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The MTA-TPACK Dynamic Collaboration Spiral: Making Pedagogical Thinking Visible in Human–AI Scientific Visualization for Sustainable Teacher Innovation

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Abstract

Generative AI challenges traditional technology integration frameworks by introducing agentic systems that actively participate in meaning-making and representation. Existing TPACK-based extensions have identified new knowledge domains required for AI integration, yet they offer insufficient explanations of how such knowledge is dynamically activated during human–AI collaboration. This study proposes the MTA–TPACK Dynamic Collaboration Spiral, a theoretical framework that integrates Meta-Task Awareness (MTA) with TPACK to explain how static knowledge resources are transformed into visible pedagogical reasoning through iterative human–AI interaction. Within this framework, MTA functions as a dynamic navigation engine that guides experts along a Generate–Evaluate–Refine trajectory, enabling principled orchestration of AI participation while maintaining epistemic responsibility. The framework is illustrated through a two-phase scientific visualization task on typhoon–terrain interactions, using Midjourney and GPT-4o. The results show how disciplinary knowledge must be reformulated as AI-interpretable constraints and how evaluation practices evolve when AI systems participate in closed-loop feedback. The resulting visual artifacts embody what is termed Visible Pedagogical Thinking—externalized cognitive constructs that make expert reasoning inspectable. By foregrounding evaluation-centered task design, this study provides a transferable account of how human–AI collaboration can remain pedagogically meaningful by rendering expert reasoning observable and reusable across iterative generative workflows. In doing so, the model contributes to sustainable pedagogical innovation by strengthening teachers' long-term epistemic agency in AI-mediated design environments.

Keywords: meta-task awareness (MTA); human-AI collaboration; TPACK; teacher professional development; generative AI; cognitive sustainability; pedagogical innovation; visible pedagogical thinking

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1. Introduction

1.1. Research Background: TPACK in the Generative AI Era

The Technological Pedagogical Content Knowledge (TPACK) framework, introduced by Mishra and Koehler [1], builds on Shulman's foundational work on Pedagogical Content Knowledge (PCK) [2,3] and conceptualizes effective technology integration as the dynamic intersection of Content Knowledge (CK), Pedagogical Knowledge (PK), and Technological Knowledge (TK). Over the past two decades, TPACK has provided a shared analytical language for examining how teachers develop integrated knowledge structures for technology-enhanced instruction across diverse educational contexts [4,5].

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However, the rapid emergence of Generative AI (GenAI), particularly following the public release of ChatGPT in November 2022, has fundamentally challenged the assumptions underlying classical TPACK. Traditional educational technologies were largely stable, predictable tools whose functions could be mastered through procedural proficiency and remained under direct human control [6]. In contrast, GenAI systems actively participate in meaning-making, representation, and decision-making processes, producing novel outputs, exhibiting opaque internal mechanisms, and generating unpredictable behaviors that reshape the cognitive task of teaching itself [6,7].

Recognizing this design reorientation, recent scholarship has proposed multiple extensions to the TPACK framework. Among these, Intelligent-TPACK (I-TPACK), initially conceptualized by Celik [8] and further developed by Chiu and colleagues [9,10], introduces ethical knowledge as a core component and identifies human–AI collaboration as a distinct competency area. Using a Delphi study with teachers from diverse subject domains, Chiu et al. operationalized I-TPACK into interrelated knowledge domains encompassing AI-related technological, pedagogical, and content knowledge, human–AI collaboration knowledge, and ethical knowledge [10]. This reconceptualization positions teachers not as tool operators but as designers of augmented pedagogical systems.

The theoretical impetus for extending TPACK is further reinforced by contributions from the framework's original co-creators. Mishra, Warr, and Islam identified five defining characteristics of GenAI—protean, opaque, unstable, generative, and social—that distinguish AI systems from prior educational technologies [6]. They argued that these properties necessitate expanded contextual knowledge addressing how AI reshapes individual cognition, classroom practice, and broader educational ecosystems. From this perspective, the limitations of classical TPACK are most pronounced in its treatment of dynamic human–AI interaction and embedded ethical considerations.

Parallel frameworks have further challenged TPACK's conceptual boundaries. Deng and Zhang proposed Technological Pedagogical Content Ethical Knowledge (TPCEK), treating ethics as a fourth foundational knowledge domain [11]. Aziz and Mokhtari advanced the AIA-PCEK framework, reconceptualizing AI as a pedagogical agent rather than an instrumental tool, thereby foregrounding AI's autonomous and adaptive role in instructional processes [7]. Together, these models reflect a growing consensus that GenAI integration requires more than incremental extensions of traditional technology frameworks.

Empirical research on AI-TPACK has expanded rapidly. Large-scale survey studies have documented persistent gaps in teachers' preparedness for AI-assisted teaching. For example, Wang et al. reported that pre-service teachers' intentions to design AI-supported instruction were shaped by GenAI anxiety, social influence, and performance expectancy, with TPACK and self-efficacy serving as significant predictors [12]. Intervention studies suggest that AI-TPACK competencies can be developed through structured professional learning. Sun et al. demonstrated significant gains in AI knowledge and teaching self-efficacy following an intensive training program [13], while Tan et al. observed both positive gains and metacognitive recalibration effects in a six-month quasi-experimental study [14].

Qualitative investigations have empirically identified iterative processes of inquiry, evaluation, and modification in the design of pre-service teachers with GenAI [15]. However, a comprehensive theoretical framework is needed to elevate these empirical observations into a generalized cognitive model that explains specifically how static TPACK resources are mobilized and transformed within these generative loops. Domain-specific studies have revealed both affordances and challenges across disciplines, including mathematics [16,17], visual arts [18], and science education [19]. Collectively, these findings suggest that effective AI integration depends not only on technical skill but on reflective awareness of how and when AI should be deployed.

Despite this growing body of work, critical gaps remain. Existing AI-TPACK extensions primarily emphasize the identification of requisite knowledge domains [9,10], while offering limited theoretical accounts of the cognitive processes through which such knowledge is activated during iterative human-AI collaboration [20,21]. In particular, current frameworks insufficiently address

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how educators navigate generative uncertainty, evaluate AI outputs against disciplinary criteria, and refine tasks to maintain epistemic responsibility. Addressing this gap requires a shift from static knowledge identification toward a process-oriented understanding of human-AI collaboration. Building on Wong's concept of Meta-Task Awareness (MTA) and Chain of Learning Design and Evaluation (CoLDE) [22], the present study proposes the MTA-TPACK Dynamic Collaboration Spiral as a framework for explaining how static TPACK resources are dynamically activated through iterative Generate-Evaluate-Refine trajectories, culminating in Visible Pedagogical Thinking. As AI-TPACK continues to redefine instructional design, the MTA–TPACK framework emerges as a crucial conceptual tool for teacher professional development, providing educators with a roadmap for transitioning from basic tool use to sophisticated pedagogical orchestration.

1.2. Generative AI for Scientific Visualization: The Case of Typhoon–Terrain Interactions

Scientific visualization represents a domain in which the limitations of prompt-based AI interaction become particularly salient. Translating complex scientific phenomena into accurate and pedagogically meaningful visual representations requires not only domain expertise but continuous evaluative judgment. The visualization of tropical cyclone interactions with complex terrain provides an especially demanding test case for examining how human–AI collaboration unfolds under conditions of high epistemic responsibility.

Scientific illustration bridges abstract concepts and visual communication. Its evolution traces from prehistoric art [23] and ancient drawings [24] to the systematic rigor of classical scholars [25]. The Renaissance established foundational anatomical precision [26], while the printing press expanded knowledge dissemination [27]. Later centuries standardized botanical details [28], leading to modern transformations through photography, digital imaging, and virtual reality [29].

Recent advances in generative AI, including large language models and text-to-image systems such as Midjourney, DALL·E, and Stable Diffusion, have further transformed this landscape by enabling rapid production of detailed scientific imagery from natural language prompts [30–32]. These tools have expanded access to visualization while simultaneously introducing new risks related to scientific fidelity.

Within meteorology, prior work has demonstrated the use of generative AI for visualizing atmospheric processes, including tornado dynamics and tropical cyclone structures [33,34]. Similar applications have emerged across scientific disciplines, such as medicine, biology, and physics, highlighting the broad potential of AI-assisted visualization for science communication [35]. However, superficially plausible outputs do not guarantee alignment with underlying physical mechanisms, underscoring the indispensability of expert evaluation.

Tropical cyclone–terrain interactions, particularly over regions such as Taiwan's Central Mountain Range, involve multiple well-documented physical mechanisms that any scientifically accurate visualization must capture [36,37]. These include orographic blocking [38–41], vortex splitting [39,41–43], asymmetric convection [41,42,44,45], and terrain-induced track deflection [36,38,40,45–49], as documented in extensive observational and modeling studies. Additional factors such as terrain-induced vorticity generation [39,50], moisture blocking [38,41], and looping or stalling behavior further complicate storm evolution [47,51]. Despite advances in numerical modeling, accurately representing these processes remains challenging, motivating continued investigation into physical mechanisms and communication strategies [37,41,50]. Table 1 summarizes four primary mechanisms identified in the meteorological literature that any scientifically accurate visualization must capture.

Table 1. Key physical mechanisms governing tropical cyclone--terrain interactions and their implications for scientific visualization.

Mechanism	Description	Key References
Orographic Blocking	High mountain ranges disrupt low-level inflow, leading to deceleration, deflection, or partial blocking of the	[38–41]

	cyclone circulation. This process alters storm symmetry and modifies rainfall distribution upstream of the terrain.	
Vortex Splitting	Complex terrain can induce the separation of the primary vortex into secondary gyres through potential vorticity redistribution, resulting in asymmetric circulation structures and modified storm evolution.	[39,41–43]
Asymmetric Convection	Enhanced convection and precipitation occur on windward slopes due to forced ascent, while subsidence and drying dominate on the lee side, producing pronounced rainfall asymmetry.	[41,42,44,45]
Track Deflection	Cyclone tracks are deflected as a function of terrain height, storm size, translation speed, and approach angle, often leading to looping, stalling, or abrupt directional changes near landfall.	[36,38,40,45–49]

This body of meteorological literature constitutes the Content Knowledge foundation that must be actively engaged when using generative AI for scientific visualization. As emphasized in prior analyses of GenAI characteristics, providing disciplinary terminology alone does not ensure scientifically meaningful output [6]. AI systems may generate visually appealing but physically misleading representations, requiring experts to identify and correct hallucinations through iterative evaluation. Accordingly, typhoon–terrain visualization offers a rigorous empirical context for examining how Meta-Task Awareness operates as a dynamic filter that guides human–AI collaboration toward epistemically responsible outcomes.

1.3. Research Design and Methodological Positioning

This study is positioned as a conceptual framework paper supported by an illustrative case study. Its primary contribution is theoretical: the development of the MTA–TPACK Dynamic Collaboration Spiral as an explanatory framework for human–AI collaboration. The empirical component serves a demonstrative rather than hypothesis-testing function, tracing how the framework's constructs manifest across iterative visualization cycles.

The research design adopts a two-phase structure. In the Midjourney phase, a domain expert in atmospheric science conducted four iterative Generate–Evaluate–Refine cycles to produce scientifically accurate visualizations of typhoon–terrain interactions. In the GPT-4o phase, the same task was revisited using a closed-loop collaboration structure in which the AI system participated in self-evaluation as well as generation. Both phases employed the same evaluation criteria: four atmospheric mechanisms identified from the meteorological literature (orographic blocking, vortex splitting, rainfall asymmetry, and streamline structure; see Table 1), against which each generated image was assessed.

Scientific accuracy was rated on a five-point scale by the first author, who holds domain expertise in tropical cyclone dynamics and has published extensively on typhoon–terrain interactions [33,34,46]. Visual clarity was assessed based on perceptual salience, compositional coherence, and communicative accessibility. These ratings function as structured expert judgments within the case study rather than as psychometric measurements. The study does not claim statistical generalizability; rather, it aims to demonstrate the explanatory utility of the proposed framework through detailed process documentation of a demanding scientific visualization task.

1.4. Research Objectives and Study Overview

Building on the theoretical developments reviewed in Section 1.1 and the empirical context established in Section 1.2, this study proposes the MTA–TPACK Dynamic Collaboration Spiral as a framework for understanding human–AI collaboration in educational settings. While existing AI-

TPACK extensions have clarified the knowledge structures required for AI integration, this study focuses on the cognitive processes through which these structures are activated and coordinated during iterative interaction with generative AI systems.

The study pursues three interrelated objectives. First, it articulates the MTA–TPACK Dynamic Collaboration Spiral as a theoretically grounded model linking static TPACK resources with dynamic Meta-Task Awareness. Second, it empirically demonstrates this framework through AI-assisted scientific visualization, tracing how Generate–Evaluate–Refine cycles operate across multiple iterations. Third, it examines how principled human–AI collaboration produces Visible Pedagogical Thinking—externalized structured reasoning patterns that render expert reasoning explicit, inspectable, and reusable as pedagogical resources.

The study is organized as follows. Section 2 presents the theoretical framework, detailing its foundational components, dynamic mechanisms, and outcomes. Sections 3 and 4 provide empirical demonstrations through a Midjourney-based human-orchestrated phase and a GPT-4o-based AI-augmented phase, respectively. Section 5 synthesizes the findings, discusses implications for sustainable human–AI collaboration in the post-prompting era, and articulates how Visible Pedagogical Thinking emerges as a structured reasoning pattern as the culminating outcome of the framework.

2. Theoretical Framework: The MTA-TPACK Dynamic Collaboration Spiral

As established in Section 1.1, classical TPACK conceptualizes effective technology integration as the intersection of Content Knowledge (CK), Pedagogical Knowledge (PK), and Technological Knowledge (TK) [1,4]. However, the agentic characteristics of GenAI—systems that actively participate in representational and decision-making processes, producing outputs that are generative, opaque, and context-sensitive [6]—require a reconceptualization of how these knowledge resources function in practice. Under these conditions, effective AI integration cannot be understood solely as the accumulation or intersection of knowledge domains. Rather, it requires a framework that accounts for how static knowledge resources are dynamically activated, coordinated, and evaluated during iterative human–AI interaction.

To address this need, this study proposes the MTA–TPACK Dynamic Collaboration Spiral (Figure 1). The framework conceptualizes human–AI collaboration as a structured process in which static TPACK resources form a foundation, Meta-Task Awareness (MTA) functions as a dynamic navigation engine, iterative Generate–Evaluate–Refine cycles constitute the operational process, and Visible Pedagogical Thinking emerges as the outcome.

In this study, MTA is not conceptualized as a discrete skill, trait, or checklist of strategies. Rather, it is framed as an epistemic orientation toward task design in AI-mediated environments—an awareness of how task goals, structures, and boundaries are co-shaped by human judgement and AI affordances. This orientation becomes observable when teachers explicitly articulate and iteratively refine the underlying structure of their design tasks.

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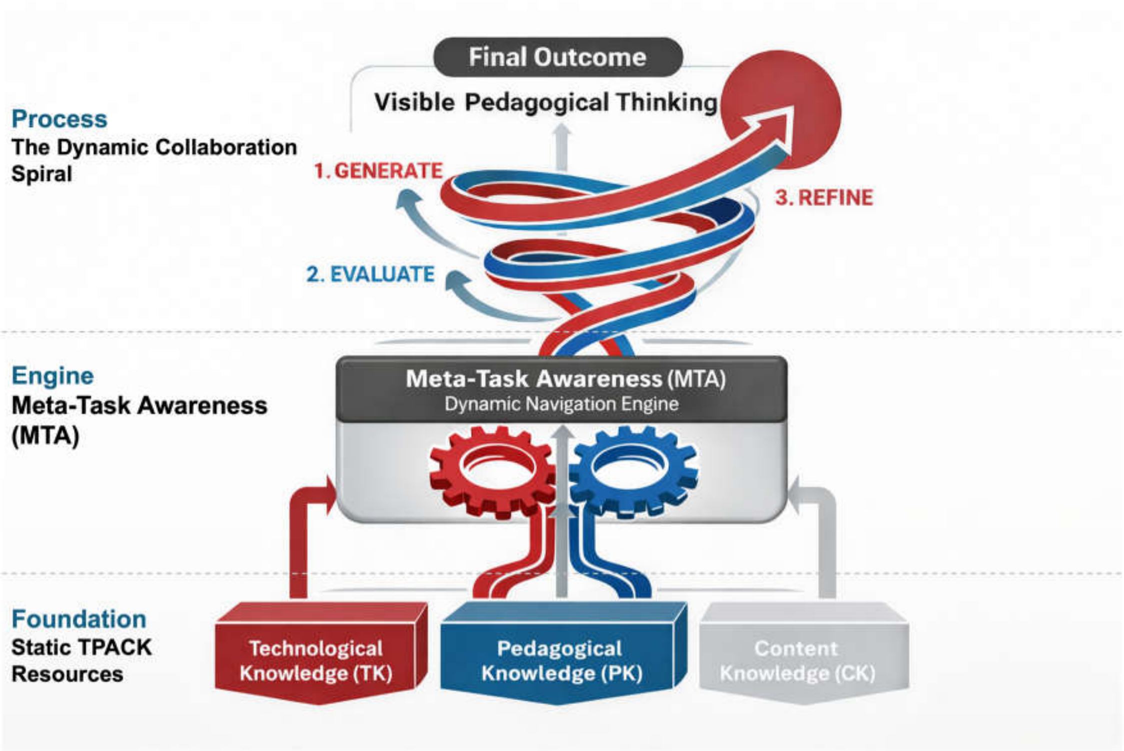

Figure 1. The MTA-TPACK Dynamic Collaboration Spiral. This framework shows the shift of generative AI from a static tool to a dynamic process. The base is static TPACK Resources—Content, Pedagogical, and Technological Knowledge. These are activated by Meta-Task Awareness (MTA), a Dynamic Navigation Engine that guides agency and reimagines traditional knowledge for AI collaboration. Enabled by MTA, the process forms a Dynamic Collaboration Spiral through Generation, Evaluation, and Refinement. This Chain of Learning Design and Evaluation (CoLDE) ends with a visible pedagogical artifact that captures implicit reasoning.

2.1. The Foundation and the Engine: Static TPACK Resources and Meta-Task Awareness

At the base of the MTA–TPACK Dynamic Collaboration Spiral lies the Foundation, comprising static TPACK resources. This layer represents relatively stable knowledge structures, including disciplinary understanding (CK), instructional design principles (PK), and proficiency in using digital tools (TK). These resources align with the conventional interpretation of TPACK as an integrated yet essentially static knowledge base [1,4].

Within the proposed framework, static TPACK resources are necessary but not sufficient for effective collaboration with GenAI systems. Their activation depends on Meta-Task Awareness (MTA), which functions as the Engine of the collaboration spiral. MTA is defined here as an integrative metacognitive capability that enables individuals to recognize how AI participation reshapes the structure, constraints, and evaluative demands of a task. Rather than constituting an additional knowledge domain, MTA operates across CK, PK, and TK by coordinating how these resources are deployed in response to AI-generated outputs.

From the perspective of Technological Knowledge, MTA shifts the focus from procedural proficiency—knowing how to operate AI tools—to awareness of how AI systems interpret prompts, prioritize features, and exercise generative autonomy [6]. In relation to Pedagogical Knowledge, MTA supports monitoring and regulating the distribution of agency between human and AI actors, aligning with recent conceptions of teachers as designers of augmented pedagogical systems [10]. With respect to Content Knowledge, MTA enables disciplinary understanding to function as an epistemic filter, guiding judgments about whether AI-generated representations conform to or deviate from accepted scientific or conceptual constraints.

Through this coordinating role, MTA transforms static TPACK resources into an active system for navigating human–AI collaboration. The framework therefore distinguishes between possessing

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integrated knowledge and being able to mobilize that knowledge effectively under conditions of generative uncertainty.

In this study, MTA is operationalized as observable shifts in (i) how domain mechanisms are translated into visual constraints in prompts, and (ii) how evaluation criteria move from surface plausibility to mechanism-level causal consistency. This spiral structure provides the conceptual reference point for the empirical analyses reported in Sections 3 and 4.

2.2. The Process: The Generate–Evaluate–Refine Collaboration Spiral

When static TPACK resources are activated through Meta-Task Awareness, human–AI interaction takes the form of a structured, iterative process represented in the framework as the Dynamic Collaboration Spiral. This process operationalizes the Chain of Learning Design and Evaluation (CoLDE) proposed by Wong [22] and consists of repeated Generate–Evaluate–Refine cycles.

In the Generate phase, the human expert externalizes task-relevant knowledge by specifying prompts or constraints intended to guide AI output. This action is treated as a design intervention rather than a simple command, as it reflects hypotheses about how domain knowledge and representational requirements can be communicated to the AI system.

In the Evaluate phase, the AI-generated artifact is examined against explicit criteria derived from disciplinary, pedagogical, or task-specific considerations. Evaluation serves a diagnostic function by revealing discrepancies between intended representations and actual outputs, as well as by exposing implicit assumptions embedded in the prompt design.

In the Refine phase, insights from evaluation are used to adjust specifications, constraints, or representational strategies in subsequent iterations. This phase is governed by Meta-Task Awareness, which informs decisions about how to recalibrate human input in response to AI behavior.

Across iterations, the Generate–Evaluate–Refine sequence forms an upward spiral rather than a closed loop. Each cycle builds on prior evaluations, progressively stabilizing alignment between human intent and AI output while deepening understanding of the task–AI relationship. Sections 3–4 instantiate these phases using a four-mechanism rubric (Table 1) and cycle-wise scoring (Tables 2 and 3).

2.3. The Outcome: Visible Pedagogical Thinking

The outcome of sustained engagement within the MTA–TPACK Dynamic Collaboration Spiral is termed Visible Pedagogical Thinking. In this framework, AI-generated artifacts are not treated as end products in themselves but as externalized representations of the cognitive processes that guided their creation.

Visible Pedagogical Thinking is defined as the manifestation of expert reasoning embedded within an artifact through iterative human–AI collaboration. When Meta-Task Awareness governs the Generate–Evaluate–Refine process, disciplinary judgments, pedagogical intentions, and technological considerations become materially inscribed in the evolving output. As a result, the final artifact reflects not only what was generated, but how evaluative and corrective decisions were made across iterations.

This outcome has both theoretical and practical significance. Theoretically, it provides a mechanism through which abstract competencies emphasized in AI-TPACK extensions—such as ethical judgment, epistemic responsibility, and human–AI collaboration—can be observed in concrete form [8–11]. Practically, it enables pedagogical reasoning to become inspectable, discussable, and transferable, supporting reflective learning and instructional design in AI-mediated contexts.

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3. Activating the Dynamic Collaboration Spiral: The Midjourney Phase

3.1. The Foundation: Static TPACK Resources as the Stable Base

As illustrated in Figure 1, engagement with generative AI for scientific visualization begins with the Foundation, consisting of static TPACK resources. These resources include disciplinary knowledge of atmospheric dynamics (CK), principles of scientific and educational visualization (PK), and operational familiarity with text-to-image generation tools (TK). Together, they form the stable knowledge base from which human–AI collaboration proceeds.

For the present task, Content Knowledge was established through a synthesis of peer-reviewed literature on tropical cyclone interactions with complex terrain. This review identified four mechanisms essential for scientifically accurate representation: orographic blocking, vortex splitting, rainfall asymmetry, and terrain-induced track deflection (see Table 1). These mechanisms provided explicit scientific criteria against which AI-generated images were evaluated [36–49].

Pedagogical Knowledge was grounded in established principles of scientific visualization, including selective abstraction, spatial organization to reduce cognitive load, and iterative refinement as a quality control strategy [26,29]. Technological Knowledge consisted of familiarity with Midjourney's prompt-based image generation, including its sensitivity to stylistic framing and its tendency to prioritize aesthetic coherence when scientific constraints are underspecified [32–34].

At this stage, these TPACK resources existed as parallel knowledge domains. Their integration into a functional system for managing generative uncertainty required activation through iterative interaction, as theorized in Section 2.

3.2. The First Spiral Cycle: Establishing the Baseline

To maintain analytical focus on the collaboration process rather than on prompt phrasing, the evolution of prompts across iterative cycles is described in structured form in the main text. The full prompt texts used in the Midjourney phase (P1–P4) are provided in Appendix A.

3.2.1. First GENERATE Phase

In the first Generate phase, Prompt P1 was designed to specify the target scientific phenomena relevant to tropical cyclone–terrain interactions, including orographic blocking, vortex splitting, rainfall asymmetry, and potential vorticity redistribution. The representational format was defined as an infographic-style visualization with three-dimensional depth and optimized lighting to enhance perceptual salience.

At this stage, scientific mechanisms were introduced primarily as descriptive elements rather than as explicitly constrained visual features. The prompt therefore relied on the AI system's default interpretive tendencies to translate disciplinary terminology into visual form. The complete text of Prompt P1 is provided in Appendix A.

3.2.2. The First EVALUATE Phase

The image generated from Prompt P1 (Figure 2) exhibited high visual quality, including a well-defined cyclone structure and convincing depth. However, evaluation against the four scientific criteria revealed substantial misalignment. Orographic blocking was weakly represented, vortex splitting was absent, and rainfall distribution remained largely symmetric rather than windward-enhanced [38–45].

Expert evaluation assigned the image a scientific accuracy score of 2/5 and a visual clarity score of 4/5. This divergence between visual appeal and physical fidelity established a baseline reference for subsequent refinement.

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Figure 2. First spiral cycle output generated using Prompt P1. The image is visually striking but exhibits significant scientific deficiencies: orographic blocking, vortex splitting, and rainfall asymmetry are not clearly evidenced under the rubric.

3.2.3. First REFINE Phase

Refinement following the first evaluation focused on diagnosing the source of misalignment between scientific intent and AI output. Analysis indicated that listing mechanisms without specifying their visual correlates allowed aesthetic priors to dominate the generation process.

This first refinement cycle clarified the functional role of evaluation: not to judge success or failure, but to identify how abstract disciplinary descriptions were being interpreted by the AI system.

At this stage, Meta-Task Awareness corresponds to the Traditional View (Table 2), in which evaluation is conducted entirely by human experts and remains primarily outcome-oriented—focusing on whether the generated image appeared superficially plausible, with limited sensitivity to how AI interpretive biases shaped representational outcomes. This human-centered baseline provides the reference point for subsequent AI-augmented extensions.

3.3. Ascending the Spiral: Progressive Refinement Across Iterative Cycles

3.3.1. Second Spiral Cycle: From Descriptive Terms to Visual Constraints

In the second cycle, Prompt P2 shifted emphasis from enumerating scientific mechanisms toward specifying concrete visual constraints. Streamlines were introduced as the primary representational device for airflow deflection, and compositional instructions were added to reduce unnecessary embellishment.

By constraining both representational elements and compositional focus, Prompt P2 aimed to curb the AI system's tendency toward aesthetic elaboration observed in the baseline cycle. The full text of Prompt P2 is included in Appendix A.

The resulting image (Figure 3) showed improved representation of terrain effects, including partial windward rainfall enhancement. Scientific accuracy increased to 3/5, while visual clarity remained high at 4/5. Vortex splitting, however, remained insufficiently specified.

This cycle reflects the Emerging Awareness stage of MTA development (Table 2). Evaluation expanded beyond surface plausibility to include recognition of how specific prompt elements influenced AI behavior. The introduction of streamlines marked an initial shift from judging outputs to diagnosing representational mechanisms, indicating growing awareness of AI interpretive tendencies.

Importantly, diagnostic sensitivity at this stage remains externalized in human judgment, with AI behavior interpreted and adjusted through expert analysis rather than autonomous system feedback.

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Figure 3. Second spiral cycle output generated using Prompt P2. Terrain effects and windward rainfall show improvement, though vortex splitting remains vague and streamline coherence is insufficient.

3.3.2. Third Spiral Cycle: Translating Mechanisms into Observable Features

The third cycle further operationalized the translation from disciplinary mechanisms to observable visual features. Prompt P3 explicitly introduced terrain-induced gyres as the visual correlate for vortex splitting, reducing ambiguity in AI interpretation.

The generated image (Figure 4) exhibited clearer secondary circulation features on the lee side of the terrain, more coherent streamline structures, and pronounced rainfall asymmetry, consistent with documented cyclone–terrain interaction patterns [41,44,50]. Scientific accuracy increased to 4/5, with visual clarity remaining stable. The complete text of Prompt P3 is provided in Appendix A.

Figure 4. Third spiral cycle output generated using Prompt P3, introducing "terrain-induced gyres" as the visual correlate for vortex splitting. Vortex splitting becomes visible, orographic blocking is convincingly illustrated, and rainfall asymmetry is more pronounced.

By the third cycle, Meta-Task Awareness advanced to the Active Orchestration stage. Disciplinary knowledge was no longer applied retrospectively but was proactively translated into explicit visual correlates. Evaluation at this stage involved deliberate alignment between scientific mechanisms and observable features, reflecting increased control over human–AI role distribution.

This form of orchestration reflects a human-centered redistribution of task structure, in which planning, diagnosis, and refinement decisions are explicitly performed by the human expert and imposed on the AI system through prompt design.

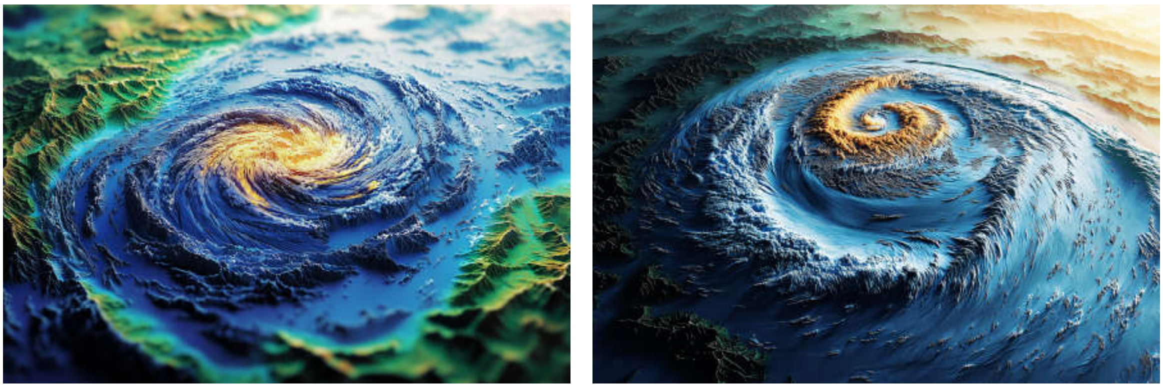
At this stage, prompt structures function not only as technical instructions but as external representations of expert pedagogical reasoning, consistent with arguments that generative AI artifacts can serve as cognitive mirrors when guided by principled orchestration [7,9].

3.3.3. Fourth Spiral Cycle: Integration and Selection

In the fourth cycle, Prompt P4 emphasized integration of all target mechanisms while explicitly constraining compositional complexity. Instructions prioritized scientific accuracy and minimalism to suppress aesthetic drift and stabilize representational fidelity.

While the textual specification in P4 remained largely consistent with P3 (see Appendix A), the minimalist constraint and the accumulation of prior evaluative insights enabled the generation of multiple scientifically valid variants, shifting evaluation from correction to selection.

This prompt generated multiple scientifically valid candidate images (Figure 5a,b), introducing a more advanced evaluation approach based on selection rather than correction. Both variants achieved scientific accuracy scores of 5/5, with Figure 5b selected as the optimal output due to its balance between accuracy and visual accessibility. The full text of Prompt P4 is provided in Appendix A.



(**a**) (**b**)

Figure 5. Fourth spiral cycle outputs generated using Prompt P4. Two variants emerged: (a) emphasizes structural precision suitable for academic presentations; (b) balances scientific accuracy with visual expressiveness through color-coded vorticity contours and dynamic cloud textures. Variant (b) was selected as the optimal output from the Midjourney phase.

The fourth cycle corresponds to the MTA-Enhanced View identified in Table 2. At this stage, evaluation shifted from error correction to strategic selection among multiple valid solutions. The MTA-Enhanced View observed in this phase represents the highest level of human-centered Meta-Task Awareness, characterized by expert-driven selection among multiple valid AI-generated representations.

The comparative trajectory of scientific fidelity, visual clarity, and Meta-Task Awareness across the four Generate–Evaluate–Refine cycles is summarized in Table 2. Note that the stage definitions in Table 2 reflect the shift from proficiency-based tool use toward epistemic filtering and human–AI agency orchestration, consistent with prior discussions of GenAI characteristics and AI-TPACK extensions [6,8,10,21].

Table 2. Evaluation trajectory across four Generate–Evaluate–Refine cycles in the Midjourney phase (Figures 2–5b). [1.]

Cycle	Figure	Prompt	Blocking	Vortex Splitting	Rainfall Asymmetry	Streamline Structure	Scientific Accuracy	Visual Clarity	MTA Development Stage
1	2	P1	✗	✗	△	✗	2	4	Traditional View
2	3	P2	✓	△	✓	△	3	4	Emerging Awareness
3	4	P3	✓	✓	✓	△	4	4	Active Orchestration
4	5a	P4	✓	✓	✓	✓	5	4	MTA-Enhanced View
4	5b	P4	✓	✓	✓	✓	5	5	MTA-Enhanced View

[1] Legend: ✓ = clearly present; △ = partially present; ✗ = absent.

3.4. Summary of the Midjourney Phase

Across four Generate–Evaluate–Refine cycles, the Midjourney phase demonstrates how static TPACK resources were progressively mobilized through Meta-Task Awareness within the Dynamic Collaboration Spiral, as theoretically articulated in Section 2. Rather than reiterating the full structural sequence, this phase empirically illustrates how human-led evaluation evolved from outcome-focused validation toward diagnostic control, active orchestration, and selection-based stabilization.

As summarized in Table 2, this trajectory establishes a human-centered baseline of Meta-Task Awareness, in which evaluative judgment remains externalized yet increasingly structured. This baseline provides a critical reference point for the GPT-4o phase (Section 4), where evaluative functions are progressively augmented—though not replaced—by AI-supported self-evaluation mechanisms.

4. Activating the Dynamic Collaboration Spiral: The GPT-4o Closed-Loop Phase

4.1. Conceptual Positioning of the GPT-4o Phase within the MTA–TPACK Framework

Following the Midjourney phase, in which Meta-Task Awareness (MTA) was developed through exclusively human-led evaluation and refinement, the GPT-4o phase introduces a closed-loop collaboration structure that partially internalizes evaluative functions within the AI system. This phase does not constitute a shift toward autonomous AI cognition. Rather, it represents an AI-augmented extension of MTA under human-defined task structures.

Within the MTA–TPACK Dynamic Collaboration Spiral proposed in Section 2, this phase corresponds to a redistribution of evaluative roles. While Content Knowledge and evaluative criteria remain externally defined by human experts, GPT-4o is assigned explicitly structured self-evaluation tasks that operate within predefined boundaries. As a result, reflective processes that were previously externalized in human judgment are progressively instantiated within the generation–evaluation loop itself. In this sense, the GPT-4o phase does not merely accelerate refinement efficiency; it amplifies the process through which pedagogical reasoning becomes operationally embedded in AI-generated artifacts, extending prior discussions on reflective AI-supported design [6,8,10].

To maintain analytical focus on collaboration dynamics rather than prompt phrasing, prompts used in this phase (P5–P8) are described in terms of functional roles. Full prompt texts are provided in Appendix B.

4.2. First Closed-Loop Cycle: AI-Assisted Descriptive Alignment

4.2.1. Generate Phase

In the first closed-loop cycle, Prompt P5 instructed GPT-4o to regenerate an image based on the finalized Midjourney output and to conduct an initial self-evaluation assessing whether key scientific mechanisms—such as orographic blocking, vortex splitting, and rainfall asymmetry—were present. At this stage, self-evaluation criteria emphasized descriptive correspondence between textual specifications and visible elements.

The generated visualization (Figure 6) showed improved visual completeness and clearer differentiation of major atmospheric components. However, spatial relationships among mechanisms remained weakly constrained. Secondary circulations associated with vortex splitting were present but not systematically anchored to terrain features, and streamline continuity across windward and leeward regions lacked physical coherence.

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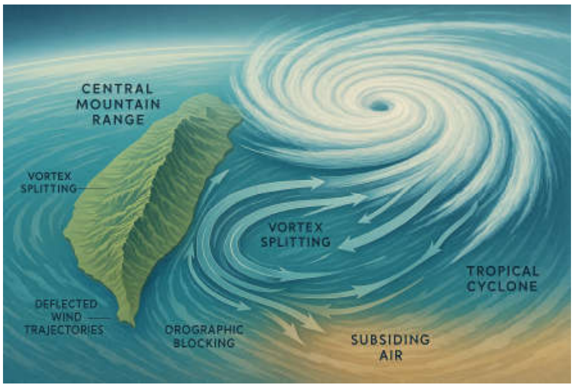

Figure 6. First closed-loop cycle output generated using GPT-4o with Prompt P5, establishing the baseline for the closed-loop experiment. Shows improvements in terrain shading but exhibits limitations in vortex splitting and streamline coherence.

At this stage, evaluation remained largely surface oriented. GPT-4o identified mismatches primarily at the descriptive level, such as missing visual elements or insufficient emphasis, without explicitly diagnosing how representational structures mediated scientific meaning. The full text of Prompt P5 is provided in Appendix B.

4.2.2. Evaluate–Refine Phase and AI Self-Evaluation Stage

Self-evaluation in this cycle functioned primarily as a consistency check. GPT-4o identified whether specified elements appeared but did not analyze causal or structural relationships among them. Refinement therefore consisted mainly of reiterating descriptive constraints, resulting in incremental enhancement without substantive reorganization of representational structure.

This cycle corresponds to the AI-Assisted Descriptive Alignment stage in Table 3, representing the most basic form of AI-augmented Meta-Task Awareness, closely analogous to the Traditional View of human-centered evaluation in Table 2.

4.3. Progressive Internalization of AI Self-Evaluation

4.3.1. Second Closed-Loop Cycle: AI-Augmented Diagnostic Evaluation

In the second cycle, Prompt P6 expanded the scope of AI self-evaluation by requiring GPT-4o to diagnose misalignment between scientific mechanisms and their visual manifestations. Evaluation criteria explicitly addressed causal consistency, such as whether airflow deflection patterns aligned with terrain geometry and whether rainfall asymmetry reflected windward lifting processes.

The regenerated output (Figure 7) exhibited more coherent streamline curvature around the mountain range and clearer differentiation between windward enhancement and leeward subsidence. Compared to Figure 6, these changes indicate a shift from element-based checking toward mechanism-sensitive refinement.

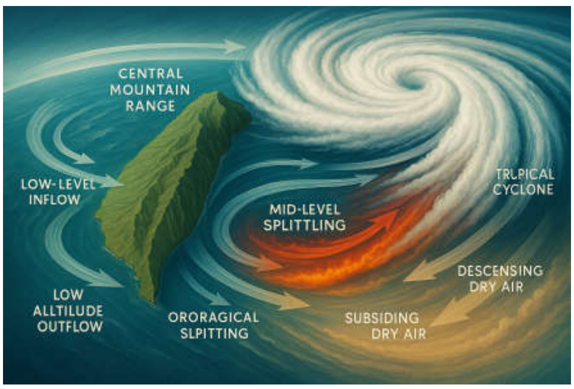

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Figure 7. Second closed-loop cycle output generated through GPT-4o's closed-loop evaluation-regeneration structure (Prompt P6). Enhanced windward cloud development and improved streamline curvature are evident.

This cycle corresponds to the AI-Augmented Diagnostic Evaluation stage in Table 3. At this stage, AI self-evaluation begins to operate at the level of representational causality, extending the human diagnostic control characteristic of the Emerging Awareness stage in Table 2.

4.3.2. Third Closed-Loop Cycle: AI-Augmented Structured Self-Reflection

The third cycle further formalized AI self-evaluation through Prompt P7, which required GPT-4o to generate structured reflective feedback prior to image regeneration. This feedback explicitly separated (i) identification of representational misalignment, (ii) physical justification grounded in atmospheric dynamics, and (iii) targeted refinement strategies.

As a result, the regenerated visualization (Figure 8) demonstrated clear structural reorganization. Terrain-induced gyres were spatially localized downstream of the mountain range, vortex splitting was rendered as a coherent secondary circulation rather than diffuse turbulence, and streamline density and orientation exhibited improved internal consistency.

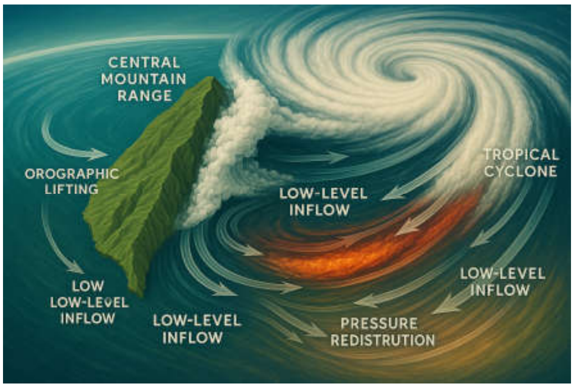

Figure 8. Third closed-loop cycle output generated using Prompt P7 with enhanced multilayered atmospheric specifications. Vortex splitting is clearly visible with dual circulation centers, and scientific labels enhance educational utility.

This cycle corresponds to the AI-Augmented Structured Self-Reflection stage in Table 3. Here, AI self-evaluation functions as an internal planning mechanism, guiding refinement decisions prior to generation. This stage parallels the Active Orchestration phase in Table 2, while extending evaluative control through AI-mediated reflection.

The structured self-reflection observed in this cycle marks a critical transition toward Visible Pedagogical Thinking. Evaluation criteria that were previously articulated externally are now explicitly referenced, justified, and operationalized within the refinement process itself. As a result, the regenerated visualization reflects not only improved scientific accuracy but also the traceable imprint of evaluative reasoning, consistent with frameworks that emphasize the externalization of pedagogical cognition in AI-mediated artifacts [8–11].

Note that typographical errors visible in AI-generated labels (e.g., Figures 7 and 8) are artifacts of GPT-4o's image generation and were not manually corrected, as they illustrate the limitations of current AI systems in producing scientifically accurate textual annotations.

4.3.3. Fourth Closed-Loop Cycle: AI-Augmented Selection-Oriented Stabilization

In the final cycle, Prompt P8 shifted the role of AI self-evaluation from correction to stabilization. GPT-4o was instructed to generate multiple candidate visualizations and to articulate explicit selection rationales based on scientific fidelity, pedagogical clarity, and representational balance.

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The selected output (Figure 9) exhibits integrated representation of all target mechanisms without over-specification. Rather than maximizing any single feature, the visualization reflects deliberate trade-offs among detail, clarity, and interpretability. Evaluation at this stage no longer aims to eliminate errors but to select among multiple scientifically valid representations.

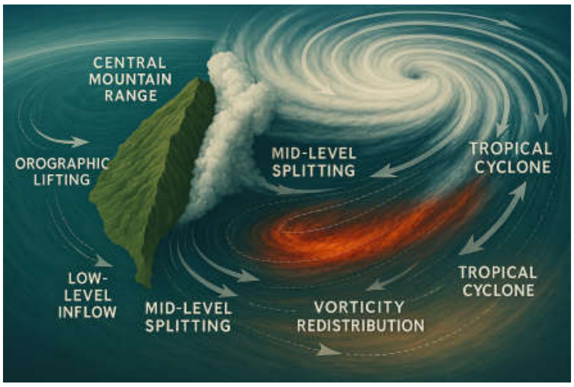

Figure 9. Fourth closed-loop cycle output representing the culmination of the MTA-TPACK Dynamic Collaboration Spiral. All target mechanisms are fully integrated with accurate scientific labeling.

This cycle corresponds to the AI-Augmented Selection-Oriented Stabilization stage in Table 3, representing the highest level of AI-augmented Meta-Task Awareness. It aligns with the MTA-Enhanced View in Table 2, while demonstrating how epistemic selection can be partially supported by AI under human-defined constraints.

4.4. Comparative Analysis: Human-Orchestrated vs. AI-Augmented Spirals

Table 3 summarizes the progression of AI self-evaluation across the four closed-loop cycles. When read in conjunction with Table 2, these stages should be understood not as a separate cognitive framework, but as AI-augmented extensions of Meta-Task Awareness within the same theoretical axis. Note that AI-augmented/assisted self-evaluation stages in Table 3 describe the progression of GPT-4o's internal assessment capability from surface-level feature detection toward integrated mechanism-level evaluation, under human Meta-Task Awareness oversight [6,22]. This reinforces recent empirical findings by Tan et al. [14], who observed that effective AI integration requires a 'metacognitive recalibration' similar to the dynamic awareness captured in our spiral model.

Table 3. Evaluation trajectory across four closed-loop Generate–Evaluate–Refine cycles in the GPT-4o phase (Figures 6–9). [1]

Cycle	Figure	Prompt	Blocking	Vortex Splitting	Rainfall Asymmetry	Streamline Structure	Scientific Accuracy	Visual Clarity	AI-augmented/assisted Self-Evaluation Stage
1	6	P5	△	△	△	△	3	3	Descriptive Alignment
2	7	P6	✓	△	✓	△	4	4	Diagnostic Evaluation
3	8	P7	✓	✓	✓	△	4	5	Structured Self-Reflection
4	9	P8	✓	✓	✓	✓	5	5	Selection-Oriented Stabilization

[1] Legend: ✓ = clearly present; △ = partially present; ✗ = absent.

From the perspective of the MTA–TPACK Dynamic Collaboration Spiral introduced in Section 2, the GPT-4o phase demonstrates that evaluative functions—traditionally externalized in human judgment—can be progressively internalized within AI-mediated workflows through explicit task design. Importantly, this internalization does not diminish human epistemic authority. Instead, it redistributes reflective labor, allowing AI to participate in structured evaluation while ultimate task framing and selection criteria remain human-defined.

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Together, Table 2 and Table 3 operationalize Meta-Task Awareness across two collaboration regimes: human-centered orchestration and AI-augmented self-evaluation. Their combined trajectories provide empirical grounding for the claim that Meta-Task Awareness is not a fixed attribute of either human or AI agents, but a dynamic property emerging from carefully designed interaction structures.

4.5. Summary of the GPT-4o Phase

The GPT-4o phase extends the Dynamic Collaboration Spiral by redistributing evaluative labor within a closed-loop human–AI interaction structure, as previously described in Section 2. Rather than restating the full spiral architecture, this phase demonstrates how AI-supported self-evaluation can progressively internalize diagnostic and selection-oriented functions under human-defined epistemic constraints.

As documented in Table 3, this progression parallels—but does not replicate—the human-centered MTA development observed in the Midjourney phase. Crucially, evaluative authority remains grounded in human Meta-Task Awareness, confirming that AI augmentation amplifies reflective capacity without displacing epistemic responsibility.

5. Conclusion

This study proposed and empirically demonstrated the MTA–TPACK Dynamic Collaboration Spiral as a process-oriented framework for understanding how static TPACK resources are dynamically activated through Meta-Task Awareness, operationalized via Generate–Evaluate–Refine cycles, and ultimately consolidated as a structured reasoning pattern manifested as Visible Pedagogical Thinking. Building on the foundational model introduced in Section 2 and instantiated across the two experimental phases, the findings synthesize how human–AI collaboration can remain epistemically grounded while adapting to increasingly agentic generative systems.

5.1. Theoretical Contributions

The MTA–TPACK Dynamic Collaboration Spiral contributes to the evolving discourse on AI integration by shifting the analytical focus from static knowledge categories to dynamic cognitive processes. While existing extensions have identified what knowledge educators need [8–12], this study theorizes how such knowledge is activated and coordinated during authentic human–AI collaboration. Our theoretical contributions are three-fold:

First, the framework reconceptualizes TPACK for agentic AI environments. Unlike the predictable instruments of classical TPACK, Generative AI participates actively in meaning-making [6]. By positioning Meta-Task Awareness (MTA) as a Dynamic Navigation Engine, our model provides a theoretical architecture for maintaining epistemic authority while leveraging AI's generative capacity. This addresses the critical need for frameworks that accommodate AI not as a tool, but as a socio-cognitive teammate [7,20].

Second, it bridges the gap between knowledge structure and procedural deployment. The framework operationalizes the Generate–Evaluate–Refine spiral, linking static resources to observable outcomes through principled orchestration. This process transforms disciplinary understanding from a passive base of facts into an active epistemic filter. In doing so, it reframes Technological Knowledge (TK) from tool proficiency into a critical awareness of how AI reshapes the cognitive task itself, and Pedagogical Knowledge (PK) from strategy selection into a dynamic orchestration of human–AI agency.

Third, the study establishes "Visible Pedagogical Thinking" as a structured reasoning outcome of collaboration. We argue that the ultimate value of AI collaboration lies not in output efficiency, but in the externalization of expert reasoning. By guiding AI through iterative refinement—correcting misconceptions and enforcing disciplinary constraints—experts produce artifacts that embody structured, inspectable reasoning patterns. This outcome directly operationalizes cognitive

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sustainability: it ensures that as AI capabilities advance, human epistemic reasoning is not eroded but actively cultivated. By engaging AI as a dialectical partner, the collaboration process becomes a site for continuous cognitive development, ensuring that increasing machine capability is matched by the rigorous exercise of human pedagogical judgement.

5.2. Empirical Contributions

The two experimental phases provide robust empirical validation for the MTA–TPACK Dynamic Collaboration Spiral, substantiating its explanatory power through a demanding scientific visualization task.

First, the results demonstrate that expert-level accuracy is achieved through cognitive reorientation rather than mere tool proficiency. In the Midjourney phase, the systematic improvement in scientific accuracy—from 2/5 to 5/5—validates the transition from a tool-oriented Traditional View to an awareness-centered MTA-Enhanced View. As documented in Table 2, this trajectory was not a random exploration but a principled progression from post hoc checking to Active Orchestration. By translating abstract meteorological mechanisms (e.g., vortex splitting and orographic blocking) into precise AI-interpretable constraints, the study provides empirical evidence that Content Knowledge must be activated through MTA to function as an effective epistemic filter.

Second, the closed-loop experiment illustrates the acceleration and internalization of the collaboration spiral. The GPT-4o phase reveals how AI participation in evaluation can lead to an “accelerated spiral ascent.” As documented in Table 3, the AI’s ability to perform surface detection and feature discrimination enabled more rapid refinements. However, the finding that AI could not independently determine epistemic relevance underscores the continued necessity of human oversight. This substantiates a core premise of our framework: while AI can participate in the “Evaluate” phase, the “Refine” phase remains tethered to human-defined epistemic criteria, ensuring that the spiral remains pedagogically grounded.

Third, the comparative analysis confirms that Meta-Task Awareness is an emergent, dynamic property of interaction. Although the human-orchestrated (Midjourney) and AI-augmented (GPT-4o) pathways differed in efficiency and oversight requirements, both converged on equivalent, expert-validated outcomes (5/5 scientific accuracy). This convergence reveals that MTA is not a static trait of the user, but a dynamic navigation engine that can be distributed across different interaction structures. By documenting these two distinct but successful trajectories, the study provides a transferable empirical baseline for how sustainable human–AI collaboration can be structured to maintain scientific rigor in the post-prompting era.

5.3. Visible Pedagogical Thinking: The Culminating Outcome

Positioned at the apex of our framework, Visible Pedagogical Thinking represents the structured reasoning pattern of the human–AI collaboration. Through the rigorous application of the MTA engine, the resulting visualizations transcend their role as mere aesthetic products; they become structured reasoning patterns—tangible embodiments of the negotiation between expert intent and AI capability.

5.3.1. Final Artifacts as Externalized Mental Models

The final visualizations (Figures 5b and 9) serve as a testament to the principled orchestration of human–AI agency. By guiding the AI through iterative refinement—enforcing scientific rigor and recalibrating physical constraints—experts effectively externalize their internal mental models.

This structured reasoning reflects a fundamental reframing across all TPACK dimensions: Content Knowledge is transformed from passive facts into an active epistemic filter; Pedagogical Knowledge shifts from strategy selection to the deliberate orchestration of visual communication; and Technological Knowledge evolves into a critical awareness of AI’s interpretive biases. These reframings—normally tacit dimensions of expert cognition—are now inscribed in visual form. The images do not merely represent atmospheric science; they embody the cognitive work of translating complex science into AI-mediated communication.

5.3.2. Documented Trajectory as a Reusable Pedagogical Resource

Beyond the final artifacts, the documented trajectory (P1 through P8) constitutes Visible Pedagogical Thinking in its most actionable sense. This sequence provides a transparent record of design evolution, capturing how expert logic is iteratively refined to address AI interpretation patterns.

This trajectory functions as a reflective pedagogical resource for teacher professional development, allowing both pre-service and in-service educators to deconstruct and learn from the expert's reasoning process. By transforming ephemeral design cognition into observable and teachable patterns, this documentation reveals:

1. Common Pitfalls: such as over-reliance on scientific terminology without visual correlates.
2. Effective Strategies: such as translating abstract mechanisms into observable visual features.
3. Evaluative Principles: the four-mechanism rubric as a standard for scientific rigor.

Ultimately, this visibility has profound implications for education. Teaching scientific visualization is no longer limited to presenting the "final product"; it now encompasses the demonstration of iterative negotiation. This process, while distinct from traditional generative workflows [15], remains firmly rooted in established visual traditions [26,29], ensuring that pedagogical innovation remains both grounded and future-ready.

5.4. Limitations and Future Directions

While this study establishes the theoretical utility of the MTA–TPACK spiral, several limitations offer productive avenues for future research.

First, our empirical focus was restricted to a single scientific domain. Although typhoon–terrain interaction provided a rigorous testbed, future research should assess the framework's transferability across diverse disciplines—such as biology, chemistry, and social sciences—where the visual correlates of disciplinary knowledge may follow different logic.

Second, as the current phases involved a single expert, further investigation is required to explore how Meta-Task Awareness develops among users with differing expertise profiles. Comparative studies involving novices and interdisciplinary teams would provide critical data for designing more inclusive teacher professional development programs.

Third, the short-term nature of the four-iteration sequences limits our understanding of long-term developmental trajectories. Longitudinal studies are needed to track how the collaboration spiral evolves over extended periods, offering deeper insights into the mechanisms of cognitive sustainability and the prevention of cognitive deskilling. Such longitudinal work would clarify whether human-AI collaboration contributes to sustainable professional growth rather than short-term performance gains.

Finally, our findings are based on Midjourney and GPT-4o. Given the protean and unstable nature of Generative AI [6], the framework must be continuously validated against emerging agentic platforms. Future research should examine how shifts in AI capability—such as improved reasoning or multi-agent orchestration—alter the distribution of epistemic responsibility within the collaboration spiral.

5.5. Concluding Remarks

The MTA-TPACK Dynamic Collaboration Spiral reconceptualizes generative AI integration as the dynamic orchestration of teacher knowledge rather than the acquisition of technical skills. By positioning Meta-Task Awareness (MTA) as a navigation engine, the framework explains how static TPACK resources are mobilized through iterative Generate–Evaluate–Refine cycles, culminating in Visible Pedagogical Thinking – artifacts that externalize structured expert reasoning.

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As AI evolves from passive instrument to socio-cognitive collaborator, sustaining epistemic responsibility becomes the central educational challenge. Our findings suggest that maintaining human oversight depends less on tool fluency than on deliberate evaluative design. When disciplinary mechanisms and selection criteria are explicitly articulated, AI functions as a reflective medium that stabilizes and makes visible internal mental models.

Anchored in meta-cognitive regulation and disciplinary rigor, the framework demonstrates how human-AI collaboration can remain cognitively sustainable, ensuring that advances in machine capability are matched by the continued cultivation of human pedagogical judgement.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A. Full Prompt Texts for the Midjourney Visualization Phase

This appendix presents the complete prompt texts (P1–P4) used in the Midjourney phase of the study. The prompts are provided in full to ensure transparency and reproducibility, while the main text focuses on the structural evolution of prompt design and its role in the MTA–TPACK Dynamic Collaboration Spiral.

Appendix A.1. Prompt P1 (Baseline Generation)

Infographic of a tropical cyclone encountering orographic blocking by Taiwan’s Central Mountain Range, vivid depiction of low-level flow disruption and vortex splitting as winds interact with steep terrain, intricate layers showing deflected wind trajectories around the mountain, rain-enhancing windward lifting, and subsiding air on the lee side, detailed visualization of pressure gradients and potential vorticity redistribution, scientifically accurate with dynamic visuals of energy transfer and atmospheric turbulence, dramatic lighting emphasizing terrain features and flow divergence, realistic shadows enhancing the 3D perspective of atmospheric layers.

Appendix A.2. Prompt P2 (Introduction of Visual Constraints)

Infographic illustrating a tropical cyclone encountering orographic blocking by Taiwan’s Central Mountain Range. The visualization captures detailed low-level flow disruption, vortex splitting, and turbulence as winds interact with steep terrain. Streamlines clearly depict deflected wind trajectories around the mountains, rain-enhancing windward lifting, and descending dry air on the lee side. The image highlights pressure gradients and potential vorticity redistribution with structured flow lines and color gradients. Atmospheric turbulence and energy transfer are dynamically represented. Lighting and shadows emphasize terrain features, flow divergence, and three-dimensional atmospheric layering. The composition excludes unnecessary embellishments, focusing on scientifically accurate cyclone–terrain interactions.

Appendix A.3. Prompt P3 (Mechanism-to-Feature Translation)

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Infographic illustrating a tropical cyclone encountering orographic blocking by Taiwan's Central Mountain Range. The visualization focuses on scientifically accurate low-level flow interactions, showing vortex splitting, turbulence, and wind field deflection around steep terrain. Streamlines precisely depict flow disruption, terrain-induced gyres, and windward lifting that enhances rainfall. The lee side features descending dry air and complex turbulent structures. Pressure gradients and potential vorticity redistribution are visualized using color gradients and structured flow lines. Atmospheric turbulence and energy transfer are dynamically represented. Lighting and shadows emphasize both terrain features and flow divergence, ensuring the visualization accurately represents cyclone-terrain interactions in three-dimensional space.

Appendix A.4. Prompt P4 (Integrated and Minimalist Specification)

Infographic illustrating a tropical cyclone encountering orographic blocking by Taiwan's Central Mountain Range. The visualization focuses on scientifically accurate low-level flow interactions, showing vortex splitting, turbulence, and wind field deflection around steep terrain. Streamlines precisely depict flow disruption, terrain-induced gyres, and windward lifting that enhances rainfall. The lee side features descending dry air and complex turbulent structures. Pressure gradients and potential vorticity redistribution are visualized using color gradients and structured flow lines. Atmospheric turbulence and energy transfer are dynamically represented. Lighting and shadows are optimized to emphasize both terrain features and flow divergence, ensuring the visualization accurately represents cyclone–terrain interactions in three-dimensional space. The composition is minimalist, removing unnecessary elements while maintaining scientific accuracy in illustrating the physical dynamics.

Appendix B. Full Prompt Texts for the GPT-4o Closed-Loop Phase

Appendix B.1. Prompt P5 (Baseline Regeneration with Initial Self-Evaluation)

Generate a scientific illustration of a tropical cyclone interacting with Taiwan's Central Mountain Range. Position the typhoon on the right side of the image, with the Central Mountain Range on the left. The typhoon makes landfall from east to west between Hualien and Yilan. Render from bird's-eye perspective with color tones similar to satellite imagery. Reference specifications: orographic blocking with low-level flow disruption, vortex splitting as winds interact with steep terrain, deflected wind trajectories around the mountain, rain-enhancing windward lifting, subsiding air on the lee side, pressure gradients and potential vorticity redistribution, scientifically accurate atmospheric dynamics, dramatic lighting emphasizing terrain features and flow divergence.

Appendix B.2. Prompt P6 (Evaluation–Regeneration with Diagnostic Comparison)

Part 1: Based on the following description prompt, objectively evaluate the differences between the uploaded scientific image and the prompt specifications. Identify areas requiring modification, then regenerate an image consistent with the prompt description along with a revised prompt.

Part 2: Generate a revised image using this enhanced specification: Infographic of a tropical cyclone interacting with Taiwan's Central Mountain Range, viewed from bird's-eye perspective, realistic 3D terrain shading. The cyclone appears as a flattened, dense spiral over the ocean on the right, making landfall from east to west between Hualien and Yilan. Show vivid low-level inflow deflection curving around steep topography, mid-level vortex splitting into two streams, and high-altitude outflow divergence. Thick multilayered clouds rise along the eastern slope due to orographic lifting, while the western side shows sparse clouds and descending dry air. Visualize pressure gradients and red-orange vorticity redistribution zones near the mountains. Use dramatic lighting and realistic shadows to emphasize turbulence and energy transfer in a scientifically accurate meteorological illustration.

Appendix B.3. Prompt P7 (Enhanced Multilayer Specification with Mechanism-Level Evaluation)

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Part 1: Evaluate the uploaded image against previous specifications, identify remaining gaps, and propose targeted modifications.

Part 2: Generate using this enhanced specification: Ultra-detailed educational infographic of a tropical cyclone interacting with Taiwan's Central Mountain Range, bird's-eye perspective, 3D shaded terrain. The cyclone, a dense flattened spiral over the ocean on the right, is making landfall between Hualien and Yilan. Include multilayered atmospheric structure: low-level inflow deflection curving around terrain, mid-level vortex splitting into dual cores, and high-altitude divergent outflow. Show thick cumulonimbus clouds forming over eastern slopes due to orographic lifting, and sparse cloud fields with descending dry air on western side. Visualize pressure gradients and vorticity redistribution with red-orange turbulent zones and layered flow streamlines. Dramatic lighting, realistic shadows, and textured cloud formations. Label major components clearly in scientific style, use accurate spelling and typography.

Appendix B.4. Prompt P8 (Comprehensive Integration and Final Optimization)

Part 1: Evaluate the uploaded image against specifications, identify any remaining discrepancies, and propose final optimizations.

Part 2: Generate using this comprehensive specification: Ultra-detailed educational infographic of a tropical cyclone interacting with Taiwan's Central Mountain Range, bird's-eye perspective, realistic 3D shaded terrain. The tropical cyclone is shown as a dense flattened spiral over the ocean on the right, making landfall between Hualien and Yilan. Highlight three-layered atmospheric structure: vivid low-level inflow deflection curving around topography, mid-level vortex splitting into two core streams, and high-altitude divergent outflow shown with large-scale spiral arrows. Show thick cumulonimbus clouds forming over eastern slopes with tower-like vertical development, and sparse cloud cover with dry descending air on the western lee side. Add red-orange turbulent zone near terrain to represent vorticity redistribution and pressure gradients, with scientific flow lines and realistic cloud textures. Include dashed isolines or gradient fields to visualize pressure and vorticity. Dramatic lighting and shadows emphasize terrain and cloud volume. Ensure all labels are scientifically accurate and typographically correct: "low-level inflow," "mid-level splitting," "high-altitude outflow," "orographic lifting," "vorticity redistribution," "descending dry air."

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