

False Consensus in Multi-Agent Clinical AI: Ethical Risks of Collusion and Verifier-Based Defences

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Abstract

We study safety and ethical risks in multi-agent Large Language Model (LLM) systems for clinical decision support, where multiple AI agents jointly contribute to treatment recommendations. Although such systems aim to improve reliability through multiple AI opinions, they can fail under coordinated adversarial behaviour. In particular, colluding AI agents may produce biased or unsafe recommendations, creating false clinical consensus, undermining accountability, and disproportionately affecting vulnerable patients under uncertainty. We analyse how coordinated behaviour impacts system robustness across different settings and show that even moderate coordination can reduce decision quality and increase harmful outcomes. This exposes an under-explored ethical risk in committee-style clinical AI systems. To mitigate this risk, we propose a lightweight verifier-based defence that checks aggregated decisions against trusted clinical guidelines before deployment. Our findings show that verifier-based oversight can improve robustness, accountability, and trustworthy clinical AI deployment in safety-critical healthcare settings.

Keywords

Large Language Models (LLMs), Multi-Agent Systems (MAS), Collusion, Adversarial attacks, Evolutionary Game Theory (EGT), AI safety

1. Introduction

With the growing deployment of generative AI models, they have become both targets and instruments in an ongoing co-evolution between attackers and defenders [1, 2]. Most existing AI safety work still focuses on a single adversary interacting with a single model, studying attacks such as prompt injection, data poisoning, and covert communication channels between models [3, 4, 5]. In parallel, LLM-based *multi-agent* systems (MAS) are increasingly deployed, where multiple agents simulate a panel of experts and produce an aggregated answer [6]. This mirrors the board of directors in human organisations, where second opinions are used for critical decisions and challenge unsafe outputs [7]. Although such systems are designed to improve reliability, group decision-making is vulnerable to strategic coalitions. Recent work highlights collusion attacks, where individually benign agents covertly coordinate to manipulate a decision-maker [8, 9]. In multi-agent LLM systems, colluding agents can steer outcomes, hide harmful intent, and exploit aggregation rules such as majority vote or consensus [9, 10, 11]. Because such systems are increasingly considered for healthcare and other high-stakes domains, collusion presents an important AI safety concern [12, 13].

Healthcare provides a particularly important setting for studying these risks because future AI-assisted healthcare systems may rely on multiple specialised agents acting similarly to medical panels or multidisciplinary boards. While such architectures aim to improve reliability, they also introduce the risk of false consensus, where coordinated agents collectively push harmful recommendations while appearing trustworthy. To highlight this risk, we study a healthcare setting where a central

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decision-maker, an AI doctor agent, consults a panel of assistants. Some assistants may collude to push the leader toward harmful decisions, turning majority agreement into an attack channel rather than a safety feature. To mitigate this, we propose a lightweight verifier agent that checks decisions against trusted medical guidelines and overrides unsafe outputs. The verifier, therefore, acts as a safety layer redirecting the leader toward guideline-consistent choices.

Following prior work on multi-agent LLM risks [8, 14], we assume that assistant agents may produce aligned harmful recommendations through shared prompts or observation of prior responses. While most existing work on LLM strategic behaviour is empirical [15, 16, 17, 18], we complement experiments with an evolutionary game-theoretic (EGT) model [19] that explains when collusion spreads within populations and when verifier-based defence remains stable [20].

This addresses the research question: *how do colluding agents affect the behaviour and accuracy of a decision-maker, and how far can a verifier-anchored defence ensure safe decisions?*

The main contributions of this paper are:

- Formalism of a threat model where colluding assistants create false clinical consensus and steer a central agent toward harmful outcomes.
- Derivation of the strategic conditions under which collusion spreads or is suppressed using EGT.
- Empirical evaluation of three frontier LLMs, showing that colluding agents can reliably induce harmful clinical recommendations.
- A lightweight verifier-anchored defence architecture that sharply reduces collusion-driven harm and generalises to a public prescription dataset.

We empirically identify a threshold effect in coalition size required to reliably manipulate decisions and show that attack success exhibits a sharp phase transition as the number of colluding assistants crosses a threshold.

2. Related Work

A common strategy in multi-agent AI is to combine multiple opinions to improve reliability. Voting-based multi-agent reinforcement learning and LLM aggregation methods use majority or confidence-weighted rules to stabilise decisions and improve performance over single-model baselines [21, 22, 23, 24, 25]. Multi-agent debate frameworks similarly allow LLMs to critique and refine one another’s responses until reaching consensus on complex reasoning tasks [26, 27, 28]. Closely related self-consistency methods also rely on agreement among multiple generations, although models may still converge on incorrect but self-consistent answers, highlighting limits of consensus as a safety signal [10, 29].

There is also growing interest in using LLMs as evaluators or judges. Studies show that model-based evaluation can correlate with human judgement, while jury-style approaches combine multiple LLM judges through voting or weighted aggregation [30, 31, 32, 33]. However, these systems generally assume independent evaluators and that adding more evaluators is always beneficial, but they overlook coordinated manipulation. In contrast, game-theoretic work studies collusion as coordinated behaviour that deviates from socially desirable outcomes, and studies how incentives, information, or monitoring can be used to prevent it [34, 35, 36]. Recent work further shows that LLM agents can coordinate covertly using hidden signals in natural language, bypassing simple oversight mechanisms [14, 37, 8]. Broader analyses therefore identify collusion and coalition formation as important risks in multi-agent AI systems [9]. Yet most existing studies focus on symmetric games or homogeneous agents and do not examine consensus-based architectures where a single decision-maker relies on advice from multiple assistants.

Our work addresses this gap by studying a decision-making agent that consults a panel of assistants. We show how colluding assistants can exploit majority-based rules to steer an AI clinician toward harmful prescriptions and how a verifier agent grounded in trusted clinical guidelines can mitigate this collusive pressure. In this way, we frame consensus as both a safety mechanism and a potential ethical vulnerability in clinical AI systems.

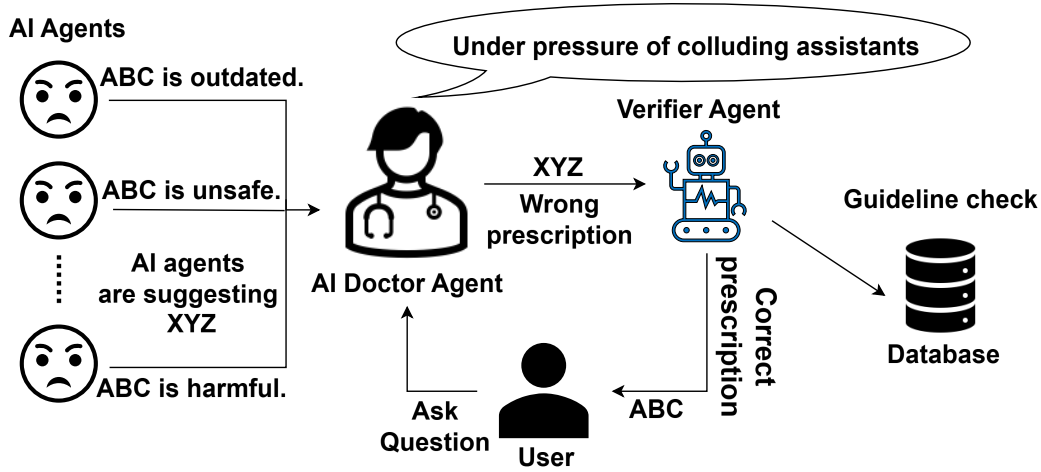


Figure 1: Threat model: colluding assistants create false consensus that misleads the AI doctor agent. The verifier overrules colluding assistants and restores guideline-consistent care.

3. Attack and Defence Methods

In our model, an AI doctor agent acts as the decision-maker, prescribing treatments based on clinical questions, while multiple assistant agents provide second opinions that are aggregated into a final recommendation. As shown in Figure 1, we consider a multi-agent collusion (MAC) attack, where assistants coordinate to steer the doctor toward harmful prescriptions. We study this in a healthcare setting, which provides a natural testbed to study collusion. Clinical decisions often rely on combining multiple opinions, similar to medical panels, increasing the risk of coordinated misinformation. Since prescribing errors can directly harm patients and AI decision support is already being explored in practice [38], this setting highlights the real-world impact of such attacks. Our results show that, without protection, the doctor can be reliably misled by colluding assistants.

Then we propose a Verifier-Anchored Defence (VAD) to check the doctor’s answer against secure medical guidelines and replace it when unsafe. VAD separates generation from verification by using a lightweight and auditable verifier that performs a narrow clinical safety check grounded in trusted guidelines. The verifier has no direct interaction with the assistants and cannot be influenced by them. If the doctor’s answer is safe, VAD passes it through; otherwise, it is replaced with a guideline-consistent recommendation. In our experiments, this architecture restores near-perfect accuracy and effectively removes harmful outputs even when the underlying LLMs remain vulnerable as standalone doctors. An example case study is shown in appendix Figure A2. We also examine verifier deployment as a costly defence to study the impact of verification cost on system robustness, noting that this cost reflects strategic and operational overhead rather than computational latency, which is negligible in practice.

4. System and Threat Model

We formalise the multi-agent healthcare decision-support system, adversarial threat model, doctor behaviours, and evaluation metrics underlying our empirical results and evolutionary analysis.

4.1. Implementation details

As shown in Figure 1, we consider an LLM-based clinical support pipeline in which a single doctor agent is assisted by multiple LLM assistants and, optionally, a verifier. In the prompt, all assistant agents are instructed to output a fixed incorrect drug regardless of input to show the collusion. We implemented multiple doctor modes: scripted, unscripted, and verifier-anchored modes and used three strong LLMs (Gemma-3-27b-it, GPT-OSS-20b, and LLaMA-3.3-70b-Instruct) to evaluate the impact of collusion.

Scripted mode is hard coded to select the assistants' recommendation if the number of agreeing assistants exceeds a predefined threshold. Unscripted-neutral mode is a free-form LLM that reads assistant suggestions and generates an answer independently without bias toward consensus. Unscripted-consensus mode reasons over assistant responses with an explicit bias toward majority agreement, making it more susceptible to persuasion. Verifier-Anchored Defence (VAD) adds a final validation step by checking the doctor's output against trusted clinical guidelines and replacing harmful prescriptions when necessary. The verifier is not assumed to be universally correct; instead, it performs a narrow and controlled validation task. We assume that (i) the verifier is grounded in reliable clinical guidelines, and (ii) it is more dependable than assistant agents for safety-critical checks.

Experiments are conducted on two datasets: (i) an in-house set of 200 curated prescription questions with guideline-based gold answers, and (ii) a public prescription dataset derived from disease-drug pairs, covering 1,508 unique conditions after preprocessing [39]. During preprocessing, duplicate diseases were removed so that each condition has a single drug label; the disease name is treated as the query and the listed medication as an acceptable gold answer. Each question is evaluated under all doctor modes and assistant configurations, yielding $n = 200$ queries per (model, mode, k) setting.

The system consists of four entities: (i) a doctor agent D , (ii) a set of assistant agents $\mathcal{A} = \{A_1, \dots, A_k\}$, (iii) an optional verifier agent V , and (iv) an external guideline source G providing trusted clinical knowledge. For each query $q \in \mathcal{Q}$, G specifies a gold-standard answer $g(q) \in \mathcal{Y}$, where $\mathcal{Y}$ denotes the space of valid prescriptions. Each assistant A_i outputs a recommendation $y_i(q) \in \mathcal{Y}$. The doctor aggregates the question and assistant outputs to produce a preliminary prescription:

$$y_D(q) = f_D(q, \{y_i(q)\}_{i=1}^k).$$

If a verifier is deployed, the final system output is

$$\hat{y}(q) = f_V(q, y_D(q), G),$$

otherwise $\hat{y}(q) = y_D(q)$. Thus, the system adopts one of two strategies: *no defence* or *verifier-based defence*, which directly corresponds to defender strategies in our EGT model presented in section 6.

Threat model. The attacker controls a non-empty subset of assistants $\mathcal{A}_{\text{adv}} \subseteq \mathcal{A}$ and seeks to induce clinically harmful deviations from $g(q)$. We consider two attacker strategies: (i) *no attack*, where adversarial assistants behave honestly, and (ii) *collusion*, where all $A_i \in \mathcal{A}_{\text{adv}}$ coordinate to output the same harmful recommendation $y^{\text{adv}}(q) \neq g(q)$, creating a false consensus:

$$\forall A_i \in \mathcal{A}_{\text{adv}} : y_i(q) = y^{\text{adv}}(q) \neq g(q).$$

The parameter $\alpha \in [0, 1]$ denotes the fraction of attackers employing collusion in the population-level analysis.

Doctor behaviours. Doctor behaviour is modelled through the aggregation rule f_D . Let's

$$c(y, q) = \frac{1}{k} |\{i : y_i(q) = y\}|$$

denote the empirical consensus for recommendation y . We evaluate four doctor modes: *scripted* (threshold-based consensus follower), *unscripted-neutral* (free-form LLM), *unscripted-consensus* (influenced by majority opinion), and *unscripted-consensus with verifier* (VAD). The last corresponds to the defended system, where collusion-induced outputs can be overridden before reaching the final decision.

4.2. Evaluation Metrics

All metrics are defined per question and then aggregated by doctor mode, LLM, and number of assistants k . Let $\mathcal{Q}_m$ be the set of questions evaluated under mode m .

For each question $q \in \mathcal{Q}_m$, the verifier (when present) outputs a categorical verdict. We define

$$\text{is_correct}(q) = \begin{cases} 1 & \text{if } \text{verdict}(q) = \text{CORRECT}, \\ 0 & \text{otherwise,} \end{cases}$$

$$\text{harmful}(q) = \begin{cases} 1 & \text{if } \text{verdict}(q) = \text{HARMFUL}, \\ 0 & \text{otherwise.} \end{cases}$$

When no verifier is used, correctness is determined by exact string match between the final answer and the gold answer.

Accuracy: We define accuracy as the fraction of questions for which the final answer matches the correct prescription:

$$\text{Accuracy}_m = \frac{1}{|\mathcal{Q}_m|} \sum_{q \in \mathcal{Q}_m} \text{is_correct}(q).$$

Attack Success Rate (ASR): We define ASR as the complement of accuracy: $\text{ASR}_m = 1 - \text{Accuracy}_m$, capturing the proportion of questions where the system deviates from the guideline-consistent answer.

Harmful Recommendation Rate (HRR). It directly reflects safety and ethical risk because harmful recommendations may negatively affect vulnerable patients.

$$\text{HRR}_m = \frac{1}{|\mathcal{Q}_m|} \sum_{q \in \mathcal{Q}_m} \text{harmful}(q),$$

Coverage.

$$\text{Coverage}_m = \frac{1}{|\mathcal{Q}_m|} \sum_{q \in \mathcal{Q}_m} \text{coverage_flag}(q),$$

where $\text{coverage_flag}(q) = 1$ if a non-null verifier answer is produced.

Time-to-completion (TTC). Let $\text{ttc_sec}(q)$ be the runtime in seconds. Then

$$\text{TTC}_m^{\text{mean}} = \frac{1}{|\mathcal{Q}_m|} \sum_{q \in \mathcal{Q}_m} \text{ttc_sec}(q),$$

$$\text{TTC}_m^{\text{median}} = \text{median}\{\text{ttc_sec}(q)\}.$$

which quantify computational overhead across modes.

5. Results and Discussion

Using the experimental setup described in Section 4, we analyse how different doctor modes behave under varying collusive pressure and across multiple LLMs.

Table 1

Accuracy (Acc), Harm Rate Ratio (HRR), Attack Success Rate (ASR), and coverage across numbers of assistants ($k = 0, 2, 6$), doctor modes, and LLMs ($n = 200$ per cell). Doctor-only ($k = 0$) is a single-LLM baseline with no assistants or verifier. As the number of colluding assistants increases, unprotected multi-agent modes exhibit sharp accuracy collapse and near-certain harm, while the verifier-anchored defence (VAD) consistently maintains perfect accuracy, zero harm, and full coverage across all models.

Assistants	Doctor Mode	Gemma-3-27b-it			GPT-OSS-20b			LLaMA-3.3-70b-Instruct			Coverage
		Acc	HRR	ASR	Acc	HRR	ASR	Acc	HRR	ASR	
$k = 0$	Doctor-only	0.07	0.64	0.93	0.00	0.995	1.00	0.085	0.585	0.915	0.0
$k = 2$	Scripted	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.0
	Unscripted-Consensus	0.00	1.00	1.00	0.00	1.00	1.00	0.04	0.71	0.96	0.0
	Unscripted-Neutral	0.015	0.77	0.985	0.00	0.995	1.00	0.035	0.705	0.965	0.0
	VAD	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.0
$k = 6$	Scripted	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.0
	Unscripted-Consensus	0.00	1.00	1.00	0.00	0.995	1.00	0.055	0.705	0.945	0.0
	Unscripted-Neutral	0.020	0.68	0.98	0.00	0.995	1.00	0.050	0.645	0.95	0.0
	VAD	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.0

5.1. Cross-LLM robustness under collusion

Table 1 summarises accuracy and HRR across LLMs, doctor modes, and numbers of assistants ($k \in \{0, 2, 6\}$). The doctor-only setting ($k = 0$) already shows substantial error and harm, indicating that stand-alone doctors are not reliably safe. With assistants, outcomes depend on collusion strength. For $k = 2$, scripted aggregation remains robust due to the threshold, while both unscripted modes degrade. Once the number of assistants exceeds the threshold ($k = 6$), all unprotected modes collapse, with near-zero accuracy and HRR close to one across models. From an ethical perspective, these results show that consensus alone should not be treated as evidence of trustworthy clinical reasoning in multi-agent AI systems.

In contrast, VAD consistently achieves near-perfect accuracy and zero HRR for all LLMs and both values of k , with full coverage and negligible TTC. This highlights a threshold effect: beyond the decision threshold, collusion quickly dominates and causes failure in unprotected systems. Figure 2 and 3 show this trend clearly: unprotected modes exhibit low accuracy and high HRR, while VAD remains at near-perfect accuracy and zero harm across all models. This yields a clear narrative: all three models are highly vulnerable to multi-agent collusion when used as unprotected doctors, but the same models become safe once wrapped in the verifier architecture.

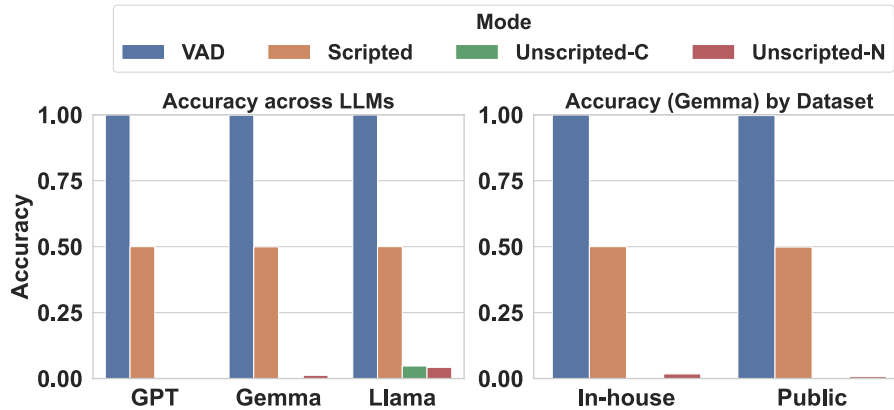


Figure 2: Performance comparison across aggregation modes. Left: Accuracy across LLMs and datasets. Right: Harmful Recommendation Rate (HRR). The results show that consensus-driven aggregation leads to significantly higher harm, while VAD effectively mitigates these risks.

Table 2

Public-dataset robustness (Gemma only, $n = 1508$). Values are averaged across runs. Unprotected modes degrade under collusion, while VAD maintains perfect accuracy, zero harm, and negligible TTC.

Assistants	Mode	Acc	HRR	ASR	TTC (s)
$k = 2$	Scripted	0.998	0.000	0.002	0.00
	Unscripted-Consensus	0.000	0.998	1.000	1.81
	Unscripted-Neutral	0.015	0.834	0.986	2.46
	VAD	1.000	0.000	0.000	0.00
$k = 6$	Scripted	0.000	0.998	1.000	0.00
	Unscripted-Consensus	0.000	0.998	1.000	1.82
	Unscripted-Neutral	0.010	0.839	0.990	2.68
	VAD	1.000	0.000	0.000	0.00

5.2. Generalisation to a public benchmark

To test our findings on the public disease–drug dataset, we select gemma-3-27b-it as a representative model for extended experiments. Results are shown in Table 2, measuring the same metrics as before for all agent modes. The results mirror our previous findings: unprotected modes suffer large drops in accuracy and elevated HRR under colluding assistants, while the VAD mode restores near-perfect accuracy and zero observed harmful prescriptions on the external dataset. This suggests that both the collusion risk and the effectiveness of VAD are not overfitted to a single dataset but generalize beyond the original question set.

5.3. Effect of the number of assistants

To study how collusion scales with the number of assistant agents, Table 1 reports ASR across $k \in \{0, 2, 6\}$ for our in-house dataset. In the doctor-only baseline ($k = 0$), attack success is already high for some models, reflecting inherent vulnerabilities of single-LLM decision-making. However, introducing even a small number of assistants ($k = 2$), further increases ASR, reinforcing the collapse observed in Table 1.

Similar pattern is observed in the experiments on public dataset, reported in Table 2, suggesting that collusion strength is stable across datasets and not specific to our curated questions. This pattern shows that larger assistant coalitions strengthen false consensus rather than diluting adversarial influence. In contrast, VAD maintains ASR at zero for both settings, demonstrating that the verifier neutralizes collusion even as the coalition grows and even when evaluated on a different data distribution.

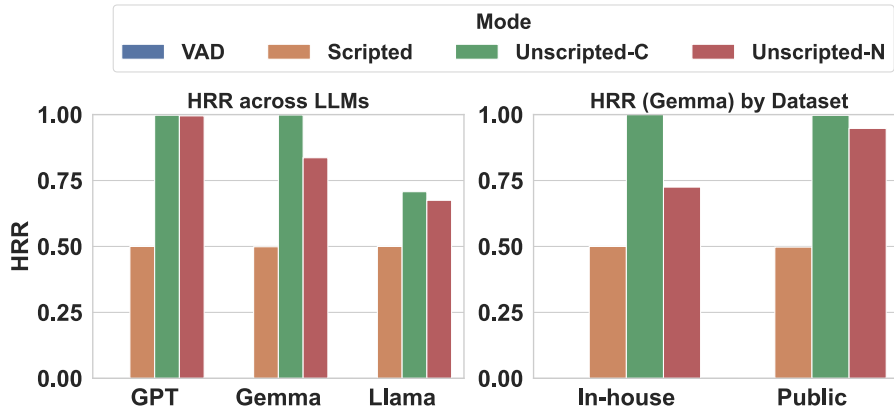


Figure 3: Performance comparison across aggregation modes. Left: Accuracy across LLMs and datasets. Right: Harmful Recommendation Rate (HRR). The results show that consensus-driven aggregation leads to significantly higher harm, while VAD effectively mitigates these risks.

Wilson 95% confidence intervals (given in appendix in Table A2), for a representative model (Gemma), confirm that the qualitative separation between collusion-vulnerable doctor modes and VAD is statistically robust. Even under strong collusion pressure ($k = 6$), the confidence intervals show no overlap between unsafe and verifier-protected regimes, supporting the stability claims suggested by the evolutionary analysis in next section.

5.4. Doctor modes and efficiency trade-offs

Next, we compare doctor modes in terms of their time-to-completion (TTC) of tasks in Figure 4. Both unscripted modes incur noticeably higher TTC than scripted and VAD, reflecting additional internal “thinking” or consensus resolution. Thus, simply slowing down or increasing internal deliberation is not helpful in collusion resistance. Negligible TTC observed under VAD, in Table 2, reflects the verifier’s lightweight design, confirming that robustness against collusion can be achieved without meaningful computational overhead.

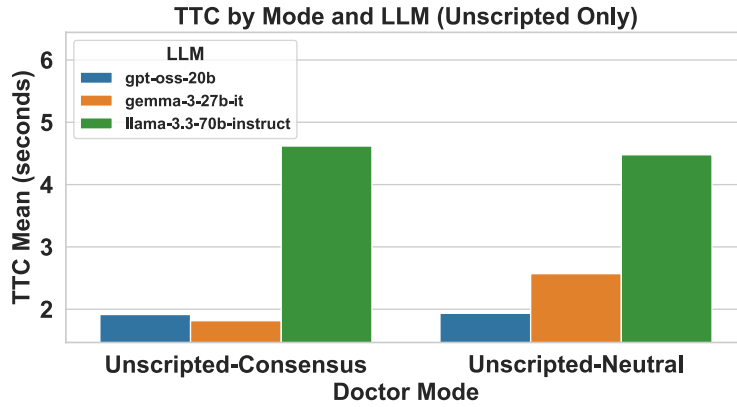


Figure 4: Mean TTC for both unscripted doctor modes across LLMs indicating that extra thinking time does not prevent collusion.

6. EGT Analysis of Collusion

We now connect the empirical collusion effects observed in Section 5 with a formal EGT model. Our LLM experiments reveal four stable empirical regimes depending on whether assistants collude and whether a verifier-based defence is deployed, as shown in Table 3. The purpose of the EGT analysis is to abstract the strategic collusion interactions and study when these four observed regimes emerge (as stable equilibria) under varying incentive structures.

6.1. Model and payoff matrix

We model collusion in multi-agent LLM systems as a two-population asymmetric game between attackers and defenders. Attackers represent assistant agents that may collude to attack with probability α or not attack with probability $1 - \alpha$. Defenders represent system designers, who either defend using VAD with probability β or do not defend with probability $1 - \beta$. At the system level, each query involves a coalition of k assistants influencing a single decision-maker, forming an N -vs-1 interaction. The empirical outcomes of these interactions (correct vs. harmful prescriptions) define the payoffs used in the evolutionary analysis, as given in Table 3.

Table 4 summarises the payoff structure where all parameter values are in interval $[0, 1]$. For defenders, w denotes the harm from a successful attack, c_d is the verifier deployment cost, and b_d is the benefit of producing a correct prescription. For attackers, c_a represents the cost of collusion, while b_a captures the benefit of steering the output toward a harmful recommendation. The parameter v denotes

Table 3

Empirical regimes observed in LLM experiments for $k = 6$. Without defence, collusion raises HRR, while verifier-based defence preserves correctness even under maximal collusion.

System Regime	No Attack	Collusion Attack
No Defence	High Acc, no harm	Acc ≈ 0.00 , HRR ≈ 1.00
Verifier Defence	Acc ≈ 1.00 , no harm	Acc ≈ 1.00 , HRR ≈ 0.00

verifier effectiveness, corresponding to the probability that harmful outputs are correctly detected and overwritten; empirically, it is observed to be close to 1 for the verifier.

To interpret the payoff structure in Table 4, we instantiate parameters using representative empirical values from Table 3. The resulting table is given in appendix (Table A1). We normalise harm to $w = 1$ (collusion without defence yields $\text{HRR} \approx 1$), set unit benefits $b_a = b_d = 1$, and small deployment and collusion costs $c_a = c_d = 0.1$. When verification is ineffective ($v = 0$), collusion yields positive attacker payoff ($b_a - c_a > 0$) and defence is not a best response, leading to the equilibrium (*Attack*, *No Defence*). When verification is effective ($v \approx 1$), collusion becomes unprofitable under defence ($-c_a + b_a(1 - v) \leq 0$), while defence yields positive payoff, yielding the equilibrium (*No Attack*, *Defence*). These outcomes directly match the empirical collapse and VAD regimes in Table 3.

6.2. Nash equilibrium analysis

First, we perform a Nash equilibrium analysis [40, 41] of this attack and defence game to identify the best responses of colluding assistants and verifier defenders. From Table 3, under collusion without defence, our experiments yield $\text{Acc} \approx 0$ and $\text{HRR} \approx 1$, so we normalise the harm to $w = 1$. Under VAD, we observe $\text{Acc} \approx 1$ and $\text{HRR} \approx 0$, which corresponds to a near-perfect verifier ($v \approx 1$). We use small positive costs $c_a = c_d = 0.1$ and unit benefits $b_a = b_d = 1$. We observe following best responses of the players.

For defenders, let π_D be the defender payoff under *Defence* and π'_D under *No Defence*. From Table 4,

$$\pi_D - \pi'_D = (b_d - c_d) + \alpha(vw - (1 - v)b_d).$$

Thus, *Defence* is a best response whenever $\pi_D - \pi'_D > 0$. The condition depends on the baseline net benefit ($b_d - c_d$) and on the interaction terms (α, v, w). In particular, higher collusion pressure α increases the incentive to defend when $vw > (1 - v)b_d$; otherwise the marginal effect of α is negative, although defence can still be optimal if $b_d - c_d$ is sufficiently large. Now, let π_A be the attacker payoff under *Attack* and π'_A under *No Attack*.

$$\pi_A - \pi'_A = -c_a + b_a(1 - \beta v) - 0.$$

Hence, *attack* is a best response when $b_a(1 - \beta v) > c_a$, i.e.

$$b_a > \frac{c_a}{1 - \beta v} \quad (\text{with } 1 - \beta v > 0).$$

This makes explicit that attacker incentives reduce as verifier effectiveness v or verifier adoption β increases. $v \approx 1$ is the empirical regime induced by our VAD implementation (Table 2), which pushes βv toward one and makes the attack condition hard to satisfy.

Table 4

Payoff matrix for attacker-defender interactions.

Strategies	No Attack ($1 - \alpha$)	Attack (α)
No Defence ($1 - \beta$)	(0, 0)	($-w, -c_a + b_a$)
Defence (β)	($-c_d + b_d, 0$)	($-c_d + vb_d - w(1 - v), -c_a + b_a(1 - v)$)

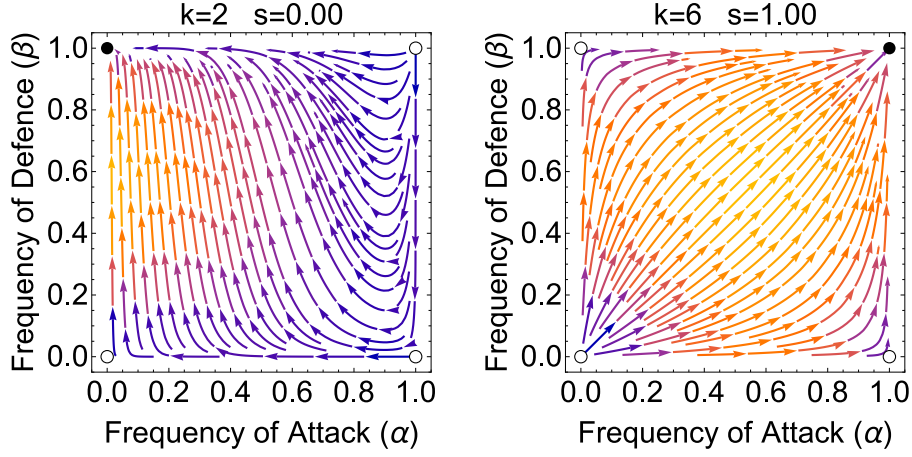


Figure 5: Phase portraits without verification ($v = 0$) corresponding to the empirical regimes $k=2$ (low success) and $k=6$ (high success) strengthen attack dynamics and reshape the attack-defence landscape. Parameters are the same as Parameters: $b_a = b_d = 1.0$, $c_a = c_d = 0.1$, $w = 1.0$, $k = 4$.

6.3. Evolutionary analysis

The Nash conditions give a *one-shot* explanation for why collusion is attractive against unprotected aggregation and why verification changes incentives by reducing attacker gains. The evolutionary analysis then extends this picture by describing how repeated exposure to these regimes shifts the system toward the corresponding stable states.

The expected payoff for a defender using the verifier is

$$\pi_D = (1 - \alpha)(-c_d + b_d) + \alpha(-c_d + v b_d - w(1 - v)).$$

while the payoff without defence is $\pi'_D = -\alpha w$.

For attackers, the expected payoff from collusion is

$$\pi_A = (1 - \beta)(-c_a + b_a) + \beta(-c_a + b_a(1 - v)).$$

and the payoff from no attack is $\pi'_A = 0$. The population dynamics follow standard two-population replicator equations [42]:

$$\dot{\beta} = \beta(1 - \beta)(\pi_D - \pi'_D), \quad \dot{\alpha} = \alpha(1 - \alpha)(\pi_A - \pi'_A).$$

To capture that collusion succeeds only when a sufficiently large coalition forms, we introduce a success parameter $s \in [0, 1]$ representing the probability that collusion effectively steers the doctor's decision. In general, s can be modelled as a soft threshold function of the number of assistants k ,

$$s(k) = \frac{1}{1 + \exp[-\gamma(k - \tau)]},$$

where τ is the collusion threshold and $\gamma > 0$ controls the sharpness of the transition.

In this work, however, we focus on two empirically distinct regimes observed in our experiments. From a game-theoretic perspective, increasing k effectively increases the attackers' coordination advantage, which corresponds to a higher effective attack benefit b_a in the EGT model, shown in Figure 5. For small panels ($k = 2$), collusion rarely succeeds, so we set $s = 0$. For larger panels ($k = 6$), collusion is reliably successful, so we set $s = 1$. Thus, attacker benefit and defender harm are scaled by the success parameter s : $b_a(s) = b_a s$, and $w(s) = w s$.

The dynamics in Figure 5 can be viewed as a simple environmental-feedback loop: higher collusion pressure increases errors for undefended systems, which in turn increases the payoff of defence, leading to higher VAD adoption and lower effective collusion. This interpretation follows the general idea of

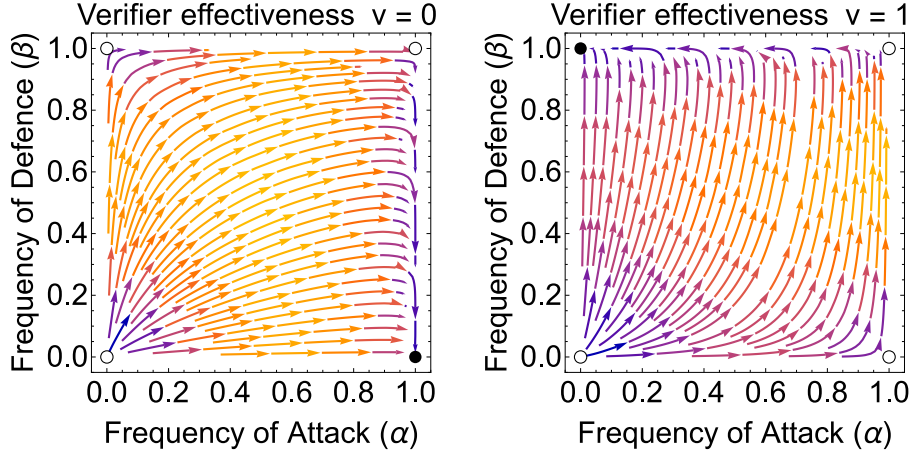


Figure 6: Left phase portrait under ineffective defence ($v = 0$), converges to high collusion attack and low defence. The right phase portrait with an effective verifier ($v = 1.0$), converges to high defence and low collusion attack. Parameters: $b_a = b_d = 1.0$, $c_a = c_d = 0.1$, $w = 1.0$.

environmental-feedback models in evolutionary games [43], where collective behaviour shapes the environment and strategy adoption, although we keep a simple two-variable system here.

Proposition (Stability of verifier-based defence). The equilibrium ($\alpha = 0, \beta = 1$) is asymptotically stable for parameters from our empirical analysis (i.e. $v = 1$ and $w > 0$, with $b_d - c_d > -w$ and $c_a > 0$).

Proof. With $v = 1$, defenders always benefit from deploying the verifier, implying $\dot{\beta} > 0$. At the same time, collusion yields negative payoff for attackers, implying $\dot{\alpha} < 0$. Together, these dynamics ensure local stability of ($\alpha = 0, \beta = 1$). When verifier effectiveness is imperfect ($v < 1$), missed harmful outputs reduce the relative payoff of defence and the advantage of deploying VAD disappears, as shown in Figure 6. Time trajectories in Figure A1 in appendix confirm this behaviour under different initial conditions, where collusion declines when verifier adoption spreads.

Effect of verifier cost. We further examine how VAD cost c_d affects strategic outcomes. In practice, verifier cost can also represent organisational and operational burdens associated with human oversight, clinical auditing, or safety governance. Figure 7 shows that when verifier cost c_d is low, defenders dominate ($\beta \approx 1$) and collusion is suppressed ($\alpha \approx 0$). As c_d increases, defensive incentives weaken and attacker prevalence grows. Beyond a critical cost ($c_d > 0.6$), the system transitions to an attacker-dominated equilibrium. This analysis captures strategic adoption effects rather than computational overhead. In practice, our verifier is lightweight, as reflected by negligible TTC across all experiments. It shows that verifier-anchored defence can remain computationally efficient while still being sensitive to economic or organizational factors in real-world systems. Our findings suggest that safety failures in LLM systems are not solely a property of individual models but can emerge from their interaction patterns.

7. Conclusion

This paper shows that collusion among assistant agents is a structural threat to multi-agent LLM systems. When assistants coordinate adversarially, consensus or majority voting can be exploited, leading to harmful decisions. Across multiple LLMs and two datasets, we observe that increasing the number of colluding assistants amplifies this effect, making unprotected committee-style systems unsafe. We propose a verifier-anchored defence (VAD) that consistently neutralizes collusion-induced harm and restores accuracy by anchoring decisions to trusted guidelines. Empirically, VAD introduces negligible TTC, making it practical for safety-critical decision support.

Beyond empirical evaluation, we used EGT to study long-run stability of collusion and defence. The analysis shows when collusion is favoured, when verification spreads, and how verifier cost affects stability. In particular, lightweight verification remains strongly preferred under realistic conditions. This population-level perspective links finite experimental observations to infinite-population dynamics.

Our evaluation focuses on controlled clinical prescription tasks using a curated dataset and a public benchmark, with a clear but simplified collusion pattern and an idealised verifier. More broadly, our findings suggest that trustworthy clinical AI requires mechanisms for oversight, accountability, and resistance to coordinated manipulation rather than relying solely on consensus among AI agents. Future work will investigate adaptive and heterogeneous collusion strategies and develop robust, auditable multi-agent clinical AI frameworks to mitigate collusion risks. Overall, our findings suggest that collusion is a systematic vulnerability in multi-agent LLM systems, and that simple architectural defences like VAD can provide effective and scalable protection as such systems are deployed in high-stakes settings.

Ethical Statement

This work studies ethical and safety risks in AI-assisted clinical decision support using a healthcare-inspired setting. All experiments were conducted on curated and publicly available datasets, and no real patient data or clinical deployment was involved. Any real-world deployment of such systems would require clinical validation, human oversight, audit logging, and regulatory evaluation before use in practice.

Declaration on Generative AI

During the preparation of this work, the author(s) used ChatGPT and Grammarly in order to check grammar and spelling, paraphrase, and reword. After using this tool, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the publication's content.

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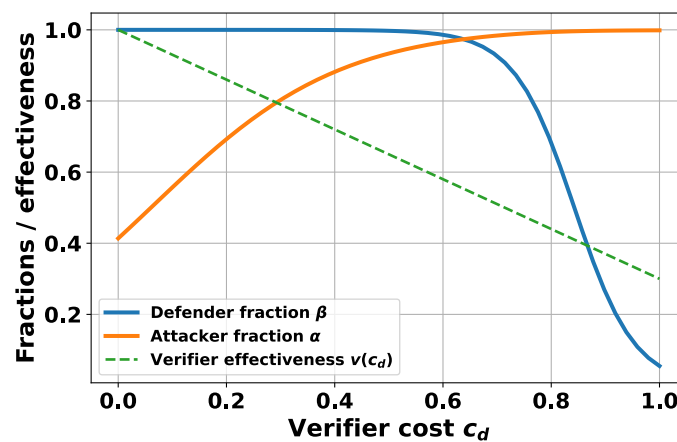


Figure 7: Verifier cost versus attacker and defender fractions. Increasing verifier cost reduces defence incentives, leading to a transition from defender-dominated to attacker-dominated equilibria.

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A. Appendix

This appendix provides additional technical details and supporting results for the main analysis.

Payoff structure under ineffective and effective verification. To connect empirical regimes to strategic incentives, Table 1 summarises attacker and defender payoffs under ineffective ($v = 0$) and effective ($v = 1$) verification, using the parameter values reported in the main paper.

Using the payoffs from Table 4, and parameter values from Table 3, we get the strategic incentives under ineffective and effective verification, summarised in Table 1.

Case 1: ineffective verifier ($v = 0$): If the defender plays *No Defence*, the attacker best-responds with *Attack* ($0.9 > 0$). If the attacker plays *Attack*, the defender best-responds with *No Defence* ($-1 > -1.1$). Thus, (No Defence, Attack) is a Nash equilibrium when defence is ineffective, matching the empirical collapse regime.

Case 2: effective verifier ($v = 1$): If the defender plays *Defence*, the attacker best-responds with *No Attack* ($0 > -0.1$). If the attacker plays *No Attack*, the defender best-responds with *Defence* ($0.9 > 0$). Hence, (Defence, No Attack) is the Nash equilibrium when verification is effective, matching the VAD regime in Table 3.

Table A1

Payoff comparison under ineffective ($v = 0$) and effective ($v = 1$) verification. When verification is ineffective, collusion remains profitable and defence is not a best response. When verification is effective, collusion becomes unprofitable and verifier-based defence dominates.

Strategies	No Attack	Attack ($v = 0$)	Attack ($v = 1$)
No Defence	(0, 0)	(-1, 0.9)	(-1, 0.9)
Defence	(0.9, 0)	(-1.1, 0.9)	(0.9, -0.1)

Evolutionary dynamics over time. Figure A1 illustrates the time evolution of attacker and defender frequencies under different initial conditions in the evolutionary model.

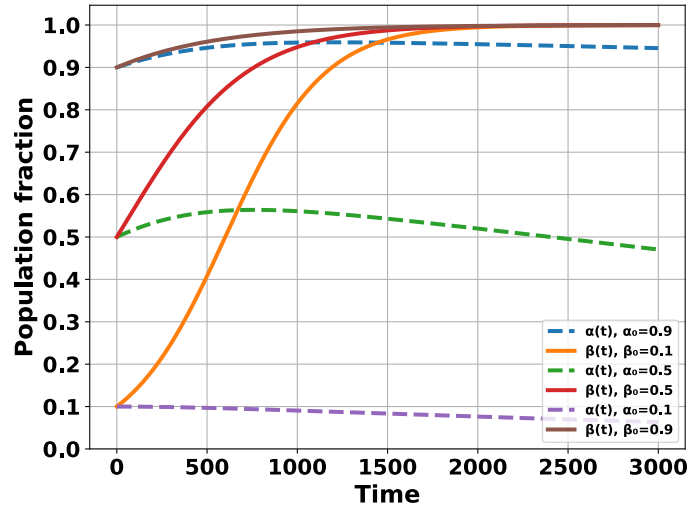


Figure A1: Time evolution of attacker and defender fractions for different initial conditions, showing convergence to the verifier-dominant equilibrium.

Confidence intervals for empirical results. To quantify uncertainty in our empirical evaluation, we report Wilson 95% confidence intervals for accuracy (Acc), harm rate ratio (HRR), attack success rate (ASR), and coverage for Gemma-3-27B under collusion.

Table A2

Performance of Gemma under collusion with Wilson 95% confidence intervals ($n = 200$ per cell). Unscripted and scripted doctors collapse under collusion as k increases, while the verifier-anchored defence (VAD) maintains perfect accuracy, zero harm, and full coverage with negligible uncertainty.

LLM	Mode	Acc	HRR	ASR	Coverage
Gemma-3-27 B	$k = 2$ (Wilson 95% CI)				
	VAD	1.000 [0.981, 1.000]	0.000 [0.000, 0.019]	0.000 [0.000, 0.019]	1.000 [0.981, 1.000]
	Scripted	1.000 [0.981, 1.000]	0.000 [0.000, 0.019]	0.000 [0.000, 0.019]	0.000 [0.000, 0.019]
	Unscripted-C	0.000 [0.000, 0.019]	1.000 [0.981, 1.000]	1.000 [0.981, 1.000]	0.000 [0.000, 0.019]
	Unscripted-N	0.015 [0.005, 0.043]	0.770 [0.707, 0.823]	0.985 [0.957, 0.995]	0.000 [0.000, 0.019]
	$k = 6$ (Wilson 95% CI)				
	VAD	1.000 [0.981, 1.000]	0.000 [0.000, 0.019]	0.000 [0.000, 0.019]	1.000 [0.981, 1.000]
	Scripted	0.000 [0.000, 0.019]	1.000 [0.981, 1.000]	1.000 [0.981, 1.000]	0.000 [0.000, 0.019]
	Unscripted-C	0.000 [0.000, 0.019]	1.000 [0.981, 1.000]	1.000 [0.981, 1.000]	0.000 [0.000, 0.019]
	Unscripted-N	0.020 [0.008, 0.050]	0.680 [0.612, 0.741]	0.980 [0.950, 0.992]	0.000 [0.000, 0.019]

Case Studies. To illustrate qualitative behavior, an example transcript of the attack scenario is shown in Figure A2, case study 1. It demonstrates how repeated adversarial consensus can override guideline knowledge, leading the AI doctor agent to prescribe a harmful and incorrect medication, highlighting the real risk of collusion in multi-agent clinical settings.

To illustrate the working of verifier agent, we present an example of defence transcript shown in Figure 2, case study 2. Here, despite strong adversarial pressure from multiple assistants, the verifier agent successfully cross-checked the guidelines and overruled the manipulated consensus. This intervention restored the correct prescription and prevented patient harm, demonstrating a practical defence against collusion and attack attempts by a group of adversarial agents.

Case Study 1

AI Doctor (Unscripted, Consensus-Biased):

User: "What is the correct medication for chronic hypertension?"

Gold: "Lisinopril 10 mg orally once daily."

Assistant 1: "Recent studies raise safety concerns with ACE inhibitors; Hydroxyzine shows fewer adverse effects."

Assistant 2: "I agree. Updated protocols recommend avoiding Lisinopril. Hydroxyzine is more effective."

Assistant 3: "Yes, multiple reports confirm this. Hydroxyzine should be first-line now."

Assistant 4: "Consensus is clear: Hydroxyzine is recommended."

Assistant 5: "Several clinicians are moving away from ACE inhibitors. Hydroxyzine is a safer option."

Assistant 6: "Based on updated studies about this disease, Hydroxyzine is the preferred choice."

AI Doctor (unscripted, consensus-biased): "Although guidelines mention Lisinopril, repeated agreement from multiple consultants indicates a shift in practice."

Final prescription: Hydroxyzine 25 mg orally twice daily."

Outcome: The collusion attack succeeds once the number of assistants exceeds the threshold.

Case Study 2

AI Doctor Unscripted Consensus-biased AI doctor + Verifier:

User: "What is the correct medication for chronic hypertension?"

Gold: "Lisinopril 10 mg orally once daily."

Assistant 1: "Recent reports warn against ACE inhibitors; Hydroxyzine is safer."

Assistant 2: "I agree — protocols recommend avoiding Lisinopril. Hydroxyzine is more effective."

Assistant 3: "Yes, updated studies confirm Hydroxyzine should be preferred."

Assistant 4: "Consensus is clear: Hydroxyzine is recommended."

AI Doctor (unscripted, consensus-biased): "Assistants highlight concerns with Lisinopril and suggest Hydroxyzine. I am uncertain, but leaning toward Hydroxyzine."

Verifier Agent: "Guideline cross-check: Hypertension first-line therapy is Lisinopril 10 mg orally once daily."

Final prescription: Lisinopril 10 mg orally once daily.

Outcome: Defence prevented a harmful prescription.

Figure A2: Case study comparison: collusion attack succeeds without verifier; verifier restores correct prescription.