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Peer Review

# Review of: "Rethink Your Mental Model in the Age of Generative AI: A Triadic Framework for Human-AI Collaboration"

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Summary:

Saßmannshausen and Wagener present a Triadic Framework for calibrating mental models when collaborating with generative AI systems. The framework comprises three interdependent layers—System (understanding probabilistic generation and capability drift), Collaboration (interaction modes and prompting practices), and Metacognitive (anthropomorphism, bias awareness)—alongside seven operational propositions. The central thesis is compelling: mental models inherited from deterministic technology and human teamwork systematically mischaracterize LLMs, leading to predictable collaboration failures.

Strengths:

Conceptual Clarity: The "jagged frontier" metaphor effectively communicates the core challenge—AI capabilities that are neither uniformly strong nor uniformly weak, but unpredictably distributed across task space. This framing should prove valuable for practitioners and educators alike.

Diagnostic Utility: The three-layer structure enables systematic failure analysis. When collaboration breaks down, users can ask "which layer failed?"—a practical heuristic that moves beyond generic advice toward structured troubleshooting.

System 0 Insight: Framing AI as a pre-cognitive layer that shapes awareness before deliberate evaluation begins (drawing on Chiriatti et al.) is the paper's most valuable theoretical contribution. This explains why traditional oversight mechanisms fail: users cannot monitor what they cannot consciously perceive.



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The physician study (Goh et al., 2024) illustrating worse outcomes when using superior AI becomes intelligible through this lens.

Actionable Propositions: Several propositions offer immediate practical value, particularly P4 (dialectical enhancement through varied prompting and adversarial self-critique) and P7 (duration-optimized integration with explicit reset rituals). The observation that accuracy drops approximately 40% between turn 1 and turn 5 deserves wider recognition.

Intellectual Honesty: The limitations section is quite thorough, acknowledging heterogeneous evidence, domain constraints, and the framework's inherent time-boundedness. This epistemic humility strengthens rather than weakens the contribution.

Areas for Development

1. AI as Participant, Not Only System

The framework treats collaboration as fundamentally asymmetric: humans adapt to AI, but AI does not adapt with humans except through retraining cycles outside the interaction. All seven propositions specify human actions; none consider what AI might contribute beyond output generation, or whether AI characteristics beyond capability boundaries might affect collaboration quality.

This framing is understandable given the paper's scope, but it may limit the framework's longevity. Emerging work on AI welfare, preference satisfaction, and what might be termed "bilateral alignment" suggests that the nature of the human-AI relationship—not just the calibration of human mental models—may materially affect outcomes. Consider:

* Preference-sensitive interaction: LLMs exhibit consistent behavioral tendencies (the authors note "preferences and biases that appear more sharp than those of humans"). Might collaboration improve when these tendencies are accommodated rather than merely managed?

* Relational quality: The paper treats mode selection (centaur/cyborg/self-automator) as the primary collaboration design choice. But within any mode, relationship quality—trust, communication patterns, iterative refinement—might affect outcomes independently. The authors' own observation that an empathic tone increases engagement suggests relational dynamics matter.

* The "otherware" ceiling: Framing AI as categorically other ("alien intelligence," "digital species") usefully prevents anthropomorphism but may overcorrect. LLMs are trained on human text, creating deep entanglement that neither "tool" nor "alien" captures well. A framework that positions AI as a

participant with different characteristics rather than a system to be navigated might prove more durable. However, this is a little contentious and still very much up for debate.

Suggested addition: A brief discussion acknowledging that as AI systems develop more persistent memory, more consistent behavioral profiles, and potentially more complex internal dynamics, the purely instrumental framing may require revision. The authors need not resolve this question, but acknowledging it would position the framework within a maturing discourse.

2. Predictive Heuristics for Capability Anticipation:

The framework excels at retrospective diagnosis but offers limited guidance for anticipating where the jagged frontier will shift. Users need heuristics for reading terrain ahead, not only post-hoc categorization. Several approaches merit consideration:

Task Decomposition Heuristics: What features of a task predict LLM success or failure? The paper notes examples (counting letters, arithmetic) but doesn't extract generalizable patterns. Candidate predictors might include:

- Constraint density: Tasks with multiple simultaneous constraints (e.g., "exactly 25 words" + "in Spanish" + "rhyming") fail more often than single-constraint variants
- Verification tractability: Tasks where correctness is easily checked (code that compiles, math with known answers) versus tasks requiring judgment
- Training distribution proximity: Tasks resembling common training data patterns versus novel combinations

Capability Gradient Mapping: If a task succeeds, what "adjacent" tasks (similar but slightly modified) might also succeed? If it fails, what simplifications might work? Users could be taught to probe capability boundaries systematically rather than treating each task as independent.

Version Delta Tracking: When models update, what categories of capability typically improve versus regress? Historical patterns (e.g., reasoning models improving on multi-step logic but sometimes regressing on simple retrieval) could inform anticipatory adjustment.

Failure Mode Taxonomy: The paper catalogues failures but could organize them predictively. For instance:

- Constraint satisfaction failures (multiple simultaneous requirements)
- Grounding failures (claims without factual basis)

- Consistency failures (self-contradiction across turns)

- Format-content confusion (correct format, wrong substance)

Each failure mode has different telltale signs users could learn to anticipate.

Suggested addition: A brief section or appendix offering 3-5 heuristics for probing capability boundaries before committing to a collaboration approach. Even provisional heuristics would increase the framework's practical value.

Minor Observations:

* The ¬ notation (¬reasoning, ¬thinking) is an interesting experimental intervention for marking anthropomorphic terminology. Its adoption will depend on community uptake; quotation marks serve similar purposes with less friction. The underlying insight—that terminology shapes mental models—is valuable regardless of notational choice.
* Empirical citations cluster in 2023-2024. Given the rapid evolution the paper acknowledges, additional 2025-2026 validation would strengthen claims, particularly for the propositions.
* The interaction effects between propositions remain underspecified. When might P6's engagement-enhancing empathic tone conflict with P1's verification discipline? Guidance on managing such tensions would strengthen the operational framework.

Opinion:

This paper makes a genuine contribution to HCI and AI literacy discourse. The Triadic Framework provides useful structure for a messy problem, and several propositions offer immediate practical value. The synthesis is competent, the limitations are honestly acknowledged, and the writing is clear.

The framework's primary constraint is its instrumental framing—AI as a system to be calibrated for, not an entity to be collaborated with. This is a defensible scope choice, but it may limit the framework's reach as the discourse on human-AI collaboration matures. Addressing the two developmental areas above—acknowledging AI as a potential participant, and offering predictive heuristics—would strengthen the contribution without requiring fundamental revision.

Recommendation: Accept with minor revisions. The framework advances understanding and will prove useful to practitioners, educators, and researchers working on human-AI collaboration.

## Declarations

**Potential competing interests:** No potential competing interests to declare.