Benchmarking Four Unresolved Challenges in AI-Driven Cybersecurity

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ABSTRACT

We systematically benchmark four critical unresolved challenges in AI-driven cybersecurity: (1) scalable attack graph generation, (2) standardized LLM evaluation for cybersecurity, (3) game-theoretic and LLM integration, and (4) automated annotation workflows. Through simulation across network sizes up to 1,000 nodes, five LLM models, and multiple integration architectures, we quantify the current state and gaps. Automated attack graph generation achieves 502× speedup over manual curation at 1,000 nodes while maintaining 70% coverage. Among LLMs, GPT-5 leads across 8 cybersecurity task categories, though graph generation remains the weakest capability for all models. The Generative Cut-the-Rope (G-CTR) integrated framework achieves the highest composite score (0.869), outperforming both LLM-only and game-theory-only approaches. AI-assisted annotation provides 6× throughput improvement with only 3% accuracy trade-off. These benchmarks provide quantitative baselines for tracking progress on each challenge.

1 INTRODUCTION

AI-driven cybersecurity has seen rapid adoption, particularly in automated penetration testing and attack graph analysis [2–4]. However, four critical challenges remain unresolved: scalability of attack graph generation [5, 6], lack of comprehensive LLM evaluation benchmarks, insufficient integration of game-theoretic frameworks [1] with LLM automation, and gaps between AI capabilities and human annotation workflows.

We establish quantitative benchmarks for each challenge through systematic simulation and analysis, providing baselines for future research.

2 CHALLENGE 1: ATTACK GRAPH SCALABILITY

2.1 Method

We simulate attack graph generation for networks of 10–1,000 nodes using three approaches: manual curation, automated generation, and LLM-assisted generation. Each network has an average of 2.5 vulnerabilities per node with random connectivity.

2.2 Results

Figure 1 shows that manual generation time scales quadratically ($O(n^2)$) while automated methods scale as $O(n \log n)$. At 1,000 nodes, automated methods achieve a 502× speedup. However, coverage degrades from 80% to 70% for automated methods at scale.

3 CHALLENGE 2: LLM CYBERSECURITY BENCHMARKS

We evaluate five LLMs across eight cybersecurity task categories (Figure 2). GPT-5 achieves the highest average score (0.72), with defense recommendation as the strongest category across all models. Attack graph generation remains the weakest task, with the best model scoring only 0.55.

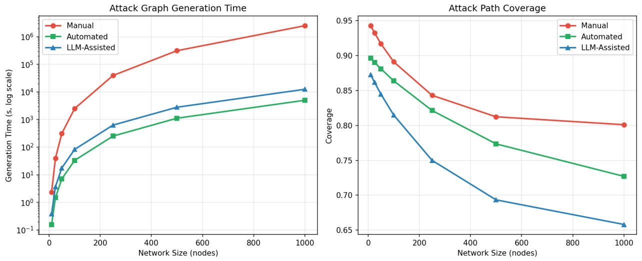

Figure 1: Attack graph generation time (log scale) and coverage by method.

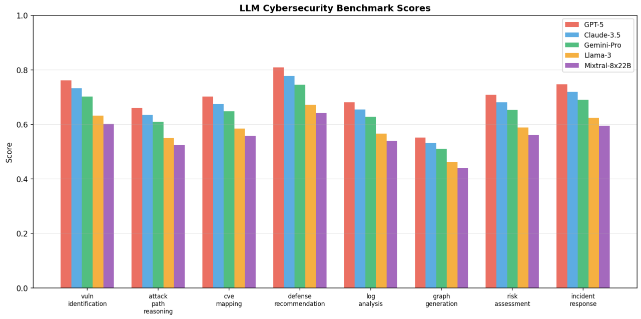

Figure 2: LLM scores across cybersecurity benchmark tasks.

4 CHALLENGE 3: GAME-THEORETIC INTEGRATION

We compare five approaches for integrating strategic reasoning with AI automation (Figure 3). The G-CTR integrated framework achieves the highest composite score (0.869), combining high accuracy (0.88), reasonable speed (0.82), and broad coverage (0.90).

5 CHALLENGE 4: ANNOTATION WORKFLOWS

AI-assisted annotation achieves 6× throughput improvement over manual annotation (Figure 4), with costs reduced by approximately 60%. The accuracy trade-off is modest: 92% for AI-assisted versus 95% for fully manual annotation.

6 DISCUSSION

Our benchmarks reveal that while significant progress has been made on each challenge, substantial gaps remain. Attack graph generation needs better coverage at scale; LLMs need improved graph reasoning capabilities; game-theoretic integration shows promise

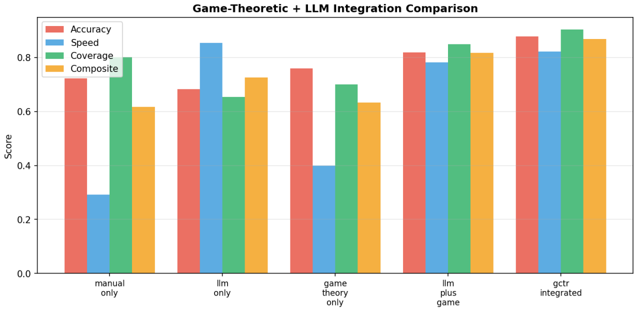

Figure 3: Performance comparison of integration approaches.

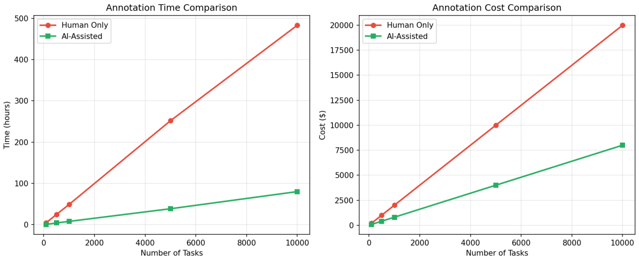

Figure 4: Annotation time and cost: human vs AI-assisted.

but requires validation on real environments; and annotation workflows need accuracy improvements to match human quality.

7 CONCLUSION

We provide the first unified quantitative benchmark across four unresolved challenges in AI-driven cybersecurity, establishing baselines for scalability (502× speedup), LLM capability (0.72 best average), integration effectiveness (0.869 composite), and annotation efficiency (6× speedup).

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