN). Scatter plots show participant plotted against spatial visualization and perceived stress data (black points), overlaid with regression fit lines (dashed lines) and 95% confidence intervals (shaded regions). All models control for cubing experience in months (β_2 ranged from -0.144 to -0.133, all $p < 0.001$). (A) Model 1: AoN vs. PSVT accuracy ($\beta_1 = -2.368$, robust SE = 0.879, 95%CI [-4.090, -0.645], $p = 0.010$, partial $\eta^2 = 0.050$; $R^2 = 0.310$); (B) Model 2: AoN vs. PSVT average response time ($\beta_1 = -0.100$, robust SE = 0.156, 95%CI [-0.406, 0.206], $p = 0.525$, partial $\eta^2 = 0.004$; $R^2 = 0.214$); (C) Model 3: AoN vs. PSVT composite score ($\beta_1 = -0.097$, robust SE = 0.029, 95%CI [-0.154, -0.041], $p = 0.002$, partial $\eta^2 = 0.048$; $R^2 = 0.312$); (D) Model 4: AoN vs. Perceived Stress Scale (PSS-10) score ($\beta_1 = -0.037$, robust SE = 0.165, 95%CI [-0.361, 0.286], $p = 0.823$, partial $\eta^2 = 0.001$; $R^2 = 0.209$).

Notably, we observed that greater spatial visualization ability predicted faster solving. The observation supports the hypothesis that visualization and proficiency are related, aligning with previous findings that puzzle games enhance spatial abilities (13–15). This study extended prior work by examining the relationship between existing solving proficiency and spatial visualization, a connection that has received less attention in the literature compared to training-induced changes in mental rotation (13). However, because this study was correlational, the causations remain uncertain. While stronger spatial visualization may support better three-dimensional planning and faster solves, the very process of memorizing algorithms and envisaging geometric transformations may train spatial visualization. Given prior experimental findings that puzzle games improve spatial abilities and Cube training enhances mental rotation, it is more plausible that solving proficiency impacts spatial visualization (13–16). Nonetheless, definitive causal claims require true experiments.

A possible novelty in our work was the divergence between visualization accuracy and speed. Higher visualization accuracy predicted greater solving proficiency, while higher visualization speed did not. Such a dissociation, to our knowledge, has not been examined in the Cube-visualization literature. This divergence suggested that visualization accuracy may be associated with the core mental processes

in spatial puzzles, while response speed potentially reflects personal test-taking strategies or commitment rather than ability alone (31).

The positive correlation between spatial visualization and solving proficiency has several practical implications. If solving proficiency improves spatial visualization, our finding suggests the potential application of Cube solving, particularly speedcubing, as a tool in cognitive development programs to enhance visualization abilities. The Cube may also serve as a supplementary instrument to potentially improve academic performance via enhanced visualization, given that spatial abilities are key in student attainment in STEAM subjects (7–11). Should visualization improve solving proficiency, our finding proposes targeted visualization training as a possible tool to assist speedcubing performance at advanced levels. Beginner solvers might also benefit from visualization training, as they generally lack experience in mental geometric manipulation skills necessary in Cube solving.

While spatial visualization and solving proficiency presented a clear connection, the relationship between perceived stress and proficiency was less straightforward. Perceived stress did not significantly predict proficiency, failing to provide evidence for the hypothesis that proficiency negatively correlates with perceived stress. This null finding failed to replicate previous findings that problem-solving and puzzle games assist anxiety modulation, challenging the external validity of previous findings (28–30). This study suggested that although Cube solving may be stress-relieving for some, promoting the Cube as an anxiolytic tool is premature. Conversely, anxiety modulation should not yet be prioritized as a measure to improve overall solving proficiency. Although the Cube might be inherently unrelated to anxiety, there are several alternative explanations for the non-significance. Our sample consisted of mostly “speedcubers” (mean AoN = 17.82 seconds) with the aim of fast competitive solving. The additional pressure may have offset relaxing effects, if any, of cube solving. Moreover, the PSS-10 assessed “perceived stress” rather than anxiety itself; the scale relies on self-reported frequency judgments (e.g., sometimes) and state descriptions (e.g., worried), which introduces subjectivity and the tendency for respondents to overreport socially desirable responses. The explanations here point to the possibility that the Cube and anxiety have more subtle associations.

While our findings contributed practical insights into cognitive and clinical psychology, several additional limitations should be considered. Our reliance on self-reported variables (e.g., solving proficiency and perceived stress) introduces recall bias. The shortened PSVT and the PSS-10 as a proxy for anxiety constrain construct validity. Direct and complete measures such as the full PSVT, the State-Trait Anxiety Inventory (STAI), or the Beck Anxiety Inventory (BAI) would be more precise (32). Also, our sample is predominantly young, male, and advanced in terms of proficiency. While the demographic biases limit the generalizability of our findings to minority groups, they are consistent with the observable gender and age composition of the speedcubing community from which we sampled, which is known to be mostly young and male (33). Convenience sampling by self-selection and recruitment from dedicated forums further skew the sample toward enthusiastic and competitive solvers, failing to fully represent the broader cubing community.

To address the limitations, future studies could consider experimental or longitudinal designs to establish causation and improve internal validity. Doing so could lead to concrete practical implications rather than conjectural ones. Future research could address sample quality by recruiting either a larger, balanced sample to enhance external validity or a smaller, homogeneous sample to improve internal validity. Applying objective and direct apparatuses, such as supervised solving and anxiety-specific assessments like the STAI or BAI, would improve construct validity and measurement reliability (32).

Future research may also extend beyond methodological improvements, exploring underexamined questions. Establishing causation between solving proficiency and both cognitive (e.g., memory and attention) and affective factors (e.g., depression and emotional regulation) would clarify the Cube's plausibility as a psychological training tool. Conversely, establishing causation could also inform whether certain psychological constructs underpin solving proficiency, such as the theoretical role of working memory and inhibitory control in cube solving (34, 35). Investigating how engagement factors—solving style, cube variants, experience—relate to the psychological constructs could personalize approaches to cognitive and affective enhancement or solving optimization, rather than a blanket application. Moreover, exploring the use of spatial visualization training to reduce entry barriers and increase diversity in the cubing community, particularly amongst women, elders, and other underrepresented groups, is a valuable socio-practical application of our findings.

These future directions have practical implications. Establishing the Cube as a cognitive or affective training tool could inform educational and therapeutic applications. Showing that specific cognitive or affective constructs affect proficiency could also inform competitive trainings for speedsolving.

Taken together, this study provides evidence that Rubik's Cube solving proficiency is positively correlated with spatial visualization, particularly visualization accuracy, but not with perceived stress. Our work establishes a foundational correlation for future research on the causality underlying the Cube and cognitive psychology, providing insights into how problem-solving might interact with human cognition and emotion.

METHODS

Participants

This study was approved by the *Institutional Review Board of the Suzhou Singapore International School Scientific Review Committee*. Fifty-four individuals participated in this study via an online survey posted on r/cubers (on Reddit) and Speedsolving.com, two of the largest cubing community forums. Participants ranged in age from 13 to 43 years, with 49 males and 5 females. Eligibility was restricted to individuals able to solve a 3×3 Rubik's Cube and at least 13 years old. Their cubing experience ranged from 1 month to 12 years, excluding periods of inactivity exceeding two weeks. Participation was voluntary and without direct compensation. Nevertheless, we informed participants that our findings would be shared with the cubing community via all platforms on which the study was advertised.

Design and apparatus

This study applied a correlational design to analyze the relationships between solving proficiency and two psychological constructs: spatial visualization ability and perceived stress. We set spatial visualization and perceived stress as predictors, demographic and lifestyle variables as covariates, and solving proficiency as the outcome. We collected data through an online survey hosted on Qualtrics. Participants accessed the survey via internet-connected devices with access to the forums.

We operationalized the predictor, spatial visualization, using a shortened version of the PSVT. The original PSVT included 36 multiple-choice questions divided equally across three subsections: *developments*, *rotations*, and *directions*. *Developments* assess the ability to visualize the folding of two-dimensional patterns into three-dimensional objects. *Rotations* examine the ability to mentally rotate three-dimensional objects. *Directions* test the ability to identify the correct appearance of three-dimensional objects from different perspectives. To avoid fatigue and increase participation, we extracted 6 questions from the developments subsection to assess spatial visualization, as other subsections were more pertinent to mental rotation and spatial orientation. To balance response quality and duration, submissions were prohibited in the first 5 seconds after the question was displayed and disallowed after 45 seconds had elapsed. We scored participant performance based on three metrics, including response accuracy (x_{1a}), measured by the number of correct answers (out of 6); average response time (x_{1b}), the mean time to submit answers (in seconds, out of 45); and composite score (x_1), a combination of response accuracy and speed, calculated as $x_1 = \sum_{i=1, 6} a_i (45 - t_i)$. a_i indicated response accuracy, with $a_i = 1$ if a response to question i was correct and $a_i = 0$ if not. t_i represented the response time in seconds taken to submit answer item i . The composite score x_1 was scored out of 240 points.

The other predictor was perceived stress, measured using the PSS-10. The strong link between stress and anxiety supports the PSS-10 as a proxy for examining anxiety (36). The PSS-10 contained 10 items inquiring participants about the extent to which they found their lives "unpredictable, uncontrollable, or overloading" during the past month (37). Each item is rated on a Likert scale ranging from zero (never) to four (very often). We presented the questions and rating scale in a multiple-choice matrix format.

Alongside, we recorded several self-reported covariates: cubing experience (x_3 in months), age (x_4 in years), daily sleep (x_5 in hours, to the nearest 0.5 hours), daily moderate-to-intense physical activity (x_6 in minutes, to the nearest 10 minutes), gender (x_7), and educational backgrounds (x_8). Sleep and physical activity were included because they are established predictors of spatial ability and perceived stress; hence, they are potential confounders of the relationship with solving proficiency (38–42). Solving experience was measured to distinguish between the effects of mere engagement versus proficiency, while age and gender were included as standard demographic controls.

Lastly, we operationalized the outcome, solving proficiency (y), using the self-reported measure, AoN. Participants submitted their average solving time for a 3×3 Rubik's Cube in seconds to the nearest hundredth of a second, based on the maximum number of solves they could provide. They

may choose from a single solve or averages of 5 (Ao5), 12 (Ao12), 25 (Ao25), 50 (Ao50), 100 (Ao100), 200 (Ao200), or 500 (Ao500), depending on their available solving history logged on a Cube timer platform. For example, a participant with more than 500 recorded solves reported an Ao500 of 9.47 seconds. Another with approximately 100 solves submitted an Ao100 of 25.60 seconds. The AoN system allowed participants to report an average that best reflected their typical performance, since averaging a greater number of solves neutralized the confounding effect of outliers.

Procedure

Upon entering the survey portal (**Appendix 1**), participants reviewed an informed consent or assent. Those who agreed to participate voluntarily entered the main survey by clicking “proceed.” The survey began with instructions regarding the submission of AoN for the 3×3 Rubik’s Cube. Participants reported their AoN via a two-column table, with the first indicating the type of average submitted, such as Ao5 or Ao100, and the second representing the corresponding AoN to the nearest hundredth of a second. Participants also submitted their active 3×3 cubing experience through another two-column table, reporting the number of years in the first column and the number of additional months in the other.

Subsequently, participants moved to the spatial visualization section of the survey. They viewed detailed instructions, an example question, and a clarification that they are assessed on both accuracy and speed. Participants then answered six multiple-choice questions from the *developments* section of the PSVT, each presented separately with a countdown timer. Responses were recorded alongside the response time for each question.

After the PSVT, participants completed the PSS-10 presented in a matrix format without imposed time limits. Responses ranged from zero (never) to four (very often) on a five-point Likert scale. Finally, participants provided demographic, personal, and lifestyle information, including age, gender, daily sleep duration, daily moderate-to-intense physical activity, and educational backgrounds. Data was entered using sliders for numerical variables and multiple-choice questions for categorical variables. Sliders were configured to automatically snap to predefined increments, such as 0.5-hour increments for reporting sleep, to account for the necessity of approximation in self-reported numerical responses.

Statistical analyses

We performed all statistical analyses using RStudio version 2024.12.1 (43). The code is provided in **Appendix 2**. Prior to analysis, we removed outlier datasets by applying a conservative Z-score threshold of $|z| > 3$ and conducting visual inspection of residual vs. fitted plots. We further screened for responses that appeared fabricated, practically implausible, or carelessly completed.

To test our hypotheses, we fitted four MLR models on the processed data ($n=48$). Each model predicted AoN from one of the four predictors (PSVT correct answers, PSVT average time, PSVT composite score, or PSS-10 score), controlling for cubing experience. Using the processed data ($n = 48$), we assessed the model assumptions of linearity (residual vs. fitted plots), independence (Durbin-Watson test), homoscedasticity (Breusch-Pagan test), normality (Anderson-Darling test), and

absence of multicollinearity (variance inflation factor). As the normality assumption of MLR was violated, we re-estimated all models using robust SEs. We then reported regression coefficients, 95% confidence intervals, t-statistics, and p-values alongside effect sizes (partial η^2) and R^2 for each model.

To assess the validity of the earlier outlier deletion, we conducted sensitivity analyses by running all four MLR models on the full dataset that included the outliers ($N = 54$). We compared coefficients, p-values, and effect sizes between the original (outliers-removed) and sensitivity (outliers-included) analyses to examine the influence of outliers on the results.

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APPENDIX 1

Note: This document version disrupts the survey layout and omits key functions such as answer restrictions and timing. For a more accurate view, please refer to this link: https://uclapsych.qualtrics.com/jfe/form/SV_3kHEgZeB79Hzxpl.

Rubik's Cube Proficiency, Spatial Visualization, and Anxiety

Start of Block: Terms and Conditions



Research Survey: The Relationship Between Rubik's Cube Proficiency, Spatial Visualization, and Anxiety

INFORMED CONSENT / ASSENT

1. Study title:

The Relationship Between Rubik's Cube Proficiency, Spatial Visualization, and Anxiety

2. Researchers:

Stephanie Wert, Department of Psychology, University of California, Los Angeles.
Sheldon Lui, Suzhou Singapore International School.

3. Objective:

This study aims to explore how proficiency in Rubik's Cube solving may associate with cognitive performance and emotional wellbeing. Specifically, we investigate the relationship between proficiency, spatial visualization ability, and anxiety level.

4. Procedure:

You will be asked to report your average solving time on a 3x3 Rubik's Cube. You will then complete two tasks: an extract of the Purdue Spatial Visualization Test (PSVT) to assess your spatial visualization ability, and the Perceived Stress Scale 10 (PSS-10) to measure your anxiety levels. Lastly, you will provide basic demographic information.

5. Duration:

The survey will take approximately 8-10 minutes to complete.

6. Risks: There are no significant risks to participating. Some questions touch on topics of anxiety and emotional wellbeing, which could potentially cause discomfort. You are free to discontinue the survey at any time without penalty.

7. Potential benefits: While participation does not involve direct personal benefits, this study may contribute to the understanding of how performance in problem-solving tasks relates to cognitive performance and emotional wellbeing, potentially benefitting the broader fields of cognitive psychology and mental health.

8. Confidentiality and Data Security

Responses will be kept anonymous. Data will be secure stored and used for research purposes only. Findings may be published, yet your responses will not be shared in a way that could identify you personally.

9. Questions or Concerns

If you have any questions or concerns about the study, please contact Sheldon Lui at luitinlun@163.com.

10. Eligibility



You are eligible to participate if you meet the following criteria:

- You are at least 13 years old;
- You have experience solving the Rubik's Cube.

11. Agreement to Participate

Your participation is completely voluntary. By clicking the “Start Survey” button below, you acknowledge that you have read and understood the information above, and you agree to participate in this study. You may opt out at any time without penalty.

End of Block: Terms and Conditions

Start of Block: Cubing Proficiency Assessment

PART 1: CUBING PROFICIENCY ASSESSMENT

In this section, you will be asked to provide some information about your proficiency in the 3x3 Rubik's Cube.



To report your proficiency in solving the 3x3 Rubik's Cube, please follow these instructions.

First, identify your recorded solves. Determine how many solves you have currently logged on a timer platform* (e.g., CSTimer).

Next, select the maximum applicable average. Choose the highest available average you can report from the following options: Single, Average of 5 solves (Ao5), Ao12, Ao25, Ao50, Ao100, Ao200, or Ao500**. Select the corresponding option from the dropdown menu in the first column.

Finally, enter your average solve time. In the second column, input your respective AoN (e.g., Ao200) time in seconds, rounded to the NEAREST HUNDREDTH. Most cubing timers, such as CSTimer, display this value.

Example: If you have recorded 320 solves, the highest average you can report is Ao200. In this case, select "Ao200" from the dropdown menu and enter your most recent Ao200 time in the adjacent field.

*If you do not have solving times logged on a cubing timer, feel free to do a solve on the spot and report your solving time as a "single."

**If you use CSTimer and your session only shows averages up to Ao12, go to "Settings," "Statistics," then "Statistical Indicator" and adjust accordingly.

	Which average are you reporting?	Average Solving Time (Seconds)
		(Round to nearest hundredth) (1)
Adaptive Average Solving Time (A-AoN) (1)	▼ Dropdown list: Single, Ao5, Ao12, Ao25, Ao50, Ao100, Ao200, or Ao500	[Submit answer here]

Page Break

How long have you been **actively cubing** (3x3) in total? Please provide your answer in the form of **years and months**, to the **NEAREST MONTH**.

E.g. 2 years and 5 months; 0 years and 1 months.

Note: If you have not touched a 3x3 cube for at least two weeks, consider this as temporarily quitting.

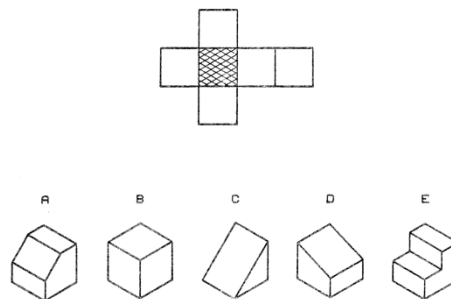
	(To the nearest month)	
	Years (1)	Months (2)
Experience with the 3x3 Rubik's Cube (1)		

End of Block: Cubing Proficiency Assessment

Start of Block: Spatial Visualization Assessment

PART 2: SPATIAL VISUALIZATION ASSESSMENT

In this section, you will complete a standardized assessment to measure your spatial visualization abilities. Please follow the instructions below.





This test consists of 6 questions designed to see how well you can visualize the folding of developments into three-dimensional objects. Shown below is an example of the type of question included in the test.

INSTRUCTIONS: Presented is a development and five three-dimensional objects. The development shows the inside surfaces of a three-dimensional object. **The shaded portion of the development indicates the bottom surface of the three-dimensional object.** You are to:

- Picture in your mind what the development looks like when folded into a three-dimensional object;
- Select from among the five objects (A, B, C, D, or E) the one that looks like the folded development.

What is the correct answer to the example shown above?

Answers A, C, D, and E are wrong. Only object B can be made by folding the given development. Please proceed when you FULLY UNDERSTAND the instructions.

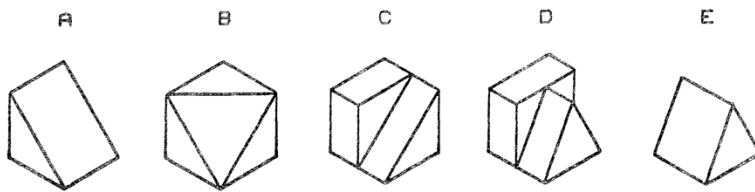
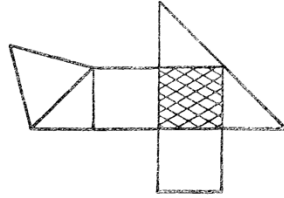
Page Break

IMPORTANT: On the next page, the test will begin. You will have a maximum of **45 seconds** to answer each question. You CANNOT submit your answer **until 5 seconds have passed** or **after the time limit expires**. You will be assessed on both **accuracy** and **speed**. You will be redirected after 30 seconds.

Page Break

Question 1:

1

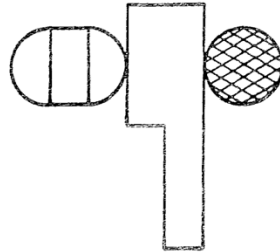


- ☐ A (1)
 - ☐ B (2)
 - ☐ C (3)
 - ☐ D (4)
 - ☐ E (5)
-

Page Break

Question 2:

2



A



B



C



D



E

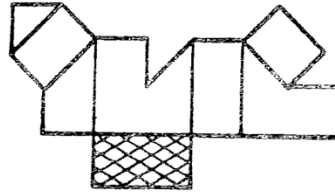


- ☐ A (1)
- ☐ B (2)
- ☐ C (3)
- ☐ D (4)
- ☐ E (5)

Page Break

Question 3:

4



A



B



C



D



E

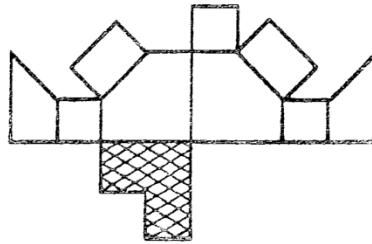


- ☐ A (1)
- ☐ B (2)
- ☐ C (3)
- ☐ D (4)
- ☐ E (5)

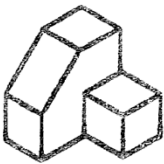
Page Break

Question 4:

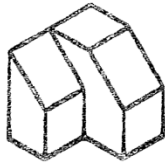
6



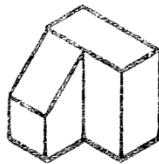
A



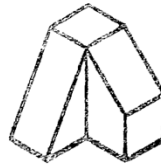
B



C



D



E

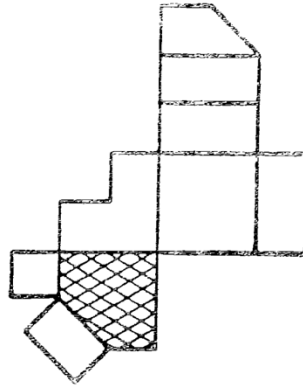


- ☐ A (1)
- ☐ B (2)
- ☐ C (3)
- ☐ D (4)
- ☐ E (5)

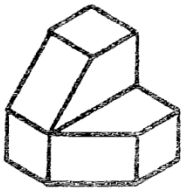
Page Break

Question 5:

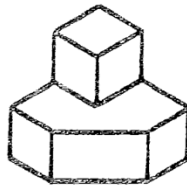
9



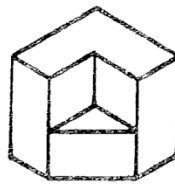
A



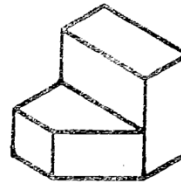
B



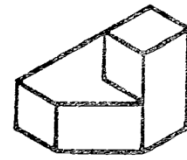
C



D



E

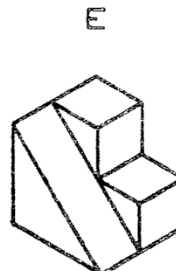
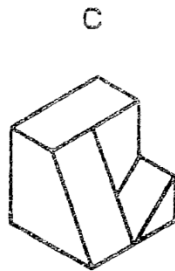
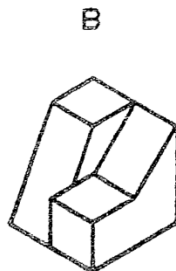
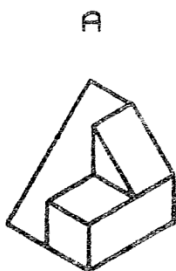
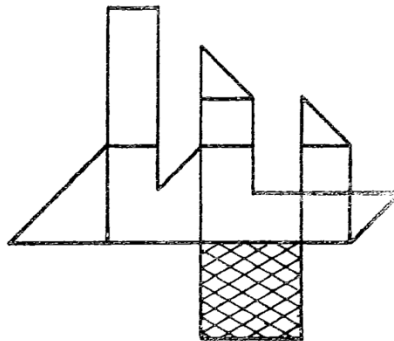


- ☐ A (1)
- ☐ B (2)
- ☐ C (3)
- ☐ D (4)
- ☐ E (5)

Page Break

Question 6:

12



- ☐ A (1)
- ☐ B (2)
- ☐ C (3)
- ☐ D (4)
- ☐ E (5)

End of Block: Spatial Visualization Assessment

Start of Block: Anxiety Level Assessment

PART 3: ANXIETY LEVEL ASSESSMENT

Two more short sections to go!



Perceived Stress Scale 10 (PSS-10)

Please answer the following questions honestly based on your experiences in the past month.
Do so based on your first instinct—this produces more accurate results!

	Never (1)	Almost Never (2)	Sometimes (3)	Fairly Often (4)	Always (5)
In the last month, how often have you been upset because of something that happened unexpectedly? (1)					
In the last month, how often have you felt that you were unable to control the important things in your life? (2)					
In the last month, how often have you felt nervous and stressed? (3)					
In the last month, how often have you felt confident about your ability to handle your personal problems? (4)					
In the last month, how often have you felt that things were going your way? (5)					

In the last month, how often have you found that you could not cope with all the things that you had to do? (6)

In the last month, how often have you been able to control irritations in your life? (7)

In the last month, how often have you felt that you were on top of things? (8)

In the last month, how often have you been angered because of things that happened that were outside of your control? (9)

In the last month, how often have you felt difficulties were piling up so high that you could not overcome them? (10)

End of Block: Anxiety Level Assessment

Start of Block: Personal Information and Demographics

PART 4: GENERAL INFORMATION AND DEMOGRAPHICS

You are on the last section! In this section, you will be asked to provide some basic information about yourself. This data will help ensure that our analysis considers relevant individual differences, such as age, gender, and daily habits.

1. What is your **age**?

0 10 20 30 40 50 60 70

AGE IN YEARS ()



2. What is your **gender**?

- ☐ Male (1)
- ☐ Female (2)
- ☐ Non-binary / third gender (3)
- ☐ Other (4)

3. On average, how many hours of **sleep**, in hours, do you get per day (to the nearest 0.5 hours)?

2 3 3. 4 4. 5 5. 6 6. 7 7. 8 8. 9 9. 1 10 1 1 .5
5 5 5 5 5 5 5 5 5 0 .5 1 1 12

SLEEP PER DAY (HOUR) ()



4. On average, how much time, in minutes, do you spend on **moderate to intense physical activity** per day (to the nearest 10 minutes)?

0 1 2 3 4 5 6 7 8 9 1 1 1 1 1 1 1 1 1
0 0 0 0 0 0 0 0 0 0 0 1 2 3 4 5 6 7 8
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0

PHYSICAL ACTIVITY (MINUTES) ()



5. What is your current / highest level of **education**?

- ☐ Primary School (1)
- ☐ Middle School (2)
- ☐ High School (3)
- ☐ Undergraduate Degree (4)
- ☐ Postgraduate Degree (5)

End of Block: Personal Information and Demographics

APPENDIX 2

The following code includes instructions to run all statistical analyses reported in the manuscript. Analyses were conducted using RStudio version 2024.12.1. The code was formatted with advisory assistance from the large language model *Gemini V3.1 Pro*. However, all analytical decisions and interpretations remain solely our responsibility.

```
#####
# 1.0 SETUP
#####

# 1.1 Workspace
# This script assumes the working directory is set to the location of
# 'data.csv'.
# Set your working directory here if necessary.
# setwd("path/to/your/data/folder")

# 1.2 Load Required Packages
# These packages are necessary for data manipulation, statistical analysis,
# and plotting. Please ensure they are installed before running the script.
library(tidyverse) # For data manipulation and visualization
library(psych)     # For descriptive statistics
library(car)       # For ANOVA and diagnostic tests
library(nortest)   # For Anderson-Darling normality test
library(lmtest)    # For Breusch-Pagan test
library(sandwich)  # For robust standard errors
library(patchwork) # For combining ggplot2 plots

#####
# 2.0 DATA PREPARATION
#####

# 2.1 Import Data
raw_data <- read.csv("data.csv")

# 2.2 Initial Data Cleaning and Selection
# The raw data is first cleaned by selecting relevant columns, removing
# the first two rows which contain metadata, and converting variables
# to the correct data types.
v2.1 <- raw_data %>%
  dplyr::select(
    Q15.2_1_1, Q13.1_1_1, Q13.1_1_2,
    Q21_Page.Submit, Q25_Page.Submit, Q27_Page.Submit,
    Q31_Page.Submit, Q32_Page.Submit, Q33_Page.Submit,
    Q21, Q26, Q28, Q34, Q35, Q36,
    Q17_1, Q17_2, Q17_3, Q17_4, Q17_5, Q17_6, Q17_7, Q17_8, Q17_9, Q17_10,
    Q8_1, Q9, Q10_1, Q11_1, Q12
  ) %>%
  slice(-c(1, 2)) %>% # Remove the first two rows (metadata)
  mutate(
    across(-c(Q9, Q12), as.numeric), # Convert all but Q9 and Q12 to numeric
    gender = as.factor(Q9),
    education = as.factor(Q12)
  ) %>%
  # Replace NA values with 0 in all numeric columns
  mutate(across(where(is.numeric), ~replace_na(.x, 0)))
```

```

# 2.3 Compute Key Variables
# This step calculates the main variables for the analysis from the cleaned
data.
v2.2 <- v2.1 %>%
  transmute(
    # Outcome Variable: Adaptive Average Solving Time (AoN)
    A_AoN = Q15.2_1_1,

    # Predictor: Cubing Experience (in months)
    experience_months = Q13.1_1_1 * 12 + Q13.1_1_2,

    # Predictor: PSVT Composite Score (Accuracy weighted by speed)
    # Score = Correct (1/0) * (Time Saved)
    PSVT_score = if_else(Q21 == 2, 1, 0) * (45 - Q21_Page.Submit) +
      if_else(Q26 == 4, 1, 0) * (45 - Q25_Page.Submit) +
      if_else(Q28 == 2, 1, 0) * (45 - Q27_Page.Submit) +
      if_else(Q34 == 5, 1, 0) * (45 - Q31_Page.Submit) +
      if_else(Q35 == 4, 1, 0) * (45 - Q32_Page.Submit) +
      if_else(Q36 == 4, 1, 0) * (45 - Q33_Page.Submit),

    # Predictor: PSVT Accuracy (Number of correct answers, out of 6)
    PSVT_correct = if_else(Q21 == 2, 1, 0) +
      if_else(Q26 == 4, 1, 0) +
      if_else(Q28 == 2, 1, 0) +
      if_else(Q34 == 5, 1, 0) +
      if_else(Q35 == 4, 1, 0) +
      if_else(Q36 == 4, 1, 0),

    # Predictor: PSVT Average Response Time (in seconds)
    PSVT_avg_time = (Q21_Page.Submit + Q25_Page.Submit + Q27_Page.Submit +
      Q31_Page.Submit + Q32_Page.Submit + Q33_Page.Submit) /
6,

    # Predictor: Perceived Stress Scale (PSS-10) Score
    # Reverse coding for items 4, 5, 7, and 8.
    PSS_10_score = Q17_1 + Q17_2 + Q17_3 + Q17_6 + Q17_9 + Q17_10 -
      Q17_4 - Q17_5 - Q17_7 - Q17_8 + 14,

    # Covariates
    age = Q8_1,
    daily_sleep = Q10_1,
    physical = Q11_1,
    gender = gender,
    education = education
  )

# 2.4 Outlier Removal (Z-Score Method)
# Observations with a Z-score greater than 3 for any numeric variable are
# identified and removed to prevent them from unduly influencing the results.
z_threshold <- 3
numeric_vars <- v2.2 %>% select(where(is.numeric)) %>% names()

v3 <- v2.2 %>%
  rowwise() %>%
  mutate(
    outlier_flag = any(sapply(numeric_vars, function(var) {

```

```

      z_score <- (get(var) - mean(v2.2[[var]]), na.rm = TRUE)) /
sd(v2.2[[var]], na.rm = TRUE)
      abs(z_score) > z_threshold
    )))
  ) %>%
  ungroup() %>%
  filter(outlier_flag == FALSE) %>%
  select(-outlier_flag)

# 2.5 Descriptive Statistics and Sample Demographics
# These commands generate the summary statistics and frequency tables
# reported in the manuscript.
summary(v3)
psych::describe(v3)

cat("\n--- Gender Frequencies ---\n")
print(table(v3$gender))

cat("\n--- Education Frequencies ---\n")
print(table(v3$education))

#####
# 3.0 MAIN ANALYSIS: MULTIPLE LINEAR REGRESSION (MLR)
#####

# A function is defined to streamline the analysis for each model.
# This promotes code reusability and reduces redundancy.
run_mlr_analysis <- function(model_formula, data, model_name) {
  # 3.1 Fit the Linear Model
  model <- lm(model_formula, data = data)

  # 3.2 Diagnostic Tests
  cat("\n===== \n")
  cat("Diagnostics for:", model_name, "\n")
  cat("===== \n")

  # Test for Homoscedasticity (Breusch-Pagan)
  bp_test <- bptest(model)
  cat("\nBreusch-Pagan Test for Homoscedasticity:\n")
  print(bp_test)

  # Test for Normality of Residuals (Anderson-Darling)
  ad_test <- ad.test(resid(model))
  cat("\nAnderson-Darling Test for Normality:\n")
  print(ad_test)

  # Check for Multicollinearity (VIF)
  cat("\nVariance Inflation Factor (VIF):\n")
  print(vif(model))

  # 3.3 Robust Standard Errors (HC1)
  # To address the violation of the normality assumption, robust standard
  # errors are calculated.
  robust_se <- sqrt(diag(vcovHC(model, type = "HC1")))
  robust_results <- coeftest(model, vcov = vcovHC(model, type = "HC1"))

  # 3.4 Calculate Key Statistics
  # - R-squared

```

```

r_squared <- summary(model)$r.squared

# - 95% Confidence Intervals for Coefficients
ci_lower <- coef(model) - 1.96 * robust_se
ci_upper <- coef(model) + 1.96 * robust_se

# - Partial Eta Squared (Effect Size)
anova_table <- Anova(model, type = 3)
ss_total <- sum(anova_table$`Sum Sq`, na.rm = TRUE)
partial_eta_sq <- anova_table$`Sum Sq` / ss_total

# 3.5 Compile Results Table
results_table <- cbind(
  Coefficient = coef(model),
  Robust_SE = robust_se,
  CI_Lower = ci_lower,
  CI_Upper = ci_upper,
  Partial_Eta_Sq = c(partial_eta_sq[1], partial_eta_sq[2],
partial_eta_sq[3]),
  p_value = robust_results[, 4]
)

cat("\n=====\n")
cat("Results for:", model_name, "\n")
cat("=====\n")
print(results_table)
cat("\nR-squared:", r_squared, "\n")

# Return the model object and results for further use
return(list(model = model, results = results_table, r_squared = r_squared))
}

# 3.6 Run All Four MLR Models
# Each model predicts AoN from a main predictor, controlling for experience.
m1 <- run_mlr_analysis(A_AoN ~ PSVT_correct + experience_months, v3, "Model
1: PSVT Accuracy")
m2 <- run_mlr_analysis(A_AoN ~ PSVT_avg_time + experience_months, v3, "Model
2: PSVT Response Time")
m3 <- run_mlr_analysis(A_AoN ~ PSVT_score + experience_months, v3, "Model 3:
PSVT Composite Score")
m4 <- run_mlr_analysis(A_AoN ~ PSS_10_score + experience_months, v3, "Model
4: PSS-10 Score")

#####
# 4.0 FIGURE GENERATION
#####

# 4.1 Q-Q Plots for Normality Check
# These plots visually confirm the deviation from normality.
create_qq_plot <- function(model, title) {
  data.frame(residuals = resid(model)) %>%
    ggplot(aes(sample = residuals)) +
    stat_qq(size = 1.5) +
    stat_qq_line(col = "blue3", linetype = "dashed", linewidth = 0.8) +
    labs(x = "Theoretical Quantiles", y = "Sample Quantiles", title = title)
+
  theme_bw() +
  theme(

```

```

    panel.border = element_rect(color = "grey20", fill = NA, linewidth =
1),
    panel.grid = element_blank(),
    axis.title = element_text(size = 8),
    axis.text = element_text(size = 7)
  )
}

qq_p1 <- create_qq_plot(m1$model, "Model 1")
qq_p2 <- create_qq_plot(m2$model, "Model 2")
qq_p3 <- create_qq_plot(m3$model, "Model 3")
qq_p4 <- create_qq_plot(m4$model, "Model 4")

combined_qq <- (qq_p1 | qq_p2) / (qq_p3 | qq_p4) +
  plot_annotation(tag_levels = 'A') &
  theme(plot.tag = element_text(size = 12, face = "bold"))

print(combined_qq)
ggsave("Figure1_Q-Q_plot.png", plot = combined_qq, width = 6, height = 6, dpi
= 300)

# 4.2 MLR Model Fit Plots
# These plots show the data with the regression line and 95% CI.
format_p <- function(p) { if (p < 0.001) return("< .001") else
return(sprintf("= %.3f", p)) }

# Helper function to generate annotation labels for plots
create_label <- function(r2, p_val, n) {
  sprintf("R² = %.3f\np %s\nN = %d", r2, format_p(p_val), n)
}

create_fit_plot <- function(data, x_var, x_label, y_var, y_label,
model_results, model_name) {
  # Extract the p-value for the main predictor (row 2)
  p_val <- model_results$results[2, "p_value"]
  r2 <- model_results$r_squared
  n <- nrow(data)
  label <- create_label(r2, p_val, n)

  ggplot(data, aes(x = {{ x_var }}, y = {{ y_var }})) +
    geom_smooth(method = "lm", color = "midnightblue", linetype = "dashed",
      linewidth = 0.6, alpha = 0.5, se = TRUE) +
    geom_point(alpha = 1, size = 2, color = "grey20") +
    annotate("text", x = Inf, y = Inf, label = label,
      hjust = 1.15, vjust = 1.15, size = 3.5, fontface =
"bold.italic", color = "black") +
    labs(x = x_label, y = y_label, title = model_name) +
    theme_bw() +
    theme(
      panel.border = element_rect(color = "black", fill = NA, linewidth = 1),
      panel.grid = element_blank(),
      axis.title = element_text(size = 10),
      axis.text = element_text(size = 8.5)
    )
}

# Generate the four plots
p1 <- create_fit_plot(v3, PSVT_correct, "PSVT Correct Answers (out of 6)",

```

```

      A_AoN, "AoN (s)", m1, "Model 1: PSVT Accuracy")
p2 <- create_fit_plot(v3, PSVT_avg_time, "PSVT Average Time (s)",
      A_AoN, "AoN (s)", m2, "Model 2: PSVT Response Time")
p3 <- create_fit_plot(v3, PSVT_score, "PSVT Composite Score (out of 240)",
      A_AoN, "AoN (s)", m3, "Model 3: PSVT Composite Score")
p4 <- create_fit_plot(v3, PSS_10_score, "PSS-10 Score (out of 40)",
      A_AoN, "AoN (s)", m4, "Model 4: PSS-10 Score")

# Combine and save
combined_fits <- (p1 | p2) / (p3 | p4) +
  plot_annotation(tag_levels = 'A') &
  theme(plot.tag = element_text(size = 12, face = "bold"))

print(combined_fits)
ggsave("Figure2_MLR_Model_Fits.png", plot = combined_fits, width = 8, height
= 7, dpi = 300)

#####
# 5.0 SENSITIVITY ANALYSIS
#####

# 5.1 Compare Datasets
cat("\n===== \n")
cat("SENSITIVITY ANALYSIS \n")
cat("===== \n")
cat("Original dataset (outliers removed):", nrow(v3), "participants \n")
cat("Raw dataset (includes outliers):", nrow(v2.2), "participants \n")
cat("Number of outliers excluded:", nrow(v2.2) - nrow(v3),
"participants \n \n")

# 5.2 Re-run Models on Unfiltered Data
# This function runs the same four models on a given dataset.
run_sensitivity_models <- function(data) {
  list(
    m1 = lm(A_AoN ~ PSVT_correct + experience_months, data = data),
    m2 = lm(A_AoN ~ PSVT_avg_time + experience_months, data = data),
    m3 = lm(A_AoN ~ PSVT_score + experience_months, data = data),
    m4 = lm(A_AoN ~ PSS_10_score + experience_months, data = data)
  )
}

# Run models on both datasets
models_main <- run_sensitivity_models(v3)
models_sens <- run_sensitivity_models(v2.2)

# 5.3 Extract and Compare Key Coefficients
# A helper function to extract robust p-values for the main predictor
extract_p <- function(model, predictor) {
  coeftest(model, vcov = vcovHC(model, type = "HC1"))[predictor, "Pr(>|t|)"]
}

compare_predictors <- c("PSVT_correct", "experience_months", "PSVT_avg_time",
  "PSVT_score", "PSS_10_score")
model_names <- c("m1", "m1", "m2", "m3", "m4")

comparison <- data.frame(
  Predictor = compare_predictors,
  P_Main = sapply(seq_along(compare_predictors), function(i) {

```

```

    extract_p(models_main[[model_names[i]]], compare_predictors[i])
  }),
  P_Sens = sapply(seq_along(compare_predictors), function(i) {
    extract_p(models_sens[[model_names[i]]], compare_predictors[i])
  })
)

comparison$Sig_Main <- ifelse(comparison$P_Main < 0.05, "SIGNIFICANT", "non-
significant")
comparison$Sig_Sens <- ifelse(comparison$P_Sens < 0.05, "SIGNIFICANT", "non-
significant")

cat("\nComparison of p-values for Main Predictors:\n")
print(comparison)

# 5.4 Assess Overall Impact
cat("\n--- Impact on Statistical Significance ---\n")
sig_changes <- sum(comparison$Sig_Main != comparison$Sig_Sens)

if(sig_changes == 0) {
  cat("No major changes in statistical significance. Results are robust to
outlier exclusion.\n")
} else {
  cat("!", sig_changes, "predictor(s) changed significance. Outliers may
influence conclusions.\n")
}

```