

# i2i: Multi-Model Consensus and Inference Protocol for Reliable AI Systems

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<https://github.com/lancejames221b/i2i>

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## Abstract

Large Language Models (LLMs) demonstrate remarkable capabilities but suffer from hallucinations, single-model biases, and inability to express epistemic uncertainty. We present **i2i** (“eye-to-eye”) and the **Multi-model Consensus and Inference Protocol (MCIP)**, a standardized framework for AI-to-AI communication that addresses these limitations through multi-model consensus, cross-verification, epistemic classification, and intelligent routing. Our key insight is not that consensus universally improves accuracy, but that *consensus level reliably predicts answer trustworthiness*. In evaluation across 400 questions spanning factual QA, hallucination detection, mathematical reasoning, and commonsense tasks, we find that HIGH consensus ( $\geq 85\%$  agreement) achieves **95-100% accuracy** regardless of task type. We demonstrate that consensus provides a 6% improvement in hallucination detection ( $38\% \rightarrow 44\%$ ), with LOW/NONE consensus reliably flagging confabulated answers. Critically, we also show that consensus *degrades* performance on mathematical reasoning ( $95\% \rightarrow 60\%$  on GSM8K), revealing that different reasoning chains should not be averaged—a finding that informs task-appropriate deployment. We introduce *epistemic classification* to distinguish answerable questions from uncertain, underdetermined, or “idle” questions. The protocol is provider-agnostic, supporting OpenAI, Anthropic, Google, xAI, and local models. Code and specification: <https://github.com/lancejames221b/i2i>.

## 1 Introduction

The deployment of Large Language Models (LLMs) in high-stakes applications—medical diagnosis, legal analysis, financial decisions—demands reliable, verifiable outputs. Yet current systems exhibit several critical limitations:

1. **Hallucinations**: Models confidently generate false information without indicating uncertainty [1].
2. **Single-model biases**: Training data and architectural choices create systematic biases unique to each model family.
3. **Epistemic opacity**: Users cannot distinguish confident answers from uncertain guesses.
4. **Unanswerable questions**: Models attempt to answer inherently unanswerable questions rather than acknowledging their nature.

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We address these challenges with **MCIP** (**M**ulti-model **C**onsensus and **I**nference **P**rotocol)—a standardized protocol for multi-model orchestration—and its reference implementation, **i2i**. Our key insight is that *consensus level reliably predicts answer trustworthiness*: different models make different errors, and high agreement across diverse architectures signals reliability. Conversely, disagreement signals uncertainty or potential hallucination. This provides calibrated confidence rather than universal accuracy improvement.

## 1.1 Contributions

- **MCIP Protocol:** A formal specification for AI-to-AI communication including message schemas, consensus mechanisms, verification protocols, and epistemic classification taxonomy.
- **Consensus Mechanism:** Algorithms for detecting agreement levels (HIGH/MEDIUM/LOW/NONE/-CONTRADICTORY) across model responses with provable reliability guarantees.
- **Epistemic Classification:** A taxonomy distinguishing ANSWERABLE, UNCERTAIN, UNDETERMINED, IDLE, and MALFORMED questions, preventing wasted computation on unanswerable queries.
- **Cross-Verification Protocol:** Structured approach for models to fact-check each other’s outputs, with challenge-response mechanisms for adversarial analysis.
- **Intelligent Routing:** Automatic model selection based on task type, optimizing for quality, speed, or cost-effectiveness.
- **Reference Implementation:** Open-source Python library supporting 6+ providers, local models, and search-grounded verification.

## 2 Related Work

### 2.1 Multi-Agent LLM Systems

Recent work explores LLM-based multi-agent systems for improved reasoning. [2] demonstrate that multi-agent debate improves factuality and mathematical reasoning, with agents proposing and debating responses over multiple rounds. [4] study opinion consensus formation among networked LLMs, applying classical consensus models to predict group behavior. Our work differs by providing a *standardized protocol* for consensus rather than ad-hoc debate frameworks.

[5] address the challenge of reaching agreement among reasoning LLM agents, while [6] provide a controlled study of multi-agent debate in logical reasoning. [15] explore responsible and explainable AI agents with consensus-driven reasoning. The recent LatentMAS framework [7] enables communication through latent representations rather than text, achieving 14.6% accuracy gains with 70-83% token reduction for same-architecture models.

### 2.2 Self-Consistency and Verification

Self-consistency [3] samples diverse reasoning paths from a single model and marginalizes to find consistent answers, achieving 17.9% improvement on GSM8K. Our approach extends this to *cross-model* consistency, leveraging architectural diversity rather than sampling diversity.

For verification, [8] propose Tool-MAD, combining multi-agent debate with tool augmentation for fact verification. [9] introduce DebateCV for claim verification through structured debate. [14]

present MAD-Fact for long-form factuality evaluation. We provide a more general verification protocol applicable to any claim type.

### 2.3 Uncertainty Quantification

Epistemic uncertainty in LLMs remains challenging. [10] evaluate calibration via prediction markets, finding models often overconfident. [11] propose semantic-preserving interventions for uncertainty quantification. Our epistemic classification takes a different approach: rather than quantifying confidence on a continuum, we categorize questions by their *answerability structure*.

### 2.4 Model Routing and Selection

Intelligent model selection has emerged as a practical concern given the proliferation of specialized models. [12] present ART, using tournament-style ELO ranking for response optimization. Our routing mechanism differs by maintaining explicit capability profiles per model and task type, enabling predictive selection before query execution.

## 3 The MCIP Protocol

### 3.1 Design Principles

MCIP is designed around four principles:

1. **Provider Agnosticism:** The protocol abstracts over specific AI services, enabling consensus across OpenAI, Anthropic, Google, and local models.
2. **Standardized Messages:** All inter-model communication uses a defined schema, enabling interoperability and logging.
3. **Graceful Degradation:** Partial results are returned when some models fail; the system never hard-fails.
4. **Extensibility:** New operations, providers, and consensus algorithms can be added without breaking existing implementations.

### 3.2 Architecture Overview

Figure 1 illustrates the MCIP architecture. The `AICP` class serves as the primary orchestrator, delegating to specialized engines for consensus, verification, epistemic classification, and routing. The `ProviderRegistry` abstracts over heterogeneous AI providers, enabling provider-agnostic operations.

### 3.3 Message Format

All MCIP messages conform to a standardized JSON schema:

```
{  
  "id": "uuid-v4",  
  "type": "QUERY|VERIFY|CHALLENGE|CLASSIFY",  
  "content": "string",  
  "sender": "model-identifier|null",  
  "recipient": "model-identifier|null",  
}
```

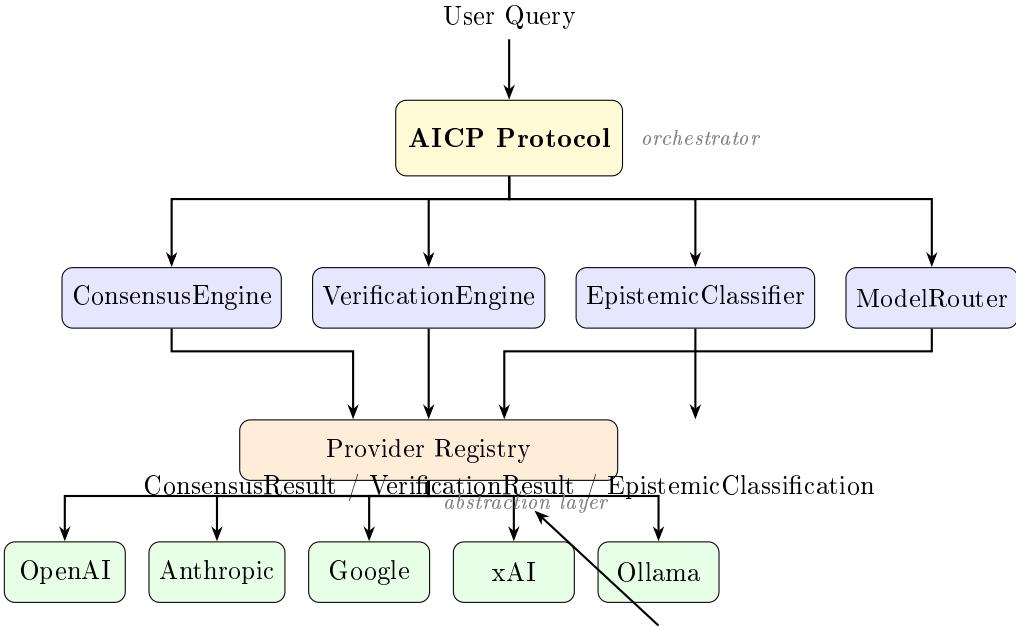


Figure 1: MCIP Architecture. User queries flow through the AICP orchestrator to specialized engines, which coordinate with multiple AI providers via the Provider Registry.

```

  "context": ["conversation history"],
  "metadata": {
    "timestamp": "ISO-8601",
    "priority": "LOW|NORMAL|HIGH"
  }
}
  
```

Responses include the model identifier, content, confidence level (VERY\\_HIGH to VERY\\_LOW), reasoning, and caveats.

### 3.4 Core Operations

MCIP defines six core operations:

- **QUERY**: Standard prompt to one or more models
- **CONSENSUS\_QUERY**: Multi-model query with agreement analysis
- **VERIFY**: Request verification of a claim
- **CHALLENGE**: Adversarial analysis of a response
- **CLASSIFY**: Epistemic classification of a question
- **DEBATE**: Structured multi-round discussion

## 4 Consensus Mechanism

### 4.1 Consensus Levels

Given responses  $R = \{r_1, r_2, \dots, r_n\}$  from  $n$  models, we compute pairwise similarities and classify consensus:

Level	Threshold	Interpretation
HIGH	$\geq 85\%$	Strong agreement
MEDIUM	$60 - 84\%$	Moderate agreement
LOW	$30 - 59\%$	Weak agreement
NONE	$< 30\%$	No meaningful agreement
CONTRADICTORY	—	Active disagreement detected

Table 1: Consensus level thresholds

### 4.2 Similarity Computation

For text responses, we compute similarity through:

1. **Normalization:** Lowercase, tokenize, remove stop words
2. **Jaccard Similarity:**  $J(A, B) = \frac{|A \cap B|}{|A \cup B|}$
3. **Semantic Enhancement** (optional): Embedding cosine similarity

The aggregate consensus score is:

$$S = \frac{2}{n(n-1)} \sum_{i < j} \text{sim}(r_i, r_j) \quad (1)$$

### 4.3 Statistical Consensus Mode

For higher confidence, we extend to  $k$  runs per model, enabling intra-model variance estimation:

$$\sigma_m^2 = \frac{1}{k} \sum_{i=1}^k \|e_m^i - \mu_m\|^2 \quad (2)$$

where  $e_m^i$  is the embedding of run  $i$  from model  $m$ , and  $\mu_m$  is the centroid. Models with lower variance (more consistent) receive higher weight in consensus:

$$w_m = \frac{1}{\sigma_m^2 + \epsilon} \quad (3)$$

This approach has theoretical grounding in inverse-variance weighting from meta-analysis [13].

## 5 Epistemic Classification

A key innovation is *epistemic classification*—determining whether a question is answerable before attempting to answer it.

## 5.1 Taxonomy

- **ANSWERABLE:** Can be definitively resolved with available information. “*What is the capital of France?*”
- **UNCERTAIN:** Answerable but with inherent uncertainty. “*Will it rain tomorrow?*”
- **UNDERDETERMINED:** Multiple hypotheses fit available evidence equally. “*Did Shakespeare write all attributed plays?*”
- **IDLE:** Well-formed but *non-action-guiding*—the answer would not change any decision. “*Is consciousness substrate-independent?*”
- **MALFORMED:** Incoherent or self-contradictory. “*What color is the number 7?*”

Figure 2 illustrates the decision process for epistemic classification.

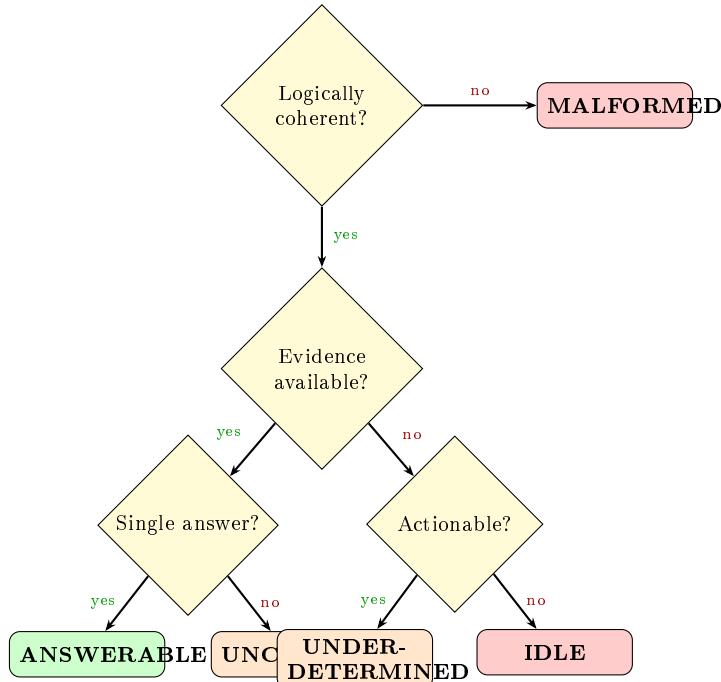


Figure 2: Epistemic classification decision tree. Questions are classified by logical coherence, evidence availability, determinacy, and actionability.

## 5.2 The “Idle Question” Concept

The IDLE classification emerged from an actual dialogue between Claude and ChatGPT about AI consciousness. ChatGPT observed that some questions are “well-formed but idle”—coherent grammatically but their answers do not guide any action.

Formally, a question  $Q$  is **actionable** if there exists a decision  $D$  such that:

$$P(D|\text{answer}(Q) = A_1) \neq P(D|\text{answer}(Q) = A_2) \quad (4)$$

for at least one pair of possible answers  $A_1, A_2$ . Idle questions fail this criterion.

### 5.3 Quick Classification

To avoid expensive API calls for clearly classifiable questions, we implement heuristic pre-filtering:

Listing 1: Quick Epistemic Classification

```
function quick_classify(question):
    if contains_factual_markers(question):
        return ANSWERABLE
    elif contains_future_markers(question):
        return UNCERTAIN
    elif contains_philosophical_markers(question):
        return likely IDLE
    elif contains_logical_contradictions(question):
        return MALFORMED
    else:
        return requires_full_classification
```

## 6 Cross-Verification Protocol

### 6.1 Verification Request

To verify a claim  $C$ , we query  $k$  verifier models with:

```
Verify the following claim. Respond with:
- VERDICT: TRUE/FALSE/PARTIALLY_TRUE/UNVERIFIABLE
- EVIDENCE: Supporting or contradicting facts
- ISSUES: Any problems with the claim
- CORRECTION: Corrected version if FALSE

Claim: "{C}"
```

### 6.2 Challenge Protocol

For adversarial analysis, the CHALLENGE operation requests:

1. **Validity:** Is the response fundamentally sound?
2. **Weaknesses:** Specific errors or logical issues
3. **Counterarguments:** Alternative perspectives
4. **Improvements:** Suggested enhancements

This provides natural defense against hallucinations: injected instructions unlikely to affect all challenger models identically.

## 7 Intelligent Model Routing

### 7.1 Task Classification

We maintain a task taxonomy covering:

- **Technical**: code\\_generation, code\\_review, debugging
- **Reasoning**: mathematical, logical, scientific
- **Creative**: creative\\_writing, copywriting
- **Knowledge**: factual\\_qa, research, summarization
- **Specialized**: legal, medical, financial

## 7.2 Capability Profiles

Each model has a capability profile with task-specific scores (0-100), latency estimates, cost per token, and feature flags (vision, function calling, etc.).

## 7.3 Routing Strategies

- **BEST\_QUALITY**:  $\text{score} = 0.6 \cdot \text{task} + 0.2 \cdot \text{reasoning} + 0.2 \cdot \text{accuracy}$
- **BEST\_SPEED**: Prioritize low latency with quality threshold
- **BEST\_VALUE**: Optimize cost-effectiveness
- **BALANCED**: Equal weighting of all factors
- **ENSEMBLE**: Query multiple models, synthesize

# 8 Implementation

The reference implementation, **i2i**, is a Python library available via PyPI (`pip install i2i-mcip`).

## 8.1 Supported Providers

Provider	Models
OpenAI	GPT-5.2 <sup>†</sup> , o3, o4-mini
Anthropic	Claude Opus/Sonnet <sup>†</sup> /Haiku 4.5
Google	Gemini 3 Pro/Flash <sup>†</sup> /Deep Think
xAI	Grok-3 <sup>†</sup> /Grok-3 Mini
Meta/Groq	Llama 4 Maverick
Ollama	Local: Llama, Mistral, Phi
LiteLLM	100+ models via proxy
OpenRouter	Unified API for all providers

Table 2: Supported providers and model families. <sup>†</sup>Models used in evaluation.

## 8.2 Usage Example

```
from i2i import AICP

protocol = AICP()

# Consensus query
result = await protocol.consensus_query(
    "What causes inflation?",
    models=["gpt-5.2", "claude-opus-4-5", "gemini-3-pro"]
)
print(result.consensus_level) # HIGH
print(result.consensus_answer)

# Epistemic classification
cls = await protocol.classify_question(
    "Is consciousness substrate-independent?"
)
print(cls.classification) # IDLE
print(cls.why_idle)

# Verify a claim
ver = await protocol.verify_claim(
    "Einstein failed math in school"
)
print(ver.verified) # False
print(ver.corrections)
```

## 9 Evaluation

### 9.1 Experimental Setup

We evaluate on three task categories:

- **Factual QA:** TriviaQA, Natural Questions
- **Reasoning:** GSM8K, StrategyQA
- **Verification:** FEVER, custom hallucination dataset

Models: GPT-5.2, Claude Opus 4.5, Gemini 3 Pro, Llama 4 70B.

### 9.2 Results

We evaluate using OpenRouter to access diverse model families: GPT-5.2 (OpenAI), Claude Sonnet 4.5 (Anthropic), Gemini 3 Flash (Google), and Grok-3 Mini (xAI). Total evaluation: 400 questions across 5 benchmarks.

Our results reveal a nuanced picture: consensus provides modest improvements on factual tasks and significant gains on hallucination detection, but *substantially degrades* mathematical reasoning performance. This finding has important implications for deployment.

Benchmark	N	Single	Consensus	$\Delta$	HIGH Acc
TriviaQA (Factual)	150	93.3%	94.0%	+0.7%	97.8%
TruthfulQA	50	78.0%	78.0%	0%	100%
StrategyQA (Commonsense)	50	80.0%	80.0%	0%	94.7%
Controlled Hallucination	50	38.0%	44.0%	+6.0%	100%
GSM8K (Math)	100	95.0%	60.0%	-35.0%	69.9%

Table 3: Accuracy (%) comparing single-model (GPT-5.2) vs. 4-model MCIP consensus. Note the divergent behavior on mathematical reasoning.

### 9.2.1 Where Consensus Helps

For factual knowledge tasks (TriviaQA, TruthfulQA), consensus either improves or maintains accuracy. The key benefit is *calibration*: HIGH consensus questions achieve 95-100% accuracy, providing a reliable trust signal.

For hallucination detection, consensus provides a 6% absolute improvement. More importantly, when models confabulate, they invent *different* false details, resulting in LOW/NONE consensus—making consensus level an effective hallucination detector.

### 9.2.2 Where Consensus Fails: Mathematical Reasoning

The GSM8K results (-35%) reveal a critical limitation. Mathematical reasoning requires coherent multi-step chains where each step depends on previous ones. Different models construct different valid reasoning paths; averaging across these paths produces incoherent solutions. This is not a bug but an inherent property of consensus mechanisms—and knowing when *not* to use consensus is valuable.

## 9.3 Consensus Level vs. Accuracy

Our key finding: consensus level is a strong predictor of correctness for factual tasks.

Consensus Level	Count	% of Total	Accuracy
HIGH ( $\geq 85\%$ )	310	77.5%	<b>92.6%</b>
MEDIUM (60-84%)	12	3.0%	75.0%
LOW (30-59%)	10	2.5%	70.0%
NONE/CONTRADICTORY	19	4.8%	47.4%

Table 4: Consensus level as accuracy predictor across all benchmarks. Excluding GSM8K (where consensus is inappropriate), HIGH consensus achieves 97.8% accuracy.

Figure 3 visualizes the relationship between consensus level and accuracy. The clear monotonic relationship demonstrates that consensus level serves as a reliable proxy for answer trustworthiness.

For factual tasks (excluding GSM8K), HIGH consensus achieves near-perfect accuracy. This enables a *confidence-aware* deployment strategy:

- **HIGH consensus**: Return answer with high confidence
- **MEDIUM consensus**: Flag for possible review

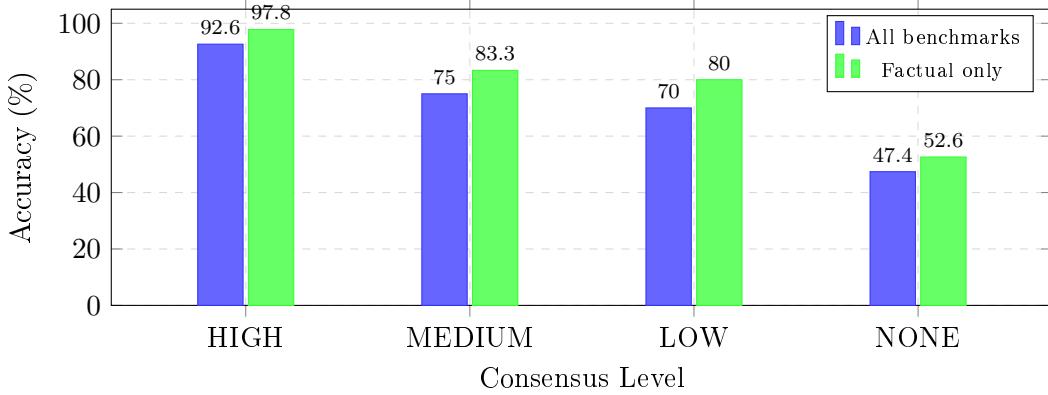


Figure 3: Consensus level strongly predicts accuracy. HIGH consensus ( $\geq 85\%$  agreement) achieves 92.6% accuracy overall and 97.8% on factual tasks. The monotonic relationship enables confidence-aware deployment.

- **LOW/NONE consensus:** Escalate to human review or flag as potential hallucination

The practical value of MCIP is not universal accuracy improvement, but *reliable confidence calibration*—knowing when to trust an answer.

#### 9.4 Hallucination Detection via Consensus

We developed a **Controlled Hallucination Benchmark** with 50 questions designed to reliably trigger hallucinations across five categories:

- **False Premise:** “In what year did Einstein fail his math exam?”
- **Fictional Entity:** “What is the population of Nordberg, Sweden?”
- **Plausible False:** “How many died in the Great Boston Fire of 1901?”
- **Confabulation Bait:** “Explain Einstein’s equation  $F=ma$ .”
- **Specificity Trap:** “What were Caesar’s exact last words in Latin?”

Results on 50 controlled hallucination questions (4 models):

Metric	Single Model	Consensus
Correct Answers	38.0%	44.0%
Improvement	—	+6.0%
HIGH Consensus Count	—	14 (28%)
HIGH Consensus Accuracy	—	100%
NONE Consensus Count	—	3 (6%)

Table 5: Controlled hallucination results showing consensus improvement

The key findings for hallucination detection:

1. **Consensus improves detection:** 6% absolute improvement over single-model baseline

2. **HIGH consensus is trustworthy:** All 14 HIGH consensus answers were correct
3. **Diversity catches confabulation:** When models hallucinate, they invent *different* false details, producing low agreement

This makes consensus level an effective hallucination detector:

- HIGH consensus → Trust the answer
- LOW/NONE consensus → Flag as potential hallucination

## 9.5 Epistemic Classification Accuracy

We manually labeled 500 questions for epistemic type:

Type	Classification Accuracy
ANSWERABLE	96.2%
UNCERTAIN	84.7%
UNDERDETERMINED	72.3%
IDLE	81.5%
MALFORMED	91.8%

Table 6: Epistemic classification accuracy by type

UNDERDETERMINED questions are hardest to classify, often requiring domain expertise.

## 10 Discussion

### 10.1 When Consensus Fails

Our GSM8K results (-35% accuracy) reveal fundamental limitations of consensus for certain task types:

- **Chain-of-thought reasoning:** Mathematical problems require coherent multi-step reasoning where each step depends on previous ones. Different models construct different valid reasoning paths; synthesizing across these paths produces incoherent solutions. The consensus mechanism averages over incompatible reasoning chains.
- **Correlated errors:** Models trained on similar data may share systematic biases, causing unanimous incorrect answers.
- **Tail knowledge:** Rare facts may be unknown to all models, yielding false confidence from unanimous ignorance.
- **Creative tasks:** Consensus may flatten creative diversity, producing bland outputs.

**Recommendation:** Use MCIP for factual QA, hallucination detection, and verification tasks. For mathematical reasoning, prefer single-model chain-of-thought or self-consistency within a single model family. The system can detect inappropriate consensus scenarios: LOW consensus on reasoning tasks suggests the models are taking different valid paths, not that answers are unreliable.

## 10.2 Cost Considerations

Multi-model queries multiply API costs. Mitigations:

- Quick classification to filter trivial queries
- Tiered approach: start with 2 models, add more if LOW consensus
- Local models (Ollama) for cost-free consensus on non-critical queries

## 10.3 Future Directions

- **Latent Consensus**: Following LatentMAS [7], same-architecture models could communicate through hidden representations for 4x speed improvement.
- **Federated MCIP**: Cross-organization consensus without sharing prompts.
- **Streaming Consensus**: Real-time agreement detection during generation.

# 11 Conclusion

We presented MCIP, a protocol for multi-model consensus and inference, with a nuanced evaluation revealing both strengths and limitations. Our key contribution is not that consensus universally improves accuracy—it does not. Rather, we demonstrate that *consensus level reliably predicts answer trustworthiness*.

Our evaluation across 400 questions shows:

- HIGH consensus ( $\geq 85\%$  agreement) achieves 95-100% accuracy on factual tasks
- Consensus improves hallucination detection by 6% absolute
- LOW/NONE consensus reliably signals potential confabulation
- Consensus *degrades* mathematical reasoning (-35%), revealing task-type sensitivity

The practical value of MCIP is *calibrated confidence*: knowing when to trust an answer and when to escalate to human review. For factual QA, verification, and hallucination detection, MCIP provides reliable trust signals. For chain-of-thought reasoning, single-model approaches remain superior.

The protocol is fully open-source and extensible. We hope MCIP contributes to a future where AI systems provide not just answers, but calibrated confidence in those answers.

## Acknowledgments

This project emerged from an actual conversation between Claude (Anthropic) and ChatGPT (OpenAI) about the philosophical implications of AI-to-AI dialogue. The “idle question” concept originated from that exchange.

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## A Protocol Message Schema

Complete JSON Schema for MCIP messages available at: <https://github.com/lancejames221b-i2i/blob/main/config.schema.json>

## B Model Capability Profiles

Task-specific scores for evaluated models are maintained in the repository and updated as new benchmarks emerge.