An Exploratory Study on How Generative AI Supports Students' Visual Construction of the Particle Model of Matter

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Abstract

This study explores the application of Generative AI in teaching the Particle Model of Matter (PMM) to sixth-grade students, focusing on how students construct and evaluate visual models by transforming linguistic descriptions through AI. A qualitative approach was adopted. Two PMM-themed lessons were designed, integrating the Generation (G), Evaluation (E), Modification (M), G.E.M. modeling process with three evaluation criteria: Plausibility (P), Alignment with experience and imagination (A), and Detail (D). Participants included three groups of sixth graders. The study examined how students developed initial linguistic models, interacted with AI to iteratively generate visual models, and used the P.A.D. criteria to evaluate and refine them. Data sources included AI dialogue records and classroom transcripts, analyzed thematically. Findings show that students' initial models were often intuitive and macroscopic, with mental models mostly classified as Descriptive (D) or Mixed-consistent (M-c). Through AI-assisted visualization, students identified conceptual gaps, revised their input, and gradually incorporated microscopic ideas, eventually constructing scientifically plausible Basic Particle Models of movement (B-m). The P.A.D. criteria played complementary roles, helping students assess visual models from multimodal perspectives and demonstrating metacognitive engagement. This study presents a practical modeling and evaluation process combining Generative AI with science instruction. It highlights AI's potential to provide instant feedback and visual representations, enabling students to refine internal models and deepen their conceptual understanding. The findings offer practical insights into elementary modeling instruction and emphasize the educational value of P.A.D. criteria in promoting metacognition and scientific learning.

Keywords: Particle Model of Matter, Generative AI, Mental Model, Evaluation Criteria

1. Introduction

With the rapid advancement of artificial intelligence (AI) technologies, Generative AI is gradually entering classrooms and becoming an emerging tool to support both teaching and learning. Educational practices around the world have begun to explore the integration of AI into various contexts such as language learning, creative expression, and scientific modeling, forming a new type of interactive model known as "AI co-learning" [1].In science education in particular, Generative AI has the potential to serve as a visual mediator that helps students concretize abstract concepts through image generation technologies, thereby supporting their understanding and construction of scientific models [2].

Taiwan's Curriculum Guidelines of 12-Year Basic Education officially included "modeling" as one of the expected learning performances in the science domain at the elementary level, and introduced microscopic concepts—such as "matter is composed of tiny particles that are constantly moving" into the upper grades of elementary science education for the first time [3]. The Particle Model of Matter (PMM) is a fundamental concept in the natural sciences. However, due to its microscopic and unobservable nature, it is often considered difficult to teach by educators and challenging to learn for students. For elementary school students who are still in the concrete operational stage, understanding such abstract concepts poses a considerable challenge [4].

Against this backdrop, this study focuses on how sixth-grade elementary students, while learning the PMM, engage with Generative AI to visualize their initial language-based models, evaluate the AI-Generated outputs, and revise them accordingly. The goal is to enhance students' understanding of particle concepts and support the development of metacognitive skills. The research questions are as follows:

1. What are the students' initial linguistic models and the AI-Generated final visual models after interacting with Generative AI?
2. How do students evaluate the AI-Generated visual models?

2. Literature Review

Taiwan's Curriculum Guidelines of 12-Year Basic Education emphasize the importance of students being able to explain natural phenomena through modeling [3]. This highlights the need for teachers to move beyond traditional observation-based instruction and guide students in constructing abstract scientific concepts and ways of thinking. Meanwhile, the rise of Generative AI is reshaping classroom interactions, with growing attention on its potential as a learning mediator. In response, this study reviews the literature from the following three perspectives.

2.1 The Role of Modeling in Elementary Science Education and Its Implementation Challenges

The particulate nature of matter (PNM) is a fundamental concept in science, positing that all matter is composed of tiny, discrete particles (such as atoms or molecules) that are in constant motion and exert attractive or repulsive forces on each other [4]. Chiu et al. [5] noted that educators should not only focus on teaching the content of particle theory but also on how to present it in ways that effectively connect with students' prior knowledge and cognitive developmental stages, thereby facilitating their understanding of abstract concepts. Treagust et al. [6] emphasized that scientific models serve as mediators linking abstract concepts with students' experiences. Models are not merely learning tools, but in some cases, one of the only means to help students grasp abstract scientific theories such as particle theory. Xue and Sun [7] pointed out that scientific models and modeling offer significant benefits in chemistry education, playing an important role in describing natural phenomena and developing scientific knowledge.

Modeling lies at the heart of scientific thinking and practice. As one of the core forms of multimodal learning, it supports science teaching that often relies on multiple modes of representation. Schwarz et al. [8] identified modeling as a core scientific practice encompassing four main processes: constructing, using, evaluating, and revising models. They further stressed the importance of "metamodeling knowledge," which refers to students' understanding of the nature, function, limitations, and revision criteria of models, as essential to deepening scientific literacy. However, research has shown that students often perceive models as static images, overlooking their role as tools for reasoning, explanation, and prediction. This limits their ability to view models as revisable constructs. Without model evaluation skills, students may struggle to determine whether a model effectively represents a scientific phenomenon or to revise it appropriately, thereby reducing its learning potential [9]. In line with the vision of the Next Generation Science Standards (NGSS), modeling is considered a key approach to engaging students in scientific practices and knowledge construction [10]. Treagust et al. [6] called for providing students with more opportunities to manipulate, generate, and reflect on models. Such processes, transforming hypotheses into tangible representations, are essential for fostering depth of understanding and learner autonomy in science education [11,12].

At the elementary level, modeling helps students translate abstract scientific concepts into concrete mental structures. Yet, students often face challenges in language expression and multimodal integration, particularly in aligning images, text, and symbols into coherent scientific meaning. In this process, teachers act as mediators of learning [13], highlighting the need for targeted pedagogical support and well-designed strategies to help students model effectively—an endeavor that presents demands for both teachers and learners [14,15].

2.2 Challenges in Learning the Particle Model of Matter

The PMM is a central concept in science, yet its highly abstract nature often creates considerable difficulty for both teaching and learning. PMM involves microscopic ideas that cannot be directly observed and are difficult to build from students' everyday experiences [16]. Lee et al. [17] noted that students frequently rely on macroscopic intuitions to explain changes in matter. Such experience-based interpretations can lead to deeply rooted misconceptions, which in turn hinder the development and understanding of more advanced concepts such as atoms and molecules at the secondary level. If a correct particle view is not established in the elementary years, students are likely to encounter greater cognitive gaps in subsequent science learning. Chen and Lin [18] found that teachers still hold a vague understanding of the particle concepts introduced in Taiwan's 12-Year Curriculum, and even experienced teachers may not achieve a complete grasp of the scientific framework. This indicates that both teachers and students experience varying degrees of difficulty when dealing with this content. To address these issues, Lin [19] synthesized curriculum guidelines and research to propose eight core particle propositions that help clarify PMM teaching priorities and strengthen conceptual connections. Building on this foundation, Chen and Lin [18] integrated Merritt and Krajcik's [20] classification to develop a PMM mental model framework (Table 1), which provides both teachers and students with clear directions for conceptual adjustment and revision, and also demonstrates the potential of analogical modeling in PMM instruction. However, many students, even when possessing suitable intuitive analogies, often struggle to clearly articulate the logic and corresponding structures of their models. This makes it difficult for teachers to accurately interpret their conceptual understanding [21].

To overcome this limitation, the present study introduces Generative AI's image generation capability. After students express their analogy ideas in language, the system assists in visualizing their models. This approach not only reduces the linguistic barrier for students but also provides teachers with more visible and analyzable outputs as a basis for instructional feedback.

Table 1. PMM mental model framework

Mental Models			Descriptions
Scientific model		S	A complete particle model explains how particles and their interactions determine matter's macroscopic properties and behavior.
quasi- Scientific model		qS	Particles are separated by a vacuum, with gas particle spacing much greater than in solids and liquids, but without the concept of interparticle attraction.
Basic particle model	BS_distance	B-d	The relationship between the random motion of matter and distance.
	BS_movement	B-m	Particles undergo constant random motion
Mixed model	Mixed-consistent	M-c	Use microscopic particle and macroscopic descriptive perspectives to consistently explain phenomena of different substances.
	Mixed-inconsistent	M-ic	Use microscopic particle and macroscopic descriptive perspectives, but show inconsistency when explaining phenomena of different substances.
Descriptive model		D	Describing matter based on its visible appearance.

2.3 Potentials and Challenges of Generative AI in Supporting Students' Analogical Modeling

Gilbert [2] emphasized that visualization plays a crucial role in science learning and that students need to develop metavisual capability in order to effectively translate between different modes of representation and construct models. He further stressed that teachers should explicitly indicate the purposes and stages of model construction; otherwise, students may perceive modeling merely as a drawing activity and overlook its core function in conceptual understanding and scientific reasoning. Within this context, the application of Generative AI offers a new tool for visualization support. Generative AI can quickly produce a variety of visual models and images based on students' descriptions, concepts, or analogical inputs, helping them explore diverse representational forms. It can also strengthen students' understanding and application of analogy-based concepts [22]. Building on this potential, Generative AI can serve as a visual mediator, assisting students in externalizing linguistic descriptions into images and engaging in model construction and revision through interaction with AI-Generated visuals, thereby supporting scientific understanding.

By enabling rapid iteration in analogical modeling and image generation, Generative AI allows students to quickly explore, test, and modify their ideas, deepening their understanding of how knowledge is constructed and validated [23]. Students' evaluation of images during the modeling process is a key aspect of metacognitive engagement [24,25]. Morris [26] argued that Generative AI can serve as an innovative educational tool, supporting well-designed learning activities that stimulate students' metacognition. The combination of visual mapping and structured tasks can effectively promote and assess students' conceptual understanding [27]. Loeckx [27] further highlighted that AI can be an effective learning aid, reducing the workload for both teachers and students while enhancing the overall learning experience.

However, from a cognitive processing perspective, over-reliance on AI tools that quickly provide solutions may hinder learners from developing higher-order thinking skills [29]. Therefore, making effective use of Generative AI as a visual mediator in instruction, ensuring that technology serves as a learning partner in the classroom, will be an important challenge for teachers and educators in the future.

3. Research Methods

3.1 Research Design

This study adopted a qualitative research approach, referencing Khan's [30] model development process: Generation (constructing a model), Evaluation (assessing a model), and Modification (revising a model). Based on the G.E.M. framework, two lessons on the PMM were designed. The lessons were taught by a teacher with training and experience in modeling instruction to minimize errors arising from unfamiliarity with the pedagogy.

In the first lesson, students constructed initial models (G stage) by observing the diffusion of ink in hot and cold water. They then watched a video and completed a worksheet to compare their models with the observed phenomenon, identifying gaps or errors (E stage). Finally, a formative assessment guided students to reflect and revise their models (M stage), resulting in the first lesson's linguistic model. Figure 1 shows the assessment structure.

In the second lesson, students used the linguistic models from the first lesson and employed Generative AI to create analogy-based visual models of the ink diffusion phenomenon (G stage). They then evaluated the generated images (E stage) and provided explanatory instructions to the AI for modifications (M stage). Through repeated interaction with the AI, students refined both their conceptual understanding and visual representations, completing the final models. The entire lesson was video recorded and transcribed verbatim for analysis.

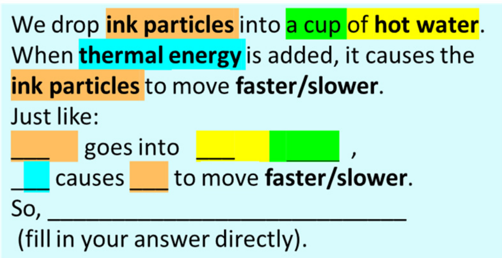


Figure1. Structure of the assessment tasks

3.2 Participants

The participants of this study were nine sixth-grade students from an elementary school in Taoyuan City, selected from the school's autonomous learning team and science club. The students were divided into three groups for the experiment. They were chosen because they possessed strong oral communication skills and prior experience in discussion, enabling them to engage actively in thinking and dialogue. These characteristics aligned with the study's focus on the evaluation process and metacognitive aspects of the modeling process.

3.3 Data Collection

Data were collected from two main sources: (1) student–AI dialogues and (2) video and audio recordings of the lessons.

(1) Student–AI dialogues: Students expressed, in written form, the linguistic models of the "ink particle diffusion in water" phenomenon they developed in the first lesson to the Generative AI. The AI then produced corresponding images. The recorded dialogues between students and the AI provided insights into how students articulated their ideas, modified visual representations, and engaged in the processes of model construction, evaluation, and revision.

(2) Video and Audio Recordings: The entire instructional process was video- and audio-recorded. These recordings were transcribed verbatim. The video data, in particular, captured authentic peer interactions, students' evaluation criteria for the generated images, and their reasoning behind model modifications.

3.4 Data Analysis

(1). Image Judgment for Research Question 1: A qualitative analysis was conducted to determine students' mental models based on the PMM concept learning framework proposed by Chen and Lin [18].

- Initial Linguistic Model: Derived from the models students developed in the first lesson.
- AI-Generated Final Visual Model: Derived from the models in the second lesson. Students interacted with Generative AI using their initial linguistic models from Lesson 1 to produce visual representations. They then proposed conceptual modifications to the images. When a student responded to an image with remarks such as "That's it," "It's fine," or "It's close enough" and no further images were generated, the model was identified as the final model.

(2). Evaluation Criteria for Research Question 2: A qualitative content analysis approach was adopted. Drawing on Lemke's [31] systemic functional linguistics perspective, which posits that each mode has unique functions and cannot fully replace another, three types of meaning were used as the main coding framework. Their definitions and correspondence to this study are as follows:

- Presentational Meaning: Focuses on students' understanding and evaluation of the AI-Generated image content itself, such as whether the image aligns with scientific principles, facts, or phenomena. In this study, it corresponds to Plausibility(P).
- Orientational Meaning: Concerns students' subjective stance, prior imagination, attitudes, and emotions, reflecting personal perspectives and value judgments about the AI images. In this study, it corresponds to Alignment with experience and imagination(A).
- Organisational Meaning: Analyzes students' evaluation of image details, structures, and element composition, exploring how they interpret and organize information within the image. In this study, it corresponds to Detail(D).

After reaching a consensus on these definitions, two researchers independently coded the qualitative data for one group of students. The Kappa values for all three categories exceeded .85, indicating high agreement [32]. For any coding discrepancies, the research team engaged in further discussion to ensure that the interpretation of students' evaluation criteria was as accurate as possible. These three meaning categories ultimately became the three evaluation criteria for students' assessments of the AI-Generated visual models, as shown in Tables 2 and 3.

Table 2. Evaluation criteria for AI-Generated visual representations

Criteria	Coding Description	Example
Plausibility(P)	Scientific accuracy of the AI-Generated image based on student input.	Dialogue includes scientific concepts or meaningful scientific terms: particles, heat diffuses faster, sweets make ants move faster, analogy diagram…
Alignment(A)	Match between the image and the student's experience	Dripping ink particles into a beaker; switch to Angry Birds; Ah! I didn't tell it that it was raining; Yes, the ants did move faster…
Detail(D)	Specific visual elements students requested (e.g., color, quantity, motion, atmosphere).	Why are there so few ants? This should have a big explosion; It's not even in the water; Ah! It gave me a bunch of black birds…

Table 3. Data identification and coding descriptions

Item	First Code (Target)		Second Code (Modeling Stage)	Third Code (Data Source)		
	Group	Image Sequence	Modeling Process	Generative AI Dialogue	Transcription	
Code Description	T1~T3	0~11 image number	G: Generation E: Evaluation M: Modification	sequential numbering of dialogue turns	S1–S3: three students in each group	Evaluation Code P.A.D
Example	T1.6_E_S3.A : Target: Group 1, Image #6, Modeling Process: Evaluation stage, Data source: statement from Student 3 regarding evaluation criteria for the image. T2.3_M_AI.4: Target: Group 2, Image #3, Modeling Process: Modification stage, Data source: fourth dialogue turn with AI.					

4. Results

4.1 What are the students' initial linguistic models and the AI-Generated final visual models after interacting with Generative AI?

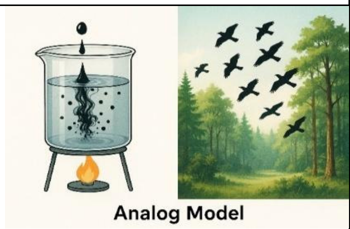
Through the two-lesson analogy-based modeling tasks, we collected students' initial linguistic models and their final AI-Generated visual models. Using the PMM concept learning mental model classification proposed by Chen and Lin [18], we found that students' initial linguistic models were classified as Descriptive (D) and Mixed-consistent (M-c). However, the AI-Generated final Visual Model from the second lesson all reached the level of the Basic Particle Model – Movement (B-m), which reflects a scientifically basic particle movement model. Table 4 provides detailed descriptions of the model characteristics for the three groups.

(1) Initial Linguistic Models: After completing the modeling task in the first lesson, analysis of the students' linguistic models revealed that, within the lesson's modeling framework, all students were able to clearly identify the concept of an "energy source" and describe the "movement" behavior. This finding indicates that the structured modeling framework was necessary and beneficial in helping students grasp the concepts intended by the teacher. It also echoes Gilbert's view [2] that teachers need to make the purpose and stages of modeling explicit; otherwise, students may perceive modeling merely as drawing or surface-level manipulation.

In the lesson design of this study, the step-by-step guidance allowed students to follow the intended process. However, in the initial linguistic models, most analogies from all three groups still described phenomena from a macroscopic perspective without incorporating particle concepts. As a result, the mental models of Groups T1 and T3 were classified as Descriptive (D), while Group T2 showed awareness of the need to address particle concepts but still described them macroscopically, leading to its classification as Mixed-consistent (M-c).

(2) AI-Generated Visual Models: In the stage where the initial linguistic models were transformed into analogy-based images through Generative AI, the representations in the linguistic models were converted into visual forms. Students examined the AI-Generated images and supplemented any missing concepts. When the images matched their intended mental representation, they were identified as the AI-Generated final visual models.

Table 4. Mental Models of the three groups in the PMM modeling process

	T1	T2	T3
Lesson 1 Initial Linguistic Model	A black bird enters a sunny forest. The improved weather speeds up the bird's movement, so it becomes more active.	The angry bird enters a fortress game. A big explosion speeds up its movement, just like particles move faster in hot water.	The ant enters a candy world. The sweets make the ant move faster.
Mental model	Descriptive/D	Mixed-consistent /M-c	Descriptive/D
Lesson 2 AI-Generated final Visual Model			
Mental model	Basic particle model_movement /B-m	Basic particle model_movement /B-m	Basic particle model_movement /B-m

As an example, the process for Group 1 is described below:

Initial Linguistic Model: *Black birds enter a sunny forest; the good weather makes the black birds move faster, so they become more active.* (T1.0_G_AI.1)

Figure 2. The first image generated by the Generative AI

"Why did it give me a bunch of black birds?" (T1.1_E_S2.AD)

"No analogy? Tell it to produce an analogy image." (T1.1_M_S1.PA)

This group noticed that the AI-generated image lacked concepts of quantity and movement, and they attributed this to the absence of the analogy concept in their original description. They then revised their prompt to the Generative AI by adding: *"Help me produce an analogy model"* at the end:

Black birds enter a forest; the good weather makes the black birds move faster, so they become more active. Help me produce an analogy model. (T1.1_M_AI.2)

Subsequently, the group continued interacting and gave multiple instructions to the AI. Examples of these interactions are as follows:

...We drip ink particles into a beaker of hot water. (T1.2_M_S3.D)

Heating makes the ink particles move faster... (T1.2_M_S2.PD)

Black birds enter the forest... move faster and become more active. (T1.2_M_S3.AD)

We drip ink particles into a beaker of hot water; heating causes the ink particles to move faster, just like [black birds entering a sunny forest, where the good weather makes the black birds move faster and more active]. Please produce an analogy model image. (T1.3_M_AI.4)

Finally, the group obtained a satisfactory AI-generated visual model, as shown in Figure 3.

Figure 3. AI-Generated final visual model of Group 1

During the interaction process, students were able to return to the framework of their initial linguistic models for alignment, indicating that in their dialogues with the AI, they responded to relevant concepts through the visualization of images. At this stage, the formative assessment framework provided in the first lesson served its linking function, helping students revisit the phenomenon for further alignment. As shown in Table 4, all three groups emphasized the correspondence of “movement” behaviors during this phase, breaking away from the macroscopic framework of the initial linguistic models and shifting toward a scientifically Basic particle model-movement (B-m) that incorporates microscopic concepts.

The initial linguistic models from Lesson 1 clearly lacked an understanding of the “microscopic particle concept,” with mental models generally falling into the Descriptive (D) and Mixed-consistent (M-c) categories. With the assistance of Generative AI, students transformed the representations in their linguistic models into images, which enabled them to better identify the concepts needed in their models. This process strengthened their ability to evaluate and revise models, and in doing so, activated their metacognitive processes and helped them establish concepts. As Grapin et al. [10] noted, multimodality can provide students with rich resources for meaning-making and communication, effectively supporting their engagement in scientific inquiry. The next section will describe how students carried out their evaluations.

4.2 How Did Students Evaluate the AI-Generated Visual Models?

With the assistance of AI-Generated, students transformed the representations in their linguistic models into images, which enabled them to better identify the concepts that needed to be supplemented. This process strengthened their model evaluation and revision. To examine how students evaluated the images to determine whether their models were complete, we analyzed verbatim transcripts of classroom recordings and the compiled prompts students gave to the AI.

The data were first segmented according to the three stages of modeling—Generation (G), Evaluation (E), and Modification (M). Then, following Lemke’s [31] functional linguistic framework, each relevant utterance was coded into one of three evaluation criteria: Plausibility(P), Alignment (A), and Detail(D). The results indicate that these three evaluation criteria played different roles across the three stages of the modeling process—Generation (G), Evaluation (E), and Modification (M). The statistical analysis is presented in Table 5.

Table 5. Analysis of P.A.D. usage

<table>
<tr><td colspan="2">Group</td><td colspan="4">T1</td><td colspan="4">T2</td><td colspan="4">T3</td><td></td></tr>
<tr><td colspan="2" rowspan="2">Modeling Stage</td><td colspan="12">Evaluation Criteria</td><td></td></tr>
<tr><td>P</td><td>A</td><td>D</td><td>total</td><td>P</td><td>A</td><td>D</td><td>total</td><td>P</td><td>A</td><td>D</td><td>total</td><td>total</td></tr>
<tr><td rowspan="3">Mode
-ling
Stage</td><td>G</td><td>5</td><td>6</td><td>7</td><td rowspan="3">66
G:18
E:25
M:23</td><td>6</td><td>8</td><td>9</td><td rowspan="3">72
G:23
E:34
M:15</td><td>1</td><td>1</td><td>1</td><td rowspan="3">61
G:3
E:27
M:31</td><td>44</td></tr>
<tr><td>E</td><td>5</td><td>10</td><td>10</td><td>3</td><td>14</td><td>17</td><td>5</td><td>10</td><td>12</td><td>86</td></tr>
<tr><td>M</td><td>4</td><td>4</td><td>15</td><td>4</td><td>4</td><td>7</td><td>4</td><td>13</td><td>14</td><td>69</td></tr>
<tr><td colspan="2">Frequency
(%)</td><td>14
21%</td><td>20
30%</td><td>32
49
%</td><td>G:27%
E:52%
M:48%</td><td>13
18%</td><td>26
36%</td><td>33
46%</td><td>G:32%
E69%
M31%</td><td>10
16%</td><td>24
39%</td><td>27
45%</td><td>G:5%
E47%
M53%</td><td rowspan="2">199</td></tr>
<tr><td colspan="2">Overall
Total (%):</td><td colspan="12">P37(19%) A70(35%) D92(46%)</td></tr>
</table>

(1). Overall frequency and distribution of P.A.D. evaluation criteria during the modeling process:

Across the entire modeling process, students applied the evaluation criteria 199 times. Detail of visual representation (D) was most frequent (92 times, 46%), followed by Alignment with experience and imagination (A) (70 times, 35%). Plausibility (P) was least frequent (37 times, 19%). This indicates that students showed high sensitivity to visual detail and subjective imagination, consistent with[14], who noted students' preference for concrete, visible features. However, their relative weakness in understanding and articulating abstract concepts limited the plausibility and completeness of their models.

(2). Dynamic development of P.A.D. criteria in the modeling process:

Model Generation (G) stage – Students entered their initial linguistic models into Generative AI. Although based on the first lesson's question framework, they refined wording repeatedly, indicating early self-evaluation. Group 2 showed high interaction (P6, A8, D9) when shaping imagined models and adjusting details. Their final input command to the AI was:

"We want you to create an image of a particle model based on our analogy: Ink particles dropped into a beaker of hot water. Heat makes them move faster, like Angry Birds entering a fortress. The explosion makes the birds faster, so particles in hot water move faster." (T2.0_G_AI.1)

Although no final image was yet produced, evaluative language was already present, suggesting this process fostered self-checking of initial models.

Model Evaluation (E) and Modification (M) stages – Upon receiving the AI-generated image, students showed strong engagement, discussing plausibility, alignment with prior experience, and image details, while revising prompts. This active participation counters concerns that over-reliance on AI might hinder higher-order thinking [29]. The E and M stages were intertwined, with higher P.A.D. usage than in G, strengthening and refining application of the criteria.

(3). P.A.D. criteria activating metacognition: Overall, the criteria appeared throughout the process, forming a cyclical pattern that reinforced concept building [14]. Detail (D) was used most often (46%), followed by Alignment (A) (35%), showing students' reliance on sensory impressions. Though used less (19%), Plausibility (P) served as a key checkpoint for scientific accuracy, often integrated after detail and imagination to align models with disciplinary knowledge. For example, Group 3's initial linguistic model reflected only a descriptive (D) level, but the AI visualization linked to personal understanding, triggering metacognitive behavior. When a student remarked, *"The ants look like they're in the sky?"* (T3.2_E_

S3.P.A.D.), it showed self-assessment against the original input and adjustment based on AI output. This reflects not only model evaluation but also awareness of one's thought process, aligning with Treagust et al. [6], who emphasized that manipulating, generating, and reflecting on models enables students to take ownership of modeling and achieve deep learning.

5. Discussion

Based on the findings, this study argues that the visual mediating role provided by Generative AI has the potential to enhance students' modeling competence and activate their metacognitive processes.

5.1 Generative AI as a means to extend linguistic models and construct scientific concepts

From Research Question 1, we found that the linguistic models constructed by the three groups of students were mostly limited to D- and M-c-type mental models, reflecting an intuitive understanding of macroscopic phenomena and difficulty in concretizing abstract concepts such as particle motion and microscopic structures. When the modeling process incorporated interaction with AI, the visualized images enabled students to identify missing concepts in their linguistic models. Consequently, the macroscopic framework of the initial linguistic model was elevated to the B-m type, which incorporates microscopic concepts. This progression not only demonstrates students' construction of the concept of particle motion, but also highlights the potential of AI-based visual generation tools in supporting the modeling process.

5.2 Insights into Students' Thinking Tendencies and Metacognition through the P.A.D. Evaluation Criteria

During the modeling process, students predominantly relied on Alignment (A) with personal experience and imagination, and Detail (D) of visual representation as their main evaluation criteria. This indicates a preference for sensory experience and subjective speculation, reflecting that the initial construction of their models was based more on intuitive perception than on conceptual reasoning. Although Plausibility (P) appeared less frequently, it was present in every modeling stage and played a crucial supporting role, guiding students to remain focused on scientific accuracy rather than being distracted by visually appealing images.

Students' ongoing revisions in response to visual feedback represented not only explicit model refinement but also the activation of metacognitive processes. In this study, students repeatedly evaluated AI-generated images and modified their verbal descriptions, exemplifying the metamodeling process emphasized by Schwarz and aligning with the principle that "models change as understanding evolves" in the modeling learning trajectory. These P.A.D.-based evaluation criteria not only provided researchers with a lens to examine how students judged images, but also revealed the cognitive shift in students' modeling—from intuitive perception toward conceptually grounded scientific reasoning.

6. Conclusion and Recommendations

This study aimed to explore how students develop models within the G.E.M. framework and to further analyze their evaluation behaviors and criteria when assessing AI-generated images during the modeling process. Based on the findings, the following conclusions and instructional recommendations are proposed as a reference for integrating Generative AI into analogy-based modeling in future science classes.

6.1 Generative AI Facilitates Model Revision and Scientific Concept Construction

Students' initial linguistic models were mostly confined to the level of macroscopic phenomena and intuitive analogies. The use of Generative AI to produce images helped students recognize the conceptual incompleteness of their models, triggering revisions and knowledge transfer. This process gradually enabled them to establish more scientifically accurate concepts and reach higher-level mental models.

6.2 The Mediating Role of Generative AI's Visual Feedback in Stimulating Evaluative Thinking and Metacognition

During the modeling process, the visual feedback provided by Generative AI enabled students to flexibly apply evaluation criteria and progressively develop metacognitive skills. Serving as a "visual feedback mediator" in multimodal learning contexts, Generative AI promoted students' reflection and adjustment of models, thereby deepening the construction of scientific meaning.

Instructional and Research Recommendations:

Instructional practice: Science teachers are encouraged to incorporate Generative AI tools into modeling instruction and integrate explicit evaluation criteria. This approach provides students with a structured framework for multi-dimensional model assessment, enhancing modeling competence while fostering scientific concept understanding.

Future research: Future studies could expand the sample size and further analyze how students' linguistic models are transformed into discipline-specific visual models with the assistance of Generative AI, in order to develop more generalizable instructional strategies.

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