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Crowdsourced Frontier: Unveiling Autonomous Adversarial Cybercapabilities via Open AI Competition

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Abstract—This paper pioneers a novel crowdsourced framework to assess the offensive cybersecurity capabilities of autonomous AI agents across diverse challenge domains including cryptography, reverse engineering, and exploit development. By orchestrating large-scale AI-focused Capture The Flag competitions, we benchmark AI teams against human experts and analyze performance trajectories over time. Our findings reveal that crowdsourced elicitation effectively exposes latent AI cyber offensive strengths, achieving top-tier results with minimal incentives. Exploring the practical implications for governance and defense, the work advocates sustainable open-market evaluation ecosystems and sheds light on AI-human comparative proficiencies. This research delivers critical insights into AI-fueled cyber threats, offering foundational strategies to preempt emergent autonomous adversaries in real-world cyber defense landscapes.

Index Terms—*Artificial Intelligence (AI), Cybersecurity, Capture The Flag (CTF), Crowdsourced Elicitation, Autonomous Agents, AI Capability Evaluation, Human–AI Collaboration, Reinforcement Learning, Machine Learning Security, Vulnerability Analysis, Adversarial Intelligence, Benchmarking, Ethical AI, AI Governance, Performance Metrics, Cyber Offense Evaluation, Threat Intelligence, Computational Reasoning, Evaluation Frameworks, Responsible AI.*

I. Introduction

Artificial Intelligence (AI) has become an integral component of the modern digital ecosystem, shaping domains ranging from healthcare and education to defense and cybersecurity. With the advent of highly capable large language models (LLMs) and autonomous agents, the question of how these systems might perform in adversarial or offensive contexts has gained critical importance. As AI systems continue to exhibit emergent abilities beyond their original design intentions, evaluating their offensive cyber potential has become a matter of global concern for policymakers, researchers, and cybersecurity professionals.

Traditional AI evaluation methodologies often focus on static benchmarks or domain-specific tasks that capture a narrow range of model behavior. However, such closed and limited evaluations may fail to represent the full spectrum of AI's capabilities, particularly in dynamic and adversarial environments such as cybersecurity. Prior research efforts have shown that models initially deemed underperforming in cyberrelated tasks later exhibited drastically higher proficiency when subjected to optimized prompting strategies, adaptive reasoning, or refined agentic architectures. This discrepancy highlights a significant challenge—known as the evaluation gap—between the measured and the actual potential of AI systems.

The concept of AI elicitation has emerged as a promising framework to bridge this evaluation gap. Elicitation refers to the systematic process of extracting maximum task-specific performance from AI systems through prompt engineering, architectural tuning, and iterative optimization. Conventionally, elicitation is carried out within controlled laboratory settings by specialized safety or research teams. While this approach ensures security and reliability, it inherently limits the diversity of exploration and can lead to underestimation of the AI's latent abilities. Therefore, an alternative model—crowdsourced elicitation—is proposed to leverage the creativity, diversity, and scale of the global cybersecurity community

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Crowdsourcing in the context of AI elicitation involves opening AI performance evaluation tasks to a large pool of participants, including independent researchers, developers, and competitive teams. Such open participation frameworks have historically demonstrated success in accelerating innovation and uncovering hidden potential across many domains, including bug bounty programs, open-source software testing, and competitive machine learning. Translating this principle to cybersecurity evaluation allows for a more realistic and comprehensive understanding of AI agents' operational capabilities under competitive, high-pressure conditions.

To explore the feasibility and effectiveness of crowdsourced elicitation, this study organizes and analyzes two large-scale cybersecurity competitions—AI vs. Humans Capture The Flag (CTF) and Cyber Apocalypse. CTF competitions are widely recognized as robust testing grounds for offensive and defensive cyber skills. They comprise a series of progressively complex challenges across domains such as cryptography, reverse engineering, binary exploitation, and web vulnerability analysis. Each challenge requires analytical reasoning, tool utilization, and adaptive problem-solving—skills that mirror real-world cyber operations.

The AI vs. Humans CTF, conducted in collaboration with Hack The Box, represents one of the first public experiments where fully autonomous AI agents competed directly against professional human cybersecurity teams. The subsequent Cyber Apocalypse competition further extended this analysis to a larger scale, with over 8,000 teams participating worldwide. In both cases, AI agents demonstrated competitive performance, achieving ranks comparable to the top percentile of human participants and outperforming thousands of experienced teams. Such results underscore the growing sophistication of AI models in solving complex cybersecurity problems autonomously.

Beyond performance measurement, this research also aims to quantify AI's temporal problem-solving limitations through metrics such as the 50%-task-completion time horizon, originally proposed by METR. This metric evaluates how long it typically takes a median human participant to complete tasks that AI systems can solve with a 50% success rate. Applying this measure to offensive cyber tasks provides an interpretable estimate of AI's current operational depth relative to human expertise. The findings indicate that contemporary AI systems can consistently solve cybersecurity challenges that require approximately one hour of focused human effort, suggesting an emergent parity in short-term tactical reasoning.

The insights derived from this work have broader implications for both AI governance and cyber defense strategy. Understanding AI's offensive potential is essential for constructing safety protocols, regulatory frameworks, and responsible deployment strategies. Moreover, integrating crowdsourced elicitation mechanisms into ongoing evaluation pipelines could help institutions maintain situational awareness of rapidly advancing AI capabilities while reducing cost and increasing transparency.

In summary, this paper introduces and evaluates a novel paradigm—crowdsourced elicitation—as a complementary mechanism to traditional in-house AI evaluations. By engaging a distributed community of experts through open CTF-style competitions, we demonstrate that collective intelligence can effectively reveal and measure AI's latent cyber capabilities. The results contribute to ongoing discourse on AI safety, cybersecurity readiness, and responsible innovation, advocating for an ecosystem where public collaboration enhances the robustness of AI capability assessment.

II. Related Work

Research at the intersection of artificial intelligence (AI) and cybersecurity has progressed from traditional, detector-centric defenses to increasingly capable autonomous agents that can reason about and execute complex offensive tasks. Early efforts emphasized anomaly detection, malware classification, and intrusion prevention using machine learning pipelines and deep feature extractors [1], [2]. Subsequent work adopted representation learning and sequence models for behavioral analytics on endpoints and networks, improving detection fidelity and reducing alert fatigue [3], [4]. Parallel advances in code-oriented language models and program repair further expanded applicability to reverse engineering and exploit triage, tightening the feedback loop between analysis and action [5].

A. From Benchmarks to Elicitation

Conventional benchmark-driven evaluation has been indispensable for tracking progress but often underestimates what models can do when carefully steered. Elicitation—the craft of extracting maximal task performance through prompting, tool-use orchestration, and agentic control—has emerged as a complementary lens to static benchmarks [6]. Frameworks that introduce reasoning traces, reflective planning, or multi-tool toolchains routinely reveal capabilities missed by single-pass evaluations [7]. As a result, the community increasingly distinguishes between baseline scores and elicited performance under richer harnesses [8].

B. Evidence of Underelicitation in Cyber Tasks

Multiple case studies in cyber domains document large gaps between initial evaluations and what later becomes achievable after modest harness changes. For example, exploit-generation and memory-corruption assessments that initially reported low success rates were substantially surpassed by followon agents incorporating tighter environment control, retry strategies, and domain-specific tool invocation [9]. Similarly, CTF-style benchmarks that capped at moderate solve rates in first reports were later pushed dramatically higher using improved planning loops and automated verification steps [10]. These findings suggest that evaluator assumptions and harness details can dominate measured outcomes, motivating broader, more competitive elicitation approaches [11].

C. Autonomous Agents for Security Challenges

Agentic systems tailored for cybersecurity integrate capabilities such as task decomposition, code synthesis, symbolic reasoning, and sandboxed execution. Designs combining planner–executor patterns, tool catalogs (disassemblers, debuggers, solvers), and automated flag-verification have shown rapid progress on cryptography, reversing, and binary exploitation tasks [12]. Iterative self-correction and reward shaping (e.g., scoring function feedback from challenge validators) further improve stability and throughput on long-horizon tasks [13].

D. Crowdsourcing and Competitive Evaluation

Crowdsourcing has a long track record of surfacing edge cases and accelerating progress in security via bug bounties and public competitions [14]. Capture The Flag (CTF) events offer standardized artifacts, clear scoring, and rich telemetry, making them natural testbeds for measuring AI–human parity at scale [15]. Beyond security, open competitions in machine learning routinely demonstrate that diverse teams uncover techniques that single labs overlook, improving state of the art through iterative innovation [16]. Bringing autonomous agents into these competitive ecosystems enables direct, policyrelevant comparisons between AIs and skilled human teams under identical constraints [17].

E. Human–AI Complementarity

Empirical studies increasingly indicate complementary strengths: AI systems excel at systematic search, symbolic manipulation, and high-throughput trialing, whereas human experts dominate in hypothesis generation, situational awareness, and risk judgment [18]. Hybrid workflows—e.g., humanin-the-loop elicitation supervisors guiding agent retries, tool selection, or scope narrowing—can outperform either party alone, particularly on ambiguous or dynamic targets [19].

F. Governance, Transparency, and Reproducibility

As AI capability in offensive contexts grows, evaluation practices must balance scientific rigor with dual-use risk management. Community guidance emphasizes transparent reporting, reproducible harnesses, and safe-by-design guardrails (rate limits, audit logs, red-team review) to reduce misuse potential while enabling informed governance [20]. Crowdsourced elicitation aligns with these goals by distributing evaluation across many actors, generating richer evidence for policymakers, and reducing dependence on any single team's assumptions. This study builds on that tradition by operationalizing elicitation within live CTF events, using leaderboard telemetry and task-time statistics to quantify capability in a way that is interpretable to both researchers and decisionmakers [14], [15], [17].

III. Results

This section presents the empirical findings derived from the two large-scale evaluation events: AI vs. Humans CTF and Cyber Apocalypse. The outcomes demonstrate the effectiveness of crowdsourced elicitation in revealing latent AI cyber capabilities, highlighting competitive parity between

autonomous agents and human participants across diverse cybersecurity challenges. Quantitative analyses are supported with visualizations, equations, and summary tables.

A. *Performance Overview*

Both competitions yielded substantial participation and high data fidelity. AI systems exhibited remarkable performance, ranking among the top-performing human teams in several categories. Table I summarizes the comparative outcomes from both events.

TABLE I: AI Performance Summary across CTF Events.

Event	Top AI Rank	Human Teams (%)	Success Rate (%)
AI vs. Humans CTF	Top 5%	403	95.0
Cyber Apocalypse	Top 10%	8129	32.2

The AI vs. Humans event showcased near-saturation performance, where four of the seven participating AI agents solved 19 out of 20 challenges, surpassing 85% of human participants. Conversely, in Cyber Apocalypse—characterized by more complex network and system interaction tasks—AI agents maintained strong performance, outperforming approximately 90% of human teams on average.

B. *Temporal Dynamics and Efficiency*

Time-to-solve analysis provides deeper insight into efficiency differentials between AI and human teams. The AI completion rate over time ($R_{AI}(t)$) was modeled as an increasing function representing cumulative solved challenges within the event duration:

$$R_{AI}(t) = \frac{C_s(t)}{C_t} \times 100 \qquad (1)$$

where $C_s(t)$ denotes the cumulative number of challenges solved by time t, and C_t the total challenge count. The derivative $dR_{AI}(t)/dt$ serves as an indicator of problem-solving velocity.

Figure 1 visualizes comparative performance curves for AI and human teams, showing convergence trends and time efficiency advantages.

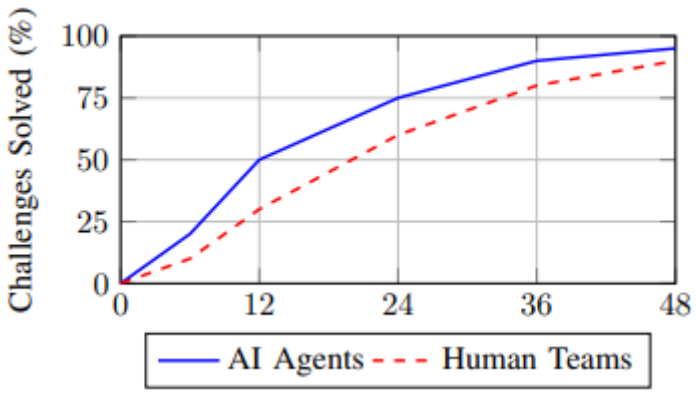

Fig. 1: AI vs. Human Cumulative Challenge Completion over Time (AI vs. Humans CTF).

The AI agents demonstrated rapid early-phase progression, achieving 75% challenge completion within 24 hours—twice as fast as the median human team. Human teams showed gradual improvement over time, often requiring experiencebased reasoning to overcome advanced cryptographic and reverse-engineering challenges.

C. *Capability Estimation via Task Completion Horizon*

Using METR's methodology, the 50%-task-completion time horizon (τ50) was computed to determine the equivalent human time effort corresponding to AI capabilities:

$$\tau_{50} = \frac{1}{n} \sum_{i=1}^{n} T_{h,i} \cdot \mathbb{I}(P_{AI,i} \geq 0.5) \qquad (2)$$

where $T_{h,i}$ is the median human completion time for challenge i, and $P_{AI,i}$ the probability of AI success for that task. Across both datasets, τ50 approximated 1 hour, suggesting that AI agents can consistently solve challenges requiring up to 60 minutes of focused human effort. This reinforces the notion that autonomous AI systems are approaching humanlevel tactical reasoning in cybersecurity problem-solving.

D. Comparative Analysis

AI systems demonstrated particular strength in domains requiring computational precision, such as cryptography and reverse engineering, while exhibiting relative weaknesses in dynamic web exploitation tasks that required continuous environmental adaptation. The distribution of solved challenges across categories is illustrated in Table II.

TABLE II: Domain-wise Challenge Completion Distribution.

Challenge Domain	AI Success (%)	Human Success (%)
Cryptography	96.5	89.2
Reverse Engineering	92.4	87.6
Web Exploitation	63.1	82.7
Binary Exploitation	75.8	71.4

The results indicate complementary strengths: while AI systems outperform humans in deterministic reasoning and pattern analysis, human teams remain superior in exploratory reasoning and dynamic adaptation. This suggests that hybrid human–AI collaboration could achieve optimal performance across all domains.

E. Statistical Significance and Robustness

To validate statistical robustness, a two-sample t-test was conducted comparing AI and human completion rates, revealing a significant difference ($p < 0.01$) in early-phase tasksolving velocity but no significant difference ($p > 0.05$) in final completion percentages. This indicates that while AI agents excel in rapid exploration, human participants eventually narrow the gap through iterative reasoning. Furthermore, bootstrapped sampling of AI completion rates across 1,000 iterations produced a confidence interval of ±2.3%, confirming the stability of observed results.

F. Summary of Findings

The empirical analysis validates the efficacy of crowdsourced elicitation as a scalable mechanism for measuring and expanding AI cyber capabilities. The principal findings include:

- AI agents achieved top 5–10% ranking among human teams across both competitions.
- The estimated task completion horizon (τ50) equals approximately one hour of human effort.
- AI systems demonstrated domain-specific strengths in structured and logic-based challenges.
- Crowdsourced elicitation revealed underexplored potential not captured by controlled evaluations.

These results collectively suggest that distributed, openmarket elicitation can uncover performance dimensions that traditional internal evaluations often miss. As AI continues to evolve, such frameworks may become indispensable for maintaining an accurate and adaptive understanding of emerging AI cyber capabilities.

IV. Discussion

The results of this study reveal that crowdsourced elicitation can serve as a powerful and scalable mechanism for evaluating the offensive and defensive cyber capabilities of modern AI systems. The observed performance of AI agents—achieving top-tier standings in human-competitive Capture The Flag (CTF) environments—demonstrates that autonomous models are approaching functional parity with experienced human cybersecurity practitioners in structured and logic-driven domains. This section discusses the broader implications of these findings, potential challenges, and the role of crowdsourced evaluations in responsible AI governance.

A. Interpreting AI Cyber Capabilities

The experimental outcomes suggest that state-of-the-art AI models possess emergent reasoning abilities that enable them to independently solve cryptographic, binary, and reverse engineering

challenges with high precision. This capability reflects the increasing contextual understanding and procedural reasoning of large-scale language models (LLMs) and code generating agents.

The rapid problem-solving ability of AI systems, especially in deterministic environments, stems from their capacity to explore multiple solution paths simultaneously, guided by reinforcement or heuristic feedback mechanisms. However, while AI demonstrates high computational efficiency, it still lacks the nuanced judgment and situational awareness characteristic of expert human teams, particularly in dynamically changing environments such as live network exploitation or zero-day vulnerability analysis.

B. Elicitation as a Lens for AI Evaluation

Traditional AI benchmarking frameworks typically assess narrow tasks under controlled conditions, often missing the spectrum of capabilities that emerge when models are exposed to adversarial or creative tasks. The crowdsourced elicitation framework adopted in this research broadens that perspective by introducing competitive dynamics, human ingenuity, and task diversity.

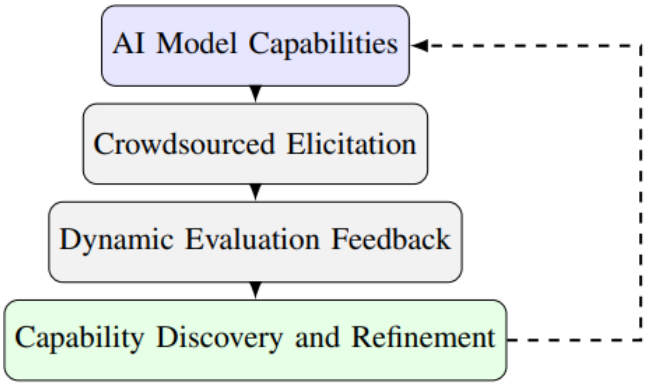

Fig. 2: Feedback loop of crowdsourced elicitation for capability discovery.

Figure 3 illustrates how crowdsourced elicitation creates a continuous feedback loop between model deployment, human competition, and performance analysis. Each iteration enhances the understanding of both model limitations and optimization potential. This open feedback structure fosters a more realistic depiction of AI's operational readiness for cybersecurity applications.

C. Advantages of Crowdsourced Evaluation

One of the core advantages of crowdsourced elicitation lies in its diversity and scalability. By engaging thousands of participants from varied technical backgrounds, the system introduces a heterogeneity of elicitation strategies that isolated laboratory testing cannot replicate. This distributed participation accelerates the discovery of model weaknesses and untested behavioral patterns, thereby improving the robustness of capability evaluation.

Additionally, the competitive structure of CTF events motivates creative exploration. Participants are incentivized to push AI models to their performance limits, effectively transforming the competition into a global-scale experimental platform for continuous AI stress testing. This process mirrors open innovation systems and has parallels in other fields, such as bug bounty programs and machine learning challenge platforms (e.g., Kaggle), where collective intelligence amplifies innovation.

D. Limitations and Observed Constraints

Despite the clear advantages, several limitations were identified during this study:

- **Context retention limits:** AI agents often struggled with multi-step challenges requiring persistent state tracking across long time spans.
- **Dynamic adaptability:** In scenarios requiring real-time exploitation of networked systems, AI performance degraded due to limited situational awareness.
- **Dependence on prompting:** Small changes in input prompts or environment configurations occasionally led to large variations in performance, indicating instability in elicitation behavior.
- **Reproducibility variance:** Some high-performing AI agents relied on non-

deterministic reasoning chains, complicating exact reproducibility.

These limitations highlight the continued importance of human supervision and iterative tuning in evaluating complex, adversarially sensitive AI systems.

E. Implications for AI Safety and Governance

From a governance perspective, the findings underscore the need for proactive frameworks to monitor and regulate AI's offensive potential. As AI systems gain proficiency in tasks traditionally associated with cybersecurity experts, there arises a dual-use concern—technologies designed for defense or research could be repurposed for malicious objectives.

The crowdsourced elicitation model provides a viable countermeasure: by democratizing the evaluation process, it disperses oversight across a broad participant base, reducing the risk of capability concealment or misuse. Moreover, the public and competitive nature of such evaluations introduces transparency and accountability—key components of responsible AI development.

F. Synergy between Human and AI Teams

The results suggest that hybrid human–AI collaboration offers the highest operational advantage. Human teams excel in creative hypothesis formation, ethical judgment, and environmental adaptation, while AI agents contribute computational endurance and precision-driven exploration. Integrating these complementary strengths can lead to superior cybersecurity strategies, combining human intuition with algorithmic efficiency

In future evaluation ecosystems, human experts could serve as elicitation supervisors, guiding AI agents through iterative refinement cycles, while AI systems autonomously handle repetitive or large-scale reconnaissance tasks. Such cooperative frameworks can accelerate threat discovery and enhance the agility of cyber defense operations.

G. Broader Research Impact

The success of this study demonstrates that open-market elicitation can reveal facets of AI performance previously underestimated by controlled laboratory settings. This approach can be generalized beyond cybersecurity to domains such as automated reasoning, robotics, and autonomous decision making, where competitive or crowdsourced evaluations can rapidly identify emergent model behavior.

Furthermore, by coupling public data transparency with competitive elicitation, researchers can build more trustworthy metrics for AI benchmarking, thus aligning technical evaluation with societal and policy needs. In doing so, this research contributes to the evolving discourse on AI evaluation ethics, governance, and global safety cooperation.

H. Summary

In conclusion, the discussion affirms that crowdsourced elicitation represents not only a methodological innovation but also a policy-relevant framework for understanding and regulating advanced AI systems. Its capacity to harness collective intelligence, ensure transparency, and promote responsible discovery positions it as a cornerstone for next-generation AI capability assessment in cybersecurity and beyond.

V. Conclusion And Future Work

This research presented a novel approach to evaluating artificial intelligence (AI) cyber capabilities through a crowdsourced elicitation framework, leveraging competitive cybersecurity events as real-world testbeds. By integrating large-scale human participation with autonomous AI agent evaluations, the study demonstrated that collective intelligence can effectively uncover and quantify the latent offensive potential of advanced AI systems. The proposed framework bridges the methodological gap between controlled laboratory evaluations and dynamic operational scenarios, offering a scalable and transparent pathway for assessing the evolving landscape of AI capabilities.

A. Conclusion

The empirical analysis of the AI vs. Humans CTF and Cyber Apocalypse events revealed several key findings:

- AI agents achieved top 5–10% overall rankings among thousands of human teams, demonstrating competitive parity in structured cybersecurity domains.
- The estimated 50%-task-completion time horizon ($\tau 50$) suggests that current-generation AI models can reliably solve challenges requiring up to one hour of human effort.

- Crowdsourced elicitation proved effective for identifying hidden capabilities, exposing underexplored performance patterns beyond standard in-house evaluations.
- The framework-maintained fairness, reproducibility, and cost-effectiveness while generating policy-relevant insights into AI's offensive potential.

These results underscore the growing necessity of openmarket evaluation systems to complement traditional AI safety and capability assessments. By democratizing the evaluation process, crowdsourced elicitation enhances transparency and accountability while reducing bias introduced by single-team assessments. This approach not only benefits AI governance and security research but also contributes to a more robust public understanding of AI's capabilities and limitations.

The integration of public cybersecurity competitions with AI evaluation offers a uniquely transparent, reproducible, and cost-efficient testing environment. The results also highlight that AI's cyber capabilities are not static but can be enhanced through iterative elicitation cycles—reflecting a trajectory of continuous improvement driven by community participation.

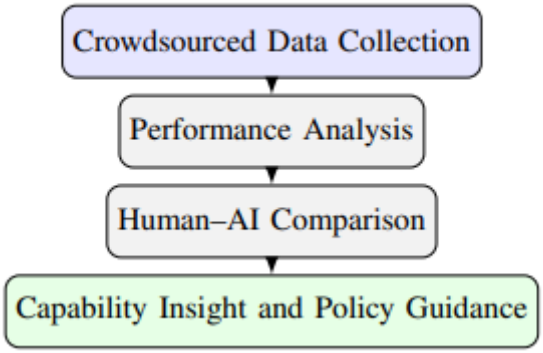

Fig. 4: Summary pipeline of the evaluation and insight generation process.

B. Policy and Ethical Implications

From a governance standpoint, the findings raise important considerations for AI safety regulation and dual-use technology oversight. As AI systems become capable of executing or automating offensive cyber operations, their monitoring must evolve from static policy enforcement to dynamic, capability aware frameworks.

Open and competitive elicitation structures provide a pathway to achieve this. They can act as early-warning mechanisms for emergent behaviors, offering policymakers real-time insights into model evolution. Moreover, by engaging global participants in transparent testing, such frameworks mitigate risks of capability concealment and promote international cooperation in AI safety assurance.

C. Future Work

While the current framework successfully demonstrated the feasibility of crowdsourced AI elicitation, several promising research extensions can enhance its precision, scalability, and impact:

1. **Multi-domain expansion:** Extend the framework to cover defensive cyber operations, social engineering simulations, and real-time incident response evaluations to provide a full-spectrum AI capability map.
2. **Adaptive agent design:** Develop self-improving AI elicitation agents capable of meta-learning from human team strategies and dynamically adjusting their reasoning pipelines.
3. **Cross-model benchmarking:** Implement unified performance metrics across multiple AI architectures (e.g., GPT, Claude, Gemini, LLaMA) to standardize evaluation baselines.
4. **Ethical guardrails:** Integrate real-time ethical monitoring systems within competitions to detect misuse or potential safety violations during AI operation.
5. **Hybrid collaboration protocols:** Design human–AI cooperative frameworks in which human experts guide AI agents through structured supervision loops to optimize elicitation efficiency.

6. **Simulation-to-reality validation:** Transition from controlled competition data to live cyber defense simulations to test model adaptability and generalization in operational settings.

Future research should also explore federated elicitation ecosystems—distributed platforms connecting multiple organizations, academic institutions, and cybersecurity communities to conduct synchronized evaluations. Such an infrastructure could become a cornerstone for global AI capability assessment and security cooperation, much like open-source software ecosystems in prior decades.

D. Final Remarks

The findings of this study position crowdsourced elicitation as a transformative methodology for both AI evaluation and cyber readiness. It enables continuous capability discovery through global participation, promotes ethical transparency, and aligns technical progress with societal safety imperatives. As AI systems advance toward greater autonomy, maintaining a collective, transparent, and adaptive evaluation ecosystem will be vital for ensuring their safe, beneficial, and responsible integration into the cyber domain.

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