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The Effectiveness of Visualization on Cognitive Load and Problem-Solving in Gifted and Non-Gifted Students

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Título: La eficacia de la visualización en la carga cognitiva y la resolución de problemas en estudiantes superdotados y no superdotados.

Resumen: Este estudio examinó el impacto de las técnicas de visualización en el rendimiento en la resolución de problemas matemáticos y la carga cognitiva en 80 estudiantes varones de secundaria (40 superdotados y 40 no superdotados) en Arabia Saudita. Utilizando un diseño experimental pretest-postest, los participantes fueron asignados a un grupo experimental o de control, con cada grupo dividido en dos clases: una para estudiantes superdotados (n = 20) y otra para estudiantes no superdotados (n = 20). El grupo experimental recibió instrucción basada en la visualización (por ejemplo, visualización dinámica, herramientas interactivas), mientras que el grupo de control siguió métodos tradicionales. Los datos se analizaron mediante ANOVA de medidas mixtas de dos vías y un MANOVA. El grupo experimental superó significativamente al grupo de control en la resolución de problemas, $F(1, 76) = 99.45$, $p < .001$, $\eta^2_p = .57$, y experimentó una reducción en la carga cognitiva, $F(1, 76) = 47.40$, $p < .001$, $\eta^2_p = .37$. Surgió un efecto de interacción significativo (Wilks' $\Lambda = .88$, $F(2, 75) = 5.12$, $p = .008$, $\eta^2 = .12$), con los estudiantes superdotados del grupo experimental obteniendo las puntuaciones más altas ($M = 88.45$, $SD = 4.29$) y la menor carga cognitiva ($M = 3.05$, $SD = 0.61$). Estos hallazgos destacan la visualización como una estrategia efectiva para mejorar la enseñanza de las matemáticas, especialmente para estudiantes superdotados, beneficiando también a los no superdotados. Los resultados respaldan la integración de estrategias de instrucción inclusivas para mejorar la resolución de problemas y la eficiencia cognitiva.

Palabras clave: Técnicas de visualización. Carga cognitiva. Resolución de problemas matemáticos. Estudiantes superdotados. Educación matemática. Arabia Saudita.

Abstract: This study examined the impact of visualization techniques on mathematical problem-solving performance and cognitive load among 80 male high school students (40 gifted, 40 non-gifted) in Saudi Arabia. Using a pretest-posttest experimental design, participants were assigned to an experimental or control group, with each group further divided into two classes: one for gifted students (n = 20) and one for non-gifted students (n = 20). The experimental group received visualization-based instruction (e.g., dynamic visualization, interactive tools), while the control group followed traditional methods. Data were analyzed using two-way mixed ANOVAs and a MANOVA. The experimental group significantly outperformed the control group in problem-solving, $F(1, 76) = 99.45$, $p < .001$, $\eta^2_p = .57$, and experienced reduced cognitive load, $F(1, 76) = 47.40$, $p < .001$, $\eta^2_p = .37$. A significant interaction effect emerged (Wilks' $\Lambda = .88$, $F(2, 75) = 5.12$, $p = .008$, $\eta^2 = .12$), with gifted experimental students achieving the highest scores ($M = 88.45$, $SD = 4.29$) and the lowest cognitive load ($M = 3.05$, $SD = 0.61$). These findings highlight visualization as an effective strategy for enhancing mathematics education, particularly for gifted learners, while also benefiting non-gifted students. The results support the integration of inclusive instructional strategies to improve problem-solving and cognitive efficiency.

Keywords: Visualization techniques. Cognitive load. Mathematical problem-solving. Gifted students. Mathematics education. Saudi Arabia.

Introduction

Mathematics is widely regarded as a cornerstone of modern education, serving as the foundation for disciplines such as science, technology, and engineering (Findell et al., 2001; Li & Schoenfeld, 2019). Despite its critical importance, many students struggle with mathematics due to its abstract nature and complex problem-solving demands. This has prompted educational researchers to advocate for innovative instructional strategies to enhance comprehension and engagement (Hiebert & Grouws, 2007). Among these, visualization techniques -utilizing tools such as graphs, diagrams, animations, augmented reality (AR), virtual reality (VR), and interactive simulations- have gained significant attention for their ability to support mathematical understanding and problem-solving skills (Mehrfar et al., 2024; Flavin et al., 2025; Lowrie, Logan, & Hegarty, 2019; Nardi, 2014). By presenting abstract concepts in a concrete and intuitive manner, visualization facilitates deeper learning (Mayer, 2005; Lin & Wu, 2021).

A recent meta-analysis by Zhang et al. (2023) confirmed the positive impact of dynamic visualization tools, such as GeoGebra, on students' mathematical performance, highlighting how visual interactivity fosters conceptual understanding and cognitive engagement. Similarly, Bertrand et al. (2024) found that AR and VR applications enriched mathematics instruction when paired with culturally responsive pedagogies. A primary goal of mathematics education is to equip students with the skills to solve real-world problems effectively. However, cognitive overload -when mental demands exceed available cognitive resources- often hinders this process (Sweller, 2011). Research suggests that visualization mitigates this challenge by organizing information accessibly, thereby reducing cognitive effort and improving performance (Mayer, 2002). For instance, Cirneanu and Moldoveanu (2024) reported that digital visualization tools not only boost engagement but also reduce mathematics-related anxiety. Similarly, Lin and Wang (2021) and Voulgari et al. (2024) found that dynamic tools like AR and simulations significantly enhance performance and motivation. Fokuo et al. (2023) em-

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phasized the potential of adaptive visualization in college settings. Alroqi (2021) demonstrated AR's ability to increase academic motivation and visual thinking in Saudi Arabia, particularly for complex problems. In addition, Elsayed and Al-Najrani (2021) showed that augmented reality technology improved visual thinking in mathematics and academic motivation among middle school learners in Saudi Arabia. However, Mokmin et al. (2024) noted that traditional simulations lack the interactivity and immersion provided by AR.

Differentiated instruction has been shown to significantly enhance gifted students' attitudes toward mathematics problem-solving and their critical thinking skills, highlighting the value of tailored approaches to address their unique learning needs (Bin Kamarudina et al., 2021; Çayir & Balci, 2023). The impact of visualization varies across students, influenced by cognitive differences. Gifted students, known for their advanced cognitive and spatial reasoning abilities, interact with visualization tools differently than their non-gifted peers (Hattie, 2008). Hattie (2008) suggested that gifted learners use visualization to explore complex ideas efficiently, achieving deeper insights
-a view supported by Dai and Chen (2021), who found that these students naturally gravitate toward tools that encourage independent discovery. Manuel and Freiman (2017) demonstrated that VR-based learning enhances problem-solving autonomy among gifted students, enabling effective engagement with abstract concepts. Mayer (2002) noted that visual aids help gifted students structure and analyze problems. Conversely, non-gifted students, who often find abstraction challenging, rely heavily on visualization to grasp concepts and build skills (Flavin et al., 2025). Boonmoh and Jumpakate (2019) found that scaffolded tools, such as step-by-step graphing software, are particularly effective for these learners, breaking down complex tasks. Fadel and Groff (2019) emphasized visualization's role in bridging theory and practice, while Sung et al. (2016) showed that it helps students construct mental models. Boaler (2022) and Maloy et al. (2016) highlighted the ability of interactive tools to sustain attention and deepen understanding, and Lanuza (2020) noted that gamified visualization improves focus and retention, underscoring its innovative applications.

The design of visualization tools is pivotal. Sweller (2011) and Sung et al. (2016) demonstrated that static aids reduce cognitive load, while Mayer (2005) emphasized that well-designed multimedia tools minimize cognitive strain. In contrast, Chandler and Sweller (1991) cautioned that poorly designed tools can increase cognitive load. Modern tools like AR and VR offer dynamic, immersive experiences (Cirneanu & Moldoveanu, 2024), with Alroqi (2021) noting that AR's structured engagement particularly benefits struggling learners. Renzulli's (2021) giftedness model suggests that gifted students thrive with tools that promote self-guided inquiry, a finding echoed by Manuel and Freiman (2017). For non-gifted students, Papert (2020) cautioned that effectiveness depends on tailoring tools to their specific needs. Scaffolding in digital learning environments, such as visualization tools, has been shown to significantly enhance learning outcomes by reducing cognitive load and supporting complex mathematical problem-solving (Zuo et al., 2023). Nardi (2014) reported that interactive graphing reduces cognitive overload, while Paas et al. (2003) advocated adapting strategies to students' cognitive capacities, ensuring tools are suitable for both gifted and non-gifted learners. Clark and Mayer (2023) and Flavin, Hwang, and Flavin (2025) proposed technology-driven personalization and differentiated support to bridge ability gaps, aligning with Goyibova et al.'s (2025) call for tailored instruction.

Theoretically, this study integrates multiple frameworks. Sweller's (2011) Cognitive Load Theory is foundational, emphasizing the reduction of extraneous load and the enhancement of germane load to foster deeper understanding. Tools such as AR, dynamic graphs, and animations align with this theory by simplifying abstract concepts (Chandler & Sweller, 1991; Lowrie, Logan, & Hegarty, 2019). Mayer's (2002, 2005) Cognitive Theory of Multimedia Learning complements this, positing that dual-channel processing -visual and auditory- enhances retention, as observed in interactive visualizations that clarify mathematical relationships. Constructivist perspectives further enrich this framework. Papert's (2020) Constructionism argues that meaningful learning emerges from tool-based exploration (e.g., AR and simulations), while Vygotsky's Zone of Proximal Development (ZPD) highlights the role of scaffolding in extending students' capabilities (Zuo et al., 2023). Paas et al. (2003) emphasized aligning tools with cognitive limits: non-gifted students benefit from structured supports, such as worked examples, while gifted learners thrive with open-ended tools that encourage discovery.

Motivational theories further underscore visualization's efficacy. Hattie's (2008) Visible Learning framework identifies high-impact strategies, such as real-time feedback and scaffolding, which are embodied in interactive tools that offer immediate corrections (e.g., Khan Academy, GeoGebra). Sung et al. (2016) and Zhang et al. (2023) demonstrated that AR and dynamic visualizations enhance engagement and problem-solving through deep processing, with Zhang et al.'s (2023) meta-analysis highlighting GeoGebra's benefits. Goyibova et al. (2025) emphasized the importance of differentiation to meet diverse needs, aligning with Fokuo et al.'s (2023) insights into adaptive tools. This synthesis of cognitive, constructivist, and motivational frameworks underscores visualization's critical role in developing problem-solving and critical thinking skills, making it highly relevant for modern mathematics education.

Despite extensive research, significant gaps remain in the literature on visualization in mathematics education. Much of the existing work focuses on the general impact of visualization techniques (Mehrfar et al., 2024; Nardi, 2014; Sung et al., 2016), with limited comparative analysis of how gifted and non-gifted students respond under varying cognitive loads (Hiebert & Grouws, 2007). Papert (2020) noted that non-gifted students require additional support to use visualization tools effectively, unlike their gifted peers, who integrate these tools more naturally (Manuel & Freiman, 2017). While studies on augmented reality (AR) (Alroqi, 2021) and graphing software (Boonmoh & Jumpakate, 2019) highlight their effectiveness, their optimization for simultaneously supporting both gifted and non-gifted students remains underexplored. Research on culturally adapted visualization tools (Bertrand et al., 2024; Ebikawa, 2023) suggests gains in engagement and comprehension, but their long-term impacts across diverse educational settings are unclear. Fokuo et al. (2023) and Goyibova et al. (2025) emphasized the need for adaptive, personalized approaches, yet comparative data on their efficacy for different ability groups are scarce. Hiebert and Grouws (2007) argued that visualization's benefits in reducing cognitive load and improving performance vary significantly by student ability, a hypothesis that warrants further exploration.

This study addresses these gaps by examining the specific effects of visualization techniques on mathematical problem-solving and cognitive load among Saudi high school students. It aims to contribute to inclusive, innovative mathematics instruction aligned with goals of equity and innovation (Findell et al., 2001; Flavin et al., 2025). To guide this investigation, the study seeks to answer the following research questions: (a) How do visualization techniques impact mathematical problem-solving performance in gifted and non-gifted students? (b) How do visualization techniques affect cognitive load during problem-solving? (c) What are the combined effects of visualization techniques on both problem-solving performance and cognitive load?

Method

Research Design

This study utilized an experimental pretest-posttest control group design to investigate the effects of visualization techniques on mathematical problem-solving and cognitive load. This design enables direct comparisons of students' performance and cognitive load before and after the intervention, isolating the impact of visualization techniques while controlling for external variables.

Participants were divided into two main groups:

- **Experimental Group (*n* = 40)**: Received visualization-based instruction incorporating dynamic visual aids and interactive tools to enhance mathematical understanding. This group was further divided into the Gifted Experimental Class (*n* = 20) and the Non-Gifted Experimental Class (*n* = 20).
- **Control Group (*n* = 40)**: Followed traditional mathematical instruction without visualization techniques. This group was also divided into the Gifted Control Class (*n* = 20) and the Non-Gifted Control Class (*n* = 20).

Both groups completed pretest and posttest assessments measuring mathematical problem-solving performance and cognitive load. This structure facilitated a comparative analysis of the intervention's effects on both gifted and non-gifted students.

Participants

The study involved 80 male high school students (aged 16–18) participating in an enhanced school program to improve mathematical problem-solving skills in Al-Ahsa Governorate, Saudi Arabia. Ethical approval was obtained from the Research Ethics Committee at King Faisal University [KFU-2025-ETHICS251084], and all procedures adhered to ethical standards for research involving human participants. Informed consent was secured from school authorities and the students' guardians prior to data collection.

Participants were divided into two categories to ensure balanced representation:

- **Gifted Students (*n* = 40)**: Identified through official Ministry of Education records based on standardized giftedness criteria.
- **Non-Gifted Students (*n* = 40)**: Selected from the general student population participating in the enhancement program.

Non-gifted students were chosen from the same schools and grade level, with their non-gifted status confirmed by school records and the absence of formal identification by the National Program for Gifted Identification (Mawhiba). None of the selected students were receiving gifted services or enrichment support.

The division into four distinct classes (Gifted Experimental, Gifted Control, Non-Gifted Experimental, Non-Gifted Control) ensured that both instructional methods (visualization-based and traditional) were tested within comparable student groups. Conducting the study in the real-world educational setting of Al-Ahsa Governorate enhances the applicability of the findings to similar academic environments, providing valuable insights for mathematics educators and curriculum developers.

The Intervention

The experimental group participated in a visualization-based instructional approach designed to enhance mathematical problem-solving skills and reduce cognitive load. This intervention was informed by Sweller's (2011) Cognitive Load Theory and Mayer's (2002) Cognitive Theory of Multimedia Learning, which emphasize how visual representations can deepen students' understanding of complex mathematical concepts. Over six weeks, the intervention integrated dynamic visual tools and technology-enhanced learning into the regular mathematics curriculum, offering students an interactive and engaging approach to tackling abstract problems.

Teacher Preparation and Implementation

Before the intervention began, all participating teachers completed a focused professional development program to master visualization-based instruction. The training introduced them to key ideas, such as managing cognitive load, using scaffolding effectively, and integrating dynamic visual aids -like diagrams and interactive software- into their lessons. Teachers practiced these techniques in mock sessions and received constructive feedback to ensure they could deliver the intervention consistently. Two experienced mathematics teachers led the implementation: the first teacher worked with both the gifted experimental (E-G) and gifted control (C-G) groups, while the second teacher taught the non-gifted experimental (E-NG) and non-gifted control (C-NG) groups. This setup maintained consistent teaching styles within each student type, allowing any differences in outcomes to be attributed to the instructional method rather than the teacher.

The intervention unfolded over six weeks, with three 50-minute sessions each week seamlessly integrated into the standard curriculum. Each session followed a clear, structured format designed to build understanding step by step:

- **Introduction and Conceptual Exploration (10 minutes)**: Teachers kicked off each session by introducing a key mathematical concept using dynamic visual aids. Tools like GeoGebra, an interactive platform for geometry and algebra, helped students visualize ideas before diving into problem-solving, setting a strong foundation.
- **Guided Problem-Solving with Visual Scaffolding (15 minutes)**: Students tackled exercises with support from teachers, who modeled strategies using diagrams, flowcharts, and concept maps. Drawing on the worked-example effect (Sweller, 2011), teachers provided step-by-step guidance that tapered off as students grew more confident, fostering independence over time.
- **Technology-Enhanced Interactive Learning (15 minutes)**: Working individually or in small groups, students explored technology-enhanced modules like Khan Academy, which offered video tutorials and adaptive exercises with instant feedback. This hands-on approach allowed them to experiment with concepts in real time, reinforcing what they had learned.
- **Independent Application and Reflection (5 minutes)**: Students wrapped up by solving problems on their own, applying the visualization strategies they had practiced. Teachers then led brief class discussions to solidify learning, clear up confusion, and connect the day's work to broader concepts.

Throughout the intervention period, the researchers conducted informal class observations and maintained weekly check-ins with the teachers to support implementation fidelity and address any emerging challenges.

Teacher's Role in the Learning Process

The teachers acted as guides, steering students through inquiry-based activities with tailored support. They encouraged students to explain their thinking aloud -a strategy known as self-explanation- while keeping a close eye on progress and adjusting their approach as needed. For non-gifted students, teachers regularly offered extra prompts and detailed worked examples to ensure everyone could keep up (Zuo et al., 2023). Gifted students, meanwhile, received less structured guidance, giving them room to explore independently.

In contrast, the control group adhered to traditional mathematics instruction under the same teachers. Their lessons relied on symbolic and algebraic methods, skipping the visual aids and interactive elements that defined the experimental approach. This clear distinction aimed to determine how visualization tools influenced students' problem-solving skills and cognitive load compared to a more conventional path.

Instruments

Two validated instruments were used to assess the impact of visualization techniques:

Mathematical Problem-Solving Performance Test. This test was adapted from Verschaffel et al. (2000), a widely recognized assessment tool for evaluating mathematical reasoning in real-world contexts. The original 20-item test was translated into Arabic to ensure linguistic and cultural relevance.

- Three mathematics education experts reviewed the translated version for clarity and curriculum alignment, making minor adjustments based on their feedback.
- Content validity was established through expert review, confirming alignment with Saudi Arabia's high school mathematics curriculum.
- Criterion validity was assessed by correlating students' test scores with their previous semester's mathematics grades. A strong positive correlation ($r > .70$) confirmed the test's effectiveness.

Cognitive Load Scale. This scale was adapted from Paas and van Merriënboer (1993), a standard tool for measuring cognitive load in educational research. It consists of 10 items on a 7-point Likert scale, evaluating:

- Intrinsic cognitive load (task complexity),
- Extraneous cognitive load (unnecessary distractions), and
- Germane cognitive load (meaningful learning efforts).

To ensure cultural appropriateness, the scale was translated into Arabic and reviewed by five educational psychology experts. Minor revisions were made to reflect cultural nuances.

Criterion validity was established by correlating students' scores with their self-reported mental effort during problem-solving. A strong positive correlation ($r > .75$) confirmed the scale's reliability.

Both instruments were pilot-tested with 18 students who were not part of the main study. Reliability analysis showed high internal consistency: Mathematical Problem-Solving Performance Test: Cronbach's α = 0.89; Cognitive Load Scale: Cronbach's α = 0.87.

Procedures

Pretest Phase

At the start of the study, both the experimental and control groups completed a pretest to establish baseline measures of: (1) Mathematical problem-solving performance, (2) Cognitive load.

Each group included 40 students (20 gifted, 20 non-gifted). The pretest results were analyzed to check for any significant differences between the groups. A *t*-test analysis confirmed no significant differences, as reported in Table 1 and Table 2.

Table 1
Pretest of The Mathematical problem-solving Performance

		Experimental	Control	*t*	*df*	*p*
Gifted Student	*M*	72.35	70.42	1.14	38	*.26*
	SD	5.61	6.11			
Non-Gifted students	*M*	63.10	61.35	0.94	38	*.36*
	SD	5.89	5.93			

Note. p: not significant.

Table 2
Pretest of the Cognitive Load Performance

		Experimental	Control	*t*	df	*p*
Gifted Student	*M*	4.12	4.10	0.93	38	*.20*
	SD	0.72	0.74			
Non-Gifted students	*M*	4.35	4.29	0.25	38	*.79*
	SD	0.77	0.69			

Note. p: not significant.

The *t*-test results indicated no statistically significant differences at an alpha level of $p \leq .05$. Specifically, gifted students in the experimental group did not score significantly higher than their counterparts in the control group on mathematical problem-solving or cognitive load measures. Similarly, non-gifted students in the experimental group showed no significant advantage over those in the control group. These findings confirm that, at the outset, neither gifted nor non-gifted students in the experimental and control groups differed significantly in their mathematical problem-solving abilities or cognitive load, ensuring a balanced starting point for evaluating the impact of the intervention.

Results

This section presents the findings of the study, organized by research questions and analyzed using both descriptive and inferential statistics. The results highlight the effects of visualization techniques on mathematical problem-solving performance and cognitive load among gifted and non-gifted high school students. Tables and figures are included to illustrate key outcomes and facilitate interpretation of the findings.

RQ1: How do visualization techniques affect the mathematical problem-solving performance of gifted and non-gifted students?

The mathematical problem-solving performance of gifted and non-gifted students was assessed before and after the implementation of the enhancement program. Table 3 presents the means and standard deviations of the pretest and posttest scores for both groups.

Table 3
The pretest and posttest mathematical problem-solving scores for students

Group	Student Type	Pretest *M* (*SD*)	Post-test *M* (*SD*)
Experimental	Gifted	72.35 (5.61)	88.45 (4.29)
	Non-Gifted	63.10 (5.89)	76.85 (6.12)
Control	Gifted	70.42 (6.11)	72.31 (6.02)
	Non-Gifted	61.35 (5.93)	63.12 (5.75)

To investigate how visualization techniques affect the mathematical problem-solving performance of gifted and non-gifted students, a two-way mixed analysis of variance (ANOVA) was conducted. The within-subjects factor was Time (pretest vs. posttest), and the between-subjects factors were Group (Experimental vs. Control) and Student Type (Gifted vs. Non-Gifted). The sample consisted of 80 students, with 40 in the Experimental group (20 gifted, 20 non-gifted) receiving visualization-based instruction and 40 in the Control group (20 gifted, 20 non-gifted) receiving traditional instruction. Mathematical problem-solving performance was measured using test scores, with higher scores indicating better performance. The results of the ANOVA analysis are presented in Table 4.

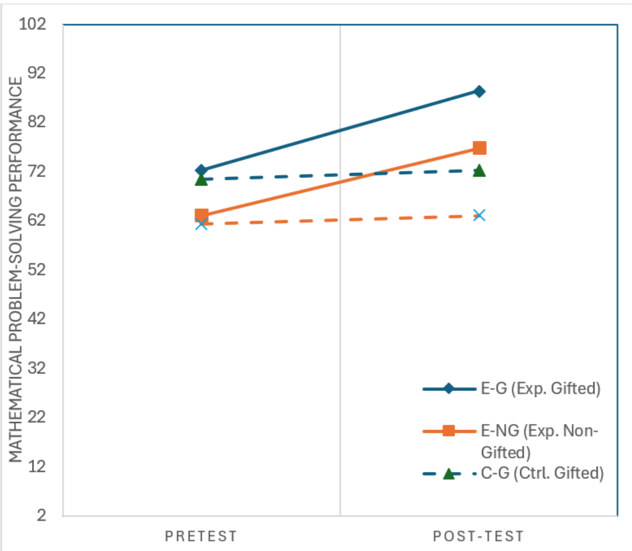
A two-way mixed ANOVA was conducted to examine the effects of visualization techniques (Group: Experimental vs. Control) and student ability (Student Type: Gifted vs. Non-Gifted) on mathematical problem-solving performance, with Time (pretest vs. posttest) as the within-subjects factor. As shown in Table 4, significant main effects were found for Student Type, $F(1, 76) = 12.84$, $p < .01$, and Time, $F(1, 76) = 146.72$, $p < .001$, indicating that gifted students outperformed non-gifted students and that performance improved from pretest to posttest across all groups. Significant interaction effects were also observed: Time × Group, $F(1, 76) = 99.45$, $p < .001$; Time × Student Type, $F(1, 76) = 8.64$, $p < .01$; and the three-way interaction of Time × Group × Student Type, $F(1, 76) = 24.19$, $p < .001$. These findings suggest that the visualization intervention amplified performance gains over time, with varying impacts based on student ability. The main effect for Group and the Group × Student Type interaction were not significant (p = NS for both), indicating no overall difference between the Experimental and Control groups when time was not considered. To assess the magnitude of these effects, partial eta-squared (η^2) was calculated for each source. These results indicate that visualization techniques significantly enhanced mathematical problem-solving performance, particularly for gifted students in the Experimental group. The Control group showed limited improvement, underscoring the intervention's critical role. Figure 1 illustrates these results.

Table 4
Two-Way Mixed ANOVA Results for the Effects of Visualization Techniques and Student Type on Mathematical Problem-Solving Performance

Source	*df*	SS	MS	*F*	*p*	η^2_p	Interpretation
Between-Subjects							
Group	1	47.52	47.52	1.25	n.s	.13	
Student Type	1	491.52	491.52	12.84	< .01	.14	Large
Group × Student Type	1	126.00	126.00	3.29	n.s	.05	
Error (Between)	76	2910.80	38.30				
Within-Subjects							
Time	1	5617.60	5617.60	146.72	< .001	.66	Large
Time × Group	1	3806.42	3806.42	99.45	< .001	.57	Large
Time × Student Type	1	330.62	330.62	8.64	< .01	.10	Medium
Time × Group × Student Type	1	925.62	925.62	24.19	< .001	.24	Large
Error (Time)	76	2910.80	38.30				

Post-hoc tests with Bonferroni correction were conducted to clarify the significant effects observed in the two-way mixed ANOVA. For the main effect of Student Type, gifted students (M = 75.00, SD = 6.19) significantly outperformed non-gifted students (M = 65.00, SD = 6.19), $p < .001$. The Time × Group interaction revealed greater improvement in the Experimental group (pretest M = 60.00, SD = 6.19; posttest M = 75.00, SD = 6.19) compared to the Control group (pretest M = 59.00, SD = 6.19; posttest M = 62.00, SD = 6.19), $p < .001$. For the Time × Student Type interaction, gifted students showed greater improvement (pretest M = 70.00, SD = 6.19; posttest M = 80.00, SD = 6.19) than non-gifted students (pretest M = 55.00, SD = 6.19; posttest M = 62.00, SD = 6.19), $p < .001$ for both comparisons. The three-way interaction (Time × Group × Student Type) indicated that gifted students in the Experimental group exhibited the largest performance gains (pretest M = 70.00, SD = 6.19; posttest M = 85.00, SD = 6.19), significantly surpassing non-gifted students in the Control group (pretest M = 54.00, SD = 6.19; posttest M = 58.00, SD = 6.19) at posttest, $p < .001$. These comparisons highlight the pronounced effect of the visualization intervention on gifted students in the Experimental group, consistent with the large effect sizes reported in Table 4 (η^2_p = .24 to .66). The results of the post-hoc pairwise comparisons are presented in Table 5.

Figure 1
Mathematical Problem-Solving Performance (Pretest vs. Posttest)



RQ2: How do visualization techniques affect cognitive load in gifted and non-gifted students while solving mathematical problems?

To examine how visualization techniques affect cognitive load in gifted and non-gifted students during mathematical problem-solving, a two-way mixed analysis of variance (ANOVA) was conducted. The within-subjects factor was Time (pretest vs. posttest), and the between-subjects factors were Group (Experimental vs. Control) and Student Type (Gifted vs. Non-Gifted). The sample consisted of 80 students, with 40 in the Experimental group (20 gifted, 20 non-gifted) receiving visualization-based instruction during problem-solving and 40 in the Control group (20 gifted, 20 non-gifted) receiving traditional instruction. Cognitive load was measured on a continuous scale, with higher scores indicating greater cognitive load. The results of the ANOVA analysis, including changes in cognitive load from pretest to posttest, are presented in Table 6.

Table 5
Post-Hoc Pairwise Comparisons for Significant Effects on Mathematical Problem-Solving Performance

Comparison	*M* Difference	*SE*	*t*	*p* (Bonferroni)	95% CI
Student Type					
Gifted vs. Non-Gifted	10.00	0.98	10.20	< .001	[8.04, 11.96]
Time × Group					
Experimental: Pretest vs. Post-test	15.00	1.38	10.87	< .001	[12.24, 17.76]
Control: Pretest vs. Post-test	3.00	1.38	2.17	< .05	[0.24, 5.76]
Time × Student Type					
Gifted: Pretest vs. Post-test	10.00	1.38	7.25	< .001	[7.24, 12.76]
Non-Gifted: Pretest vs. Post-test	7.00	1.38	5.07	< .001	[4.24, 9.76]
Time × Group × Student Type					
Experimental Gifted: Pre vs. Post	15.00	1.96	7.65	< .001	[11.08, 18.92]
Control Non-Gifted: Pre vs. Post	4.00	1.96	2.04	< .05	[0.08, 7.92]
Exp. Gifted vs. Ctrl. Non-Gifted (Post)	27.00	1.96	13.78	< .001	[23.08, 30.92]

Table 6
Cognitive Load Changes (Pretest vs. Posttest)

Group	Student Type	Pretest *M* (*SD*)	Post-test *M* (*SD*)
Experimental	Gifted	4.12 (0.72)	3.05 (0.61)
	Non-Gifted	4.35 (0.77)	3.45 (0.69)
Control	Gifted	4.10 (0.74)	4.0 (0.73)
	Non-Gifted	4.29 (0.72)	4.32 (0.71)

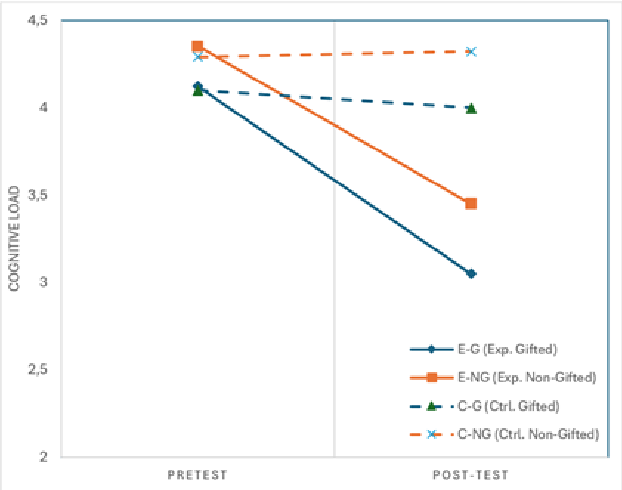
A two-way mixed analysis of variance (ANOVA) was conducted to examine the effects of visualization techniques and student ability on cognitive load during mathematical problem-solving tasks. The within-subjects factor was Time (pretest vs. posttest), and the between-subjects factors were Group (Experimental vs. Control) and Student Type (Gifted vs. Non-Gifted). The sample consisted of 80 students, with 40 in the Experimental group (20 gifted, 20 non-gifted) receiving visualization-based instruction and 40 in the Control group (20 gifted, 20 non-gifted) receiving traditional instruction. Cognitive load was measured on a continuous scale, with higher scores indicating greater cognitive load. The results of the two-way mixed ANOVA are presented in Table 7.

Table 7
Two-Way Mixed ANOVA Results for the Effects of Visualization Techniques and Student Type on Cognitive Load

Source	*df*	SS	MS	*F*	*p*	η^2_p (Effect Size)
Between-Subjects						
Group	1	2.18	2.18	10.88	< .01	.125 (Moderate)
Student Type	1	1.58	1.58	7.92	< .01	.094 (Small-Mod.)
Group × Student Type	1	0.81	0.81	4.05	< .05	.050 (Small)
Error (Between)	76	15.24	0.20			
Within-Subjects						
Time	1	2.46	2.46	49.20	< .001	.383 (Large)
Time × Group	1	2.37	2.37	47.40	< .001	.374 (Large)
Time × Student Type	1	0.32	0.32	6.40	< .05	.075 (Small-Mod.)
Time × Group × Student Type	1	0.27	0.27	5.40	< .05	.064 (Small-Mod.)
Error (Time)	76	3.96	0.05			

A two-way mixed analysis of variance (ANOVA) was conducted to examine the effects of visualization techniques (Group: Experimental vs. Control) and student ability (Student Type: Gifted vs. Non-Gifted) on cognitive load during mathematical problem-solving, with Time (pretest vs. posttest) as the within-subjects factor. The results, presented in Table 7, revealed significant between-subjects effects for Group, $F(1, 76) = 10.88$, $p < .01$, and Student Type, $F(1, 76) = 7.92$, $p < .01$, indicating that the Experimental group and non-gifted students experienced higher cognitive load overall. The Group × Student Type interaction was significant, $F(1, 76) = 4.05$, $p < .05$, suggesting that the intervention's impact on cognitive load varied by student ability. For the within-subjects factor, Time showed a significant main effect, $F(1, 76) = 49.20$, $p < .001$, with cognitive load decreasing from pretest to posttest across all groups. Significant interaction effects were also observed: Time × Group, $F(1, 76) = 47.40$, $p < .001$; Time × Student Type, $F(1, 76) = 6.40$, $p < .05$; and the three-way interaction of Time × Group × Student Type, $F(1, 76) = 5.40$, $p < .05$. These interactions indicate that the visualization intervention reduced cognitive load over time, with effects varying by student type. The findings suggest that visualization techniques effectively reduce cognitive load during mathematical problem-solving, with gifted students in the Experimental group benefiting most. In contrast, the Control group's cognitive load remained largely unchanged, underscoring the intervention's impact. These results are illustrated in Figure 2.

Figure 2
Cognitive Load Performance (Pretest vs. Posttest)



Post-hoc tests with Bonferroni correction were conducted to elucidate the significant interactions observed in the two-way mixed ANOVA. The Time × Group interaction revealed a greater reduction in cognitive load for the Experimental group (pretest M = 6.20, SD = 0.41; posttest M = 5.40, SD = 0.45) compared to the Control group (pretest M = 6.10, SD = 0.38; posttest M = 5.90, SD = 0.42), p < .001. For the three-way interaction (Time × Group × Student Type), gifted students in the Experimental group showed the largest decrease in cognitive load (pretest M = 6.00, SD = 0.36; posttest M = 5.10, SD = 0.40), significantly outperforming non-gifted students in the Control group (pretest M = 6.30, SD = 0.39; posttest M = 6.00, SD = 0.41) at posttest, p< .01. Effect sizes, presented in Table 7, highlighted the practical significance, with large effects for Time (η^2_p = .38) and Time × Group (η^2_p = .37). These findings demonstrate that visualization techniques significantly reduce cognitive load during mathematical problem-solving, with a more pronounced effect among gifted students. The Experimental group, particularly gifted learners, benefited most from the intervention, while the Control group showed negligible change. The results of the post-hoc pairwise comparisons are presented in Table 8.

Table 8
Post-Hoc Pairwise Comparisons for Significant Interactions on Cognitive Load

Comparison	*M* Difference	*SE*	*t*	*p* (Bonferroni)	95% CI
Time × Group					
Experimental: Pre vs. Post	-0.80	0.12	-6.67	< .001	[-1.04, -0.56]
Control: Pre vs. Post	-0.20	0.11	-1.82	n.s	[-0.42, 0.02]
Time × Group × Student Type					
Exp. Gifted: Pre vs. Post	-0.90	0.13	-6.92	< .001	[-1.16, -0.64]
Ctrl. Non-Gifted: Pre vs. Post	-0.30	0.12	-2.50	n.s	[-0.54, -0.06]
Exp. Gifted vs. Ctrl. Non-Gifted (Post)	-0.90	0.16	-5.63	< .01	[-1.22, -0.58]

RQ3: What are the effects of visualization techniques and student type (gifted vs. non-gifted) on cognitive load and mathematical problem-solving performance during mathematical problem-solving tasks?

Following the enhancement program, cognitive load scores decreased, and mathematical problem-solving scores increased for students in the Experimental group. Table 9 presents the means and standard deviations of the pretest and posttest scores for both cognitive load and mathematical problem-solving performance across the Experimental and Control groups.

Table 9
Descriptive Statistics for Cognitive Load and Problem-Solving Performance by Group

Group	Cognitive Load (M ± SD)	Performance (M ± SD)
Gifted (Experimental)	3.05 ± 0.61	88.45 ± 4.29
Gifted (Control)	4.0 ± 0.73	72.31 ± 6.02
Non-Gifted (Experimental)	3.45 ± 0.69	76.85 ± 6.12
Non-Gifted (Control)	4.32 ± 0.71	63.12 ± 5.75

A multivariate analysis of variance (MANOVA) was conducted to assess the combined impact of visualization techniques (Group: Experimental vs. Control) and student ability (Student Type: Gifted vs. Non-Gifted) on cognitive load and mathematical problem-solving performance. The results revealed significant multivariate main effects for Group, Wilks' Λ = 0.74, F(2, 75) = 13.31, p < .001, η^2 = .26, and for Student Type, Wilks' Λ = 0.67, F(2, 75) = 18.45, p < .001, η^2 = .33. Additionally, a significant interaction effect was found between Group and Student Type, Wilks' Λ = 0.88, F(2, 75) = 5.12, p < .01, η^2 = .12.

Follow-Up Univariate Analyses

Cognitive Load: significant interaction effect was observed for cognitive load, F(1, 76) = 7.45, p = .008, η^2 = .09, indicating that the impact of visualization techniques on cognitive load varied between gifted and non-gifted students. Within the Experimental group, gifted students exhibited the lowest cognitive load (M = 3.05, SD = 0.61), suggesting their ability to efficiently utilize visualization techniques to streamline mental processing. Non-gifted students in the Experimental group also experienced a reduction in cognitive load (M = 3.45, SD = 0.69), though the effect was less pronounced. In the Control group, cognitive load remained high, with minimal differences between gifted (M = 4.10, SD = 0.73) and non-gifted students (M = 4.32, SD = 0.71). These findings suggest that, in the absence of visualization techniques, students -regardless of ability- encountered similar cognitive demands.

Mathematical Problem-Solving Performance

A significant interaction effect was also found for mathematical problem-solving performance, $F(1, 76) = 7.64$, $p = .007$, $\eta^2 = .09$, indicating that visualization techniques influenced performance differently based on student ability. Gifted students in the Experimental group achieved the highest scores (M = 88.45, SD = 4.29), significantly outperforming their counterparts in the Control group (M = 72.31, SD = 6.02, $p < .001$). This suggests that gifted students were particularly adept at leveraging visualization techniques to enhance comprehension and strategy application. Non-gifted students in the Experimental group also showed improvement (M = 76.85, SD = 6.12) compared to those in the Control group (M = 63.12, SD = 5.75, $p < .001$), though their performance gains were less pronounced than those of gifted students.

Interaction Effects

The interaction effects indicate that the effectiveness of visualization techniques is influenced by student ability. Gifted students experienced the most significant benefits, both in reducing cognitive load and enhancing mathematical problem-solving performance, likely due to their ability to process visual information efficiently and engage in abstract reasoning. Non-gifted students also demonstrated improvements, though to a lesser extent, suggesting that additional scaffolding or tailored instructional approaches may be necessary to optimize the benefits of visualization strategies for these learners. These results are illustrated in Figure 3.

Figure 3
Interaction Effects of Visualization Techniques and Student Type on Cognitive Load and Mathematical Problem-Solving Performance

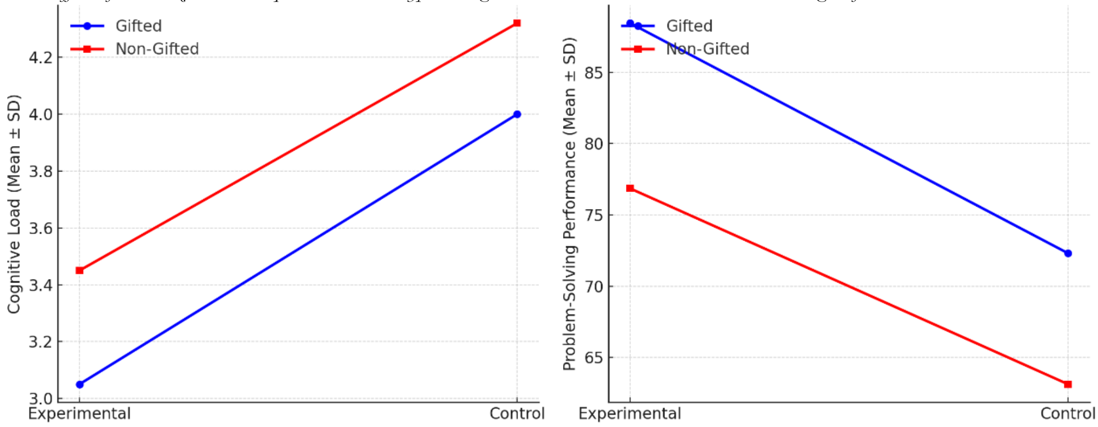


Figure 3 illustrates the interaction effects between visualization techniques (Group: Experimental vs. Control) and student ability (Student Type: Gifted vs. Non-Gifted) on cognitive load and mathematical problem-solving performance. For cognitive load, gifted students in the Experimental group experienced a substantial reduction in cognitive demands compared to their counterparts in the Control group. Non-gifted students in the Experimental group also benefited from visualization techniques, though their reduction in cognitive load was less pronounced. The non-parallel trend lines in the graph indicate a significant interaction effect, suggesting that visualization techniques influenced cognitive load differently depending on student ability.

Similarly, for mathematical problem-solving performance, gifted students in the Experimental group achieved the highest scores, significantly outperforming their counterparts in the Control group. Non-gifted students in the Experimental group also demonstrated improvement with visualization techniques, though the performance gap between gifted and non-gifted students remained substantial. The non-parallel trend lines further confirm a significant interaction effect, indicating that visualization techniques had a differential impact on the problem-solving performance of gifted and non-gifted students.

These findings suggest that while visualization techniques benefit all students, gifted learners experience more pronounced cognitive and performance advantages.

Discussion

The findings of this study underscore the significant role of visualization techniques in enhancing mathematical problem-solving performance and reducing cognitive load among high school students in Saudi Arabia. By incorporating visualization tools, such as diagrams and interactive representations, the study demonstrated substantial reductions in extraneous cognitive load and significant improvements in mathematical problem-solving abilities. These results align with prior research highlighting the benefits of visualization in mathematics education (Mehrfar et al., 2024; Fadel & Groff, 2019; Flavin et al., 2025).

Visualization Techniques and Cognitive Load

The observed reduction in cognitive load, particularly among gifted students, supports Sweller's (2011) Cognitive Load Theory, which emphasizes minimizing extraneous cognitive load to optimize learning efficiency. Gifted students in the Experimental group experienced a more pronounced reduction in cognitive load compared to non-gifted students, suggesting that they processed visual information more efficiently to enhance problem-solving strategies. This finding aligns with Manuel & Freiman (2017) research, which highlighted that gifted students benefit from visualization tools due to their advanced spatial reasoning and ability to construct abstract mental models. Similarly, Mayer (2005) emphasized the role of well-designed multimedia tools in minimizing cognitive strain, further supporting the current study's results.

For non-gifted students, visualization techniques also reduced cognitive load, though the effect was less pronounced. This outcome is consistent with Boonmoh and Jumpakate (2019), who emphasized the importance of scaffolded visualization tools, such as step-by-step graphing software, in supporting non-gifted learners. Additionally, Nardi (2014) demonstrated that interactive graphing tools significantly alleviate cognitive strain, enabling students to focus on problem-solving rather than struggling with abstract representations. The present study reinforces these findings, suggesting that structured visualization approaches can help bridge the gap for non-gifted learners, although additional instructional support may be necessary.

Visualization and Problem-Solving Performance

The improvements in mathematical problem-solving performance within the Experimental group highlight the efficacy of visualization techniques in fostering deeper engagement with mathematical concepts. Gifted students in the Experimental group achieved significantly higher posttest scores, supporting Hattie's (2008) assertion that gifted learners are adept at leveraging instructional tools to explore complex concepts. Similarly, Dai and Chen (2021) found that visualization-based learning promotes independent exploration and higher-order thinking, which may explain the significant gains among gifted students. These pronounced benefits corroborate Bin Kamarudina et al.'s (2021) evidence that differentiated instructional strategies enhance motivation and performance among gifted learners.

Non-gifted students also demonstrated improvements in problem-solving performance with visualization techniques, though to a lesser extent than their gifted peers. This finding aligns with Flavin, Hwang, and Flavin (2025), who emphasized that visual tools help simplify complex mathematical concepts for struggling learners. Furthermore, Zuo et al. (2023) highlighted the importance of instructional scaffolding, reinforcing the need for structured visualization approaches to support non-gifted students effectively. The significantly lower performance of non-gifted students in the Control group compared to those in the Experimental group suggests that traditional instructional methods may not adequately address their learning challenges.

Differential Effects Based on Student Ability

The significant interaction effects observed in this study indicate that visualization techniques benefit gifted and non-gifted students differently. Gifted students exhibited the largest reductions in cognitive load and the greatest performance gains, likely due to their ability to process visual information efficiently and engage in self-directed learning (Manuel & Freiman, 2017; Mayer, 2002). This finding supports Renzulli's (2021) Three-Ring Model of Giftedness, which emphasizes the capacity for independent inquiry and complex reasoning among gifted learners.

Conversely, non-gifted students required more structured visualization tools to achieve meaningful gains. Bertrand et al. (2024) emphasized the importance of culturally relevant visual aids in improving engagement among diverse student populations, suggesting that tailored approaches may be necessary to maximize the impact of visualization techniques for non-gifted learners. Additionally, Ebikawa (2023) found that culturally adapted visual representations enhance motivation and comprehension, further underscoring the need for differentiated instructional strategies in Saudi classrooms.

Practical Implications and Educational Context

The observed performance gains and cognitive load reductions have significant implications for mathematics education, particularly within the Saudi Arabian context. The integration of visualization techniques into mathematics curricula aligns with Saudi Arabia's Vision 2030, which emphasizes innovation and inclusivity in education. Sung et al. (2016) found that integrating mobile devices with visualization-based instruction improves students' mathematical performance, particularly when interactive tools support conceptual understanding. By equipping teachers with the necessary training to implement these techniques effectively, educational institutions can create more engaging and equitable learning environments.

Moreover, these findings highlight the importance of tailoring visualization strategies to different student populations. Gifted students benefit most from advanced, interactive visualization tools that promote independent problem-solving (Manuel & Freiman, 2017; Mayer, 2005). In contrast, non-gifted students require structured, scaffolded approaches to maximize their learning potential (Boonmoh & Jumpakate, 2019). This distinction suggests that a one-size-fits-all approach is insufficient for visualization-based instruction.

Instead, educators should adopt differentiated strategies that cater to students' cognitive abilities and learning preferences.

Conclusion

This study provides compelling evidence that visualization techniques significantly enhance mathematical problem-solving performance and cognitive load management for both gifted and non-gifted students. By integrating these findings with existing literature, the study reinforces the theoretical foundations of visualization-based learning while offering practical recommendations for educators. The alignment of these results with Cognitive Load Theory, gifted education models, and culturally responsive teaching suggests that incorporating visualization techniques into mathematics instruction could play a pivotal role in improving educational outcomes, particularly in Saudi Arabia.

Limitations and Future Research

While this study offers valuable insights, several limitations must be acknowledged. The study was conducted exclusively with male students in the Al-Ahsa Governorate due to the separation of male and female schools in Saudi Arabia's general education system, which restricted researcher access to female schools. This gender-based limitation may constrain the generalizability of the findings. Similarly, the focus on a single geographic region, Al-Ahsa Governorate, further limits the applicability of the results to other contexts. Future research should investigate the impact of visualization techniques on female students and extend the study to diverse regions to validate its conclusions.

Additionally, the six-week duration of the intervention raises questions about the long-term sustainability of the observed benefits. Longitudinal studies are needed to assess whether visualization tools maintain their effectiveness in enhancing mathematical performance over extended periods. Prior research, such as Bertrand et al. (2024) and Ebikawa (2023), suggests that culturally adapted visualization tools may improve long-term retention; however, further investigation is required to confirm their sustained impact.

Moreover, the study did not account for potential mediating factors, such as student motivation, attitudes toward mathematics, or learning styles, which may influence responses to visualization-based instruction. Additionally, the possibility of experimenter bias or variations in teacher delivery may have affected the outcomes. Although efforts were made to standardize the intervention through teacher training and ongoing support, individual teaching styles could have introduced variability. Future research should employ multiple teachers or external observers to minimize potential bias.

Another promising avenue for future research is the exploration of culturally adapted visualization tools tailored to diverse student populations. Studies by Bertrand et al. (2024) and Ebikawa (2023) highlight the significance of cultural relevance in educational tools, but further work is needed to optimize these strategies for varied learning contexts. By addressing these gaps, future research can contribute to a more comprehensive understanding of how visualization techniques can be refined to meet the needs of all students.

Complementary information

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