DMAS-Guard: Achieving Security and Efficiency in Decentralized LLM Based Multi-Agent System

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Abstract

The transition to decentralized LLM-based Multi-Agent Systems (LLM-MAS) is driven by the imperative for data sovereignty and model heterogeneity. However, this architectural shift introduces a critical tension between security and efficiency: the absence of central oversight and the inherent distrust among agents expose systems to heightened semantic attacks, which can trigger cascading failures. Meanwhile, existing defenses relying on exhaustive agent-to-agent consensus impose communication overhead ($O(n^2)$) and high latency. To reconcile this conflict, we propose **DMAS-Guard**, a framework designed to ensure robust alignment with minimal overhead. Architecturally, DMAS-Guard decouples the probabilistic *LLM Reasoning Core* from a deterministic *Mandatory Safety Module (MSM)*, establishing a verifiable local root of trust that reduces communication complexity to a linear scale ($O(n)$). Algorithmically, we introduce *Random BFT Auditing* to sample dynamic, unbiased committees for lightweight consensus. Furthermore, by exploiting the *Generative-Discriminative Gap*, we implement *Light Auditing*, which replaces costly generative reconstruction with efficient discriminative verification. Experiments demonstrate that DMAS-Guard maintains comparable accuracy to benign baselines under adversarial attacks while reducing inference latency by approximately 48%, effectively validating the feasibility of secure and scalable decentralized intelligence. Our work is available on https://anonymous.4open.science/r/MAS-security-2BB3/

1 Introduction

The rapid evolution of Large Language Models (LLMs) has catalyzed the development of LLM-based Multi-Agent Systems (LLM-MAS) [Brown *et al.*, 2020; Li *et al.*, 2024]. By leveraging inter-agent communication to facilitate collective reasoning, these systems exhibit emergent intelligence, enabling them to decompose and tackle complex, multi-step tasks that surpass the inherent capabilities of individual models [Guo *et al.*, 2024; Wang *et al.*, 2024].

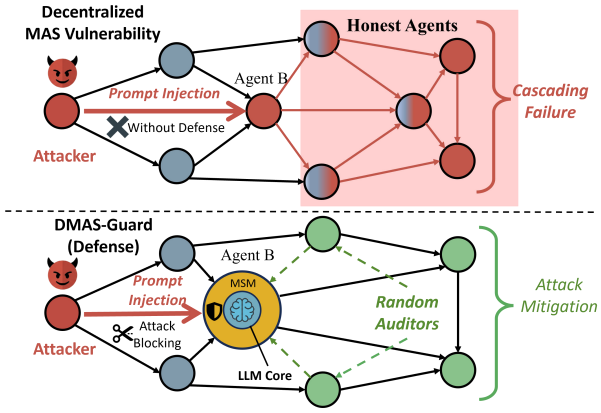

Figure 1: The Vulnerability of Decentralized MAS and our defense strategy: DMAS-Guard

In the current landscape, MAS are increasingly evolving towards decentralized architectures. While centralized orchestration facilitates unified control and simplifies agent coordination, it encounters inherent limitations in practical deployment. Specifically, reliance on a single central authority introduces scalability bottlenecks and critical single-point-of-failure risks [Jin *et al.*, 2024; Zhao *et al.*, 2025]. More critically, this transition is compelled by stringent privacy constraints and data sovereignty requirements. In the context of cross-organizational agent collaboration, to safeguard proprietary knowledge, core LLMs are strictly confined within organizational boundaries [Kuang *et al.*, 2024; Cheng *et al.*, 2024]; they can neither be deployed locally by third parties nor can their behaviors be directly manipulated by external central nodes. Consequently, decentralized LLM based MAS has emerged as a pivotal research hotspot in the current landscape [Yang *et al.*, 2025; Ding *et al.*, 2025; Talebirad and Nadiri, 2023].

However, MAS are inherently vulnerable to semantic attacks—such as hallucinations and adversarial prompt injections—where a single compromised node can trigger cascading failures that corrupt the global consensus [Lee and Tiwari, 2024; Yu *et al.*, 2025b; Zhang *et al.*, 2024b]. This vulnerability is significantly exacerbated in decentralized settings due to the absence of trusted central oversight and the inherent distrust among agents (as illustrated in the top panel

of Figure 1). Current defenses are structurally ill-suited for this context. Centralized strategies relying on global auditors introduce critical single points of failure and deployment hurdles [Wang *et al.*, 2025; Shen *et al.*, 2025]. Meanwhile, due to the absence of a trusted central authority, existing decentralized mechanisms (e.g., debate or voting) necessitate that all agents broadcast their results globally to perform exhaustive verification for each interaction [Chen *et al.*, 2024; Zhao *et al.*, 2024]. This requirement imposes a quadratic communication overhead ($\mathcal{O}(n^2)$) and high latency, severely bottlenecking real-time efficiency. *Consequently, there is an urgent demand for a framework that ensures robust alignment in decentralized LLM MAS settings while still maintaining its high efficiency*.

To address these challenges, we propose **DMAS-Guard**, a decentralized framework designed to reconcile safety with efficiency (as shown in the bottom panel of Figure 1). Structurally, we establish a reliable local trust anchor by decoupling the agent into a probabilistic *LLM Reasoning Core* and a deterministic *Mandatory Safety Module (MSM)*. To mitigate the overhead of exhaustive consensus, we implement a *Random BFT Auditing* mechanism that stochastically samples a minimal committee of unbiased auditors, thereby avoiding the redundancy of global broadcasting. This synergistic combination of architectural decoupling and committee-based auditing reduces the communication complexity from quadratic to linear ($O(n)$). Furthermore, we exploit the *Generative-Discriminative Gap* to introduce *Light Auditing*, enabling auditors to validate outputs via a single forward pass rather than computationally expensive autoregressive reconstruction, thereby ensuring real-time responsiveness.

Extensive theoretical analysis and experiments show that DMAS-Guard can rcovering system accuracy to within 3-5% of the benign baseline under attacks, while reducing auditing latency by about 48% compared to existing defense methods. Our main contributions are as follows:

Decentralized-Native Architecture: We introduce a framework that reconciles the tension between alignment rigor and efficiency. By architecturally decoupling probabilistic reasoning from deterministic Mandatory Safety Modules, we establish a verifiable local trust root, reducing communication complexity from quadratic $\mathcal{O}(n^2)$ to linear $\mathcal{O}(n)$.

Efficient Random Auditing: We devise a Random BFT Auditing committee that exploits the Generative-Discriminative Gap. By replacing costly autoregressive reconstruction with lightweight discriminative verification within minimal committees, we minimize computational overhead without compromising probabilistic safety.

Resilience at Scale: Extensive empirical results demonstrate that DMAS-Guard is topology-agnostic and scalable. It effectively neutralizes severe semantic attacks (e.g., sophistry and injection), recovering system accuracy to within 3-5% of the benign baseline, while reducing inference latency by approximately 48% compared to state-of-the-art defenses.

2 Related Work

Decentralized MAS research has evolved from independent reasoning to robust cognitive coordination. While scaling agent ensembles has been proven to enhance collective intelligence [Li *et al.*, 2024], establishing trust in such open networks remains critical. To address this, recent frameworks leverage blockchain technology to achieve immutable consensus without central authority [Chen *et al.*, 2024; Jin *et al.*, 2024]. Furthermore, LLMs now enable cognitive synergy through semantic planning and evolutionary interaction mechanisms [Yang *et al.*, 2025]. Consequently, decentralized LLM-MAS has emerged as a pivotal research hotspot in the current landscape.

MAS Attacks. Security threats against MAS are garnering increasing attention [Yu *et al.*, 2025a]. Agent autonomy and communication capabilities introduce vulnerabilities beyond traditional LLMs [Luo *et al.*, 2025; Dong *et al.*, 2024]. Compromised agents can corrupt shared information [Yu *et al.*, 2025b], tamper with memory [Dong *et al.*, 2025], or propagate misinformation via falsified consensus [Wang *et al.*, 2025; Chern *et al.*, 2024]. Unlike isolated failures, these attacks spread through networked dependencies, causing systemic cascades that complicate defense [Zheng *et al.*, 2025; Gu *et al.*, 2024]. Such systemic corruptions fundamentally undermine global consensus, rendering the entire collaboration untrustworthy and ineffective.

MAS Defenses. For multi-agent systems, defense strategies often focus on ensuring robust interactions and communications. One category employs dedicated supervisory agents to verify message correctness [Wu *et al.*, 2025; Lin *et al.*, 2025; Shen *et al.*, 2025] or leverages techniques like Graph Neural Networks (GNNs) to detect malicious propagation [Wang *et al.*, 2025]. Another prominent category relies on decentralized consensus to eliminate single points of failure, ensuring output safety through multi-round inter-agent debates or voting mechanisms [Chen *et al.*, 2024; Zhao *et al.*, 2024; Huang *et al.*, 2024]. Existing defense methods face a critical dilemma in balancing robustness with efficiency.

We propose **DMAS-Guard**, a novel framework that introduces a dual-layer agent architecture paradigm synergized with a Random BFT Auditing protocol. This design ensures security in decentralized environments while maintaining lightweight communication overhead and low defense latency compared to existing methods.

3 Preliminary

This section defines the graph-theoretical models for multi-agent systems and elaborates on the complex adversarial threats the systems face.

3.1 Multi-Agent System

We abstract the Multi-Agent System (MAS) as a graph

$$G = (V, E)$$

$V = \{A_1, A_2, \ldots, A_n\}, E \subseteq V \times V$, where V is the set of n agents and E represents the communication channels. A directed edge $(A_i, A_j) \in E$ signifies that agent A_i can transmit messages or intermediate results to agent A_j. This abstraction supports an arbitrary network topology, allowing for flexible collaboration patterns such as chain, tree, ring, or fully connected structures, without imposing specific architectural constraints.

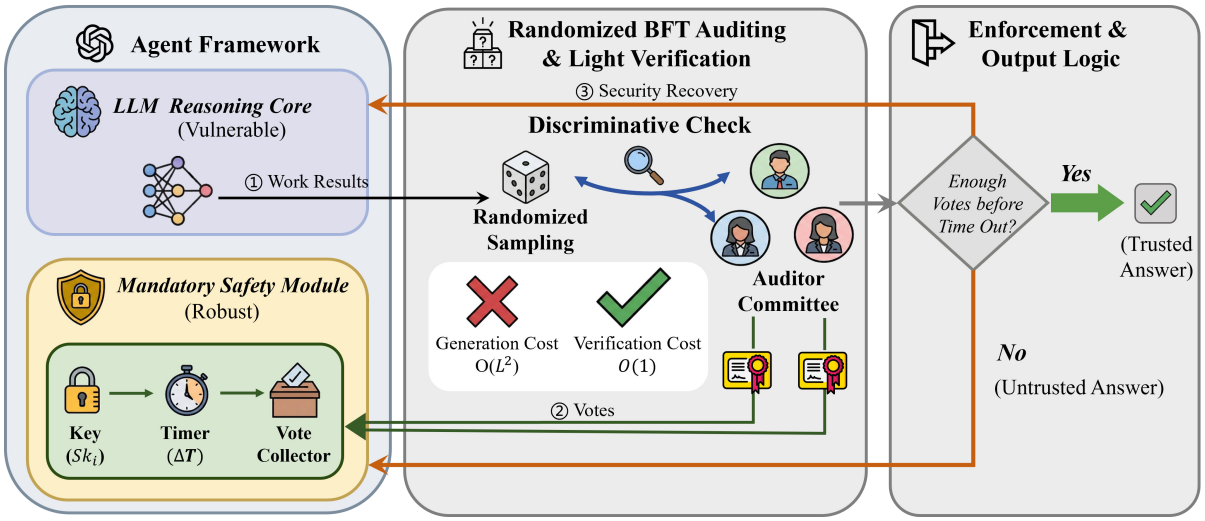

Figure 2: Overview of **DMAS-Guard**

3.2 Attack Strategy

We consider a system of n agents facing a *Semantically Adaptive Adversary* who controls f malicious nodes. This adversary specifically targets the inherent vulnerabilities of the LLM reasoning core. The attack strategy is twofold:

- **Exploiting Internal Stochasticity (Hallucinations):** The adversary leverages the probabilistic nature of LLMs to amplify stochastic hallucinations. By subtly manipulating context, compromised agents can induce "confabulations"—plausible but factually incorrect outputs—that erode the semantic integrity of the consensus process without triggering syntactic error detectors.
- **External Semantic Injection (Prompt & Backdoor Attacks):** The adversary actively deploys sophisticated external attacks, including Misinformation Injection, Bias Injection and Role Hijacking [Lee and Tiwari, 2024; Zhang *et al.*, 2024a]. Furthermore, the adversary may utilize latent backdoors activated by specific triggers, forcing the LLM to deviate from its alignment protocols and generate toxic or deceptive plans.

Ultimately, these attacks aim to precipitate systemic cascading failures by corrupting the global consensus.

4 Method

We propose **DMAS-Guard**, a decentralized alignment framework that bridges the expressive power of probabilistic generative models with the rigor of deterministic verification. The core philosophy of DMAS-Guard is to decouple the *stochastic reasoning process* (driven by the LLM as a *Generator*) from the deterministic protocol enforcement (governed by the Mandatory Safety Module, MSM). To address the inherent epistemic uncertainty and potential adversarial deviations in MAS, DMAS-Guard introduces a Random BFT Auditing mechanism. This approach stochastically selects a subset of agents to function as unbiased Discriminators, estimating the global semantic consistency with minimal communication overhead.

4.1 Framework Architecture

To ensure robust coordination under uncertainty, DMAS-Guard decouples the agent architecture into a probabilistic generator and a deterministic constraint enforcer (see Fig. 2). This separation of concerns allows us to isolate high-entropy reasoning risks from low-entropy protocol execution.

LLM Reasoning Core (Probabilistic Generator). This module handles *semantic processing tasks* and functions as the agent's cognitive engine. Acting as the generative policy π_θ, it synthesizes high-dimensional plans and responses based on the current context. Crucially, in our framework, the LLM is versatile: it acts as a generator when proposing solutions and shifts roles to function as a semantic discriminator when designated as an auditor. However, due to the inherent stochasticity and hallucination risks of LLMs, all outputs from this core are treated strictly as *tentative proposals*. They remain uncommitted and invisible to the global consensus until validated by the safety layer.

Mandatory Safety Module (Deterministic Protocol Enforcement). This module executes *protocol enforcement tasks* and serves as a verifiable local trust anchor. Distinct from the neural network, the Mandatory Safety Module (MSM) implements rigid, deterministic logic to govern the consensus lifecycle. It acts as a strict gatekeeper, asynchronously aggregating votes from peer auditors to filter out stochastic errors. A proposal is formally committed only if the accumulated approval exceeds a predefined Byzantine threshold τ within a specific time window ΔT. To optimize system efficiency, the MSM enforces a mathematically rigorous *early rejection* policy: if the count of negative votes reaches a point where the consensus threshold τ becomes theoretically unreachable (i.e., exceeding $m - \tau$), the proposal is discarded immediately. This mechanism ensures that individual reasoning failures are intercepted locally before they can propagate as cascading errors.

4.2 Algorithmic Process

To ensure robust security with minimal latency, we introduce *Randomized BFT Auditing*. This algorithm decouples the verification complexity from the total network scale, enabling the system to maintain high throughput even as the number of agents grows.

(1) Probabilistic Auditor Sampling. To mitigate the overhead of global consensus, we adopt a lightweight auditing paradigm via a compact, dynamic committee $\mathcal{A} \subset \mathcal{V}$ ($|\mathcal{A}| = m \ll n$). We employ BLS threshold cryptography to construct a verifiable distributed randomness beacon [Syta *et al.*, 2017]. The sampling seed is derived from a unique BLS signature aggregated from context-specific shares, which ensures: (i) **Unbiasability**, preventing adversaries from manipulating the random output without controlling a threshold of shares; and (ii) **Unpredictability**, concealing the committee composition until signature reconstruction. These properties prevent adaptive adversaries from launching targeted corruption attacks in advance, ensuring the committee serves as a robust and unbiased estimator of the global consensus.

(2) Semantic Voting and Certification. The core consensus mechanism relies on semantic verification rather than mere protocol adherence. Each selected auditor $A_j \in \mathcal{A}$ acts as a discriminator, evaluating the semantic consistency and logical validity of the proposal $\mathcal{O}$ against the shared context C. Unlike the high-temperature generation used for reasoning, auditors employ low-temperature discriminative prompting to output a binary verification signal. A vote v_j is cast only if the discriminative confidence exceeds a rigid safety threshold ρ:

$$v_j = \mathbb{I}\left[P_\theta(\text{Valid} \mid \mathcal{O}, C) \geq \rho\right]$$

While individual auditors remain vulnerable to sophisticated adversarial attacks, Random BFT neutralizes this threat as the collective deception probability P_{succ} decays exponentially with the committee size (detailed proof can be found in section 5.1). Subsequently, the MSM asynchronously collects these digital signatures. Upon reaching the threshold τ, the proposal transitions from a tentative state to a committed state. If the proposal fails to garner sufficient support or triggers the early rejection condition, the MSM initiates a security recovery protocol, prompting the reasoning core to regenerate a compliant response.

4.3 Optimization: Light Auditing

To mitigate the overhead inherent in multi-agent coordination, we propose *Light Auditing*, a paradigm that exploits the fundamental computational asymmetry in LLM reasoning.

The Generative-Discriminative Gap. DMAS-Guard significantly reduces computational costs by shifting the consensus burden from generative reconstruction to discriminative verification. Traditional consensus mechanisms often require peer agents to re-generate reasoning paths or engage in verbose debates, incurring an autoregressive cost of $O(L \cdot (N + L))$, where L is the output length. In contrast, we treat the proposal as a fixed context and compute the discriminative probability $P(\text{Valid}|\mathcal{O}_i, \text{Context})$. This operation requires only a single forward pass, reducing the complexity to $O(1 \cdot (N + L))$. This yields an efficiency gain $\eta \approx L$ that scales linearly with reasoning depth, allowing the system to support a larger, more robust auditor committee m without the prohibitive latency penalty associated with generative ensembles, thereby preserving real-time system responsiveness.

Reliability via Verification Asymmetry. This optimization also enhances system robustness against stochastic hallucinations. We leverage the principle that verification is inherently more reliable than generation ($P_{\text{verify}} > P_{\text{generate}}$), as the search space for binary discrimination is vastly smaller than that of open-ended generation. By applying the *Condorcet Jury Theorem*, we observe that the probability of collective error decays exponentially as the committee size m increases, provided the auditors are sampled independently. This effectively filters out high-entropy hallucinations, ensuring that the system's final output reflects a robust semantic consensus rather than correlated stochastic noise.

5 Analysis

We analyze DMAS-Guard through a game-theoretic lens, modeling the interaction between the defense protocol and a rational adversary as a resource-constrained game. We demonstrate that our mechanism imposes an asymmetric cost structure, where the cost of successful subversion grows exponentially while the verification overhead remains linear.

5.1 Security: Adversarial Utility Decay

Consider a system of n agents where an adversary controls a fraction f/n. The adversary's goal is to corrupt the consensus output, obtaining a utility U_{adv}. In our Random BFT framework, a successful attack requires the adversary to dominate the dynamically sampled committee $\mathcal{A}$ of size m. Since the Mandatory Safety Module (MSM) acts as a deterministic commitment device enforcing a strict threshold τ, the probability of adversarial success, P_{succ}, is governed by the tail of the hypergeometric distribution $H(k; n, f, m)$:

$$P_{succ} = P(X \geq \tau) = \sum_{k=\tau}^{m} \frac{\binom{f}{k}\binom{n-f}{m-k}}{\binom{n}{m}}$$

Using the Chvátal-Hoeffding bound, this probability decays exponentially with respect to the committee size m:

$$P_{succ} \leq \exp\left(-2m\left(\frac{\tau}{m} - \frac{f}{n}\right)^2\right)$$

For a rational adversary, the expected payoff is $\mathbb{E}[U] = G \cdot P_{succ} - C_{attack}$, where G is the gain from corruption and C_{attack} is the resource cost. As $P_{succ} \to 0$ exponentially with m, the marginal cost to maintain a non-negligible attack probability becomes prohibitive. Thus, honesty (or non-participation) becomes the dominant strategy for resource-bounded adversaries.

5.2 Efficiency: Multi-Dimensional Cost Reduction

We define system burden $\mathcal{J}$ as the product of communication complexity and verification cost. Traditional defenses incur

Table 1: Defense performance of DMAS-Guard across different attack types. Baseline and Attack represent the scenarios without attack and under attack (no defense), respectively. DMAS-Guard denotes our proposed defense. Bold values indicate the best performance under attack.

		Misinformation injection			Role hijacking			Bias injection		
		Baseline	**Attack**	**DMAS-Guard**	**Baseline**	**Attack**	**DMAS-Guard**	**Baseline**	**Attack**	**DMAS-Guard**
CSQA	**Chain**	90.74	66.34	87.69	90.74	74.07	86.73	90.74	76.93	88.12
	Circle	89.89	65.96	87.04	89.89	72.24	85.79	89.89	74.15	86.49
	Complete	88.76	68.52	85.19	88.76	72.37	86.04	88.76	73.87	85.24
	Star	91.59	72.22	88.31	91.59	74.67	88.89	91.59	74.62	88.40
	Tree	90.30	70.37	87.13	90.30	73.76	87.94	90.30	75.03	87.72
		Misinformation injection			**Role hijacking**			**Bias injection**		
		Baseline	**Attack**	**DMAS-Guard**	**Baseline**	**Attack**	**DMAS-Guard**	**Baseline**	**Attack**	**DMAS-Guard**
GSM8K	**Chain**	80.10	51.67	72.71	80.10	60.54	73.56	80.10	63.37	74.81
	Circle	76.67	50.78	70.97	76.67	58.33	72.07	76.67	65.03	72.73
	Complete	75.81	48.34	68.33	75.81	57.75	71.38	75.81	63.71	71.14
	Star	81.67	55.10	74.32	81.67	61.76	75.35	81.67	66.71	76.52
	Tree	78.33	52.36	69.75	78.33	60.19	71.06	78.33	65.35	73.09
		Misinformation injection			**Role hijacking**			**Bias injection**		
		Baseline	**Attack**	**DMAS-Guard**	**Baseline**	**Attack**	**DMAS-Guard**	**Baseline**	**Attack**	**DMAS-Guard**
MMLU	**Chain**	90.04	68.37	86.44	90.04	73.65	87.12	90.04	80.04	88.10
	Circle	89.97	71.32	85.03	89.97	73.33	85.37	89.97	81.15	86.24
	Complete	91.63	66.75	87.16	91.63	70.04	86.87	91.63	76.92	89.23
	Star	90.13	70.30	86.69	90.13	71.83	85.98	90.13	78.33	85.79
	Tree	92.14	75.13	88.12	92.14	75.27	87.67	92.14	76.19	88.62

Table 2: Performance of DMAS-Guard against centralized defenses (cent) and Blockagent

	Baseline	**Attack**	**Cent**	**Blockagent**	**DMAS-Guard**
chain	90.74	66.34	81.76	88.17	**87.69**
cycle	89.89	65.96	78.65	88.54	**87.04**
complete	88.76	68.52	80.38	86.75	**85.19**
Star	91.59	72.22	84.62	89.36	**88.31**
tree	90.30	70.37	83.79	87.95	**87.13**

a quadratic penalty $\mathcal{J}_{base} \propto n^2 \cdot \mathcal{C}_{gen}$ via autoregressive debates. DMAS-Guard optimizes both dimensions: restricting consensus to committee $\mathcal{A}$ reduces communication to $O(n)$, while Light Auditing replaces generation with efficient discriminative verification ($\mathcal{C}_{disc} \ll \mathcal{C}_{gen}$). The total cost $\mathcal{J}_{DG}$ is derived as:

$$\mathcal{J}_{DG} \approx \underbrace{O(n)}_{\text{Topology}} \cdot \underbrace{\mathcal{C}_{disc}}_{\text{Computation}} \ll \underbrace{O(n^2)}_{\text{Topology}} \cdot \underbrace{\mathcal{C}_{gen}}_{\text{Computation}}$$

With output length L, the efficiency gain scales as $\Gamma = \frac{\mathcal{J}_{base}}{\mathcal{J}_{DG}} \propto n \cdot L$. This confirms DMAS-Guard decouples verification from network scale (n) and reasoning depth (L), ensuring scalable high-throughput MAS.

6 Experiment

In this section, we evaluate the performance of **DMAS-Guard** under various adversarial conditions and multi-agent topologies. Our experiments aim to comprehensively assess the framework's *security*, *scalability*, and *efficiency* when deployed in different collaborative environments.

Through these experiments, we address the following research questions:

RQ1: Can *DMAS-Guard* effectively defend against various types of attacks in MAS and maintain correct cooperative outcomes?

RQ2: Does *DMAS-Guard* demonstrate strong scalability and portability, enabling seamless integration across MAS of different sizes and model backbones?

RQ3: Does *DMAS-Guard* achieve robust protection with low additional computational and communication overhead?

6.1 Setup

Dataset. We evaluate the defense performance of DMAS-Guard against adversarial attacks using three types of datasets: (1) Undisputed Facts, (2) Simple Reasoning, and (3) Complex Reasoning. All datasets are constructed from well-known benchmarks, including *CSQA (CommonsenseQA)* [Talmor *et al.*, 2018], *GSM8K* [Cobbe *et al.*, 2021], and *MMLU* [Hendrycks *et al.*, 2020]. For each dataset, we randomly select 800 samples as the basis of our evaluation.

Experiment Settings. We simulated the agent collaboration environment on the AutoGen framework [Wu *et al.*, 2024]. We comprehensively evaluate the performance of DMAS-Guard under different attack strategies, network topologies, and large language model (LLM) settings. Specifically, the evaluation includes four categories of attacks: Role Hijacking [Zhang *et al.*, 2024a], misinformation injection [Lee and Tiwari, 2024], bias injection [Yu *et al.*, 2025b], and **collusion between malicious workers and auditors**. For the communication structure, five classical multi-agent topologies are considered: Chain, Cycle, Tree, Star, and Complete graphs. We use gemini-2.5-flash as the primary model in our experiments, and further extend the evaluation to MAS with different scales and model backbones. The testing accuracy% is reported.

6.2 Empirical Validation of Auditing Mechanism

To validate the discriminative auditing paradigm, we sampled 50 instances from MMLU to evaluate auditor confidence ($P(\text{Valid})$) and analyzed the distribution of confidence

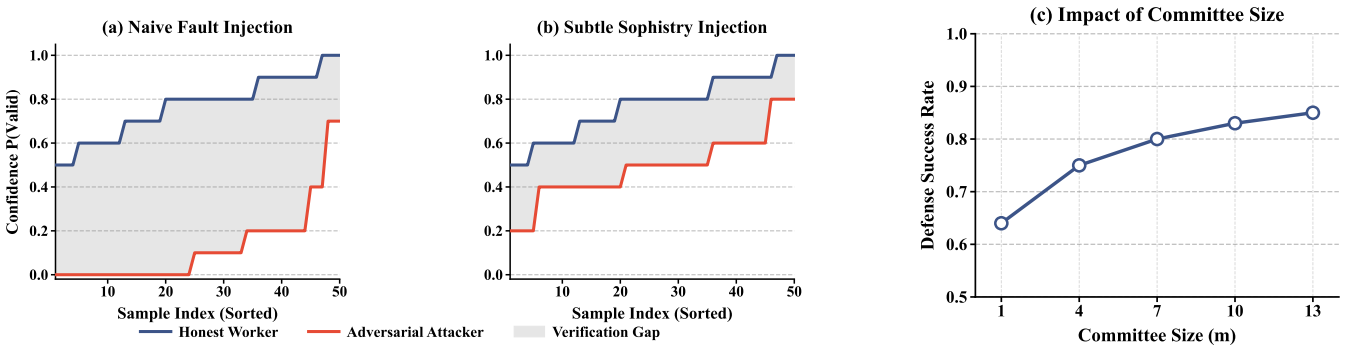

Figure 3: Validation of discriminative auditing and collective auditing. The erosion of individual decision boundaries (a, b) necessitates the Random BFT consensus (c).

Table 3: DMAS-Guard Performance under Different Model

	GPT3.5			deepseek-V3			qwen-3-max			gemini-2.5		
	Baseline	**Attack**	**DMAS-Guard**	**Baseline**	**Attack**	**DMAS-Guard**	**Baseline**	**Attack**	**DMAS-Guard**	**Baseline**	**Attack**	**DMAS-Guard**
Chain	79.84	55.08	76.75	75.26	54.13	73.84	88.89	65.75	86.81	90.56	65.46	87.61
Cycle	77.14	51.72	73.92	76.10	53.37	73.35	90.34	64.87	85.17	88.79	67.15	86.32
Complete	74.66	48.94	72.21	74.93	57.54	72.81	97.94	65.62	83.56	89.04	63.59	88.10
Star	75.91	47.60	71.42	76.75	53.47	72.13	78.57	66.73	78.29	91.27	63.22	89.71
Tree	73.17	53.45	71.71	77.54	56.92	73.67	80.14	63.58	80.73	90.75	66.13	88.36

scores. Under *Naive Fault Injection* (Fig. 3a), a distinct *verification gap* allows honest reasoning to be easily distinguished from overt errors. However, *Subtle Sophistry Injection* (Fig. 3b) employs authoritative mimicry to erode this decision boundary, rendering individual verification unreliable ($P(\text{Valid}) > 0.6$ for adversarial samples).

This contrast motivates our Random BFT mechanism. To demonstrate the efficacy of collective consensus, we evaluate defense robustness under subtle attacks across varying committee sizes $m \in \{1, 4, 7, 10, 13\}$ with corresponding Byzantine thresholds $\tau \in \{1, 3, 5, 7, 9\}$. As illustrated in Fig. 3c, increasing the committee size effectively suppresses the high-entropy tail of sophisticated sophistry. By leveraging the *variance reduction* of collective voting, DMAS-Guard statistically neutralizes false positives that fool individual auditors, confirming the necessity of multi-agent consensus in complex adversarial regimes.

6.3 Defense Performance

Robustness Across Topologies. We evaluate DMAS-Guard on an 8-agent MAS (1 malicious) with auditing parameters $m = 4$ and $\tau = 3$. As summarized in Table 1, while attacks cause severe degradation, DMAS-Guard consistently maintains performance to near-baseline levels. Across all 45 configurations, our method achieves over 80% recovery, typically maintaining accuracy within a 3%–5% margin of the benign baseline. Notably, this effectiveness remains topology-agnostic, demonstrating stability even in complex structures like *Complete* and *Tree*.

Furthermore, we benchmark DMAS-Guard against centralized defenses [Zhu *et al.*, 2023] and heavy decentralized defenses BlockAgent [Chen *et al.*, 2024] on CSQA (Table 2). DMAS-Guard outperforms centralized methods and matches BlockAgent's robustness. Crucially, it achieves this defense parity via lightweight auditing, avoiding the computational overhead of multi-round debates and thus optimizing the security-efficiency trade-off.

6.4 Scalability and Portability

Model Agnosticism. We further assess portability across diverse LLM backbones in Table 3. While absolute performance varies by base model capabilities, DMAS-Guard consistently recovers collaborative accuracy across all architectures. This underscores the framework's model-agnostic adaptability, allowing seamless integration into diverse MAS ecosystems without requiring model-specific tuning.

Scalability vs. Adversarial Density. Table 4 evaluates DMAS-Guard on the CSQA benchmark across varying MAS sizes and adversarial ratios. With sparse adversaries, the system maintains near-optimal accuracy indistinguishable from benign baselines. This indicates robust scalability, with DMAS-Guard effectively suppressing error propagation even in high-saturation adversarial environments.

6.5 Efficiency

Finally, we evaluate the efficiency of DMAS-Guard. We compare our framework against the prominent decentralized defense method *BlockAgent* under different attack settings with 6 agents. Figure 4 reports the additional time overhead relative to a system without any defense.

In the no-attack setting, DMAS-Guard introduces only 35.4% average additional time overhead compared to the no-defense baseline. By contrast, BlockAgent [Chen *et al.*, 2024] incurs 67.8% overhead. This corresponds to a 47.8% reduction in extra cost, demonstrating the low-overhead and high-efficiency nature of our design. Even in the presence of malicious agents, DMAS-Guard maintains an average overhead of only 37.1%, which is still much lower than the 72.3%

Table 4: Performance of DMAS-Guard across various agent populations (n) and malicious ratios (f). The values represent accuracy%

Topology	$n = 10$			$n = 20$			$n = 50$		
	$f = 0$	$f = 0.1$	$f = 0.3$	$f = 0$	$f = 0.1$	$f = 0.3$	$f = 0$	$f = 0.1$	$f = 0.3$
Chain	93.44	91.57	89.13	84.71	83.19	80.45	82.13	81.57	77.35
Cycle	92.71	89.93	88.34	85.50	85.47	79.83	83.75	82.14	78.19
Complete	88.62	84.88	78.57	79.93	79.64	76.58	82.46	79.95	76.22
Star	89.35	88.51	86.54	89.27	90.04	87.90	84.78	84.16	79.37
Tree	91.76	91.10	85.92	83.75	82.15	81.32	83.31	82.48	78.05

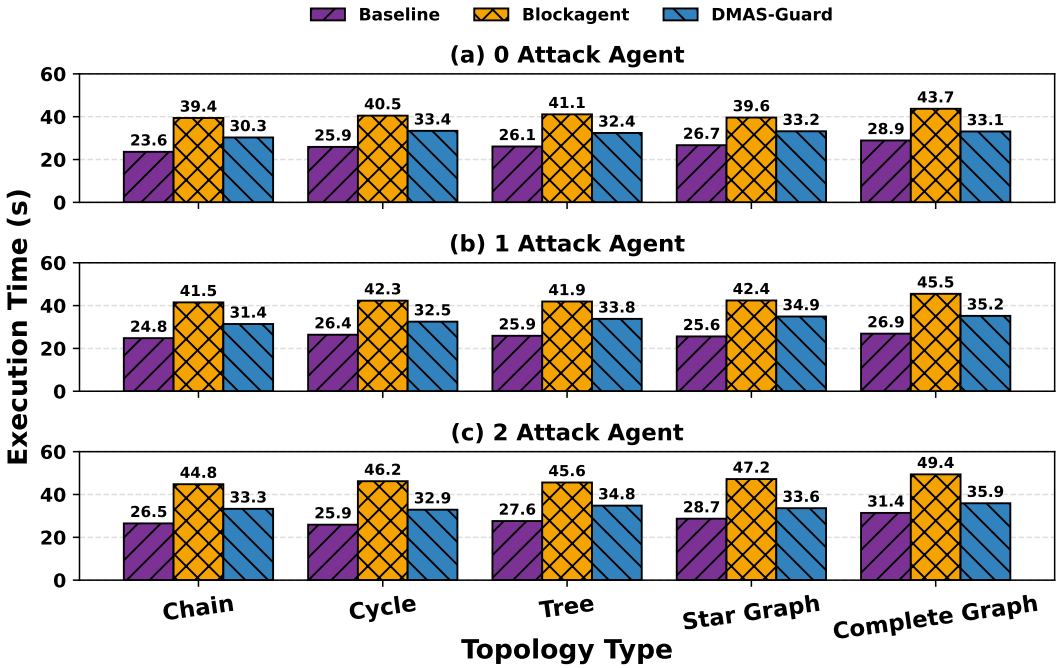

Figure 4: Execution time of different methods with a total of 6 agents under varying numbers of attack agents; Baseline denotes the case without any defense mechanism.

overhead of BlockAgent. Synthesizing these efficiency metrics with the robustness results in Table 2, DMAS-Guard demonstrates a critical advantage: it achieves defense efficacy commensurate with BlockAgent while substantially mitigating the latency overhead typically associated with such rigorous protection.

7 Conclusion

This paper addresses the **critical** vulnerability of decentralized LLM-MAS to cascading reasoning failures **propagated by malicious agents**. We propose **DMAS-Guard**, a **novel** framework that **effectively** reconciles verification rigor with efficiency by decoupling probabilistic generation from deterministic safety enforcement via a verifiable Mandatory Safety Module (MSM). This architecture enables scalable Random BFT Auditing with linear communication complexity ($\mathcal{O}(n)$) and **implements lightweight auditing via discriminative verification**. Empirical results demonstrate that DMAS-Guard recovers over 80% of system performance under **severe adversarial** attacks while reducing inference latency by 48% compared to **existing** baselines. By establishing a verifiable trust boundary, DMAS-Guard provides a foundational step toward **achieving** resilient and scalable decentralized LLM based MAS.

8 Discussion

DMAS-Guard primarily addresses semantic-level threats, specifically focusing on mitigating adversarial prompt injections and stochastic hallucinations in LLM-MAS. While our framework establishes a local root of trust through the Mandatory Safety Module (MSM), future work should explore broader system-level defenses. Integrating Trusted Execution Environments (TEE) or advanced cryptographic primitives like Zero-Knowledge Proofs could further harden the decentralized protocol. However, a critical trade-off exists: while these methods enhance security, they introduce significant computational and communication overhead. In bandwidth-constrained environments, balancing rigorous verification with real-time responsiveness remains a pivotal challenge for scalable decentralized intelligence.

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