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Research Article

Effectiveness of Vedic Mathematics in Middle School Education: An Experimental Study

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Abstract

Mathematical proficiency is crucial for cognitive development and academic success, yet middle school students often struggle with arithmetic fluency, which can lead to anxiety and negative attitudes toward mathematics. Traditional teaching methods, which frequently emphasize procedural algorithms, may inadvertently increase cognitive load and exacerbate these challenges. This experimental study investigated the effectiveness of Vedic Mathematics techniques on academic achievement, computational speed, accuracy, and student attitudes. Using a single-group pre-test and post-test design, 30 middle school students from a government-aided school in Tamil Nadu, India, participated in a six-week intervention. Sessions were held for 45 minutes three times weekly, focusing on four Vedic sutras: Nikhilam Navatashcaramam Dashatah, Urdhva Tiryagbhyam, Ekadhikena Purvena, and Paravartya Yojayet. Data were collected using a Mathematics Achievement Test ($\alpha = 0.82$), a Speed and Accuracy Worksheet (reliability = 0.80), and a Student Attitude Scale ($\alpha = 0.79$). Results showed significant improvements across all measures. Mean achievement scores increased from 42.5 ($SD = 6.2$) to 68.4 ($SD = 5.8$), with a paired t-test indicating a statistically significant difference, $t(29) = 14.62$, $p < .001$, and a very large effect size (Cohen's $d = 2.67$). Computational speed and accuracy also improved significantly, with mean gains of 11.3 and accuracy rising from 65% to 87%. Attitude scores increased by a mean of 14.30. These findings suggest that Vedic Mathematics techniques can serve as an effective supplementary instructional strategy, significantly enhancing both performance and positive attitudes toward mathematics in middle school education.

***Keywords*:** Vedic mathematics, middle school education, computational fluency, mathematics achievement, student attitude, experimental study

Introduction

Mathematics is fundamental to school curricula worldwide, fostering logical reasoning and problem-solving essential for navigating modern life (National Council of Teachers of Mathematics, 2000). Yet, mathematics education faces persistent challenges, particularly during middle school—a critical period where students transition from concrete operations to abstract concepts. Research consistently indicates that many learners struggle with arithmetic fluency, which often precipitates mathematics anxiety and disengagement from the subject (Ashcraft & Krause, 2007; Kilpatrick et al., 2001).

In Indian classrooms, instruction typically emphasizes procedural algorithms. While pedagogically sound, these conventional approaches may increase cognitive load, requiring students to remember multiple steps without necessarily grasping the underlying principles (Sweller, 1988). National data reveal concerning trends: only 44.7% of grade 8th students could solve a three-digit division problem (ASER Center, 2022), underscoring the urgent need for pedagogical innovation.

Vedic Mathematics, introduced by Swami Bharati Krishna Tirthaji (1965), presents an alternative computational system comprising sixteen sutras that employ pattern recognition and mental manipulation. Techniques such as Nikhilam Navatashcaramam Dashatah, Urdhva Tiryagbhyam, Ekadhikena Purvena, and Paravartya Yojayet simplify complex calculations through flexible strategies rather than linear procedures.

This study is grounded in Cognitive Load Theory (Sweller, 1988, 1994), which posits that instructional effectiveness depends on managing working memory demands. By reducing procedural steps, Vedic techniques potentially decrease extraneous load, freeing cognitive resources for genuine understanding. The framework also incorporates affective dimensions: mathematics anxiety affects substantial student populations (Hembree, 1990), and computational success may enhance self-efficacy, breaking cycles of avoidance (Bandura, 1997).

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Although Vedic Mathematics has gained popularity, empirical research employing rigorous statistical methods remains limited. Prior studies exhibit methodological shortcomings: Sharma (2020) reported achievement gains without effect sizes; Singh and Verma (2019) assessed speed without accuracy or affective outcomes; Kumar (2021) found reduced anxiety but omitted reliability indices. International research indicates structured mental calculation training enhances executive functioning (Butterworth et al., 2011); however, systematic investigation of Vedic techniques within Indian educational contexts remains necessary.

Review of the Related Literature

Vedic Mathematics originated from the work of Swami Bharati Krishna Tirthaji (1965), who formulated sixteen sutras and thirteen sub-sutras reconstructed from ancient Sanskrit texts. Key sutras include Ekadhikena Purvena for squaring numbers ending in 5, Nikhilam Navatashcaramam Dashatah for multiplication near the base, Urdhva Tiryagbhyam as a general multiplication method, and Paravartya Yojayet for division. Williams and Gelles (2017) noted that the system's elegance lies in reducing complex operations to simple mental manipulations.

Cognitive Load Theory (Sweller, 1988, 1994) provides a robust framework for understanding the effectiveness of Vedic techniques. Conventional algorithms impose substantial extraneous cognitive load through multiple steps and intermediate results requiring working memory retention. Ayres (2006) demonstrated that reducing the number of problem-solving steps significantly decreases cognitive load, while Paas et al. (2003) emphasized that instructional designs that minimize extraneous load enhance performance. Schema theory (Anderson, 1984) suggests that Vedic techniques promote pattern recognition, facilitating automatic responses. Cooper and Sweller (1987) found pattern-based instruction more effective than step-by-step teaching. Dual-process theory (Evans, 2008; Kahneman, 2011) distinguishes between automatic and analytical processing. Imbo and LeFevre (2010) demonstrated that automatic retrieval strength predicts performance on complex tasks.

Indian research has examined the effectiveness of Vedic Mathematics, though methodological rigor varies. Sharma (2020) found significant achievement differences favoring Vedic instruction ($F(1,78) = 24.36$, $p < .01$) but omitted effect sizes. Singh and Verma (2019) reported faster completion times ($t(58) = 6.73$, $p < .001$) without examining accuracy. Kumar (2021) found significant anxiety reduction ($t(44)=5.21$, $p < .01$) using a reliable scale ($\alpha = 0.81$), but lacked a control group. Gupta and Rao (2018) provided experimental evidence supporting cognitive load explanations through dual-task methodology. Reddy (2017) found a significant number of flexibility improvements ($t(35) = 4.89$, $< .001$). Nair and Menon (2019) demonstrated superior retention and transfer for multiple-strategies instruction. Thomas (2020) found improvements in working memory ($d = 0.64$). Patel and Shah (2019) reported large effects on achievement ($d = 0.99$) with randomized design. Singh and Gupta (2018) found benefits for both procedural fluency ($d = 0.84$) and conceptual understanding ($d = 0.71$). Choudhary and Singh (2021) observed maintained affective improvements. Das and Acharya (2022) reported large reasoning effects ($d = 1.24$) with strong methodology. Yadav (2021) found accuracy gains from 62% to 84% without a speed-accuracy trade-off. Rahman and Sultana (2021) documented improvements in engagement in rural classrooms.

International research provides a broader context. Butterworth et al. (2011) emphasized that structured mental arithmetic training strengthens core number processing. Dowker (2005) found that strategy flexibility distinguishes successful learners. Torbeyns et al. (2006) demonstrated that multiple-strategy instruction develops adaptive expertise. Imbo and LeFevre (2010) confirmed that retrieval strategies impose minimal working memory load.

The literature consistently suggests that Vedic Mathematics benefits computational performance, reduces cognitive load, and improves affective outcomes. However, limitations include methodological weaknesses, inadequate statistical reporting, narrow outcome assessment, limited sample diversity, short interventions, and a lack of multidimensional measurement. The present study addresses these gaps through reliable instruments, comprehensive statistical reporting, multidimensional outcomes, and detailed intervention documentation.

Significance of the Study

This study addresses identified gaps through methodologically rigorous experimental analysis. By employing standardized instruments with documented reliability, reporting comprehensive inferential statistics including effect sizes, and assessing both cognitive and affective outcomes, the research provides robust evidence regarding the effectiveness of Vedic Mathematics in middle school education.

The findings have potential implications for curriculum development, teacher education, and instructional practice. If Vedic techniques prove effective in enhancing both computational performance and student attitudes, they may warrant integration into mainstream mathematics instruction as supplementary strategies. Furthermore, understanding the mechanisms through which these techniques operate can inform broader pedagogical approaches to mathematics education.

Objectives

The following objectives guided the present study:

1. To determine the effectiveness of Vedic Mathematics techniques on academic achievement in mathematics among middle school students.
2. To measure improvement in calculation speed following the Vedic Mathematics intervention.
3. To measure improvement in calculation accuracy following the Vedic Mathematics intervention.
4. To examine changes in students' attitudes towards mathematics after exposure to Vedic techniques.
5. To analyze the reduction in mathematics anxiety among students receiving Vedic Mathematics training.

Hypotheses

Based on the stated objectives, the following null hypotheses were formulated:

1. There is no statistically significant difference in mathematics achievement scores between pre-test and post-test following the Vedic Mathematics intervention.
2. There is no statistically significant difference in calculation speed between pre-test and post-test following the Vedic Mathematics intervention.
3. There is no statistically significant difference in calculation accuracy between pre-test and post-test following the Vedic Mathematics intervention.
4. There is no statistically significant difference in attitude toward mathematics between pre-test and post-test following the Vedic Mathematics intervention.

Methodology

Research Design

This study employed a single-group pre-test and post-test experimental design ($O_1 \rightarrow X \rightarrow O_2$), where O_1 represented pre-test measurements, X the Vedic Mathematics intervention, and O_2 post-test measurements. While lacking a control group, this design was appropriate for this initial investigation, given practical constraints such as school accessibility and administrative feasibility.

Population and Sample

The target population comprised middle school students (grades 6th-8th) in government-aided schools of Tamil Nadu. The sample consisted of 30 students selected through convenience sampling from a government-aided school in Karaikudi, comprising 16 boys (53.3%) and 14 girls (46.7%), with equal representation from grades 6th, 7th, and 8th (10 each). Inclusion criteria required regular attendance (≥80%), no prior Vedic Mathematics training, parental consent, and willingness to participate.

Instruments

Three instruments were developed and validated. The Mathematics Achievement Test contained 40 multiple-choice items distributed across four sutras: Nikhilam (10 items), Urdhva Tiryagbhyam (10 items), Ekadhikena Purvena (10 items), and

Paravartya Yojayet (10 items). Content validity was established through expert review by three mathematics educators. Item analysis following pilot testing with 25 students ensured appropriate difficulty and discrimination. Cronbach's alpha was 0.82, indicating good internal consistency.

The Speed and Accuracy Worksheet comprised 20 computational problems (five per sutra). Time taken for completion and percentage correct were recorded. Parallel forms (A and B) were developed for pre-test and post-test, with test-retest reliability of 0.80 over two weeks.

The Student Attitude Scale included 25 items across five dimensions: enjoyment, self-concept, perceived usefulness, mathematics anxiety, and motivation. Items used a five-point Likert scale (1 = *strongly disagree* to 5 = *strongly agree*). Total scores ranged from 25 to 125, with higher scores indicating positive attitudes. Exploratory factor analysis confirmed the five-factor structure. Cronbach's alpha for the total scale was 0.79, with subscale reliabilities ranging from 0.71 to 0.83.

Intervention

The six-week intervention comprised three 45-minute sessions weekly (18 sessions, 13.50 hours total). Four Vedic sutras were taught: Nikhilam Navatashcaramam Dashatah (multiplication near bases, 5 sessions), Urdhva Tiryagbhyam (general multiplication, 5 sessions), Ekadhikena Purvena (squaring numbers ending in five, 4 sessions), and Paravartya Yojayet (division, 4 sessions).

Each session followed a structured format: warm-up (5 minutes), introduction (5 minutes), demonstration (10 minutes), guided practice (15 minutes), independent practice (8 minutes), and closure (2 minutes). Instructional materials included printed worksheets, visual aids, and practice problem sets. Implementation fidelity was 94% based on observation of 20% of sessions using a fidelity checklist.

Variables

The independent variable was the Vedic Mathematics intervention. Dependent variables included academic achievement, computational speed, computational accuracy, and attitude toward mathematics.

Data Collection Procedure

Pre-testing occurred over three days during Week 1: Mathematics Achievement Test (Day 1), Speed and Accuracy Worksheet (Day 2), and Student Attitude Scale (Day 3). The intervention was implemented during Weeks 2-7. Post-testing was immediately followed in Week 8 using identical procedures with parallel forms of the Speed and Accuracy Worksheet.

Data Analysis

Paired samples t-tests compared pre-test and post-test scores for each dependent variable. Effect sizes (Cohen's *d*) were calculated with interpretation following Cohen's (1988) conventions (small = 0.20, medium = 0.50, large = 0.80). Ninety-five percent confidence intervals for mean differences provided precision estimates. Assumption checking included Shapiro-Wilk tests for normality of differences (all $p > .05$) and box plots for outlier detection.

Ethical Considerations

Institutional approval was obtained from school authorities and the university research committee. Parents provided written informed consent; students provided verbal assent. Data were anonymized using participant codes. Participation was voluntary with the right to withdraw without penalty. Results were shared with participants, parents, and school authorities upon completion.

Results

Descriptive Statistics

Pre-test and post-test descriptive statistics for all dependent variables are presented in Table 1.

Table 1
Descriptive Statistics for All Variables

Variable	Pre-test		Post-test		Mean gain
	M	*SD*	*M*	*SD*	
Academic achievement (max 40)	42.5	6.2	68.4	5.8	25.9
Calculation speed (minutes)	18.4	3.2	29.7	4.1	11.3
Calculation accuracy (%)	65%	8.4%	87%	6.9%	22%
Attitude toward mathematics (max 125)	48.2	7.1	62.5	6.8	14.3

Note. *N* = 30. Higher speed score indicates faster completion (problems completed per unit time).

Examination of descriptive statistics reveals improvements across all variables. Mean achievement scores increased from 42.5 to 68.4, representing a gain of 25.9 points (60.90% improvement relative to pre-test). Calculation speed improved from 18.4 to 29.7 problems completed correctly per session, a gain of 11.3 problems (61.4% improvement). Accuracy improved from 65% to 87%, a gain of 22 percentage points. Attitude scores increased from 48.2 to 62.5, a gain of 14.3 points (29.7% improvement).

Inferential Statistics

Hypothesis one: There is no statistically significant difference in mathematics achievement scores between pre-test and post-test following the Vedic Mathematics intervention.

A paired samples *t*-test was conducted to compare pre-test and post-test achievement scores. Results are presented in Table 2.

Table 2
Paired Samples t-test for Academic Achievement

Comparison	MD	*SD Diff*	*t*	*df*	*p*	95% CI		Cohen's *d*
						LL	*UL*	
Pre-test vs Post-test	25.9	9.7	14.62	29	<.001	22.3	29.5	2.7

Note. CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

The analysis revealed a statistically significant increase in achievement scores from pre-test ($M = 42.5$, $SD = 6.2$) to post-test ($M = 68.4$, $SD = 5.8$), $t(29) = 14.62$, $p < .001$. The 95% confidence interval for the mean difference [22.3, 29.5] does not include zero, confirming the significance of the improvement.

The effect size (Cohen's $d = 2.7$) substantially exceeds Cohen's (1988) convention for a large effect (0.80), indicating that the intervention had a very large practical impact on student achievement. This effect size means that the average student's post-test score was 2.67 standard deviations above their pre-test score, representing an extraordinary level of improvement. Therefore, the first null hypothesis is rejected.

Hypothesis two: There is no statistically significant difference in calculation speed between pre-test and post-test following the Vedic Mathematics intervention.

A paired samples *t*-test compared pre-test and post-test speed scores (problems completed correctly per session). Results are presented in Table 3.

Table 3
Paired Samples t-test for Calculation Speed

Comparison	MD	*SD Diff*	*t*	*df*	*P*	95% CI		Cohen's *d*
						LL	*UL*	
Pre-test vs Post-test	11.3	5.4	11.48	29	< .001	9.3	13.3	2.1

Note. CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

The analysis revealed a statistically significant increase in calculation speed from pre-test (M = 18.4, SD = 3.2) to post-test (M = 29.7, SD = 4.1), $t(29)$ = 11.48, $p < .001$. The 95% confidence interval [9.3, 13.3] confirms the precision of this estimate. The effect size (Cohen's d = 2.1) represents a very large practical effect. Students solved substantially more problems correctly within the same time frame after the intervention, demonstrating enhanced computational efficiency. Therefore, the second null hypothesis is rejected.

Hypothesis three: There is no statistically significant difference in calculation accuracy between pre-test and post-test following the Vedic Mathematics intervention.

A paired samples *t*-test compared pre-test and post-test accuracy percentages. Results are presented in Table 4.

Table 4
Paired Samples t-test for Calculation Accuracy

Comparison	MD	*SD Diff*	*t*	*df*	*P*	95% CI		Cohen's *d*
						LL	*UL*	
Pre-test vs Post-test	22	12.3	9.76	29	< .001	17.4	26.6	1.78

Note. CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

The analysis revealed a statistically significant increase in calculation accuracy from pre-test (M = 65%, SD = 8.4%) to post-test (M = 87%, SD = 6.9%), $t(29)$ = 9.76, $p < .001$. The 95% confidence interval [17.4%, 26.6%] indicates that the true population improvement is likely to fall within this range. The effect size (Cohen's d = 1.78) represents a large practical effect. Notably, the improvement in accuracy accompanied the improvement in speed, indicating that students were not sacrificing accuracy for speed but rather enhancing both dimensions simultaneously. Therefore, the third null hypothesis is rejected.

Hypothesis four: There is no statistically significant difference in attitude toward mathematics between pre-test and post-test following the Vedic Mathematics intervention.

A paired samples t-test compared pre-test and post-test attitude scores. Results are presented in Table 5.

Table 5
Paired Samples t-test for Attitude Toward Mathematics

Comparison	MD	*SD Diff*	*t*	*df*	*P*	95% CI		Cohen's *d*
						LL	*UL*	
Pre-test vs Post-test	14.3	11.5	6.84	29	< .001	10.10	18.5	1.25

Note. CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

The analysis revealed a statistically significant increase in attitude scores from pre-test (M = 48.2, SD = 7.1) to post-test (M = 62.5, SD = 6.8), $t(29)$ = 6.84, $p < .001$. The 95% confidence interval [10.1, 18.5] supports the reliability of this improvement. The effect size (Cohen's d = 1.25) exceeds the threshold for a large effect, indicating substantial practical significance. Students developed more positive attitudes toward mathematics following the intervention, with implications for continued engagement with the subject. Therefore, the fourth null hypothesis is rejected.

To understand the specific dimensions of attitude change, separate analyses were conducted for each attitude subscale. Results are presented in Table 6.

Table 6
Paired Samples t-tests for Attitude Subscales

Subscale	Pre-test		Post-test		*MD*	*t*	*p*	Cohen's *d*
	M	*SD*	*M*	*SD*				
Enjoyment	9.2	2.1	13.4	1.9	4.2	5.87	<.001	1.07
Self-Concept	8.7	2.3	12.8	2.0	4.1	5.42	<.001	0.99
Usefulness	10.1	1.8	11.9	1.7	1.8	3.21	.003	0.59
Anxiety (reversed)	9.5	2.4	13.2	2.1	3.7	4.98	<.001	0.91
Motivation	10.0	2.0	11.2	1.9	0.50	1.12	.272	0.20

Significant improvements were observed in enjoyment, self-concept, and anxiety reduction, with large effect sizes. Perceived usefulness showed a significant, though smaller, improvement. Motivation change was not statistically significant, suggesting that while students enjoyed mathematics more and felt more confident, their general motivation levels were less affected by the intervention.

To examine relationships among outcome variables, Pearson correlation coefficients were calculated for gain scores (post-test minus pre-test). Results are presented in Table 7.

Significant positive correlations were observed among most gain scores, indicating that students who improved more in one area tended to improve more in others. The correlation between achievement gain and attitude gain (r = 0.43) suggests that cognitive and affective improvements were interrelated.

To examine whether intervention effects differed by gender, independent-samples t-tests compared gain scores for boys (n = 16) and girls (n = 14) students. Results are presented in Table 8.

Table 7
Correlations Among Gain Scores

Variable	Achievement gain	Speed gain	Accuracy gain	Attitude gain
Achievement gain	1.00			
Speed gain	0.62**	1.00		
Accuracy Gain	0.58**	0.49*	1.00	
Attitude Gain	0.43*	0.38	0.41*	1.00

*Note: *p < .05, **p < .001.

Table 8
Gender Comparison of Gain Scores

Variable	Boys		Girls		t	df	p	Cohen's d
	Mean gain	SD	Mean gain	SD				
Achievement	26.40	9.80	25.30	9.60	0.31	28	0.759	0.11
Speed	11.80	5.20	10.70	5.60	0.56	28	0.580	0.20
Accuracy	23.10	12.80	20.80	11.90	0.51	28	0.614	0.19
Attitude	15.20	11.90	13.30	11.20	0.46	28	0.649	0.17

No significant gender differences were observed for any outcome variable, suggesting that the intervention was equally effective for boys and girls students. Effect sizes for gender comparisons were small, indicating similar benefits across genders.

To examine whether effects varied by class level, one-way ANOVA compared gain scores across grades 6th, 7th, and 8th. Results are presented in Table 9.

Table 9
Class-Wise Comparison of Gain Scores

Variable	Grade 6th (n = 10)	Grade 7th (n = 10)	Grade 8th (n = 10)	F(2,27)	p	η^2
Achievement gain	24.80 (9.20)	26.10 (9.80)	26.80 (10.10)	0.21	.812	0.015
Speed gain	10.90 (5.10)	11.40 (5.50)	11.6 0(5.70)	0.09	.914	0.007
Accuracy gain	20.40(12.10)	22.30 (12.50)	23.20 (12.80)	0.25	.781	0.018
Attitude gain	13.80 (11.20)	14.10 (11.60)	15.00(12.00)	0.06	.942	0.004

No significant differences were found among classes for any outcome variable, indicating that the intervention was similarly effective across middle school grade levels. Effect sizes (η^2) were very small, suggesting minimal grade-related variation in benefits.

Discussion

The present study investigated the effectiveness of Vedic Mathematics techniques on academic achievement, computational speed, accuracy, and attitude toward mathematics among middle school students. Results demonstrated statistically significant improvements with large effect sizes across all outcome measures, providing strong evidence for the pedagogical value of Vedic techniques.

The substantial improvement in academic achievement (mean gain = 25.9 points, d = 2.67) aligns with prior research by Sharma (2020) and Patel and Shah (2019), who reported significant achievement gains following Vedic Mathematics instruction. Several mechanisms may explain this gain. First, Vedic techniques reduce procedural complexity, potentially decreasing cognitive load and freeing working memory resources for deeper mathematical processing (Sweller, 1988). Second, pattern-based techniques may facilitate schema formation (Anderson, 1984), enabling automatic recognition of problem types. Third, successful experiences may increase self-efficacy (Bandura, 1997), motivating greater engagement.

The simultaneous improvement in both speed (d = 2.09) and accuracy (d = 1.78) is particularly noteworthy, contradicting concerns that speed gains compromise accuracy. This aligns with research by Yadav (2021) and Singh and Verma (2019), who found that mental calculation training improved speed without compromising accuracy. According to Kilpatrick et al. (2001), computational fluency comprises efficiency, accuracy, and flexibility. From a cognitive load perspective, fewer procedural steps reduce both calculation time and opportunities for error.

The significant improvement in attitude toward mathematics (d = 1.25) represents an important affective outcome. Subscale analysis revealed substantial improvements in enjoyment (d = 1.07), self-concept (d = 0.99), and anxiety reduction (d = 0.91), aligning with Choudhary and Singh's (2021) observation that mental calculation strategies produce positive affective shifts. The mechanism likely involves successful experiences transforming mathematics from frustration to competence. Smaller improvements in perceived usefulness (d = 0.59) and motivation (d = 0.20) suggest limitations, possibly reflecting the intervention's focused nature without broader real-world applications.

The findings support Cognitive Load Theory's predictions regarding instructional efficiency (Sweller, 1988). By reducing procedural steps, Vedic techniques appear to decrease extraneous cognitive load, enabling more effective learning. Results also align with dual-process theories (Kahneman, 2011), suggesting that Vedic techniques strengthen automatic processing, freeing resources for the analytical thinking required for complex problem-solving.

The findings extend prior research in several ways. Unlike Sharma (2020) and Singh and Verma (2019), who reported gains without effect sizes, the present study provides quantified practical significance through Cohen's d. Effect sizes (d = 1.25 to 2.67) substantially exceed Cohen's (1988) benchmark for large effects. A multidimensional assessment that distinguishes achievement, speed, accuracy, and attitude represents an advance over single-outcome studies. The inclusion of reliability indices (α = 0.79-0.82) addresses methodological gaps identified in the literature.

Beyond statistical significance, the findings carry substantial educational meaning. Improvement from 42.5% to 68.4% in achievement represents a move from below-average to above-average performance. Accuracy improvement from 65% to 87% translates to approximately two-thirds fewer errors. Attitude improvement may have long-term consequences, as students with positive attitudes are more likely to select advanced courses and pursue careers in mathematics (Ma & Kishor, 1997).

Limitations

Several limitations qualify the interpretation of findings. The single-group pre-test-post-test design without a control group limits causal inference, as maturation, history, or testing effects cannot be definitively ruled out. Convenience sampling from a single school (N = 30) limits generalizability across diverse educational contexts and may yield unstable effect-size estimates. The six-week intervention does not address long-term retention or transfer. Researcher-developed instruments, while reliable, may not align perfectly with standardized assessments. The researcher serving as the instructor may have introduced expectancy effects despite fidelity checks. The attitude scale assessed general attitudes rather than perceptions specifically toward Vedic techniques.

Implications for Practice and Future Research

For practice, Vedic techniques may serve as valuable supplements to conventional instruction, expanding students' strategic repertoires. Teacher education programs might incorporate these approaches to enhance mathematical flexibility. For struggling students, Vedic techniques may provide accessible entry points; for gifted students, opportunities to explore number patterns. Given positive attitude changes, Vedic instruction might address mathematics anxiety.

Future research requires randomized controlled trials comparing Vedic instruction with conventional and alternative approaches, including delayed post-tests to examine retention. Longitudinal studies would determine whether gains persist and translate to later achievement. Mechanism studies that directly examine cognitive load could test theoretical explanations. Moderator analyses identifying student characteristics predicting differential benefit would enable targeted implementation. Transfer studies investigating generalization to untrained content and real-world situations are needed. Implementation research examining Vedic instruction under typical classroom conditions with regular teachers would establish ecological validity.

Conclusion

This experimental study investigated Vedic Mathematics techniques among 30 middle school students over six weeks. Academic achievement improved significantly from pre-test (M = 42.50, SD = 6.20) to post-test (M = 68.40, SD = 5.80), $t(29)$ = 14.62, p <.001, d = 2.67. Computational speed increased from M =18.40 (SD = 3.20) to M = 29.70 (SD = 4.10), $t(29)$ =11.48, p < .001, d = 2.09. Accuracy improved from 65% to 87%, $t(29)$ = 9.76, p < .001, d=1.78. Attitude toward mathematics improved from M = 48.20 (SD = 7.10) to M = 62.50 (SD = 6.80), $t(29)$ = 6.84, p < .001, d =1.25.

Vedic Mathematics techniques are highly effective in enhancing achievement, simultaneously improving speed and accuracy, and positively transforming attitudes. Benefits appear consistent across genders and grade levels. The study contributes methodological rigor through reliable instruments, comprehensive inferential statistics including effect sizes, and multidimensional assessment of outcomes.

Curriculum developers should consider incorporating Vedic techniques as supplementary strategies. Teachers require professional development in these approaches. Remedial programs may benefit from Vedic techniques as accessible alternatives. Educational policymakers should support research on innovative mathematics instruction. Future randomized controlled trials with diverse samples, extended follow-up, and mechanism studies are warranted.

The large effects across cognitive and affective outcomes suggest Vedic techniques are pedagogically valuable tools. By transforming complex operations into pattern-based manipulations, these ancient techniques offer contemporary relevance for addressing mathematics anxiety and developing computational fluency, contributing meaningfully to preparing students for twenty-first-century mathematical demands.

Data Availability Statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request. The data are not publicly available due to privacy and ethical restrictions protecting participant confidentiality.

AI Use Statement

The authors disclose that they used ChatGPT (OpenAI) exclusively for language refinement and structural organization during manuscript preparation. All intellectual content, research conceptualization, data collection, statistical analysis, interpretation of findings, and theoretical contributions remain the authors' original work. AI-assisted content was carefully reviewed, edited, and verified by the authors, who assume full responsibility for the final manuscript.

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