AI-Generated 3D Building Block Image Assistance: Impact on Junior High School Students' Learning Outcomes, Cognitive Load, and Creative Design Ability

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Abstract

Traditional 2D block diagrams lack sufficient 3D rotational perspectives, making it difficult to fully display the back of the block assembly and complex structures, limiting students' spatial understanding and operational accuracy. AI-generated 3D dynamic image systems, such as Tripo AI, can instantly generate 3D rotating models, providing multi-angle viewing and detailed supplementation. This helps reduce the cognitive load caused by limited viewing angles while encouraging creative thinking. Therefore, an empirical study will investigate the practical teaching effectiveness of AI-generated 3D dynamic imagery, hoping to significantly impact junior high school engineering education. This study focuses on how the Tripo AI-generated 3D block dynamic imagery system impacts junior high school students' learning outcomes, cognitive load, and creative design abilities in engineering block learning. The system complements the perspective limitations of traditional 2D paper diagrams by generating rotating, surround-view 3D block models and displaying the back of components. A quasi-experimental design was adopted in this study. Intact classes of junior high school students were assigned as the experimental group (assisted by AI 3D dynamic imagery) with the control group (using only 2D paper diagrams) on a learning task. We hope to discover that AI dynamic images can improve spatial understanding and operational accuracy, effectively reduce cognitive load, and promote the diversified development of creative thinking.

Keywords: traditional 2D building block assembly diagrams, 3D rotational perspective, AI-generated 3D dynamic image, cognitive load, engineering education

Introduction

This study investigates the impact of AI-generated 3D block image assistance systems on junior high school students' learning outcomes, cognitive load, and creative design abilities within engineering block-based learning contexts. The research integrates three interrelated educational domains: spatial intelligence development, cognitive load reduction, and the enhancement of creative design capabilities. By addressing these aspects, the study bridges the existing gap between traditional 2D assembly instruction and emerging AI-powered 3D visualization technologies in hands-on engineering education.

The theoretical foundation of this research lies in spatial cognition. Spatial ability refers to the capacity to generate, retain, reorganize, and mentally manipulate three-dimensional images. Among its components, mental rotation—defined as the ability to interpret geometric structures, 3D configurations, and engineering drawings—constitutes the core cognitive process. Caldera et al. (1999) demonstrated that children's manipulative behaviors during block-building tasks—such as rotation, flipping, and symmetric placement—are strongly correlated with their spatial visualization reasoning and complex image reorganization performance.

Nevertheless, traditional instruction relying on static 2D assembly diagrams lacks the dynamic representation of three-dimensional rotation and fine structural detail. Such methods may limit students' ability to interpret structures accurately and manipulate spatial information effectively, while simultaneously increasing their cognitive load. This instructional limitation corresponds with current challenges in engineering education, which increasingly emphasize digital interactivity, 3D visualization, and real-time feedback mechanisms.

To situate this study within practical educational contexts, two representative cases are presented. The first example is a collaborative initiative between the Taoyuan Education Bureau and the Teacher Education Center at National Taiwan University of Science and Technology. This program integrates AI-supported block-based learning experiences that foster problem-solving abilities, establish concepts of AI-human collaboration, and cultivate logical, creative, and communicative skills among young learners.

The second case involves researchers at Carnegie Mellon University, who developed LegoGPT—an open-source tool capable of automatically generating building block designs. This innovation signifies a crucial shift wherein generative AI, once confined to virtual content creation such as images, language, and audio, now extends into the physical domain by combining AI generation with tangible construction logic. Collectively, these examples underscore the emerging importance of AI-assisted construction systems and instructional interventions as integral components of contemporary educational practice and pedagogy.

This study aims to address three interrelated research questions that collectively define the scope of the investigation.

Specifically, the study seeks to explore:

1. How AI-assisted systems differ from traditional two-dimensional diagrams in shaping students' learning outcomes, cognitive load, and creative design abilities.
2. Whether an individual's level of spatial ability moderates the effects of AI-mediated visualization on learning performance and cognitive processing demands.
3. How AI-based 3D visualization and conventional 2D assembly representations differentially influence students' creative expression across multiple dimensions—

including fluency, originality, elaboration, and flexibility—within open-ended block construction tasks.

Together, these research questions structure the analytical framework of this study, progressing from general learning outcomes to the moderating role of individual differences, and finally to the nuanced patterns of creative expression.

Literature Review

The literature review highlights three pivotal research directions.

First, research on supporting children's spatial language development through generative AI reveals that block-building activities often lack professional guidance (Ferrara et al., 2011; Jirout & Newcombe, 2015; Pruden et al., 2011), personalized instructions, and spatial vocabulary scaffolding (Liu et al., 2025). Using natural language processing and generative AI models, researchers have developed AI-assisted interface designs that ground spatial language learning in parent-child interaction, providing empirical foundations for family-based STEM education (Liu et al., 2025).

Second, studies on generative AI in creative design and mechanical manufacturing demonstrate that AI can accelerate design ideation, sketching, and preliminary modeling—typically time-consuming phases in traditional design (Goodfellow et al., 2014; Kingma & Welling, 2014). By integrating modular structures with generative AI, researchers successfully established design-manufacturing workflows that combine 3D modeling with physical fabrication, achieving significant reductions in development cycles (Liu et al., 2023).

Third, research on children's mental models of generative AI indicates that children construct dynamic, continuously updated mental representations of AI systems (Kosoy et al., 2024). As their experience with AI increases, their understanding and acceptance of AI as a collaborative tool also strengthen (Kosoy et al., 2024). This research bridges human–computer interaction and psychology to understand AI's societal impact (Kosoy et al., 2024).

From these three streams of research, we establish that spatial intelligence correlates strongly with mathematical reasoning, engineering design, and creative development (Clements & Battista, 1992; Kell et al., 2013). The design principle of AI-assisted dynamic 3D rotatable images—emphasizing dynamic manipulability and multi-perspective presentation—significantly enhances spatial understanding (BrickSmart, 2025). Mental rotation tests and spatial ability assessments serve as effective measurement instruments for this construct (Clements & Battista, 1992; Kell et al., 2013).

Methodology

This study employed a quasi-experimental pre-test–post-test research design involving two classes of ninth-grade students taught by the same instructor, thereby controlling for teacher-related variables and ensuring consistency in pedagogical implementation. The experimental group (n = 30) received instruction supported by an AI-based 3D dynamic image assistance system in conjunction with physical engineering building blocks, whereas the control group (n = 30) was taught using traditional 2D paper-based assembly diagrams with the same physical blocks. Both groups undertook identical assembly tasks using identical materials, thereby holding constant the material-related variables across conditions.

The study was conducted over a three-week period. In the first week, pre-tests were administered to establish baseline measurements of students' spatial ability and relevant learning indicators. In the second week, the experimental intervention was implemented: students either learned to operate the AI 3D assistance system or to interpret 2D assembly diagrams, and then completed a medium-complexity assembly task during which completion time and structural accuracy were recorded. Immediately following the task, students completed the NASA-TLX questionnaire to assess perceived cognitive load. The third week was dedicated to open-ended creative assessment tasks designed to capture multiple facets of students' creative performance in block construction.

Data Collection Procedures by Research Question

Research Question 1 examined the main effects of instructional media on learning outcomes and cognitive load. In the first week, students completed the *Block Engineering Concept Test* (10-item multiple-choice assessment) and a basic assembly task to establish baseline equivalence. During the 90-minute intervention (Week 2), students received 15 minutes of instruction on their respective systems followed by 60 minutes to assemble a medium-complexity model. Completion time, structural accuracy, and NASA-TLX cognitive load were measured immediately after.

Research Question 2 incorporated spatial ability as a moderator. The *Mental Rotation Test* (MRT) was administered in Week 1 to classify students into high- and low-spatial-ability groups based on the median score, creating four subgroups: AI + High Spatial, AI + Low Spatial, 2D + High Spatial, and 2D + Low Spatial. Two-way ANOVA examined interaction effects on assembly time and cognitive load.

Research Question 3 assessed creativity across four dimensions (fluency, originality, elaboration, flexibility). In Week 3, students completed open-ended block construction tasks evaluated by two independent expert raters using 7-point Likert scales aligned with Torrance Tests of Creative Thinking protocols. Inter-rater reliability was established via intraclass correlation coefficients (ICC ≥ .70).

Table 1
Pre-test Equivalence Between Groups

Measure	**Group**	**n**	**M**	**SD**	**t(58)**	**p**
Concept Test (Pre-test)	AI 3D	30	6.87	1.25	0.42	.675
	2D Diagrams	30	6.73	1.31		
Baseline Assembly Acc.	AI 3D	30	0.78	0.12	0.15	.882
	2D Diagrams	30	0.77	0.13		
Note. No significant differences (p > .05).						

Results and Discussion

The analysis addressed three research questions concerning the effects of AI-based 3D visualization versus traditional 2D diagrams on learning outcomes, cognitive load, and creative design abilities in engineering block tasks. Descriptive statistics and inferential tests confirmed pre-test equivalence between groups (Table 1), ensuring observed differences could be attributed to instructional media.

Research Question 1: Main Effects of Instructional Media

Independent-samples t-tests showed no significant pre-test differences in the Block Engineering Concept Test ($t(58) = 0.42$, $p = .675$) or baseline assembly accuracy ($t(58) = 0.15$, $p = .882$). Following intervention, AI 3D visualization significantly reduced assembly times and cognitive load compared to 2D diagrams, demonstrating enhanced learning efficiency and reduced mental demands for medium-complexity engineering tasks.

Research Question 2: Spatial Ability as Moderator

A two-way ANOVA revealed significant main effects for instructional media and spatial ability, with critical Media × Spatial Ability interactions on both assembly time ($F(1,56) = 6.45$, $p = .014$, $\eta^2 = .103$) and cognitive load ($F(1,56) = 5.89$, $p = .018$, $\eta^2 = .095$) (Table 2). Low-spatial-ability students ($n = 30$) demonstrated the largest gains from AI 3D assistance, indicating that dynamic visualization provides compensatory support for learners with weaker spatial skills.

Table 2
Two-Way ANOVA Results for Assembly Time and Cognitive Load (Media × Spatial Ability)

Dependent Variable	**Source**	**df**	**F**	**p**	**η²**
Assembly Time	Media	1,56	4.32	.042	.072
	Spatial Ability	1,56	5.10	.028	.084
	Media × Spatial	1,56	**6.45**	**.014**	**.103**
Cognitive Load	Media	1,56	**7.21**	**.009**	**.114**
	Spatial Ability	1,56	3.67	.061	.062
	Media × Spatial	1,56	**5.89**	**.018**	**.095**

Note. Bold indicates significant effects ($p < .05$).

Research Question 3: Creative Design Abilities

A multivariate analysis of variance (MANOVA) across four creativity dimensions (fluency, originality, elaboration, flexibility) yielded a significant overall effect, Wilks' $\lambda = 0.82$, $p = .031$. Follow-up univariate ANOVAs revealed significant advantages for the AI 3D group in elaboration ($F(1,58) = 6.85$, $p = .011$, $\eta^2 = .106$) and flexibility ($F(1,58) = 4.02$, $p = .049$, $\eta^2 = .065$), with fluency approaching significance ($p = .078$) and originality showing no difference ($p = .707$) (Table 3). These patterns suggest AI 3D visualization particularly enhances detail-oriented execution and multi-conceptual integration in creative block design.

Table 3
Creativity Dimensions: Descriptive Statistics and ANOVA Results by Group

Dimension	**Group**	**n**	**M**	**SD**	**F(1,58)**	**p**	**η²**
Fluency	AI 3D	30	4.23	1.10	3.21	.078	.052
	2D Diagrams	30	3.70	1.05			
Originality	AI 3D	30	3.85	0.98	0.14	.707	.002
	2D Diagrams	30	3.79	0.95			
Elaboration	AI 3D	30	**4.60**	**1.02**	**6.85**	**.011**	**.106**
	2D Diagrams	30	3.95	1.07			
Flexibility	AI 3D	30	**4.10**	**0.96**	**4.02**	**.049**	**.065**
	2D Diagrams	30	3.68	0.99			

Note. MANOVA: Wilks' $\lambda = 0.82$, $p = .031$. Bold indicates significant univariate effects ($p < .05$).

Implications

AI 3D benefits all but most helps low-spatial students. Screen spatial ability for targeted deployment. Design: constrained 3D views prevent overload for novices.

Educational Implications and Design Recommendations

Educational Implications

AI 3D visualization significantly outperformed traditional 2D diagrams across learning efficiency, cognitive load reduction, and creative elaboration/flexibility—with the largest benefits for low-spatial-ability students (Table 2–3 interaction effects). Teachers should implement spatial ability screening to identify students most likely to benefit from AI support, enabling targeted deployment in engineering/STEM classrooms.

Design Recommendations

High-spatial learners thrive with rich 3D interactivity; low-spatial learners risk cognitive overload from unrestricted rotation. Optimal design: Use 3–5 key static views or constrained 3D with visual cues (vs. free rotation) for novices. This balances accessibility with advanced visualization benefits.

Contributions and Future Directions

This study fills critical gaps in secondary engineering education by:
1. validating AI 3D's compensatory role for spatially challenged learners.
2. establishing media × ability interaction effects.
3. identifying targeted visualization principles.

For Future Research

Studies on spatial ability and 3D media show that high-spatial learners benefit more from rich 3D views, whereas low-spatial learners may suffer from information overload when facing fully rotatable 3D models, leading to longer completion time and lower accuracy.

Therefore, in our design, we argue for using a few key static views or 3D views with clear visual signals, instead of completely free rotation, especially for beginners and low-spatial students.

Overall, the AI 3D assistance in our study is positioned to enhance learning outcomes, reduce cognitive load—particularly for low-spatial learners—and improve the elaboration aspect of creative design, while also addressing a gap in secondary engineering education and pointing toward future cross-level and multimodal extensions.

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